A COMPARATIVE EVALUATION OF DATA MINING CLASSIFICATION TECHNIQUES ON MEDICAL TRAUMA DATA

An Empirical Research Report

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By

Kutlwano K.K.M Ramaboa

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Supervisor: Prof. Trevor Wegner

PREFACE

This report is not confidential, and may be used freely by the Department of Statistical Sciences, University of Cape Town.

I wish to thank the following:

- Prof. T Wegner, my supervisor, for believing in me, and for the valuable advice and professional guidance.
- Francina, my mother, who made this possible.
- Robert.
- The Red Cross War Memorial Children's Hospital, especially Nelmarie du Toit and Dr Sebastian van As, who helped me understand the hospital's database.

DECLARATION:

I certify that, except for the support noted above, this research is my own work, and that none of the material has been plagiarized. All references used are accurately reported and identified in the bibliography.

Signed: Ramaboa (Kutlwano K.K.M Ramaboa) Date: June 2004

SYNOPSIS

The purpose of this research was to determine the extent to which a selection of data mining classification techniques (specifically, Discriminant Analysis, Decision Trees, and three artificial neural network models – Backpropagation, Probabilistic Neural Networks, and the Radial Basis Function) are able to correctly classify cases into the different categories of an outcome measure from a given set of input variables (i.e. estimate their classification accuracy) on a common database. The medical child trauma data from the Red Cross War Memorial Children's Hospital (Cape Town) was used to illustrate the degree to which the various data mining classification techniques are able to reproduce the assignment of patients (i.e. re-classify patients) into the different known outcomes of child trauma injuries (*viz.* assault, burn, fall, miscellaneous, transport, and unknown).

Due to software limitations and the computational time required on some of the classification techniques, twenty samples of approximately 5000 patient records from a database containing 89780 records of patients who had been to the hospital between June 1991 and December 2001 were analysed. The following variables - 'Abuse', 'Admission', 'Age', 'Anaesthetic', 'Anatomy', 'Pathology', 'Place', 'Race/Gender', 'Resuscitation', 'Year of birth', and 'Treatment', were found to be important in predicting (i.e. reproducing) the outcomes of medical child trauma injuries.

Major Findings

The data mining classification techniques were compared in relation to their accuracy in the re-classification of the outcomes of medical child trauma injuries. Of the five classification techniques investigated, the predictive ability of the probabilistic neural network, was superior to the other techniques in this research (an average of 66.8530% of cases were correctly classified by the model, across all twenty samples), whilst the radial basis function network, gave the lowest classification results (an average of 59.3691% of cases were correctly classified by the model, across all twenty samples). The predictive ability of the decision tree trained using the CART algorithm, discriminant analysis, and the backpropagation neural network, were comparable (an average of 63plus% of cases were correctly classified by the techniques, across all twenty samples).

Major Conclusions and Recommendations

Of the five classification techniques, the decision tree trained using the CART algorithm was found to be the most thorough technique in predicting the known outcomes of medical child trauma injuries, not only because of its ability to replicate the *a priori* outcomes of medical child trauma injuries better than the other techniques on balance (per category), but it was the only technique that was able to simultaneously manage large amounts of data, is accurate, interpretable and comprehensible. This study therefore recommends that decision trees grown using the CART algorithm be considered ahead of other classification techniques when seeking predictions in new/unknown medical trauma cases.

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CHAPTER 1 INTRODUCTION

The primary focus of this thesis is on data mining, in particular, the performance of five data mining classification techniques when applied to medical trauma data from the Red Cross War Memorial Children's Hospital in Cape Town.

1.1 Problem Background

Data mining is defined by Hand, Mannila, and Smyth (2001) as the "analysis of (often large) observational data sets to find unsuspected relationships and to summarise the data in novel ways that are both understandable and useful to the data owner". This definition mentions the use of large quantities of historical data sets - 'observational data', which suggests that data mining deals with data that has already been collected for some purpose other than for data mining.

The growth of data has come about as a result of the advancement of computer processing and storage technologies over the past few decades. This has forced organisations to move away from traditional ways of keeping data (such as production reports, managed queries, executive information systems, and online analytical processing), and to store the hundreds of gigabytes or even terabytes of data online (Bigus, 1996). According to Hand et al. (2001) "it was from the growth of the databases that interest grew into the possibility of tapping these data and extracting from them information that might be of value to the owner of the database", hence the employment of data mining techniques, to reveal hidden information in the form of facts, rules and graphical representations of the data (Bigus, 1996).

Data mining is being applied anywhere where there are large quantities of data - for example, in the medical, science, commerce, and finance arenas, for activities that include prediction, time series forecasting, clustering, modelling, summarisation, visualisation etc. These data mining activities can be categorised into two goals -- directed and undirected data mining (Berry & Linoff, 2000).

In directed data mining (also known as dependence techniques), interesting patterns are extracted by describing one variable of interest in terms of the rest of the available variables; and in undirected data mining (also known as interdependence techniques), there is no single variable of interest, instead interesting patterns are extracted by establishing some relationship among all the variables.

1.1.1 The Role of Statistics in Data Mining

Data mining is complementary to other data analysis techniques such as statistics. The major difference between the two approaches is in terms of data size (Hand et al., 2001) – data mining requires gigabytes and terabytes of data that have already been collected, whereas with statistics, the data are not so large, and "are collected with particular questions in mind, and then analysed to answer those questions". Data mining however, applies techniques used in statistics; these include inter alia, standard exploratory techniques, predictive techniques such as regression, discriminant analysis, and decision trees; and descriptive techniques such as cluster analysis.

There are instances where traditional statistical techniques cannot capture the complex relationships between the data, and "it is here where advantages of using data mining techniques such as neural networks are really compelling" Bigus (1996). Other non-statistical areas that data mining draws on include machine learning, and database technology (Hand et al., 2001).

1.1.2 The Data Mining Process

Data mining is part of the larger process called the knowledge discovery in databases (KDD) process which "consists of applying data analysis and discovery algorithms" Fayyad, Piatesky-Shapiro, and Smyth (1996) that organisations use to extract knowledge from their databases.

The data mining process can be represented by the following seven-step model (see Figure 1.1 below):

Step 1 - the requirements or goals of an organisation are identified.

Step 2 - suitable data is selected. Often, someone who understands the data is needed to aid the knowledge seeker (that is, the data miner).

Step 3 - the data is prepared for analysis - according to Bigus (1996) "IBM and independent consultants confirm estimates that data preparations might take anywhere between 50% and 80% of the resources spent in a data mining operation".

Steps 4 to 5 - the necessary data mining tools and techniques, such as traditional statistical techniques and neural networks are applied on the function to be performed (for directed data mining, the data is usually split into training and testing samples (to run and test the performance of the technique respectively).

Steps 6 to 7 - the model is then deployed and the results assessed to determine the model's return on investment. This last step is the most important of the data mining process, because a good model allows for benefits of data mining to be measured. For optimal results, if the data miner is not satisfied with the outcome, the process is repeated and re-evaluated.

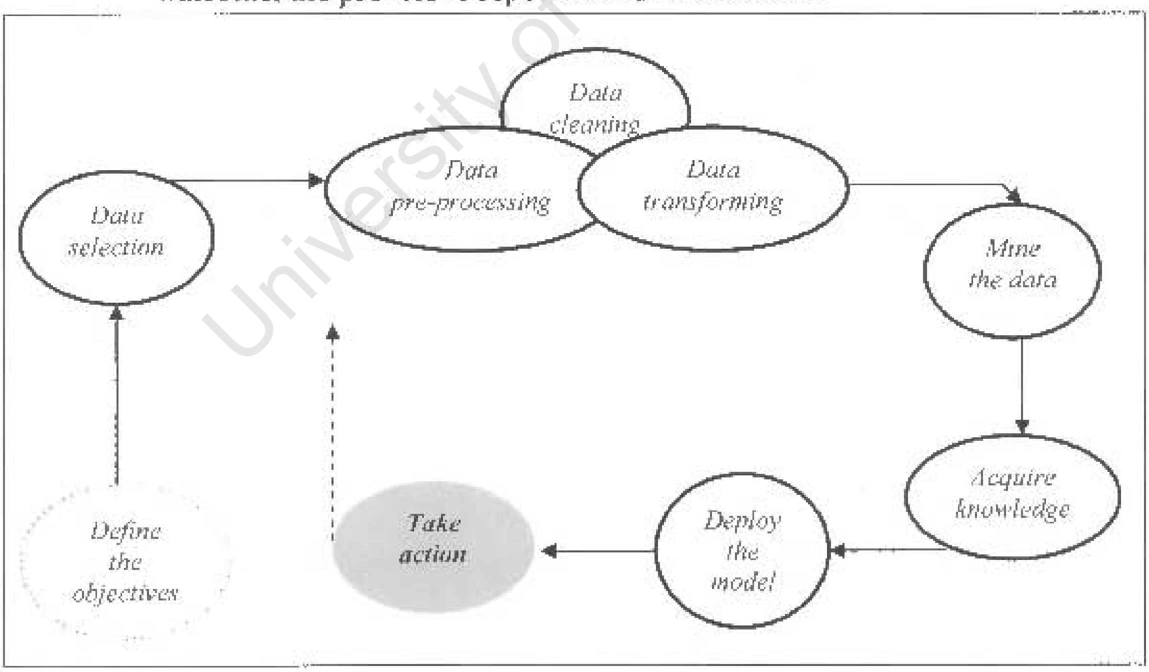


Figure 1.1 The Data Mining Process (*Adapted from literature*, and Lin & McClean (2001))

1.2 Statement of the Problem

For this research, the goal is prediction, a directed data mining activity which involves "using some variables or fields in the database to predict unknown or future values of other interest" (Fayyad et al, 1996). There are two types of prediction problems (Apte & Weiss, 1997) – classification and regression. Classification involves "assigning an object to one of a number of predetermined groups on the basis of observations made on the object" (James, 1985), thus it is used when the variable of interest (target measure) being predicted is categorical in nature. On the other hand, regression is used when the target measure being predicted is continuous.

In this study, the objective is to determine, using the medical trauma data with *a priori* known outcomes of child trauma injuries (*viz.* assault, burn, fall, miscellaneous, transport, and unknown) for illustrative purposes, the extent to which different data mining techniques are able to correctly reproduce the classification of cases (i.e. patients) into the different outcomes of child trauma injuries from a given set of input variables. Since the target measure being predicted is categorical in nature, we are looking at a classification problem.

1.3 Motivation for Research

Most organisations require managers to continuously make classification decisions that are often based on what happened in the past. For example, bank managers need to make decisions about approving or disapproving a loan for a credit application; doctors need to make decisions on whether a patient is likely to get cancer or not, retailers need to be able to identify customers who are likely to switch to another provider, manufacturers need to predict customers who will submit warranty claims, etc.

This research was encouraged in part by Dr Sebastian van As, head of the Red Cross War Memorial Children's Hospital's trauma unit. The hospital approached the Department of Statistical Sciences at the University of Cape Town because they needed to find a better way of capturing the information from the Trauma Unit Record (refer to Appendix B), and it was from these discussions where the idea of finding a technique that could 'confirm' or reproduce the assignment of known categories of an outcome measure from a given set of input variables evolved, hence the use of the medical trauma data to illustrate the data mining methodology.

Several classification techniques such as linear discriminant analysis, kernel density estimators, *K*-nearest neighbour, decision trees, and artificial neural networks exist which are used for classification of cases in data mining. These techniques encompass statistical, machine learning, and connectionist approaches, and they all have their strengths and weaknesses for different applications and data types. For this research, due to software limitations and the nature of the target measure being predicted, the following five data mining classification techniques were chosen for comparative purposes – decision trees grown using the CART algorithm, discriminant analysis, backpropagation neural network, probabilistic neural network, and radial basis function.

1.4 Likely Contributions to Knowledge

The benefits are two-fold:

- To illustrate the extent to which the various data mining classification techniques are able predict or extract known outcomes of EGS
to replicate/reproduce the known outcomes of child trauma injuries based on a given set of input measures.
- GES.
To assess the usefulness of the data mining process when applied to medical child trauma data.

1.5 Research Objectives

The following objectives have been identified for this research:

Primary objectives:

- To determine from a subset of identified classification techniques, the technique that most accurately reproduces the known outcomes of child trauma injuries.

- To determine from a subset of identified classification techniques, the technique that could be used with ease to reproduce the known outcomes of child trauma injuries, and possibly classify future unknown child trauma cases.

Secondary objectives:

- To determine the accuracy of each of these techniques in classifying (i.e. reproducing) the different category outcomes of child trauma injuries.

- To uncover from the twenty-two questions on the Trauma Unit Record those that will help better classify (i.e. reproduce) the outcomes of child trauma injuries.

- To assess the usefulness of the data mining process when applied to medical child trauma data.

1.6 Research Hypotheses

The research objectives can be expressed as the following hypotheses:

Primary Hypotheses:

- There is no difference in the classification accuracy between all the different techniques that have been proposed for this research.

- All the various classification techniques can be used with ease to reproduce the known outcomes of child trauma injuries.

Secondary Hypotheses:

- The accuracy of each technique in classifying the different category outcomes of child trauma injuries is the same.

- All the twenty-two questions on the Trauma Unit Record are important in the classification of the category outcomes of child trauma injuries.

- The data mining process can be applied successfully on medical child trauma data.

1.7 Review of Comparative Studies

Several empirical studies have been carried out on the selection of data mining classification techniques identified for this research in a number of domains:

- Lin & McClean (2001) studied the differences between discriminant analysis, logistic regression, neural networks, C5.0 decision tree, and hybrid classifiers to predict corporate failure. Decision trees and neural networks were found to provide better results.

- Grassi, Caricati, Intraligi, Buscema, and Nencini (2002) compared the performance of linear discriminant analysis and backpropagation neural network in predicting substitutive therapy received by intravenous drug users (IDUs) prescribed by medical staff. The backpropagation network performed better than discriminant analysis.

- West, D (2000) investigated the credit scoring accuracy of five neural network models – backpropagation, mixture-of-experts, radial basis function, learning vector quantization, and fuzzy adaptive resonance, and compared them with linear discriminant analysis, logistic regression, *K*-nearest neighbour, kernel density estimators and decision trees. The results of the research suggest that mixture-of-experts and radial basis function neural networks outperform the other techniques in determining credit scoring applications.

- Platt, Platt, and Yang (1999) compared the performance of two varieties of probabilistic neural networks - (one with normalised input data and the other without normalisation), the backpropagation network, and discriminant analysis, in predicting the bankruptcy of U.S. oil and gas companies. They found that the backpropagation and probabilistic neural network without pattern normalisation and discriminant analysis produced superior estimation results for bankrupt companies, than the probabilistic neural network with normalised data. The percentage of correctly classified companies using the probabilistic neural network without pattern normalisation was 74%, whilst that of the probabilistic neural network normalised data was 66%.

- Liebich, Shan, Xu, Zhang, and Zhao (2002) used the probabilistic neural network, the learning vector quantization network, and discriminant analysis, to distinguish cancer patients from healthy persons according to the levels of nucleosides in human urine. Both the probabilistic neural network and the learning vector quantization network were able to correctly classify the patients well (85% of patients were correctly classified), whilst the accuracy of discriminant analysis was comparable to the other two techniques (80% of patients were correctly classified).

The studies above show no clear pattern of techniques producing consistently good results, and in our search for comparative studies, we have not come across any research that jointly compares the performance (that is, the predictive accuracy) of the different neural network models, discriminant analysis and decision trees, using medical child trauma data. There has also been little research conducted in the medical domain that applies data mining techniques, and some of the reasons for this lack of "progress" in the healthcare arena as cited by Adya & Werts (2001) include the difficulty in finding accurate and complete data, and the unwillingness of hospitals to share data for privacy reasons.

1.8 Limitations of Research

As mentioned above, the focus of this study is on the classification activity, and not the other activities of data mining such as clustering, forecasting, etc. The analysis of results was limited to a selection of statistical techniques and neural network models that are typically used for classification. These are: classification trees grown using the CART algorithm, generalised discriminant analysis, the backpropagation network with one layer of hidden nodes, the probabilistic neural network, and the radial basis function network.

Other limitations to the research were:

- *Computational time* - due to the computational time required to process data in some of the techniques, the results were generated based on twenty samples of approximately 5000 cases each. The results were repeated in order to try and use all the available data, and to confirm the stability of the techniques over various samples.

- *Assumptions* - for discriminant analysis, a detailed analysis has not been done to check if all the requirements of optimality were met.

- *Setting of parameter values* - all the techniques were mostly run using the default settings in the statistical package used for the analysis since it was not possible to explore all the different combinations of parameters, though the parameter values were set to be constant across the various techniques[1].

- *Database restrictions* - the database used for this research was restricted to children (19 years and under) who were admitted to the trauma unit of the Red Cross War Memorial Children's Hospital in Cape Town between June 1991 and December 2001. Since up to four injuries (could be one or multiple visits to the hospital) can be recorded on the Trauma Unit Record (refer to Appendix B) per patient, for this study we only considered a patient's injury which was first recorded because of the large number of missing values for the subsequent injuries/visits. In order to maintain patient privacy, folder numbers have been omitted from the analysis.

[1] We do acknowledge that different results may follow if different values of the parameters are set.

1.9 Structure of the Research

The theoretical backgrounds of the different data mining classification techniques that are being compared in this research have been separated into different chapters as follows:

In Chapter 2 we consider tree-structured methods used for classification. Here the stages involved in growing an optimal decision tree are described, and then a detailed description of how CART grows an optimal tree is given. Linear Discriminant Function Analysis, a statistical classification technique, is the subject of Chapter 3. Here, the different procedures used to evaluate the performance of discriminant analysis, the test and different criteria used to find discriminating variables are considered.

The focus of Chapters 4 and 5 is on artificial neural networks. More specifically, Chapter 4 is a general introduction to artificial neural networks. Here we briefly discuss the biological motivation for artificial neural networks, followed by a brief historical overview of the research into artificial neural networks. Later, we look at the four different types of artificial neural network architectures, the different methods used to set connection weights between layers in a network, and the transfer functions commonly used on the network's weighted input signal.

In Chapter 5, we look at the supervised neural networks commonly used in classification problems: the Backpropagation network, the Probabilistic neural network, and the Radial Basis Function network. For each network, we look at its architecture, how the network is trained, some of its advantages and disadvantages, and a few application areas in practice.

Chapter 6 looks at the methodology employed in attaining the results for the different data mining classification techniques being investigated in this research, and Chapter 7 examines the results obtained from the analysis of the different classification models when applied to the trauma data. In Chapter 8 we discuss the results, evaluating the accuracy and usability of each technique in order to come up with the classification technique that can be used to confirm the assignment of cases of a known outcome measure. Finally, in Chapter 9, we draw conclusions and make the necessary recommendations.

CHAPTER 2 DECISION TREES

In this chapter we look at the use of tree-structured methods in classification problems. In Section 2.1 we give a general definition of decision trees, then look at how they are grown, and the methods used to limit the growth of the tree. In Section 2.2, a detailed description of how CART grows a decision tree and the methods it uses to obtain the best tree is given. We conclude the chapter by looking at some advantages, disadvantages, and applications of decision trees in practice.

2.1 Definition of a Decision Tree

A decision tree is a top-down tree-structured classification technique, whose objective is to provide a rule for predicting the values of the dependent variable[1], based on the values of its independent[2] variables (Breiman, Friedman, Olshen, and Stone, 1984). The tree is made up of nodes and branches (see Figure 2.1), and at each node of the tree, there is a classification question that partitions (represented by branches) the data into subsets. The node that contains the initial data is called the root node (t_1), and nodes below the root node that are split further are called non-terminal nodes, children, or offspring (t_2 and t_3). A node with branches below it is also called a parent node (could be a root or non-terminal node), whilst those nodes where no further splitting occurs are called terminal nodes or leaves (t_4, t_5, t_6, and t_7).

[1] A dependent variable (also known as a response, target, objective, or output variable) is a random variable under study (van den Honert, 1997).

[2] An independent variable (also known as a feature, factor, explanatory, or input variable) is a random variable that is assumed to influence the outcome of the dependent variable (van den Honert, 1997).

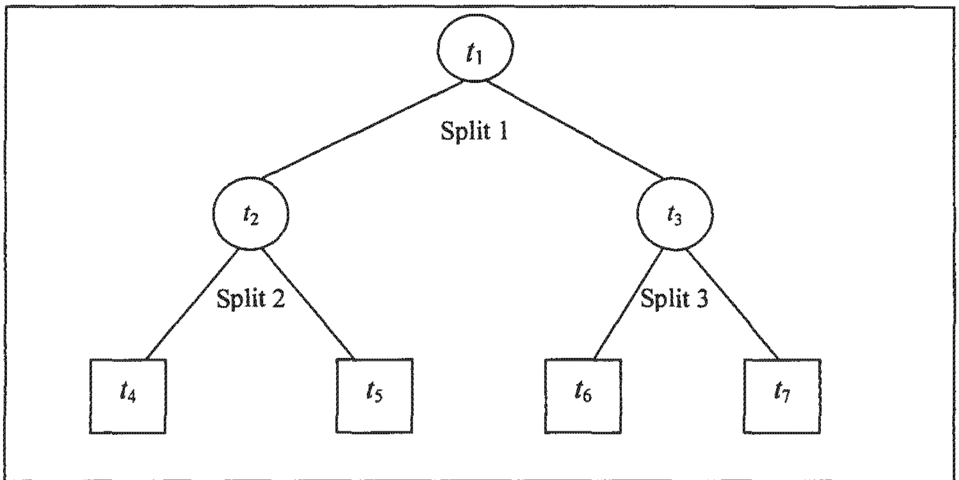


Figure 2.1 A Decision Tree (*Source*: Breiman et al., 1984)

There are two main types of decision trees, and these depend on the nature of the dependent variable:

- *Classification trees*: the decision tree produced when the dependent variable is categorical (that is, measured on a nominal scale). The independent variables used can be continuous and/or categorical.

- *Regression trees*: the decision tree produced when the dependent variable is continuous (that is, measured either on an interval or ratio scale). The independent variables used can be continuous and/or categorical. However if an independent variable is categorical, the variable should be binary encoded (i.e. representing the categories of a variable in binary form) to make it numeric.

The two types of decision trees have the same basic structure: when cases are fed to the tree, they are partitioned recursively[3], and during each iteration, the cases are split on the independent variable that produces the most effective classification, until it reaches the terminal nodes. The terminal nodes represent the classification of cases. Thus for classification trees, the

[3] Recursive partitioning is defined by Berry & Linoff (2000), as "an iterative process of splitting the data up into partitions, and then splitting it some more until no more useful splits can be found".

label assigned to a terminal node represents the distinct groups (categories) of the dependent variable (cases are assigned to a group based on their 'similarity', in terms of values of the independent variables). For regression trees, each terminal node is "assigned a value based on the mean (or some other mathematical function) of the values that reached that node" Berry & Linoff (2000). Note that at any level of the tree, once a split is made, the resulting nodes are also assigned a label.

There are various decision tree algorithms, and according to Berson, Smith, and Thearling (1999) early versions of the algorithms date back to the 1960s. These include inter alia: CART (Classification and Regression Trees), ID3 (Induction of Decision Tree) and its successors C4.5 and C5.0, CHAID (Chi-Square Automatic Interaction Detection), IC (Interval Classifier), and QUEST (Quick Unbiased Efficient Statistical Tree). The differences in the constructions of the trees produced by these algorithms relate to growing the tree, and limiting the growth of the tree.

2.1.1 Growing a Decision Tree

The process of growing a decision tree starts with finding data cases (called the learning sample or training data set) whose values (or outcomes) of the dependent variable are known. The aim is to use this learning sample to 'learn' how to classify cases using the known values of the dependent and independent variables, and then to define a rule that will be used to classify new cases on the basis of the values of its independent variables.

The main concern with growing a decision tree is determining how to partition the data into smaller subsets (could be binary or multiple subsets). This involves finding the best possible distinguishing question to ask at each branch point of the tree (that is, finding the independent variable and its associated value that does the best job of separating the cases). The idea is to select a split such that the data in each of the descendant nodes is 'purer'[4] than the data in the

[4] 'Pure' in the context of decision trees means that the subsets of the learning sample are homogenous with respect to the different groups predicted.

parent node (Breiman et al., 1984).

2.1.2 Limiting the Growth of the Tree

The full initial tree grown is usually very large, which may result in overfitting[5]. Thus splitting is normally continued until one of the following stopping criteria is met (Berson et al. 1999):

- each node is pure (that is, there is no reason to ask further questions because all the remaining cases have identical characteristics), or
- a node satisfies a specified minimum number, or fraction of cases.

Once the tree has been fully grown, some of the nodes and branches (the non-informative ones) are removed to produce a simpler decision tree that classifies new cases as accurately as the initial tree grown (this process is called pruning). Pruning is often used to prevent overfitting by removing the branches that fail to generalise (Berry & Linoff, 2000).

The above concepts are addressed differently by the various decision tree algorithms, as will be illustrated in the next section using CART.

2.2 The CART Methodology

CART, which stands for Classification and Regression Trees (so called because it can produce both classification and regression trees), is a decision tree algorithm developed by Leo Breiman, Jerome Friedman, Richard Olshen and Charles Stone (1984).

[5] Overfitting occurs when a tree memorises the classification of the sample from which it was derived, and is therefore not able to perform well on another sample of cases drawn from the same population (Hand et al., 2001).

2.2.1 Growing a Tree using the CART Algorithm

The CART algorithm partitions data into binary (that is, two discrete) subsets at each branch point of the tree (refer to Figure 2.2). In the figure, t_1 is the root node, non-terminal nodes are represented by circles, terminal nodes are represented by rectangular boxes, and the number below the rectangular boxes represents the group label assigned to that node - in the figure below, there are six *a priori* groups classified. The group label for non-terminal nodes are not shown.

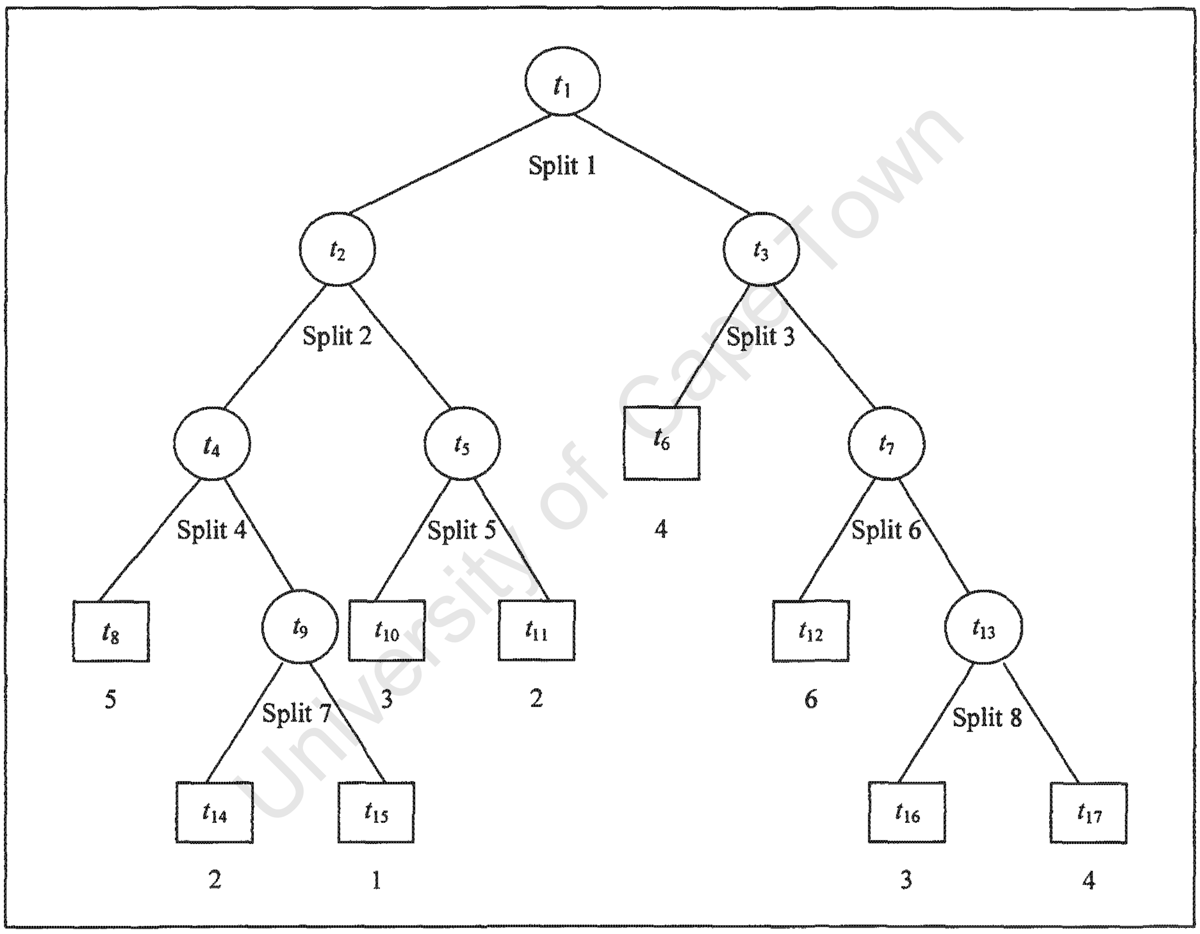


Figure 2.2 A Binary Decision Tree (*Source*: Breiman et al, 1984)

The question asked at each branch point of the tree depends on the nature of the independent variable:

- if X is a continuous variable, then the CART methodology searches over all possible values c for splits of the form: $X \leq c$ at each node, for all c ranging over $(-\infty, \infty)$.

- if X is a categorical variable, then the CART methodology searches over all possible values D for splits of the form: $x \in D$ where $D \subset X$.

For any split, υ, a case is sent to the left subnode if the inequality is satisfied and to the right subnode otherwise. According to Breiman et al. (1984) there are a finite number of possible splits that must be examined at each node, and these depend on the nature of the independent variable:

- for a continuous variable with r distinct values, the number of permissible splits is $r - 1$, each possible position being located halfway between two data points (Hand et al., 2001).

- for a categorical variable with k distinct categories, the number of permissible splits is $2^{k-1} - 1$ if the variable is nominal, and $k - 1$ if the variable is ordinal.

The following notations will be adopted in demonstrating the methods used in growing a decision tree using CART:

t	the parent node
t_l	the left node
t_r	the right node
n_t	the number of cases associated with the parent node
n_{tl}	the number of cases associated with the left node
n_{tr}	the number of cases associated with the right node
n_{tj}	the number of cases of node t with j number of groups, where $j = 1, 2, \ldots J$
$p(tl) = \frac{n_{tl}}{n_t}$	the proportion of cases of node t that go to the left node

$p(tr) = \frac{n_{tr}}{n_t}$ the proportion of cases of node t that go to the right node. (*Note*: $p(tl)+p(tr) = 1$)

$p(j|t)$ the proportion of the cases in node t that belong to group j, for $j = 1, 2, \ldots J$ and $\sum_{j=1}^{J} p(j|t) = 1$).

$C(i|j)$ the cost of misclassifying a group j case as a group i case, where

$$\begin{cases} C(i|j) \geq 0 & i \neq j \\ C(i|j) = 0 & i = j \end{cases}$$

a) Selection of Splits

CART uses a number of impurity measures, that is, measures of homogeneity, to split the data. Since the dependent variable used in this research is categorical, we only consider impurity measures used for classification trees. These measures are derived from the impurity function, which is defined as a nonnegative function, φ, of the probability of a case belonging to each of the J groups of the dependent variable, that is:

$$\varphi(p(1), p(2), \ldots, p(J)) \qquad \text{where } p(j) \geq 0 \qquad \text{for } j = 1, \ldots, J \quad \text{and} \quad \sum_j p(j) = 1.$$

From the impurity function, we derive the impurity index, $i(t)$ (a function of the probability of a case belonging to each of the J groups), at any node t, that is:

$$i(t) = \varphi(p(1|t) + p(2|t) + \ldots + p(J|t)) \text{ for } j = 1, \ldots, J$$

Thus when a node is pure, $i(t) = 0$, and when a node contains all groups with equal relative proportions, then $i(t) = \max$. For any split, υ, we define the goodness of split, $\Delta i(\upsilon, t)$, to be the decrease in impurity (or increase in homogeneity), that is:

$$\Delta i(\upsilon, t) = i(t) - p(tr)i(t_r) - p(tl)i(t_l)$$

At any node *t*, the independent variable (and its associated value) that is adopted is the one that maximises the goodness of split between the parent node and its children, since this is equivalent to selecting those splits that minimise the overall tree impurity, *i*(*t*). There are various impurity indices used in CART, and they are (Breiman et al (1984), Aluja-Banet & Nafia: Blasius & Greenacre (1998), Cronin & Worth (2003):

- *The Gini Index* (also known as Simpson's diversity):

$$i(t) = \sum_{j \neq i} p(j|t)\,p(i|t) = 1 - \sum_{j} p(j|t)^2$$

Using the Gini index, the independent variable that is adopted is the one that gives the largest decrease in diversity.

- *The Twoing Index*:

$$\varphi(\upsilon, t) = \frac{p(tl)p(tr)}{4}\left(\sum_{j} \left| p(j|t_l) - p(j|t_r) \right| \right)^2$$

The twoing index works by dividing the *J* number of groups of the dependent variable into two clusters at each node that are similar in some characteristic, such that "considered as a two-group problem, the greatest decrease in node impurity is realised" Breiman et al. (1984), when the cases are partitioned.

- *Misclassification Costs*:

The proportion of cases misclassified by the tree, known also as the error rate, or resubstitution estimate, *r*(*t*), is derived by estimating the expected misclassification cost of a randomly selected case of unknown group falling into *t* and classified as belonging to group *i*. The idea here is to select *i* to minimise this estimate. That is, assuming equal misclassification costs:

$$r(t) = \min_i \sum_j C(i \mid j) p(j \mid t) = 1 - \max_j p(j \mid t)$$

- *Deviance*

The deviance (D_i) of a node t is given by:

$$D_i = -2 \min_i \sum_j n_{ij} \log p(j \mid t)$$

A pure node will have a deviance of zero, whilst a node that contains all groups with equal relative proportions will have an increasingly positive deviance.

- *Entropy*

Given a probability distribution, entropy is the information needed to identify the probability distribution conveyed in the partitioning of cases into the J groups of the dependent variable, and is defined as:

$$i(t) = \sum_j p(j|t) \log p(j|t)$$

The main idea is to partition the data using the value of the independent variable that increases knowledge by minimising information loss (or reducing entropy) between the parent node and the child nodes. Terminal nodes are reached where no independent variable that produces any gain in information is found. What this implies is that each level of the decision tree shows the order of importance of the independent variables, since the independent variable with the greatest gain among the independent variables not yet considered will be located at the top of the decision tree.

According to Berry & Linoff (2000), there is no single best choice of measure of impurity, hence the analyst must determine the impurity measure that gives the best result for the data set in hand.

2.2.2 Limiting the Growth of a Tree using the CART Algorithm

CART will initially grow a tree until all the cases in a node are pure in some sense, at which point the splitting process is stopped. The initial tree grown is usually very large, and to try and use it for classification purposes would be unrealistic, as the goal for which the tree is grown may be achieved by nodes higher up the tree. Thus the size of the initial tree grown is usually reduced to remove the non-informative subtrees.

a) The Pruning Process

The pruning process starts with the full initial tree grown, which we call T_{max}, and successively removes the non-informative subtrees of T_{max} by measuring the reduction of the error rate for each subtree relative to the size of the subtree. To determine the 'optimal tree' CART uses a minimal cost complexity pruning procedure.

i) Minimal Cost-Complexity Pruning (Weakest-Link Cutting)

To illustrate how the minimal cost-complexity pruning using weakest-link cutting works, we define a cost-complexity measure, $R_\alpha(t)$, for the tree, t, to be (Breiman et al., 1984):

$$R_\alpha(t) = \mathrm{R}(t) + \alpha$$

where $R(t)$ is the resubstitution estimate (or misclassification cost)

α is the complexity parameter (defined as , a penalty imposed for each additional terminal node, where $0 \le \alpha \le 1$)

For any branch t_i, we also define $R_\alpha(t_i) = R(t_i) + \alpha|\tilde{T}_i|$ (where $\tilde{T}_i$ is the number of terminal nodes in t_i). The idea is to find values of α that minimise $R_\alpha(t)$. According to Breiman et al. (1984) as long as $R_\alpha(t_i) < R_\alpha(t)$ the branch t_i has a smaller cost complexity than the single node t, and when the two cost-complexities become equal (at some value of α), the node t will have the smaller cost complexity since it is smaller than t_i, hence will be preferred. To find the value of α at which the two complexity measures are equal, we solve the inequality:

$$R_\alpha(t_i) < R_\alpha(t) \quad \text{that is,} \quad \alpha < \frac{R(t) - R(t_i)}{|\tilde{T}_i| - 1}$$

Now, the weakest link cutting method works by finding the first node at which the two complexity measures are equal. This is repeated for all sub branches, until a tree that is able to generalise is reached.

ii) The Optimal Tree

According to Breiman et al. (1984), choosing the optimal tree is related to giving honest estimates of the error rate $\hat{R}(t_i)$, since the smallest tree of the sequence with minimum error rate is selected. That is, using this estimate, the best subtree t_{i0}, is defined as the subtree that minimises $\hat{R}(t_i)$ such that $\hat{R}(t_0) = \min_i \hat{R}(t_i)$. This growing process however is dependent on the data, which makes the overall tree unstable (or biased). To overcome this, a test sample or a cross validation procedure is used.

1. *Cross Validation*

There are two different types of cross validation procedures, the *test sample* cross validation and the *V-fold* cross validation. In the *test sample* cross validation, the training data is randomly divided into two. One half of the data is used to train the tree and the other half is used to test the tree. Since the training data is randomly divided, the two resulting samples are independent, and the estimator (of the optimal tree) is unbiased. A disadvantage with this approach however is that unless the training data is large, the performance of the optimal tree produced is based on half the data (Ripley, 1996).

A computationally more expensive approach that makes use of all data is the *V-fold* cross validation. Here, the training data is randomly divided into V subsets (V is usually taken as ten (Breiman et al. 1984)), each containing approximately the same number of cases. The tree is then grown using 90% (that is, $(V-1)/V$) of the training data, and the remaining 10% is used to test the tree. This is then repeated V times, using for each repetition, a different test set. The optimal tree selected is the one that has the minimum error.

Breiman et al. (1984) further suggest that the optimal tree should be chosen by gauging the uncertainties in the estimates of the error rate to be within one standard deviation of the minimum (the 1 SE rule). This way the simplest tree is grown whose accuracy is comparable to $\min_i \hat{\mathrm{R}}(t_i)$, that is, the tree selected is t_{i1} where $i1$ is the maximum i satisfying:

$$\hat{\mathrm{R}}(t_{i1}) \leq \hat{\mathrm{R}}(t_{i0}) + \mathrm{SE}(\hat{\mathrm{R}}(t_{i0})).$$

2.3 Advantages and Disadvantages of Decision Trees

Decision trees are a popular data mining classification technique because of the following reasons (Berry & Linoff (2000), Berson et al. (1999), Breiman et al. (1984)):

- *no data pre-processing required*: decision tree construction requires little or no pre-processing of raw data. They also allow for lack of homogeneity in the data since they are not sensitive to differences in scale between the independent variables, or to outliers, missing values, and skewed distributions.

- *no loss of cases*: the cases are divided at each branch point without losing any data.

- *easy to understand*: decision trees generate understandable rules. This is easily done by tracing the path from the root to the terminal nodes where the cases settle, to generate the rule that led to the classification.

- *quick training time*: compared to the other data mining techniques, training times for decision trees are quick.

- *ability to show important variables*: since decision tree algorithms put the independent variable that does the best job of splitting at the root node of the tree, they provide a clear indication of the variables that can be effectively used to classify the data (even though the same variable may appear at other levels of the tree).

- *distributional assumptions*: decision trees make no distributional assumptions about the input data.

Some of the drawbacks attributed to decision trees include:

- *cannot determine relationship between variables*: since every split in a decision tree is a test on a single independent variable, it is not possible to determine any relationship between the independent variables.

- *tree interpretation*: if a variable is never split in the final tree, one might think that the variable is not significant, when in fact the variable might be masked by other variables.

- *loss of information*: some decision tree algorithms first bin all continuous variables and then treat them as if they were categorical, which can destroy valuable information. Others split categorical variables on every value taken on by the variable leading to a very bushy tree that soon runs out of cases on which to base further splits.

2.4 Applications of Decision Trees

Decision trees are mostly used when the task is a classification one (Berry & Linoff, 2000). Some areas where decision trees have been used include:

- Burgess, Callum, Enright, Goel, Madramootoo, Prasher, and Yang (2003) used CART to classify hyperspectral data taken on corn field with different tillage and residue management strategies. The performance of CART was compared to logistic regression, and their results showed that the decision tree was able to perform better than logistic regression under the different strategies. From this study, they were also able to see which data (that is, planting season) to use from the decision tree that most accurately classified the hyperspectral data.

- Cronin & Worth (2003) used CART to predict chemical toxicity. The performance of the decision tree was compared to discriminant analysis and logistic regression. The decision tree model was found to be the most appropriate model to use because the other models did not meet the underlying statistical assumptions (about the nature of the data) which are not required by decision trees.

- Chae, Ho, Kim, Park, and Tark (2003) used the CHAID algorithm to analyse healthcare quality indicators. From this they were able to identify important factors that influence in-patient mortality.

- Doull & Rozman (2001) used decision trees to identify rate-determining steps in the toxicity of chemicals.

2.5 Summary

The purpose of this chapter was to look at the methodology employed in tree-structured techniques to provide classification decisions. We specifically looked at how the CART algorithm grows the best tree and the methods it uses to limit the growth of the tree, and we concluded the chapter by looking at some advantages, disadvantages, and applications of decision trees.

CHAPTER 3 LINEAR FUNCTION DISCRIMINANT ANALYSIS

The focus of this chapter is on the statistical classification technique - linear discriminant function analysis, also known as discriminant analysis (DA). We start by looking at the different procedures used to evaluate the performance of discriminant analysis, and later present the tests that are used to find the discriminating variables. We conclude the chapter by looking at some of the assumptions made for discriminant analysis and the application of the discriminant analysis in practice.

3.1 Introduction

Discriminant analysis is a classification technique commonly used to determine variables that discriminate well between two or more mutually exclusive groups of a categorical dependent variable (Klecka, 1980). There are two steps involved in discriminant analysis:

- In the first step, the number of independent variables (which must be interval or ratio scaled) is reduced by means of factor analysis or a principal components procedure, using cases for which group membership is known to identify the discriminating variables. The data reduction technique is applied so that the independent variables "that are related are reduced such that only one variable that best characterises each grouping best represents the underlying factor" (Mullet & Myers, 2003).

- The second step is a classification one, where a classification rule is developed using the discriminating variables to predict group membership of new cases (new cases are classified into groups such that those that reside in a particular group are more similar to each other than to cases belonging to other groups). The popular Bayes' theorem is employed in making decisions regarding any differences between the groups (refer to Appendix A).

There are two procedures used to evaluate the effectiveness of discriminant analysis as a classification tool: one procedure uses canonical functions (that is, the selection of discriminating variables), and the other procedure uses classification functions to predict group membership of cases. However, before discussing how the discriminating variables are selected, we will first look at the use of classification functions in determining group membership of cases.

3.2 Classification Functions

R. A. Fisher (1936: Klecka, 1980) was the first to suggest that classification should be based on a linear combination of the discriminating variables, which maximises group differences while minimising variation within the groups. The linear classification function formed is of the form (see Klecka, 1980):

$$Z_k = b_{k0} + b_{k1}X_1 + b_{k2}X_2 + \ldots\ldots\ldots\ldots\ldots + b_{kp}X_p$$

where Z_k is the classification score for group k.

X's are values of the discriminant variables.

b_k's are the unstandardised discriminant coefficients that maximise the distance between the means of the grouping variable. In particular,

$b_{k0} = -0.5 \sum_{j=1}^{p} b_{kj} X_{jk}$ and $b_{ki} = (n. - g) \sum_{j=1}^{p} a_{ij} X_{jk}$, where $n.$ is the total number of cases over all groups, g is the number of groups, and a_{ij} is an element from the inverse of the within-groups sum of cross-products matrix.

When the original values of a case are applied to the model, a case will be classified as belonging to the group for which it has the highest classification score.

To evaluate the effectiveness of the model as a predictive tool, a classification matrix, which shows the percentage of correctly classified and misclassified cases is used (see Table 3.1):

Table 3.1
Classification Matrix
Rows: Observed, Columns: Predicted classifications

	Percent Correct	Small	Medium	Large
Small	80.00	8	2	0
Medium	70.00	1	7	2
Large	60.00	0	4	6
Total	70.00	9	13	8

There are two other measures that are used in discriminant analysis to classify new cases into groups - the Mahalanobis distance measure and posterior probabilities.

3.2.1 Classification using the Mahalanobis Distance Measure

One of the ways in which a case can be classified into a group, is to measure its distance from each of the group centroids (a centroid is the mean value for the discriminant score for a given category of the dependent variable, and is defined by Klecka (1980) as "an imaginary point which has coordinates that are the group's mean on each of the variables"). However, when the variables are correlated and do not have the same measurement units and standard deviations, the concept of 'distance' is not well defined (Nolan, 2002).

Mahalanobis (1963: Klecka, 1980) was the one who proposed a generalised distance measure, which accounts for the correlation between the variables. The Mahalanobis distance is defined by Klecka (1980) as:

$$D^2\left(x\middle|C_k\right) = (n. - g) \sum_{i=1}^{p}\sum_{j=1}^{p} a_{ij}(x_i - x_{ik})(x_j - x_{jk})$$

where $D^2\left(x\middle|C_k\right)$ (denoted D^2) is the squared Mahalanobis distance from a specific case x_i, to the centroid of group k.

Using the Mahalanobis distance measure, a case is classified into the group with the smallest D^2. This may or may not be the group that the case originally came from, but it is closer to that group than to any other group.

3.2.2 Classification using Posterior Probabilities

Klecka (1980) suggests that by classifying a case into the closest group according to the Mahalanobis distance measure, "we are implicitly assigning it to the group for which it has the highest probability of belonging". These probabilities are called posterior probabilities since they state the probability of belonging to a particular group after performing the analysis. That is, the probability that a case x belongs to group i is (James, 1985):

$$P(G_i \mid x) = \frac{P(x \mid G_i)}{\sum_{i=1}^{g} P(x \mid G_i)}$$

where $P(x \mid G_i)$ is an estimate of the proportion of cases from group i in a sample.

Using posterior probabilities to classify new cases, a case is classified as belonging to the group for which it has the highest posterior probability.

3.3 Testing the Discriminant Function's Significance - Canonical Functions

Since we are looking for numerous potential discriminating (independent) variables, matrices of variances and covariances, and of the pooled within-group variances and covariances are formed. The two matrices are then compared using the F-statistic (ratio of the two variances), introduced by Fisher (1936: Manly 1986), to determine whether or not there are any statistical significant differences (with respect to the mean of a particular (independent) variable) between the k groups. If the observed mean differences for a variable are significantly different in different groups, then the F-statistic is as large as possible and the variable is said to discriminate well between the groups.

When the F-statistic is employed to find the significant discriminating functions, then the discriminant function becomes known as the canonical discriminant function.

3.3.1 Canonical Functions

Canonical discriminant functions are linear combinations of the original variables chosen such that the first discriminant function reflects group differences as much as possible (that is, it gives the maximum possible F-statistic) the second discriminant function reflects as much as possible of the group differences not displayed by the first function (that is, gives the next largest possible F-statistic), the third discriminant function reflects as much as possible of the group differences not displayed by the first and second functions, and so on. Each function is independent or orthogonal to others (that is, the discriminating power between groups do not overlap). In general the number of these canonical discriminant functions will be the smaller of the number of (independent) variables, g, and the number of groups minus one, k-1 (Klecka, 1980).

Computationally, a canonical correlation analysis, which studies the relationships between the groups and the discriminant function, is performed to determine the canonical functions and canonical roots (that is, the eigenvalues associated with the respective canonical function - here the largest eigenvalue will be associated with the first discriminant function).

The canonical discriminant coefficients are standardised (by multiplying the coefficients from the discriminant function by the corresponding pooled standard deviations), to ensure that they have an equal weight in the analysis. Adjusting the coefficients changes neither the amount of discrimination nor the relative positions of the groups (Klecka, 1980); instead, the origin of the discriminant function axes is shifted to coincide with the grand centroid (defined as "the point in the space where all the discriminating variables have their average values over all cases" Klecka (1980)). The standardised coefficients are used to compare the relative importance of the independent variables, where the larger the standardised coefficient, the greater the discriminating power between the groups of that variable.

3.4 Selection of Variables into the Discriminant Equation

A stepwise procedure is commonly used to select the discriminating variables. There are two stepwise procedures that can be employed, and they are (Klecka, 1980):

1. *Forward stepwise analysis*: The stepwise procedure begins by selecting the independent variable that discriminates most between the groups (of the dependent variable). This is then paired with each of the remaining variables, one at a time, and the pair that discriminates most between the groups, is selected. The procedure continues, combining the selected pair with each of the remaining variables to form triplets, where the triplet that discriminates most between the groups, is selected. This continues until all possible combinations that discriminate well between the groups have been selected or until the selection of additional combinations of the remaining variables does not change the discriminating power of the model.

2. *Backward stepwise analysis*: this procedure is the reverse of the forward stepwise procedure. Initially, all independent variables are selected and at each step, the variable that discriminates least between the groups is eliminated. This is repeated until only those variables that contribute the most in discriminating between the groups are left.

Klecka (1980) argues that even though the stepwise procedure is a logical and efficient way to seek the best combination, the sequence in which variables are selected does not necessarily coincide with their relative importance, hence there is no "guarantee that the end product is indeed superior to all others". Manly (1986) on the other hand argues that the problem with stepwise discriminant analysis is "the bias that the procedure introduces into significant tests", as some combinations of the independent variables can "produce (significant) discriminant functions by chance alone" so as to yield maximum discrimination, thus increasing the likelihood of erroneously rejecting the null hypothesis of no discrimination between the groups.

3.4.1 Criteria used for the Selection of Variables into the Discriminant Equation (Tests of Significance)

The following tests are used to select the discriminating variables:

i) Wilk's Lambda

Wilk's Lambda, λ, is a statistic used to test for group differences in discriminant analysis. The lambda assumes values between 0 and 1, where a lambda close to 0 indicates that the variable contributes a lot towards the discriminating power of the model. According to Klecka (1980), Wilk's Lambda can be tested for significance by converting it into an approximation of the F-statistic. The relationship between the two measures is given by the formula (Wegner, 2002):

$$F_{(R,\,K)} = \frac{1-\lambda(K)}{\lambda(R)}$$

where R is the numerator degrees of freedom, and K the denominator degrees of freedom.

When the F-statistic is used in this manner, the *partial* F-statistic, which is used as the F-to-enter (see below) is used instead of the overall F-statistic (Klecka, 1980).

ii) Tolerance

One of the requirements for discriminant analysis is for the variables to not be correlated. The tolerance value is used to check for this, and is computed as one minus the r-square ($1 - R^2$) of the respective variable with all the other variables included in the model. In general, when a variable is a linear combination of the other variables, the tolerance value will approach zero.

iii) *F*-to-enter

The *F*-to-enter is defined by Dixon (1973: Klecka, 1980) as "a partial multivariate *F*-statistic which tests the additional discrimination introduced by the variable being considered after taking into account the discrimination achieved by other variables already entered". Hence, the variable with the small *F*-to-enter indicates that the variable is not contributing enough to the overall discrimination.

iv) *F*-to-remove

The *F*-to-remove is "also a partial multivariate *F*-statistic, but it tests the significance of the decrease in discrimination should that variable be removed from the list of variable already selected" (Klecka, 1980). Klecka (1980) also suggests that the *F*-to-remove can be used on the final step, to rank the discriminating variables in the order in which each variable makes a unique contribution to the prediction of group membership. Here, the variable with the largest *F*-to-remove indicates the greatest contribution to the overall discrimination over and above the contributions already made by the other variables. The variable with the second largest *F*-to-remove indicates the second most contribution, and so on.

3.5 Assumptions made for Discriminant Analysis

For the discriminant analysis procedure and the tests of significance to be optimal, certain assumptions about the data must be met. It is assumed that the:

- independent variables follow a multivariate normal distribution.

- variance/covariance matrices of variables are the same across all groups. The discriminating variables may have different variances from each other, but for each discriminant variable, the groups formed should have similar variances and means on that variable, since this will lead to distortions in the canonical discriminant functions and the classification equations (Klecka, 1980)

- independent variables are not correlated since the standardised discriminant coefficients will not reliably assess the importance of the discriminating variable.

According Manly (1986), even though failure of one or more assumptions occurs, this does not mean that discriminant analysis is a "waste of time", and that the only problem that may arise is in trying to establish the significance of the results.

3.6 A Brief Discussion on General Discriminant Analysis

General discriminant analysis unlike the traditional discriminant analysis allows one to use both categorical and continuous independent variables, and is not restricted to interval or ratio scaled variables only. However, according to Statsoft (2001), "no "experience" (in the literature) exists regarding issues of robustness and effectiveness" of general discriminant analysis. In our search for information on general discriminant analysis, we did not come across any literature that was able to explain how the technique is formulated, hence our literature review of the discriminant analysis technique has been limited to the linear model.

3.7 Applications of Discriminant Analysis

Discriminant analysis is one of the most commonly used statistical techniques because of its ability to show important variables and to provide a classification rule for predicting group membership of new cases. Some application areas include:

- Cronin & Worth (2003) used discriminant analysis to predict chemical toxicity. The performance of the discriminant analysis was compared to the CART decision tree and logistic regression. The difficulty they experienced with the discriminant analysis technique was its inability to meet the underlying statistical assumptions about the data (of normality of the independent variables and equal covariance matrices across all groups of the dependent variable).

- Corse & Smith (1998) used discriminant analysis to determine the characteristics that differentiated women who abstained during pregnancy from those who reduced substance use and those who showed no change, in order to evaluate the impact of the ANGEL program on change in drug or alcohol use over the course of pregnancy. From their study, they were able to find important characteristics that could be used to distinguish between the three groups of pregnant women, and they were also able to use the discriminant function to identify women who abused drugs and/or alcohol at the start of prenatal care.

- Cronan, Epley, and Perry (1987) used discriminant analysis to predict the success of mortgage applications. Their main interest was to come up with a model that could best explain the variables used by loan officers to classify acceptable applicants from those that should be rejected.

- Hora & Wilcox (1982) used discriminant analysis to try and estimate its classification accuracy. From their research, they concluded that the new estimation methods they proposed were dependent on the availability and validity of the assumptions.

3.8 Summary

In this chapter a linear classification technique – linear function discriminant analysis was introduced. We started by looking at the different methods employed by the discriminant analysis procedure in making classification decisions, and later presented the tests used to find the discriminating variables. We concluded the chapter by looking at some of the assumptions made for discriminant analysis, and application areas of discriminant analysis in practice.

CHAPTER 4 ARTIFICIAL NEURAL NETWORKS

This chapter is an introduction to artificial neural networks. In Section 4.1 we briefly discuss the biological motivation for artificial neural networks, a brief historical overview of the research into artificial neural networks then follows, and in Section 4.3 we look at the four different types of artificial neural network architectures, the different methods used to set the connection weights between layers in a network, and the transfer functions commonly used on the network's weighted input signal. Section 4.4 looks at some of the advantages and disadvantages common to the different artificial neural network models, and we conclude the chapter by listing a few examples of application areas for neural networks.

The human brain has been studied for thousands of years, and as suggested by Anderson and McNeill (1992), with the advent of modern electronics "it was only natural to try and harness this thinking process", hence the establishment of neural network simulations. An artificial neural network (ANN) is defined by Patterson (1996), as "an attempt to simulate within specialised hardware or sophisticated software, the multiple layers of simple processing elements called neurons".

4.1 Biological Inspiration of Neural Networks

Research into the field of artificial neural networks has been inspired by man's knowledge of the workings of the biological nervous system. There are many different types of neurons in the human brain, and it is from these that the various types of artificial neural networks get their inspiration, and biological terminology (Patterson, 1996).

A neuron has four basic components (Fausett, 1994): the dendrites, soma or cell body, axon, and synapses (see Figure 4.1 below). The dendrites (tree-like structures) receive electrical impulses from other neurons across a synaptic gap by means of a chemical process. These electrical impulses are then modified by a weight at the receiving synapse, and when sufficient input is received, the soma processes these incoming signals and transmits the processed value over the axon to the output cells or other cells, through the synapses (the tips of the branches of the axon).

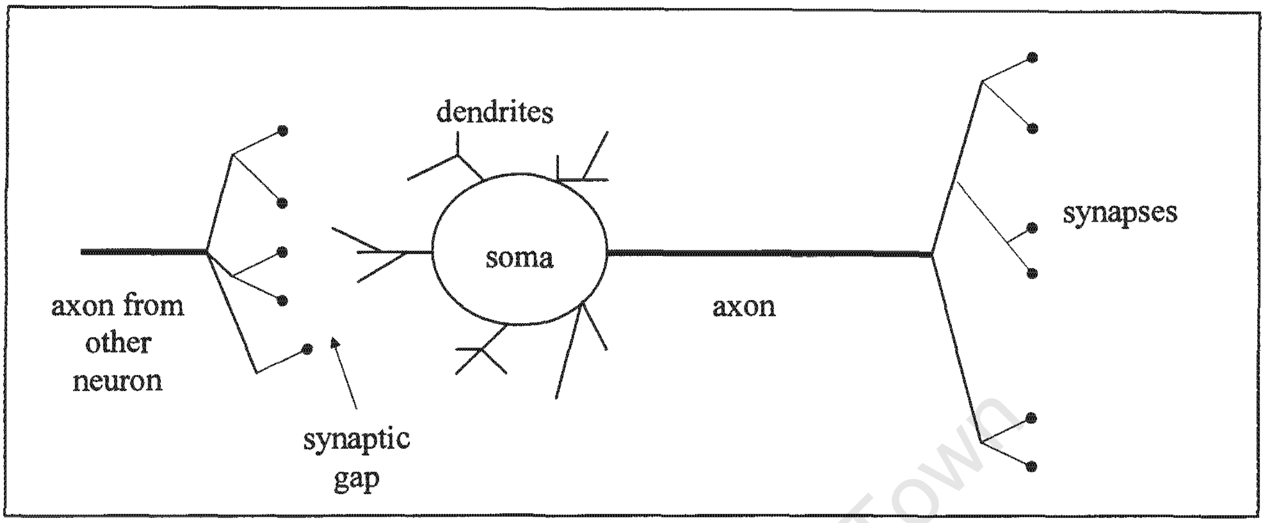


Figure 4.1 A Basic Neuron (*Adapted from*: Fausett, 1994)

The signal carried along the axon creates an internal electric potential called a membrane potential. This is a result of three different concentrations of ions - potassium, sodium or chloride - on either side of the axon, which may be increased or decreased by the input activity received from other cells through the synapses (Patterson, 1996). If the potential difference across the neuron is large, that is, exceeds a certain threshold value, the chemical substances released at the terminating branches may either excite or inhibit other neurons (synapses with larger surface areas are believed to be excitatory, while those with smaller surface areas are inhibitory (Patterson, 1996)).

4.2 A Brief Historical Overview of Neural Network Research

The first attempts towards artificial neural network simulations probably came in 1943 when Warren McCulloch and Walter Pitts wrote a paper on their understanding of neurology[1] (Tarassenko, 1998). This paper was important because it proved that through the proper choice of threshold levels, a network could perform basic Boolean logic functions on its inputs. Around the same period, in 1949, Donald Hebb suggested the first learning law for artificial neural networks by defining a method of updating synaptic weights. He hypothesised that "if two neurons were active simultaneously, then the strength of the connection between them should be increased" (Haykin, 1994).

In the 1950s, Nathanial Rochester and colleagues led the first effort to simulate a neural network at the Dartmouth Summer Research project on Artificial Intelligence. They used Hebb's model and "discovered that some changes were essential before cell assemblies could be formed to exhibit certain properties predicted of the model" (Patterson, 1996). They later generalised the model to include the inhibition of active cells to prevent others from becoming active.

In the years following the Dartmouth project, Frank Rosenblatt, a psychologist, began work on the Perceptron (Patterson, 1996) (so called because the device could apparently perceive). A single layer perceptron is a unit made up of three layers: an input sensory layer, connected to an associated layer with adjustable weights, and an output or classification layer. With the perceptron, Rosenblatt not only demonstrated how a network could be trained to recognise a pattern chosen beforehand, but also laid foundations for both the supervised and unsupervised training algorithms (see later) that are the focus of neural network literature today.

In 1959 Bernard Widrow and Marcian Hoff developed a simple neural element similar to the perceptron called ADALINE (ADAptive LInear NEuron) and MADALINE (Multiple

[1] '*A logical calculus of the ideas immanent in the nervous activity*', Bulletin of Mathematical Biology, 5, 115- 133, 1943

ADALINEs) (Patterson, 1996). The ADALINE was similar to the perceptron, but employed the Least-Mean-Squares (LMS) learning or Delta rule or Widrow-Hoff learning method - a supervised learning method, which adjusts the weights to reduce the difference between the network input to the output neuron and the desired output, resulting in the smallest mean squared error.

4.2.1 The Fall and Reawakening of Neural Network Research

Unfortunately the excitement of perceptron networks was seriously dampened in 1969 when Marvin Minsky and Seymour Papert published their book, *Perceptrons* (Patterson, 1996), in which they argued about the limitations of the perceptron. Consequently funding for neural network research was either reduced or terminated.

During the early 1970s, keen researchers such as Teuvo Kohonen, and James Anderson continued their investigations, and as a result, developed associative techniques, the most well known today being Kohonen's self-organizing map (Haykin, 1994). Other researchers who continued their investigations were Stephen Grossberg and colleagues (Anderson & McNeil, 1992). Their interest was focused on the mathematical dynamics of artificial neural networks.

In 1972, Henry Klopf developed a basis for learning in artificial neurons based on the biological principle of neural learning called heterostasis, and in 1974 Paul Werbos developed the backpropagation learning algorithm, which adjusted the weights in multilayer feedforward networks. This proved to be a major breakthrough in artificial neural network computing, since it overcame the limitations suffered by single layer perceptrons. Around the same period, Japanese researcher Kunihiko Fukushima developed a stepwise trained multilayered neural network for interpretation of handwritten characters - the neocognitron, a hierarchical feedforward network that learns through either supervised or unsupervised methods (Patterson, 1996).

Several events also took place in the 1980s that highlighted the use and growing awareness of neural networks (Anderson & McNeil, 1992):

- In 1982, John Hopfield presented a paper at the National Academy of Science demonstrating how to create useful devices out of neural networks that did not just model the brain. In the same year, a US-Japan Joint Conference on Cooperative-Competitive Neural Networks for Computing was held in Kyolo, Japan.

- In 1990, a US Department of Defence Small Business Innovation Research Program named 16 topics, which specifically targeted neural networks, with an additional 13 targeting the possible use of neural networks.

Today, despite some of the difficulties neural networks are still facing of slow training times as the size of the input space increases (which was raised by Minsky and Papert), and their complex nature, the field of neural networks has made significant progress, and its future looks very promising.

4.3 The Artificial Neural Network

Artificial neural networks consist of a large number of processing elements, which go by names such as neurons, nodes, or units. Characteristics of artificial neural networks that are suggested by the properties of biological neurons include:

- *Design*: artificial neural networks are made by arranging nodes (that is, neurons) into layers, which are then connected to one another. There are three types of nodes that make up the artificial neural network: the input, hidden, and the output nodes.

- *Transmission*: nodes in the input layer receive input from the external environment. This is then transmitted to other layers in the system, and when a certain condition is satisfied, the output layer nodes fire their output to other nodes for further processing or to the external environment.

- *Weights*: connection weights in an artificial neural network determine the strength of connection within the network. Positive weights have an excitatory influence, and negative weights have an inhibitory influence (Haykin, 1994).

- *Fault tolerance*: like biological neural systems, which are able to recognise many input signals that are different from any signal we have seen before, and tolerate damage to the neural system itself, artificial neural networks can be designed to be insensitive to small damage to the network, and the network can be retrained in cases of significant damage (Fausett, 1994).

An artificial neural network is characterised by its architecture (that is, the number and pattern of connections between the nodes), its learning/training algorithm and transfer function (that is, the functional transformation performed on the input to give the desired output) (Fausett, 1994).

4.3.1 Architecture of an Artificial Neural Network

Figure 4.2 below shows a simple artificial neural network architecture with three inputs and a single output. The network receives inputs $x_{(n)}$, which are then multiplied by connection weights, $w_{(n)}$. In the simplest case, these products are summed, using the combination function, fed through a transfer function to generate a result (note that the combination function and a transfer function make up the activation function), and then output.

Fausett (1994) defines the number of layers in a neural network to be "the number of layers of weighted interconnected links between the slabs of neurons", and for this research, we have chosen to adopt Fausett's definition, hence in the different types of network architectures described below, the input nodes are not counted as a layer, because computations are not performed there.

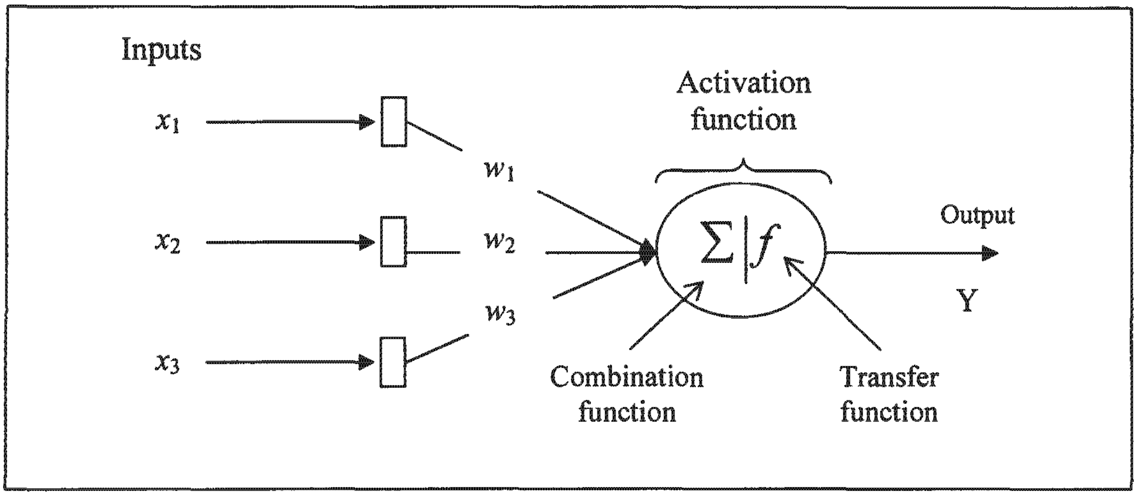


Figure 4.2 A Simple Artificial Neural Network (*Adapted from*: Patterson, 1996)

a) Single-layer Feedforward Networks

A single layer feedforward network has one layer of connection weights between the input nodes and the output nodes (see Figure 4.3). In the figure the input signals are propagated only in one (forward) direction, and the nodes are fully connected, that is, the input nodes are connected only to the output nodes and are not connected to other input nodes, and the output nodes are not connected to other output nodes.

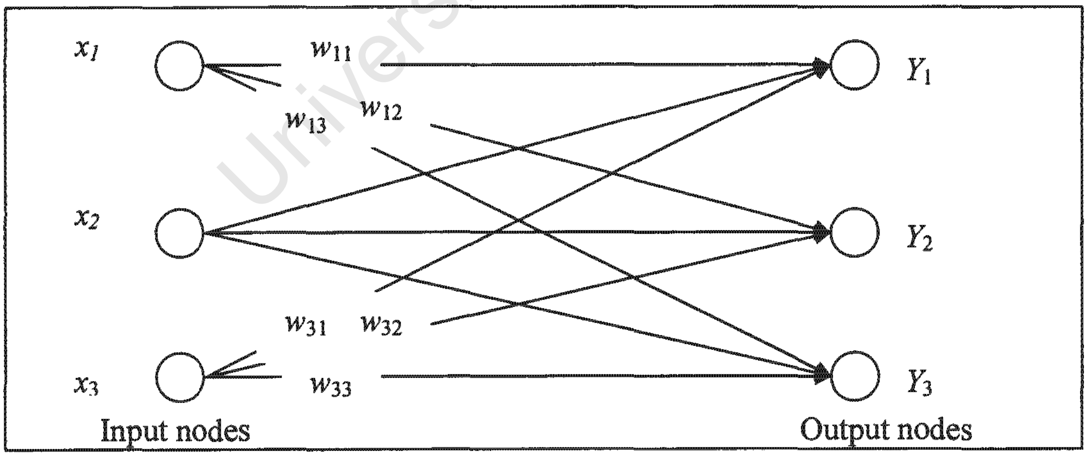


Figure 4.3 A Single-layer Feedforward Network (*Source*: Fausett, 1994)

b) Multilayer Feedforward Networks

A multilayer network is a network with one or more layers of nodes between the input nodes and the output nodes. The interior layer of nodes are called hidden layer nodes. According to Haykin (1994) by adding one or more hidden layers, "the network is enabled to extract higher-order statistics, and this is particularly valuable when the size of the input layer is large".

Figure 4.4 shows a multilayer fully connected feedforward neural network with one layer of hidden nodes. Here, input signals are propagated to the hidden nodes (or first layer of hidden nodes for networks with more than one layer of hidden nodes). The output signals from this layer are then used as input to the next layer, and so on until the signals reach the output layer, where they leave the system.

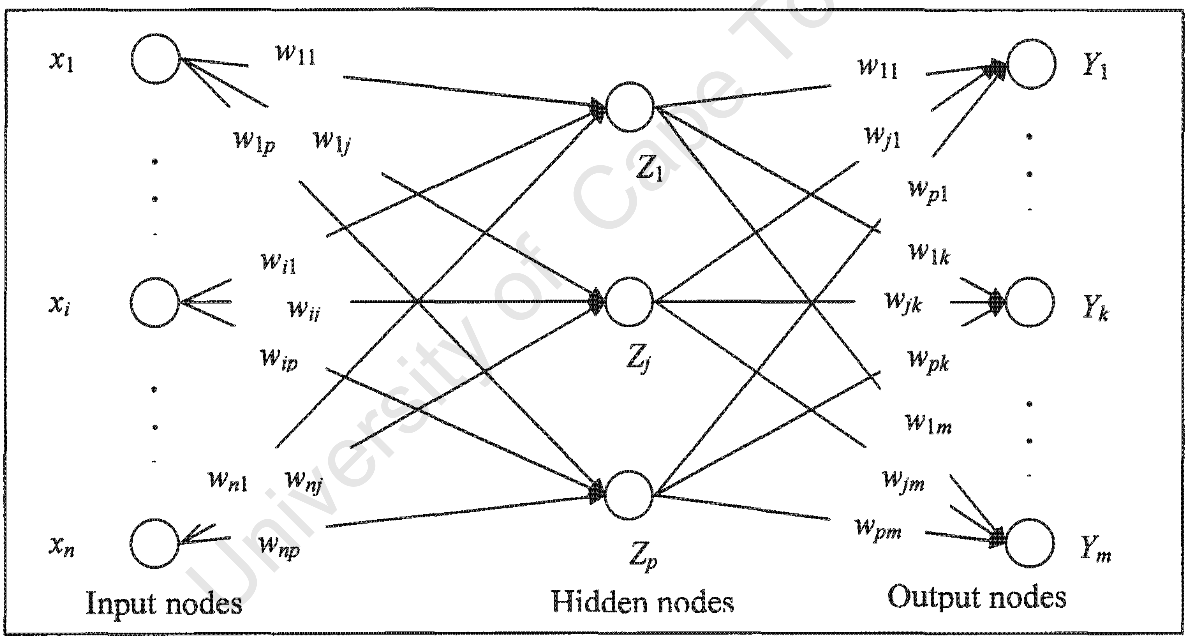


Figure 4.4 A Multilayer Feedforward Network (*Source*: Fausett, 1994)

c) Recurrent Networks

A recurrent network, unlike a feedforward network, is a feedback network, since it has signals travelling in both directions (these originate from the hidden nodes as well as the output nodes).

This is done by introducing loops to the network. According to Haykin (1994), the presence of feedback loops "has a profound impact on the learning capability of the network, and on its performance". A special type of a recurrent network (a competitive layer network) is shown in Figure 4.5. This has a closed-loop signal path from a node back to itself.

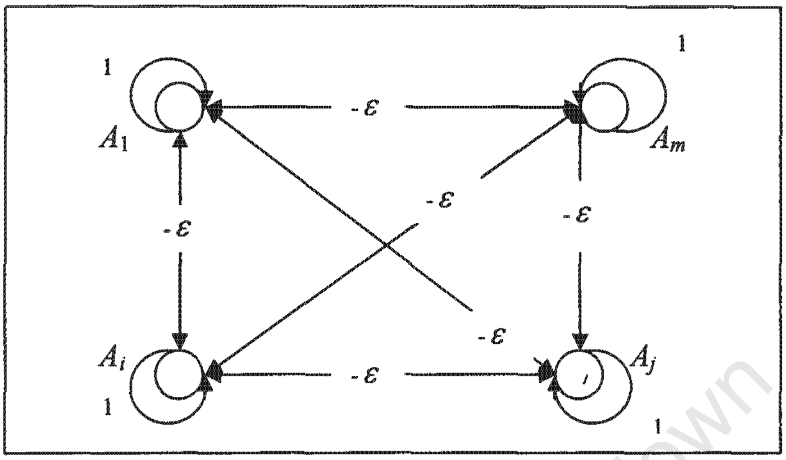


Figure 4.5 A Competitive Layer Network (*Source*: Fausett, 1994)

d) Lattice-structured Networks

A lattice-structured network (see Figure 4.6) is a feedforward network whose input nodes are connected to an n-dimensional array of output nodes (that is, the output nodes are arranged in rows and columns).

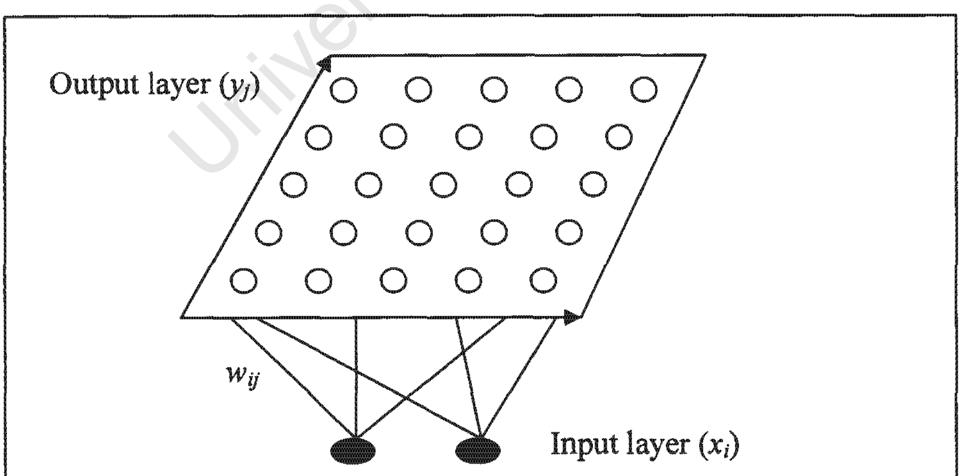


Figure 4.6 A Lattice-structured Network (*Source*: Hertz, Krogh, and Palmer, 1991)

4.3.2 Setting the Connection Weights

Network 'learning' or 'training' is the process of setting connection weights between nodes in a network. There are three different types of learning methods – supervised, unsupervised, and reinforcement learning:

- **Supervised Learning**

In supervised learning, a network is presented with training data, which consists of known input and output values. The learning process involves comparing the computed output and the actual output to determine the error. The objective is to have as low an error as possible, hence the training phase is usually repeated and the individual weights adjusted until an acceptable network performance is reached.

When this is done, the network's performance is usually tested on unseen data (known as test data) "since networks are susceptible to memorising a given pattern" Patterson (1996). If the network does not give reasonable results for the test data, this implies that the network has memorised the general patterns involved within the system, and the training period is not over.

- **Unsupervised Learning**

In unsupervised learning (also called self-organised learning), actual outputs are not known to the network. Instead the network learns by looking for trends in the input patterns, and modifies the weights so the most similar input patterns are assigned to the same output node. This type of learning is appropriate for clustering problems.

- **Reinforcement Learning**

In reinforcement learning, training consists of presenting a network with training data, which consists of known input and output values, though here, unlike in supervised learning, the error is not used to adjust the weights. Instead the only feedback the input gets is whether each output is correct or not. The network then uses this information to improve its performance. In general, connection weights for the nodes that give a correct answer are updated, and a penalty is imposed on those nodes that give an incorrect answer by reducing the weight values (Patterson, 1996).

a) Learning Laws

To aid the process of setting connection weights, learning laws are used in neural networks, and some of these are discussed below:

- **Hebb's Rule**

Hebb's rule is a learning rule that was introduced by Donald Hebb in 1949. Hebbian learning has the following form:

$$w_{ij}^{new} = w_{ij}^{old} + \eta\, x_i\, y_j \qquad \text{or} \qquad \Delta w_{ij} = \eta\, x_i\, y_j$$

where w_{ij} is the weight connection between nodes i and j, η is the learning rate parameter that is used to control the amount of weight adjustment at each step of training, x_i is the input node, and y_j the output node.

- **Delta Rule**

The Delta rule, also known as the Wildow-Hoff learning rule, the Least Mean Square (LMS) Rule, and the Adaline Rule (Fausett, 1994), is a further variation of Hebb's Rule. The Delta rule works by changing the connection weights so as to minimise the error or difference (that is, the delta) between the actual output and the computed output. The delta in the output layer is transformed by the derivative of the transfer function and is then back propagated into previous layers until the first layer is reached to adjust the connection weights. Backpropagation derives its name from this method of computing the error term.

The Delta Rule is often used for single layer networks and is given by:

$$w_i^{new} = w_i^{old} + \eta(t-y)x_i \qquad \text{or} \qquad \Delta w_i = \eta(t-y)x_i$$

where t is the desired or target output, and y is the actual output computed by the network.

Adding a single layer of hidden nodes to the linear neural network that uses the delta rule turns the neural network into a non-linear one, and the learning law is then known as the gradient descent rule.

- **Gradient Descent Rule**

The Gradient Descent Rule[2] is similar in the Delta Rule in that the derivative of the transfer function is still used to modify the delta before it is applied to the connection weights. Thus, the transfer function, f, must be differentiable as the weight updates are based on the gradient of the error function E, which can be minimised by adjusting the weight values. Through the use of gradient descent methods, the form of the weight update rule is given by $\Delta w_{ij} = \eta \frac{\partial E}{\partial w_{ij}}$.

- **Kohonen's Learning Law**

The Kohonen learning law, also known as the Competitive learning law, is used in unsupervised networks developed by Teuvo Kohonen (Patterson, 1996). Typically, nodes in a given input layer compete for the opportunity to represent the input pattern (that is, to update

[2] They are called descent methods because they guarantee a decrease in the size of the adjustment made to the weight at each step.

their weights), and the node that is more responsive is declared the winner, and is permitted an output. The winner will then have its weights and those of neighbouring nodes strengthened.

The Kohonen learning law is given by:

$$\Delta w_{ij} = w_{ij} + \eta \Lambda(i, i^*)(x_i - w_{ij}) \qquad \text{for all } i \neq j$$

where η is a learning rate parameter, which decreases with time, $\Lambda(i, i^*)$ is the neighbourhood function, and i^* is the winning node.

b) Types of Learning Processes

There are two standard ways in which the learning laws described above are applied (Patterson, 1996):

1. *On-line learning process*: here, the connection weights are updated each time a new input (and target) pattern is presented to the network.

2. *Off-line or batch learning*: here, the connection weights are updated only after a complete pass (known as an epoch) through the training set. After an epoch of training, the total error, $E_{total} = \sum E$, is computed and each weight is then adjusted according to the accumulated errors.

4.3.3 Transfer Functions

A network's transfer function is a function that performs a transformation on the network's weighted input signals. Typically the same transfer function is used for all nodes in any given layer of the network, and the types of transformations a network can approximate depend on the network's architecture (Haykin, 1994). Examples of commonly used transformations include:

- the linear/identity function: $f(x) = x$ for all x

- the binary/threshold/Heaviside function: $f(x) = \begin{cases} 1 & \text{if } x \geq \theta \\ 0 & \text{if } x < \theta \end{cases}$

- the binary/logistic sigmoid: $f(x) = \dfrac{1}{1+\exp(-\beta x)}$ where β is the steepness parameter (output values range between 0 and 1)

- the bipolar sigmoid:
$$g(x) = 2f(x) - 1 = \frac{2}{1+\exp(-\beta x)} - 1 = \frac{1-\exp(-\beta x)}{1+\exp(-\beta x)}$$
(output values range between -1 and 1. Note, when $\beta = 1$ the bipolar sigmoid becomes the hyperbolic tangent function)

4.4 Advantages and Disadvantages of Artificial Neural Networks

Some of the advantages for artificial neural networks include (Fausett (1994), Patterson (1996) and Siganos & Stergiou (1996)):

- *High parallel computation rates*: artificial neural networks simulate the parallel computations a biological neuron is able to perform simultaneously.

- *Ability to generalise*: artificial neural networks generalise "when they compute or recall full patterns from partial or noisy input patterns, when they recognize or classify objects not previously trained on, or when they predict new outcomes from past behaviours" (Patterson, 1996).

- *Fault tolerance/robust performance*: artificial neural networks continue to perform well when part of the network is disabled or when presented with noisy data.

- *Adaptive learning*: the ability of a learning algorithm to find a set of weights that performs the desired mapping with a tolerable error rate.

- *Distribution assumptions*: artificial neural networks do not need any data distribution assumptions about the input data (Becerra-Fernandez, Walczak, and Zanakis, 2002).

The major issues of concern today for artificial neural networks according to Gupta & Smith (2000), Siganos & Stergiou (1996), and Tarassenko (1998) are:

- *Black boxes*: it is not possible to infer from the network parameters how the network is solving the problem.

- *Training times*: neural network programs sometimes require a long time to train the huge amount of data of large databases.

- *Parameter selection*: there is no art in determining the optimal combination of training parameters including the network architecture, (number of hidden layers and nodes), the learning rate, and number of training epochs.

4.5 Applications of Artificial Neural Networks

Neural networks are being used in many different areas. This can be credited to their ability to "solve problems that are too complex for conventional technologies – problems that do not have an algorithmic solution or for which an algorithmic solution is too complex to be found" Siganos & Stergiou (1996). A few examples of areas in which artificial neural networks are being applied include (Fausett (1994), Gupta & Smith (2000), and Patterson (1996)):

- *signal processing*: neural networks are used to reduce noise on telephone lines.
- *control*: neural networks are used in cars to help drivers reverse, and to drive cars (autonomous driven vehicle).
- *pattern recognition*: neural networks are trained to recognise handwritten characters.
- *business*: neural networks are used in marketing to identify customers who are likely to respond positively to a product and to target any advertising towards these customers; in banking and finance to determine to whom to lend money, and to forecast pricing of derivative securities, futures and hedging, exchange rate forecasting; by insurance companies to predict claim frequency and claim cost in order to set premiums and to detect fraud; etc.
- *medicine*: mostly for classification of disease given a set of symptoms.

4.6 Summary

In this chapter, we presented a general introduction to artificial neural networks by first considering the biological inspiration of artificial neural networks. An overview of the research into artificial neural networks was then discussed, and the common different types of network architectures were presented, together with the different methods used to set connection weights between layers in a network. Finally, we concluded the chapter by looking at some advantages, disadvantages, and applications areas of neural networks.

CHAPTER 5 SUPERVISED NEURAL NETWORKS FOR CLASSIFICATION

The focus of this chapter is on supervised neural networks commonly used in classification problems - the Backpropagation network, Probabilistic neural network, and the Radial Basis Function network. For each network, we look at its architecture, how the network is trained, application areas, and some of its advantages and disadvantages.

5.1 Introduction

Supervised neural networks are networks whose connection weights are determined by comparing the computed output and the actual output to determine the error, and adjusting the connection weights so that the computed output closely matches the actual output.

5.2 The Backpropagation Network

The backpropagation network is a supervised network that gets its name from the way in which corrections are made to the weights. The errors computed during the learning phase are propagated backwards, until the weights connected to the first hidden layer are adjusted. The process is repeated for each training pattern until the total output error is reduced.

5.2.1 Architecture of the Backpropagation Network

The backpropagation network is a fully connected feedforward network, which usually has three layers: an input layer, at least one hidden layer, and an output layer, see Figure 5.1 below:

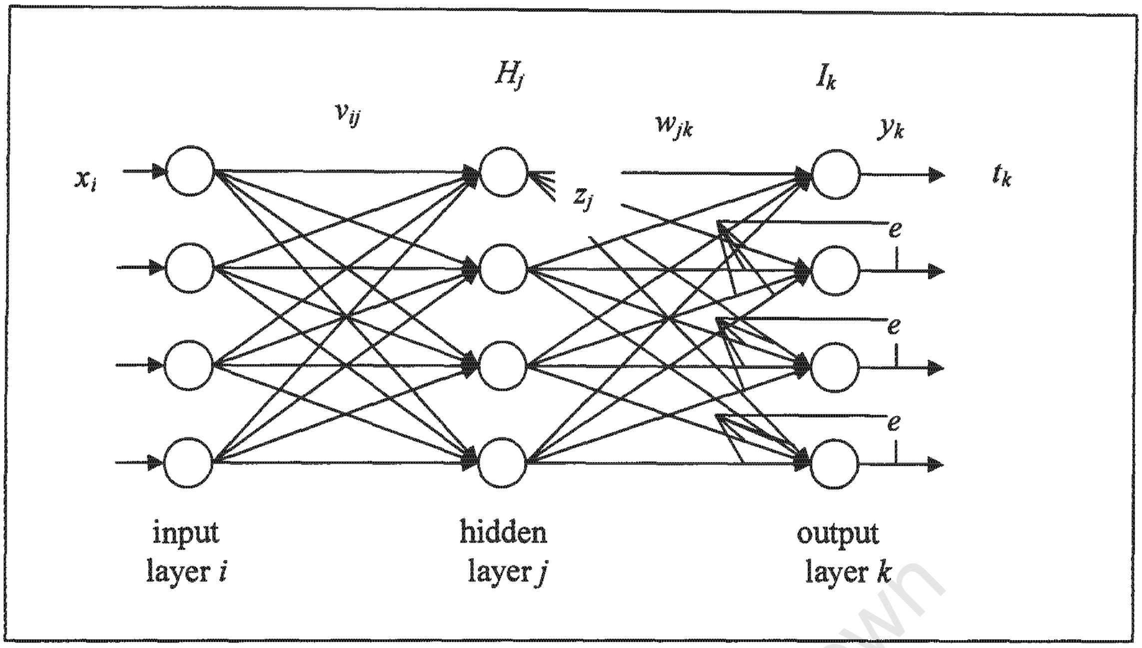


Figure 5.1 Structure of a Backpropagation Network (*Adapted from*: Patterson, (1996))

5.2.2 Network Learning using the Backpropagation Algorithm

There are three stages involved in training a network using the backpropagation learning algorithm (Fausett, 1994): the feedforward of input patterns, the calculation and backpropagation of the associated errors, and the adjustments of the weights.

To simplify the derivation of the backpropagation, a network with one layer of hidden nodes will be used. The following notations will be adopted in training the backpropagation network: (*refer to* Figure 5.1)

x_i	input pattern to input layer node i.	
v_{ij}	weights connecting the ith input layer node to the jth hidden layer node.	
$H_j = \sum_j v_{ij} x_i$	net input to hidden layer node j.	(5.1)
$z_j = f(H_j)$	output pattern (activation) from hidden layer node j.	(5.2)
w_{jk}	weight connections between hidden layer node j and output layer node k.	

$e = t_k - y_k$	error computed during the learning phase	
$I_k = \sum_k w_{jk} z_j$	net input to output layer node k.	(5.3)
$y_k = f(I_k)$	actual output pattern (activation) from output layer node k.	(5.4)
t_k	target or desired output of output layer node k.	
$\Delta v_{ij} = \eta \frac{\partial E}{\partial v_{ij}}$	weight update between input node i and hidden node j.	
$\Delta w_{jk} = \eta \frac{\partial E}{\partial w_{jk}}$	weight update between hidden node j and output node k.	
η	learning rate parameter, where $0 \leq \eta \leq 1$.	
$E = \frac{1}{2} \sum_k \left(t_k - y_k\right)^2$	global error (i.e. the sum of the squared differences of the desired output t_k and the actual calculated output y_k of each output node k).	

Before learning, the connection weights are set to small random values (Patterson, (1996) suggests values between −1 and 1). The algorithm proceeds as follows:

1. *The FeedForward of Input Patterns*

Each input node i, receives an input pattern, x_i, which is then propagated to each of the hidden nodes j, where the total weighted input for the input pattern is computed ($H_j = \sum_j v_{ij} x_i$). The hidden nodes then apply their transfer function (usually the sigmoid function), and compute an output ($z_j = f(H_j) = f(\sum_j v_{ij} x_i)$). This is then propagated to each of the output nodes k (note that if there is more than one hidden layer, the transfer function above is used for all hidden layers until the output layer is reached). The output nodes then apply their transfer function, and compute an output ($y_k = f(I_k) = f(\sum_k w_{jk} z_j) = f(\sum_k w_{jk} f(\sum_j v_{ij} x_i))$). This is then compared to the target output, t_k, to determine the associated error for that pattern ($E = \frac{1}{2} \sum_k \left(t_k - y_k\right)^2$).

The global error is used to compute new weights for the connections that lead back to the different nodes (except the input nodes), and is a function of the connection weights, v_{ij} and w_{jk}, which are the parameters that need to be minimised in order to reduce E.

2. *The Calculation and Backpropagation of Associated Errors (the gradient descent method)*

The backpropagation of errors proceeds as follows (see Patterson, 1996):

a) First the error from the output nodes is propagated back to the hidden nodes. The gradient of this global error, $\frac{\partial E}{\partial w_{jk}}$, can be written using the chain rule:

$$\frac{\partial E}{\partial w_{jk}} = \frac{\partial E}{\partial I_k}\frac{\partial I_k}{\partial w_{jk}} = \frac{\partial E}{\partial I_k}\left(\frac{\partial}{\partial w_{jk}}\sum_k w_{jk} z_j\right) = \frac{\partial E}{\partial I_k}(z_k)$$

where $$\frac{\partial E}{\partial I_k} = \frac{\partial E}{\partial y_k}\frac{\partial y_k}{\partial I_k}$$

Note that $$\frac{\partial E}{\partial y_k} = \frac{\partial}{\partial y_k}\left(\frac{1}{2}\sum_k\left(t_k - y_k\right)^2\right) = -\left(t_k - y_k\right) \text{ and } \frac{\partial y_k}{\partial I_k} = \frac{\partial}{\partial I_k} f(I_k) = f'(I_k)$$

Therefore $$\frac{\partial E}{\partial I_k} = -(t_k - y_k)f'(I_k)$$

Now let $$\delta_k = (t_k - y_k)f'(I_k)$$

The weight update between hidden node j and output node k is then defined as:

$$\Delta w_{jk} = -\eta \frac{\partial E}{\partial w_{jk}} = -\eta(t_k - y_k) f'(I_k) y_k = -\eta \delta_k y_k \tag{5.5}$$

b) Since the weights connecting the ith input layer node to the jth hidden layer node have no target values from which to compute errors, the δ_k values are used as errors for each of the hidden nodes j. We now need to find an expression for the weight update, Δv_{ij}, between input node i and hidden node j:

$$\Delta v_{ij} = -\eta \frac{\partial E}{\partial v_{ij}} = -\eta \frac{\partial E}{\partial H_j} \frac{\partial H_j}{\partial v_{ij}}$$

where
$$\frac{\partial H_j}{\partial v_{ij}} = \frac{\partial}{\partial v_{ij}} \sum_i v_{ij} x_i = x_i$$

$$\frac{\partial E}{\partial H_j} = \frac{\partial E}{\partial z_j} \frac{\partial z_j}{\partial H_j} = \frac{\partial E}{\partial z_j} f'(H_j)$$

and
$$\frac{\partial E}{\partial z_j} = \frac{\partial}{\partial H_j} \left(\frac{1}{2} \sum_k (t_k - y_k)^2 \right).$$

Now using (5.3, p55) and (5.4, p55)

$$\frac{\partial E}{\partial H_j} = \frac{\partial}{\partial H_j} \left(\frac{1}{2} \sum_k \left(t_k - f(\sum_k w_{jk} z_j)\right)^2 \right)$$

$$= -\sum_k \left(t_k - f\left(\sum_k w_{jk} z_k \right) \right) f'\left(\sum_k w_{jk} z_k \right) w_{jk}$$

and using (5.1, p54), (5.2, p54), and (5.5)

$$\frac{\partial E}{\partial H_j} = -\sum_k (t_k - z_k) f'(I_k) w_{jk}$$

Now let $\delta_j = f'(H_j) \sum_k \delta_k w_{jk}$

The weight update between the hidden layer nodes *j* and the input layer nodes *i*, can be written as:

$$\Delta v_{ij} = \eta f'(H_j) \sum_k \delta_k w_{jk} (x_i) = \eta \delta_j x_i$$

3. *Updating the Connection Weights*

After the errors have been propagated backwards, the connection weights between each input node and each hidden node are updated in the following way:

$$v_{ij}(\text{new}) = v_{ij}(\text{old}) + \Delta v_{ij} = v_{ij}(\text{old}) + \eta \mathrm{f}'(H_j) \sum_k \delta_k w_{jk} (x_i)$$

and the connection weights between the each hidden node and each output node are updated in the following way:

$$w_{jk}(\text{new}) = w_{jk}(\text{old}) + \Delta w_{jk} = w_{jk}(\text{old}) + \eta (t_k - y_k) \mathrm{f}'(I_k) y_k$$

The above two steps are then repeated until the global error has been reduced to an acceptable level.

5.2.3 Choice of Learning Rate Parameter

The learning rate parameter, η, determines the size of the weight adjustment for each iteration, hence influences the rate at which learning is achieved. Choosing a learning rate that is too high causes the weights to diverge, leading to oscillations about the minimum. On the other hand, a learning rate that is too small causes slow convergence, causing the network to learn very slowly. This is often resolved by adding a momentum, α, to the weight adjustment. The weight update at a given time t, is stabilised by adding the gradient decreasing term with a fraction of the previous change as follows:

$$\Delta w_p(t+1) = -\eta \frac{\partial E}{\partial w_p(t)} + \alpha \Delta w_p(t) \qquad \text{where } 0 < \alpha < 1$$

The addition of the momentum term smoothes the weight change by cancelling the oscillations about the minimum, which makes learning faster when the learning rate is high. On the other hand, when the learning rate is too small, the momentum amplifies the learning rate causing faster convergence (Patterson, 1996).

5.2.4 Advantages and Disadvantages of the Backpropagation Network

The main advantage with the backpropagation algorithm is that it is easy to understand, and robust, that is, continues to operate even if there is error in some of the connections (Tarassenko, 1998).

Some of the disadvantages known for the backpropagation algorithm include (Patterson, 1996):

- *Overfitting*: this occurs when the network learns the training sample perfectly, and is not able to generalise on the test sample.

- *Saturation*: some nodes will stop learning if their incoming weights become large.

- *Scaling*: when the size of the network increases, the network becomes more computationally intensive, and the time required to train the network grows exponentially (Haykin, 1994).

- *Local minima*: this occurs when the minimum error of a function does not improve the performance of the network and learning is stopped even though there is some other combination of weights not in the network that could produce a much better solution (Fausett, 1994).

- *Selection of network parameters*: there is no optimal selection of the many training parameters, including the number of hidden layers, the learning and momentum rates, and the number of training epochs (Gupta & Smith, 2000).

5.2.5 Applications of the Backpropagation Network

According to a study conducted by Wong et al. (1997: Gupta & Smith, 2000) approximately 95% of reported neural network business application studies utilise the backpropagation network. The backpropagation network has been applied successfully in areas already mentioned in Chapter 4 (Section 4.5). In addition, the following authors used the backpropagation network in the following manner:

- Andree, Lourens, Taal, and Vermeulen (1995) used the backpropagation network to predict energy deposition patterns in a calorimeter. The performance of the backpropagation network was compared to that of another feed-forward neural network trained using the Patch algorithm, the probabilistic neural network and a *k*-nearest neighbour classifier. The performance of the backpropagation network was found to be superior to the other techniques, though the authors concern with the network was the difficulty in searching for an optimal network size and parameters.

- Bejou, Palmer, and Wray (1993) used the backpropagation network to study relationship quality (between buyers and sellers) in the financial services sector. The backpropagation network was compared to regression analysis. The result of their study indicated that the neural network was able to explain the relationship quality between the two levels of indicators of relationship quality and the five input variables used in the study better. From their study, they also realised that "the neural network may offer superior solutions to a wide range of marketing prediction problems characterised by complex and interdependent, causative variables".

5.3 Probabilistic Neural Networks

Probabilistic neural networks (PNNs) or kernel density estimators are feedforward networks that were first proposed by Donald Specht in 1988 (Patterson, 1996). They came about when Parzen (1962: Patterson, 1996) introduced a technique for estimating the unknown underlying distribution or probability density function (pdf) of input data. To derive such an estimator from a set of input data, the Parzen method is usually used.

The Parzen method employs Bayesian decision making theory (refer to Appendix A) based on an estimate of the probability (usually Gaussian) of the input data. The general form of the probability density function is given by (see Patterson, 1996):

$$f(x) = \frac{1}{n\lambda}\sum_{i=1}^{n}\varphi\left(\frac{x - x_i}{\sigma}\right)$$

where n is the sample size.

x is a vector of continuous random variables.

x_i is a continuous, independent, identically distributed random variable.

φ is the weighting function that must be integrable and bounded (that is, $\int_{-\infty}^{\infty}|\varphi(y)|dy < \infty$), normalised (that is, $\int_{-\infty}^{\infty}\varphi(y)dy = 1$), and must approach zero as the sample size increases (that is, ($\lim_{y\to\infty}|y\varphi(y)| = 0$)).

σ is the scaling or smoothing parameter (also called window or kernel width), which should decrease as the sample size increases. Note that σ must be chosen such that it is asymptotically unbiased (that is, $\lim_{n\to\infty}\sigma(n)=0$), and consistent (that is, $\lim_{n\to\infty} n\sigma(n)=\infty$).

Different values of the smoothing parameter (window) are used to estimate the underlying distribution on small samples of the input data. According to Patterson (1996), the use of an exponential Parzen type transfer function permits the PNN to learn to build non-linear decision boundaries, which approach the true distribution of the input data.

5.3.1 Architecture of the PNN

The PNN consists of four layers - an input layer followed by three computational layers (see Figure 5.2). All input patterns are normalised to unit length (that is, $x^* = \frac{x}{\|x\|}$), before processing.

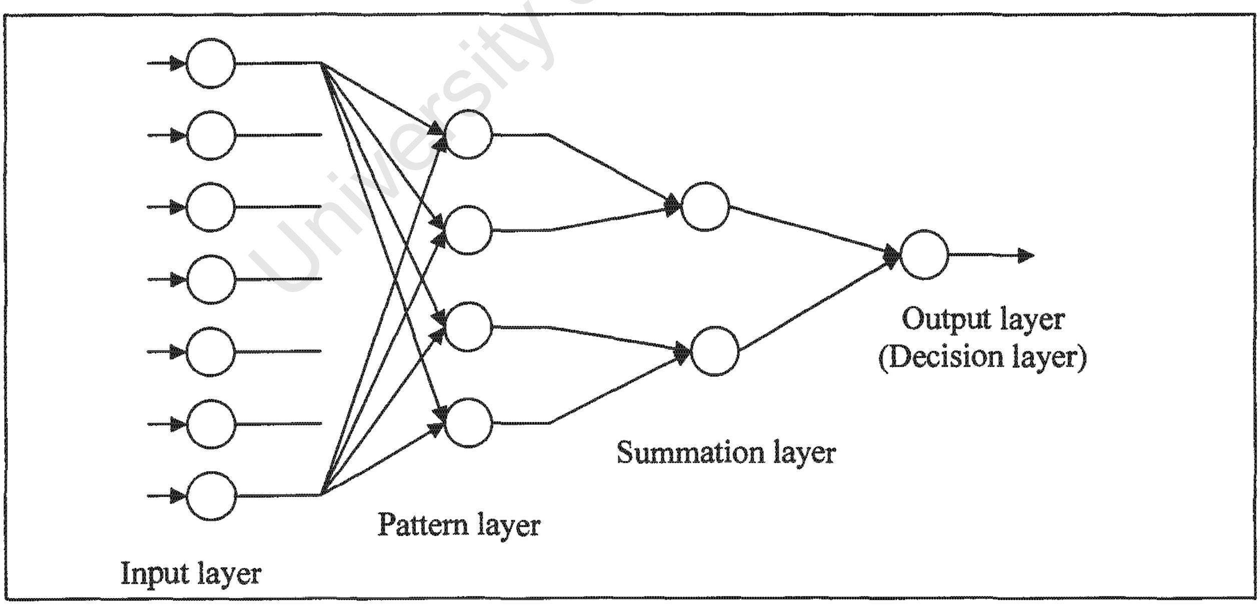


Figure 5.2 A Probabilistic Neural Network (*Source*: Butler and Caudill, 1992)

5.3.2 Network Training using the PNN

Training using the PNN is instantaneous as input data in fed to the network only once (Fausett, 1994). The input layer accepts and distributes the normalised input patterns through their adjustable weighted output connections to each node in the next layer, the pattern layer.

1. *The Pattern Layer*

There is one node in the pattern layer for each training case. The nodes in the pattern layer perform a weighted sum of the incoming signals (the weight vectors are also normalised to unit length), then apply a non-linear transfer function, which estimates the contribution of each case to the probability density function of each node, before passing the output to the summation layer. Thus the output of the j^{th} pattern-layer node is given by:

$$f(x, w_j) = \exp\left(\frac{\sum_{i=1}^{n}(x_i - w_{ij})^2}{2\sigma^2}\right)$$

where w_{ij} is the weight between node i in the pattern layer and node j in the summation layer.

2. *The Summation Layer*

The summation layer contains one node for each group of the output/dependent variable. Here, the pattern layer outputs are selectively connected to nodes in the summation layer depending on the group they represent (Patterson, 1996). The weights on the connections to the summation layer are also normalised to unit length, thus the summation layer merely adds the outputs from all the pattern-layer nodes connected to it. The outputs of the summation layer are transmitted to the output-layer node(s), the decision layer.

3. *The Output Layer*

The output layer nodes each have one node for each group of the dependent variable, thus will correspond to the number of nodes in the summation layer. The nodes compute the product of the summation node output and the weight coefficient w_k. The output generates a binary output signal that produces the classification decision using Bayesian theory.

5.3.3 Advantages and Disadvantages of the PNN

One of the main advantages of the PNN is the speed with which it can be trained. The PNNs single-pass training technique provides it with enormously fast training times, particularly in comparison with a highly iterative network such as backpropagation network (Patterson, 1996).

Other advantages the PNN possesses are (Fausett (1994), Patterson (1996)):

- its ability to identify commonalities in the training cases, which allows it to perform classification of unseen cases from the predefined groups without having to retrain the entire network.

- its ability to tolerate noisy samples and to deal with problems that have only very few cases for some of the groups. The PNN also does not suffer from the local minima problem like the backpropagation network, as it uses nonparametric estimation methods.

Some of the limitations associated with PNNs are its inability to deal with extremely large data sets - the size of the pattern layer can grow very large when large training sets are used (Patterson, 1996). To lessen this problem, group sample patterns can be substituted for large groups of individual patterns, provided the samples are representative estimators of the group probabilities (Butler and Caudill, 1992). Another drawback as suggested by Yang (Yang, 1996: Platt et al. 1999) is that the normalisation of input patterns, which is done before they enter the model, distorts the original character of the data space (that is, if the relationship between the input and output variables was linear, it can become non-linear after normalisation).

5.3.4 Applications of the PNN

Probabilistic neural networks are used mostly for classification, though according to Patterson (1996), PNNs are also used for other mapping techniques. Some of the areas where the PNN has been used include:

- Basheer & Hajmeer (2003) used the PNN to classify bacterial growth/no growth as affected by a set of operating conditions. The PNN was compared to the backpropagation network and both linear and nonlinear logistic regression. The neural network models were found to perform better than the regression models. Of the two neural network models, the PNN was superior to the backpropagation network because it was easier to build, robust to noisy data, and faster to train. However, the one disadvantage the authors found with the neural networks was their inability to be "written practically in a simple equation-like form".

- Liebich et al. (2002) used the PNN to classify cancer patients from healthy persons according to the levels of nucleosides in human urine. The performance of the PNN was compared to linear discriminant analysis, and the learning vector quantization network. Their results showed that the predictive accuracy of the PNN was higher than the other techniques, and by combining all the three techniques, they were able to correctly classify 100% of the data due to the "tendency of various classification methods in identifying healthy persons and cancer patients".

- Platt et al. (1999) compared the performance of two varieties of probabilistic neural network models (one with normalised input data and the other without normalisation), the backpropagation network, and discriminant analysis, to bankruptcy prediction of U.S. oil and gas companies. They found that the backpropagation and probabilistic neural network without pattern normalisation and discriminant analysis produced superior and comparable estimation results for bankrupt companies.

5.4 Radial Basis Function Networks

A Radial Basis Function Neural network (RBFNN) is a supervised feedforward network with three layers: an input layer, a hidden layer (which contains radial basis function transfer functions), and an output layer (see Figure 5.3 below):

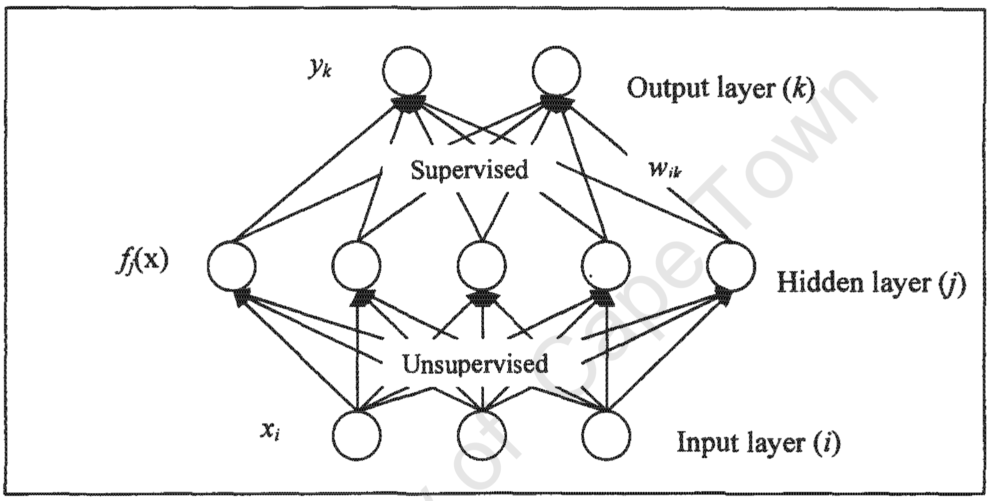


Figure 5.3 A Radial Basis Function Network (*Adapted from*: Hertz et al, (1991))

5.4.1 Learning of the Radial Basis Function Neural Network

Network learning through the layers can be described as follows:

1. Each input node i, receives an input pattern, x_i, which is then propagated to each of the hidden nodes j. During this stage, an unsupervised technique (such as competitive learning (Hertz et al., 1991) or K-means clustering (Tarassenko, 1998)) is used to find

'weights' between the two layers. These 'weights' represent centres of clusters of the input pattern (that is, the unsupervised technique groups the input patterns into clusters).

2. The clustered patterns are then used in the hidden layer nodes, the next stage in the learning process. The input to the hidden nodes is computed by taking the distance between inputs, x_i, and the cluster centres, c_i ($\|x-c\|$), and passing it through the radial basis function transfer function, f (these are functions that perform a non-linear transformation from the n-dimensional input space to the k-dimensional output space, by forming a linear combination of non-linear basis functions (i.e. f: $R^n \rightarrow R^k$).). The most common distance measure used is the Euclidean distance, while the Gaussian exponential function is the most typical transfer function used in the hidden layer (Patterson, 1996). The Gaussian RBF is defined by (see Patterson, 1996):

$$f(x) = \alpha \exp\left(-\sum i\left[(x_i - c_i)/\sigma_i\right]^2\right)$$

where α is a constant, c_i the centre, and σ_i the width or smoothing factor, determined by "an ad hoc choice such as the nearest neighbour technique" (Hertz et al., 1991). The widths, σ_i, which represent a measure of the spread of the data associated with each centre, c_i, are set once the clustering procedure is complete. They can be set equal to the average distance between the two nearest cluster centres, c_i, and the training patterns, x_i, which belong to that cluster as follows (Hush and Home, 1993: Tarassenko, 1998):

$$\sigma_i^2 = \frac{1}{p_i} \sum_{x \in C_i} (x - c_i)^T (x - c_i)$$

where C_i is the set of training patterns grouped with centre c_i, and p_i is the number of training patterns in C_i.

In the hidden layer, the network is first initialised by setting the centres, c_i, to equal to some of the training patterns, x_i, so as to give a good approximation to the function, f, at these points (Patterson, 1996). Tarassenko (1998) suggests that for adequate coverage of the input space, the number of basis function centres, c_i, needs to be greater than the number of clusters in the data.

After the parameters have been set, that is after c_i and σ_i have been determined using unsupervised learning, the hidden nodes outputs the sum of the weighted basis functions, $f(x) = \alpha \exp\left(-\sum i\left[(x_i - c_i)/\sigma_i\right]^2\right)$. Note that the output for the input patterns at each hidden node, j, are identical since the Gaussian functions are radially symmetric.

3. In the output layer, the basis functions are fixed while training continues to determine the connection weights, w_{jk}, between hidden layers j and output layers k, using a supervised learning algorithm such as the Least Mean Square (LMS) algorithm (Tarassenko, 1998) in order to compute the error. The transfer function used here is linear rather than sigmoid.

To show the weight adjustment between hidden layer nodes j and the output layer nodes k for the radial basis function network, we define the following:

$z_j = f_j(x)$	output pattern (transfer function) from hidden layer node j
w_{jk}.	weight connections between hidden layer node j and output layer node k
$I_k = \sum_k w_{jk} z_j$	net input to output layer node k
$y_k = f(I_k)$	actual output pattern (transfer function) from output layer node k

Equation (5.5, p57), which shows the weight update between hidden node j and output node k, becomes (see Tarassenko, 1998):

$$\Delta w_{jk} = -\eta \delta_k y_k \qquad \text{where } \delta_k = -\frac{\partial E}{\partial I_k} = (t_k - y_k) f'(I_k)$$

For a linear function, the identity function is the most typical function used, thus

$$f'(I_k) = f'\left(\sum_k w_{jk} z_j\right) = \frac{\partial y_k}{\partial I_k} = \frac{\partial f}{\partial I_k}\left(\sum_k w_{jk} z_j\right) = 1$$

Since $y_k = I_k$ (i.e. $f(x) = x$) for a linear unit, then we have $\delta_k = (t_k - y_k)$, and since the standard error function, $E = \frac{1}{2}\sum_k \left(t_k - y_k\right)^2$, is used as a measure of performance, the partial derivatives: $\frac{\partial E}{\partial c_{jk}}$ and $\frac{\partial E}{\partial w_{jk}}$ are calculated in order to determine the weight adjustment.

The application of a supervised learning algorithm from the hidden layers to the output layers continues in order to adjust the connection weights until an acceptable minimum is found, and training is stopped when no further reduction of the mean squared error is achieved. The output of the output layer nodes k, is then given by:

$$y_k = \sum_{j=1}^{J} w_{jk} f_j(x).$$

5.4.2 Advantages and Disadvantages of Radial Basis Function Networks

Some of the known advantages of radial basis function neural networks include (Tarassenko (1998)):

- Quick training time, since training data is presented only once and validation data is not used during the training phase. This presents a real advantage for radial basis function networks since finding optimal connection weights is a very time consuming process, because of the volume of labelled data required.

- Ease of design decisions about the number of layers, since non-linear functions can be modelled using a single layer.

- They are less susceptible to problems with non-stationary inputs because of the behaviour of the radial basis function hidden nodes (Bigus, 1996).

The main disadvantage with radial basis function networks as pointed out by Tarassenko (1998) is that the initial learning phase of the RBF is the unsupervised clustering phase, hence important information could be lost in this phase. Another disadvantage of the RBF network noted by Smith (1996) is that it is "impractical for problems with a large number of independent variables since the required number of hidden nodes increases geometrically with the large number of inputs".

5.4.3 Applications of the Radial Basis Function Network

Some areas where the RBF network has been applied include:

- Singh & Singh (2001) used the RBF network to forecast short term load on an hourly basis for power systems. They obtained excellent results using the network. From their study they commented about the fast training time of the network, and how they were able to select input variables based on performance of the network.

- Chen (2000) designed a stepwise RBF network for dryness prediction in a clothes dryer (that is, for the dryer to automatically shut-off once it reaches a particular degree of dryness specified by the user). The performance of the RBF network was compared to the backpropagation network and to both the linear and nonlinear regression models. The RBF network outperformed both the backpropagation network and regression models.

- Morlini (1999) used the RBF to model partially classified ecological data. The performance of the RBF network was compared to that of discriminant analysis. The RBF network was found to be suitable for modelling the partially classified data since no information was wasted, because network parameters can be determined using both labelled and unlabelled data. Another advantage the RBF network had over discriminant analysis was that they do not need the assumption of multivariate normality.

- Hutchinson, Lo, and Poggio (1994) used the RBF network, the backpropagation network, linear regression, and project pursuit regression (PPR) to estimate the pricing and hedging of S&P 500 futures options. Their goal was to see if any of the techniques could yield similar values to those generated by the Black-Scholes formula. Both the neural network models were found to give superior results, though their concern was the difficulty in matching the network architecture and parameters to the dataset in hand.

5.5 Summary

In this chapter both supervised and unsupervised neural networks commonly used in classification problems were discussed. We looked at the architecture of each network, how each network is trained, some advantages and disadvantages, and a few application areas for each network.

CHAPTER 6 METHODOLOGY

This chapter outlines the procedure followed in the analysis of the trauma unit data provided by the Red Cross War Memorial Children's Hospital. The data mining process was used for this research (refer to Figure 6.1).

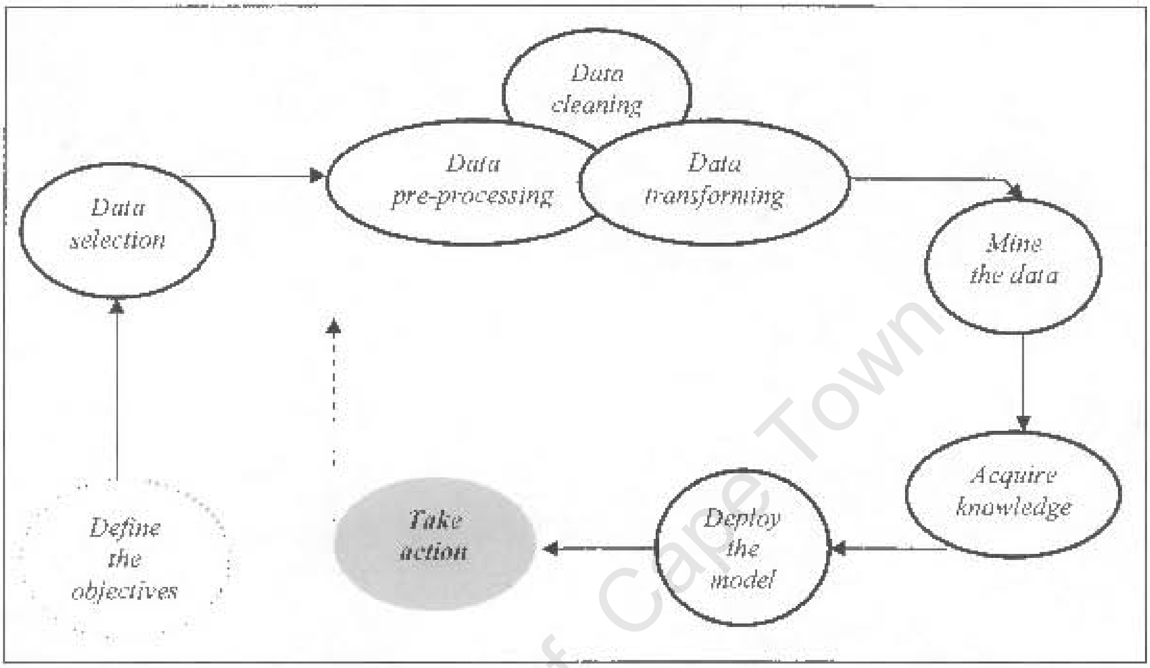


Figure 6.1 The Data Mining Process (*Adapted from literature*, and Lin & McClean (2001))

6.1 Research Objectives

The research objectives identified for this study are outlined in Chapter 1 (Section 1.5).

6.2 Data Selection

The data from the Red Cross War Memorial Children's Hospital had been stored in Microsoft Access relational database software, and was initially recorded on a form called 'The Trauma Unit Record' (refer to Appendix B for a copy of the Trauma Unit Record), which consists of twenty-two sections/questions that a patient completes on arrival at the hospital. The data related to 95669 patients who had visited the hospital between June 1991 and December 2001 (refer to Appendix C for a spreadsheet sample of the database).

6.2.1 Description of the Database

The different questions (which we will refer to as variables) asked on the trauma unit record are:

Variable:	Description:	Data Type:	Number of Categories:
▪ Surname	Surname of patient		
▪ Name	Name of patient		
▪ Folder Number			
▪ Address	Address where the accident occurred		
▪ Date	Date of injury.	numeric	
▪ Birth	Date of birth.	numeric	
▪ Hours	Number of hours passed since injury occurred.	numeric	
▪ Race/Gender	The race and gender of a patient.	categorical	8
▪ Causes	Causes of injury	categorical	39
▪ Place	The place where the injury occurred.	categorical	10
▪ Admission	Whether a patient was admitted to the trauma unit, other wards or not admitted.	categorical	3
▪ Disposal	The place where patients are sent from the trauma unit.	categorical	10
▪ Unconscious	Whether patient was conscious on arrival at the hospital.	categorical	2
▪ Shock	Whether patient was in shock or not.	categorical	2
▪ Resuscitation	Type of resuscitation administered, if any.	categorical	3
▪ Anaesthetic	Whether anaesthetic was administered.	categorical	3
▪ Self Infliction	Whether the injury was self-inflicted.	categorical	2

Variable:	Description:	Data Type:	Number of Categories:
▪ Abuse	Whether patient was injured as a result of abuse or not.	categorical	3
▪ Anatomy	The part of the body injured.	categorical	40
▪ Abbreviated Injury Score (AIS)	Severity of injury.	categorical	4
▪ Pathology	Description of injury.	categorical	25
▪ Treatment	The type of treatment given.	categorical	9

6.2.2 Data Acquisition

Whilst in Access, a query was designed by merging the various tables containing the different variables using 'Folder number'. This query was then used to create a data matrix containing all the information that would be used in the analysis.

6.3 Data Cleaning

For each variable (except the 'Name', 'Surname' and 'Folder number' variables which have been omitted from the spreadsheet sample of the database in order to maintain patient privacy) , the data was sorted in ascending order to see if there were nonsense values or values that did not fall within the specified number of categories for categorical variables. Cases whose values fell outside the specified range or had values that did not make sense were deleted.

6.3.1 Missing Values

According to Berry & Linoff (2000) neural networks cannot deal with missing values, and dropping the cases containing missing values could result in training data that "will probably be skewed since the subset of cases for which all independent variables are filled in is not likely to be representative of the population". However for this research, since most of the variables were categorical, it was felt that using tools such as mean substitution to estimate the missing values would skew the data in favour of the outcome that appeared frequently in each variable, therefore all the cases with missing values were also deleted[1]. The data was also sorted by the date of 'Birth' variable, and patients who at the time of completing the Trauma Record form were older than nineteen years old were deleted from the database. For the 'Address' variable though, since there were a lot of missing values, it was decided to discard the variable from the analysis.

Deleting missing cases from the database did not affect our analysis since the relative proportion of the groups in the dependent variable was not altered (see Chapter 7, Section 7.1). The data cleaning stage resulted in 89780 patients entering the study from the original 95669.

6.3.2 Data Preparation and Transformation

Some of the variables had large numbers of categories. This could pose a problem especially with the CART decision tree algorithm, since the number of possible splits that must be examined at each node is based on the partitioning of the categories, the number of permissible splits being $2^{k-1} - 1$, where k is the number of distinct categories in a variable. Depending on the size of k, the tree could take a very long time to train. The large number of categories could also affect the speed that neural networks take to train, as well as their ability to perform well on unseen data (Tarassenko, 1998). It was therefore essential to find ways of reducing the number of categories for certain variables

Working with management from the Red Cross War Memorial Children's hospital (who had prior knowledge of the data), the large numbers of categories for some of the variables, as mentioned below, were reduced by grouping similar categories together.

[1] Decision trees can deal with missing values, however, for comparative reasons, the same criteria was applied to all the techniques.

The following categorical variables were reduced in size to:

Variable:	Number of Categories Before:	Number of Categories After:
▪ Causes	39	6
▪ Place	10	3
▪ Race/Gender	8	4
▪ Disposal	10	3
▪ Anatomy	40	4
▪ Pathology	25	12
▪ AIS	4	3
▪ Treatment	9	7

The variables with dates, that is, 'Date' of injury and date of 'Birth', were used to come up with an 'Age' variable, and then transformed into categorical variables, first by splitting the date into three variables (day, month, and year), then grouping the variable with years into three categories (early-nineties, late-nineties, and millennium – for 'Date' of injury (name changed to 'Year of injury'), and seventies, eighties and nineties – for date of 'Birth' (name changed to 'Year of birth')). The day and month variables were not used in the research, hence were deleted from the trauma unit spreadsheet.

For the different techniques used in the analysis, it was not necessary to code the categorical variables since the statistical package used would automatically code the data for analysis, in a manner that would not introduce ordering of the data that could be misleading.

6.3.3 Scaling

According to Berry & Linoff (2000) inputs to a neural network must be scaled to be in a particular range, usually between –1 and 1. This was not done manually, however all the neural network techniques were set to automatically normalise (this accounts for scaling differences between the variables) the data before any analysis was run.

6.4 Mining of the Data

The fourth step of the data mining process involves applying the identified data mining techniques to the data. Before applying the classification techniques to the data, it was necessary to reduce the dimensionality of the input variables in order to "yield a network with good generalisation properties" Statsoft (2001).

6.4.1 Input Variable Selection

The idea of reducing the dimensionality of the input space is to find the optimum combination of variables that gives the best classification results. The techniques are then run through the data using only those variables, and leaving the insignificant variables from the analysis.

For the neural network techniques, the approach of using Pearson's chi-squared[2] test to select variables that are strongly related to the dependent variable was employed to select subsets of variables.

This approach however, was not useful in reducing the number of variables, hence another facility - *Sensitivity Analysis* (which indicates the importance of each independent variable to a particular neural network model) – was used on each neural network to determine the variables that could be discarded for the actual analysis. Five samples of approximately 5000 cases (see later) were run to assess the performance of each technique. The sensitivity ratio reported for each network indicated those variables that

[2] The Chi-squared statistic tests the null hypothesis that a categorical input and categorical output variables are not related (the F-statistic is employed if the input variable is continuous).

had a ratio of one or lower (this means that the performance of the network is not affected or will be enhanced when the affected variables are left out of the model).

Before discarding any variables from the analysis, we applied the non-neural network techniques - decision trees and discriminant analysis, to the same five samples to determine the variables that were not important in classifying the outcomes of child trauma injuries.

There was some discrepancy between the different techniques in the variables that gave the best classification results. Some variables were not significant for all the techniques, and those were discarded immediately. For the inconsistent variables, the factor that determined whether to keep or discard the variable was the number of times the variable was insignificant/unimportant on the five samples that were used. Those variables that were only flagged as insignificant for a particular technique were kept in the model, and those variables that were flagged as insignificant for two or more techniques were discarded.

6.4.2 Modelling of the Classification Techniques

In order to compare the performance or predictive accuracy of the different classification techniques, all models were run on exactly the same variables. The parameters set to obtain the best performance on the different models were:

a) Decision Trees

The standard classification tree (CART or C&RT) for continuous and categorical independent variables was used, and the optimal tree structure obtained was built by specifying the following parameters:

- Goodness of fit measure: - Gini
- Prior class probabilities: - estimated

- Stopping option for pruning: - FACT style direct stopping
- Fraction of objects - 0.05
- V-fold cross validation - number of folds: 10, standard error rule: 1

b) Discriminant Analysis

The best-subset and stepwise discriminant function analysis was used to build a linear discriminant function model for continuous and categorical independent variables. This module was specifically chosen because of the ability to deal with categorical variables, though "no 'experience' (in the literature) exists regarding issues of robustness and effectiveness of these techniques, when they are generalized in the manner provided in this very powerful module" Statsoft (2001). The parameters that gave optimal results were specified as follows:

- Priors: - estimated
- Stepwise selection criteria: - F statistic
- p to enter/p to remove: - 0.05
- Best subset measure: - Wilk's Lambda

c) Backpropagation, Probabilistic, and Radial Basis Function Neural Networks

The backpropagation, probabilistic and radial basis function neural network architectures were all run using the statistical package's wizard, which requires minimum intervention on the part of the analyst, and is guaranteed to retain the best network for deployment. The following criteria were specified for all the architectures:

- Stop search based on: - networks tested
- Number of networks tested: - 25
- Criteria to retain networks: - balanced performance
- Classification threshold: - highest confidence

- Accept/reject threshold: - 0.05

6.4.3 Criteria used to evaluate the Predictive Accuracy of the Neural Network Architectures

To ensure that a network will perform well on data it has not seen before (that is, to avoid overfitting), some data is held back and is not used for training the network. By default the statistical package automatically partitions observations to training, selection/validation and test/generalisation subsets in the proportions 2:1:1 respectively. The observations in the training set are used to train the network (that is, to estimate the network weights and other parameters), observations in the selection set are used to perform an "independent check" of the network's performance during training, to determine when to terminate training the network (this set is not used to modify parameters of the network), and observations in the test set are applied to a fully trained network as a final independent check of the final network performance to verify the model's reliability (Statsoft, 2001).

The summary statistics computed once a network is trained that can be used to evaluate the performance of a network are the model's summary, classification, and confusion matrices.

a) Model Summary

The model summary report is a spreadsheet that is usually split into eight sections (see Table 6.1 below):

- *Profile* – this indicates the network type, the number of input and output variables, the number of hidden layers, and the number of nodes in each layer. In the model summary report shown, the *MLP 2:2-3-1:1* represents a multilayer perceptron with two input variables, one output variable and three layers of 2, 3, and 1 nodes respectively (that is, three nodes in the hidden layer).

- *Train Perf./Select Perf./Test Perf.* – this indicates the performance of the networks on the training, selection and test subsets respectively.

- *Train Error/Select Error/Test Error* – this indicates the error rates on the subsets.

- *Training* – this gives a description of the training algorithm used to train the network – in the model summary report shown, the BP5b means five epochs or passes through the training data, using the backpropagation algorithm at which point training was terminated due to over learning and the optimal network obtained.

Table 6.1

Example of a Model Summary Report

	Profile	Train Perf.	Select Perf.	Test Perf.	Train Error	Select Error	Test Error	Training
1	BP 2:2-3-1:1	0.812500	0.750000	0.750000	0.323055	0.297239	0.303986	BP5b

Selection of the optimal network is based on the lowest classification error rate obtained on the selection set, and the performance measure (that is, the proportion of observations in the subset correctly classified) on the selection subset is used to discriminate between and choose between networks. Another criteria used to determine the optimal network is to look at the selection- and test-errors, if they are comparable (that is, if the absolute difference between the errors is close to zero), then one can be sure that the network has generalised successfully.

b) Classification Matrix

A classification matrix provides a summary on the classification performance (see Table 6.2 below for an example of a classification matrix of a two-group problem). Here, the first row indicates the actual number of observations that were in the sample; the second row indicates the number of observations predicted correctly by the network; the third row indicates the number of observations that are wrongly predicted by the network; and the fourth row indicates unknown observations (that is, classification is vague, reflecting a point in areas of overlap between the groups).

Table 6.2

Example of a Classification Matrix

	1	2
Total	17	15
Correct	11	14
Wrong	6	1
Unknown	0	0
Correct(%)	65	93
Wrong(%)	35	7
Unknown(%)	0	0

c) Confusion Matrix

A confusion matrix is a square matrix with as many rows and columns as there are groups in the dependent variable, which provides a more detailed breakdown of the misclassifications (refer Table 6.3).

Table 6.3

Example of a Confusion Matrix

	1	2
1	11	1
2	6	14

6.5 Practical Constraints in Modelling

When we started analysing the data, all the 89780 cases were used in the analysis. This worked for some of the techniques, except for the probabilistic neural network (PNN) which could not handle the large number of cases. The time it took to train the network was either too long or the computer would crash as a result of running out of memory. Thus, the data file size was reduced to determine the level that could produce results for the PNN network with ease, and this only was achieved with 5000 cases.

In order to utilise all the cases that had entered the study, and to check the consistency of the performance of the different models on different samples, a *Random Sample Filtering* facility was used to generate twenty samples of 5000 cases from the 89780 cases. This facility was used because it generates random samples (without replacement) that are as accurate (that is, falls within the same confidence limits (Statsoft, 2001)), as those that would be obtained if all the observations were used. The samples generated did not as a result of this contain exactly 5000 cases each, but a number of cases close to 5000.

Whilst learning to use the software, we had modelled the different techniques by specifying different parameters to determine the combination of parameters (e.g. using the sum-squared instead of the cross entropy error function set as default for classification problems for the backpropagation network) that would yield the best performance, but none that we tried yielded results that were better than those obtained when the analysis was run using the parameters assigned as defaults.

6.6 Summary

This chapter sought to outline the methodology (by applying the data mining process) used in the classification of the trauma unit data from the Red Cross War Memorial Children's Hospital using different data mining classification techniques. The criteria used to analyse the data in order to achieve the optimal predictive accuracy by the different classification techniques was discussed. In the next chapter, we continue with the fifth step of the data mining process by reporting the results obtained from the data mining classification techniques.

CHAPTER 7 FINDINGS

7.1 Pre-Analysis Results

7.1.1 The Proportion of Cases in the Dependent Variable Before and After Data Cleaning

The dependent variable, 'Causes' of injury, which had thirty-nine categories initially, was reduced to six main categories –'Transport', 'Assault', 'Burn', 'Fall', 'Miscellaneous', and 'Unknown'. The number and percentage of cases in each of the 'Cause' categories before and after data pre-processing are shown graphically in Figure 7.1 and Figure 7.2 respectively.

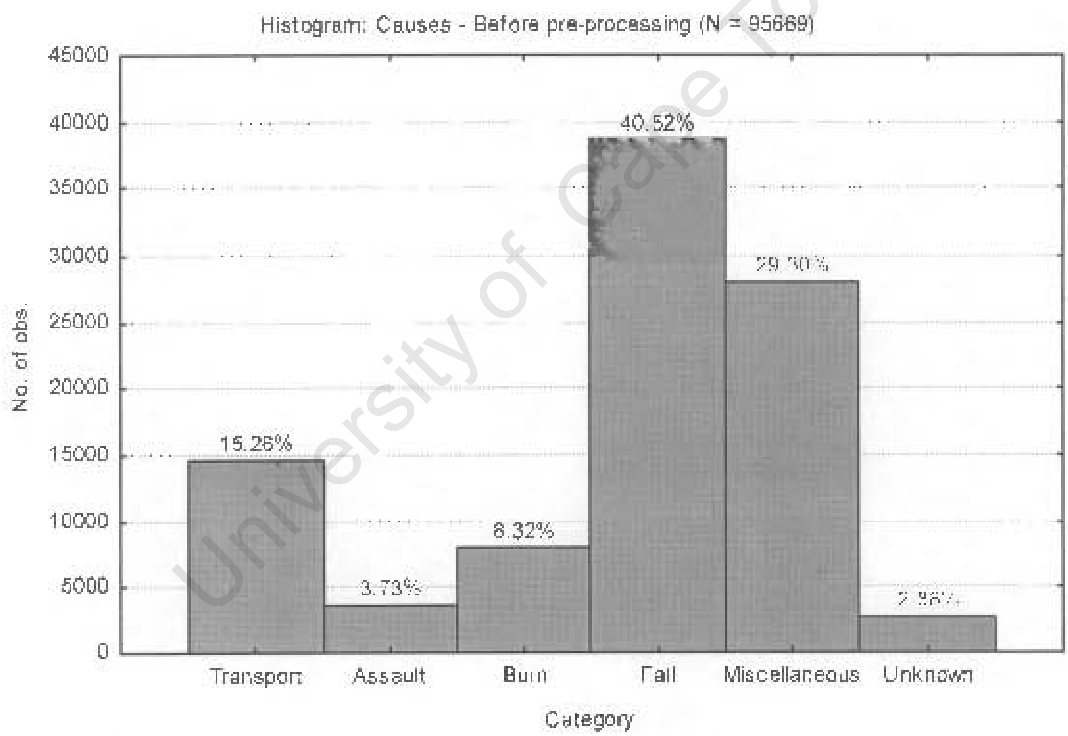


Figure 7.1

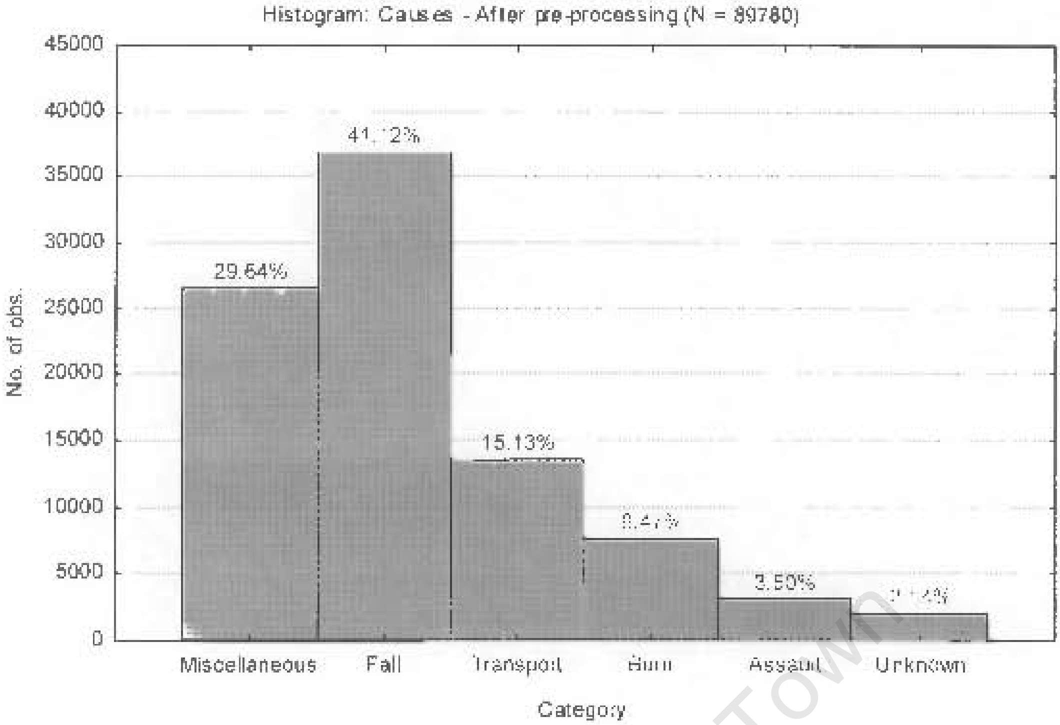


Figure 7.2

The figures show that the proportion of cases in each of the 'Causes' categories before and after the data cleaning stage of the data mining process is approximately equal – none of the categories increased nor decreased by over one percent.

The proportion of cases for the dependent variable in the twenty samples generated are also approximately equal (refer to Appendix D).

7.1.2 Input Variable Selection

Table 7.1 below shows the results computed using Pearson's chi-squared approach to select variables that are strongly related to the dependent variable, for the neural network models. From the table, all the input variables were strongly related to the dependent variable ($p<0.001$).

Table 7.1 – Best Predictors for Categorical Dependent variable (Causes)

Variable	Chi-square/F-statistic	p-value
Pathology	94918.98	0.00
Place	23919.99	0.00
Admission	21838.75	0.00
Abuse	15201.17	0.00
Treatment	14810.73	0.00
Anatomy	11091.85	0.00
Age	7671.30	0.00
Disposal	6530.72	0.00
Anaesthetic	4614.62	0.00
Resuscitation	4429.23	0.00
AIS	2977.70	0.00
Year of Birth	2822.54	0.00
Race/Gender	2549.57	0.00
Unconscious	1329.64	0.00
Time	972.11	0.00
Shock	773.70	0.00
Hours Since Injury	682.05	0.00
Self Infliction	629.65	0.00
Year of Injury	167.79	0.00

a) Results from the Sensitivity Analysis Facility

The output from the *Sensitivity Analysis* facility is reported in Appendix E.1. The sensitivity ratio reported for each network indicates the strength of the relationship between the independent and dependent variables for a particular neural network model. A ratio of one or lower indicates that the variable is a bad predictor, which means that the performance of the network will be enhanced when the affected variables are left out of the model.

b) Results from Decision Trees and Discriminant analysis

Also shown in Appendix E.2 and Appendix E.3 respectively, are the decision tree *predictor importance* results and the *test of significance* results given by the discriminant analysis technique. The *predictor importance* results show a ranking of the variables – where good predictors will have a rank close to one hundred and bad predictors will have a rank close to zero. The highlighted variables have a rank of twenty or less. On the other hand, the *test of significance* results shows the p-value for each of the independent variables. In this instance, the null hypothesis being tested is that the independent variable does not discriminate well between the groups of the dependent variable. Variables that are highlighted are those whose significance level is greater than 5% (that is, $p > 0.05$).

After combining the different results from the sensitivity analysis, decision tree, and discriminant analysis techniques, the variables that were found to be important for predicting the outcomes of injury, and would subsequently be used in all the classification techniques, were:

- Abuse
- Admission
- Age
- Anaesthetic
- Anatomy
- Pathology
- Place
- Race/Gender
- Resuscitation
- Treatment

The rest of the variables were discarded.

7.2 Evaluating the Results of the Classification Techniques

In this section, the application of the five classification techniques to the trauma data is illustrated. The performance measure used to evaluate the accuracy of the five techniques into one of six groups (Transport, Assault, Burn, Fall, Miscellaneous, and Unknown) of the dependent variable, was the overall classification rate (that is, the number of correctly classified cases).

7.2.1 A Summary of the Performance of Decision Trees

Table 7.2 below is a summary of the overall percentage of correctly classified cases obtained from the twenty random samples using the CART algorithm (refer to Appendix F for the individual classification matrices which provide a detailed breakdown of the classifications of each group).

From the table, of the twenty samples generated, the minimum overall percentage of correct classifications is 61.0566% (model no. 13) and the maximum overall percentage of correct classifications is 64.2308% (model no. 6). On average the CART algorithm correctly classified 63.2271% cases (averaged over all the 20 samples).

Examining the model that gives the best classification results (model no.6 – refer to Table 7.3 below), we can see that the classification tree is better at predicting group membership for the 'Burn' group (96.0526% of cases are correctly classified) than for the 'Unknown' group (none of the cases are correctly classified). The model moderately classified the other groups.

Table 7.2

Model Summary Report - Classification Trees

Model no.	Valid N	Overall Percent Correctly Classified
1	4835	63.4747
2	4886	62.9349
3	4902	63.5659
4	4913	63.1793
5	4936	63.2699
6	**4940**	**64.2308**
7	4984	64.2255
8	4985	63.4504
9	4986	63.3172
10	4987	63.2845
11	4989	62.5376
12	4994	64.1169
13	4997	61.0566
14	5015	63.4696
15	5018	62.5947
16	5025	62.5473
17	5034	64.0047
18	5048	62.5594
19	5092	63.0793
20	5157	63.6417

Table 7.3

Classification Matrix for Best Model (**no. 6**) - Valid N = 4940

	Percent Correct	Transport	Miscellaneous	Fall	Assault	Unknown	Burn
Transport	55.4767	547	145	247	27	18	2
Miscellaneous	62.1199	87	712	246	51	30	25
Fall	63.8947	114	620	1515	53	62	11
Assault	70.8333	1	4	6	34	3	0
Unknown	0.0000	0	0	0	0	0	0
Burn	96.0526	1	8	3	2	1	365
Total	64.2308	750	1489	2017	167	114	403

7.2.2 A Summary of the Performance of Discriminant Analysis

Summary results of discriminant analysis are shown in Table 7.4 below (refer to Appendix G for a detailed breakdown of the classifications of each group for the individual classification matrices).

From the table, of the twenty samples generated, the minimum overall percentage of correct classifications is 62.0365% (model no. 11) and the maximum overall percentage of correct classifications is 65.0184% (model no. 20). On average discriminant analysis correctly classified 63.6128% cases (averaged over all the 20 samples).

Examining the model that gives the best classification results (model no.20 – refer to Table 7.5 below), we can see that the discriminant analysis is also better at predicting group membership for the 'Burn' and 'Fall' group (91.95656% and 75.1192% of cases are correctly classified respectively) than for the 'Unknown' group (8.7379% of the cases are correctly classified). The 'Assault' group is also weakly classified (33.1429% of the cases are correctly classified), and the model moderately classified the other groups.

Table 7.4

Model Summary Report - Discriminant Analysis

Model no.	Valid N	Overall Percent Correctly Classified
1	4835	64.5502
2	4886	63.7536
3	4902	63.8515
4	4913	63.7899
5	4936	64.3233
6	4940	63.1781
7	4984	64.5064
8	4985	63.4303
9	4986	62.7758
10	4987	63.0840
11	4989	62.0365
12	4994	64.3973
13	4997	62.5976
14	5015	63.3300
15	5018	62.3555
16	5025	63.7811
17	5034	63.7267
18	5048	63.8074
19	5092	63.9631
20	**5157**	**65.0184**

Table 7.5

Classification Matrix for Best Model (**no. 20**) - Valid N = 5157 Rows: Observed, Columns: Predicted classifications

	Percent Correct	Miscellaneous	Fall	Transport	Burn	Assault	Unknown
Miscellaneous	50.4836	783	592	134	8	16	18
Fall	75.1192	263	1576	227	2	23	7
Transport	65.4545	67	191	504	1	6	1
Burn	91.9565	25	11	1	423	0	0
Assault	33.1429	32	54	27	1	58	3
Unknown	8.7379	20	58	13	0	3	9
Total	65.0184	1190	2482	906	435	106	38

7.2.3 A Summary of the Performance of the Backpropagation Network

Table 7.6 below is a summary of the best performing neural network models trained using the backpropagation algorithm (refer to Appendix H for the classifications of each group on the individual classification matrices for each sample, and to Appendix I for the confusion matrices, which provide a detailed breakdown of the misclassifications of cases for each sample).

From the table, the architecture for all the networks is similar – ten input variables were presented to the network, there were forty-three nodes (four networks had forty-two nodes) in the first layer, eleven nodes in the hidden layer, six nodes in the output layer corresponding to the number of groups in the dependent variable, and one output variable. The lowest selection performance is 0.602429 (model no. 6) and the highest selection performance is 0.636364 (model no. 15). The number of training passes that gave the network with the best performance ranges from zero (this means that the optimal network was obtained on the first training run) to fifteen. Looking at the absolute difference between the selection- and test-errors, it is evident that the network that gives the best classification results is not the one that generalises successfully (the absolute difference between the errors has to be close to zero for the network to generalise successfully).

Of the twenty samples generated, the minimum overall percentage of correct classifications is 60.4453% (model no. 6) and the maximum overall percentage of correct classifications is 65.6015% (model no. 4). On average the backpropagation network correctly classified 63.2841% cases (averaged over all the 20 samples).

Examining the model that gives the best classification results (model no.4 – refer to Table 7.7 below), we can see that the backpropagation network is better at predicting group membership for the 'Burn' and 'Fall' group (93.19% and 76.54% of cases are correctly classified respectively) than for the 'Unknown' group (9.47% of the cases are correctly classified). The

'Assault' and 'Miscellaneous' groups are also weakly classified (31.93% and 46.98% of the cases are correctly classified respectively), and the model moderately classified the 'Transport' group.

Table 7.6

Model Summary Report - BP

Model no.	Profile	Train Perf.	Select Perf.	Test Perf.	Train Error	Select Error	Absolute diff. (Select error – Test error)	Test Error	Training	Valid N	Overall Percent Correctly Classified
1	10:43-11-6:1	0.647375	0.629139	0.652318	1.200577	1.265946	0.0654	1.210415	BP2b	4835	64.4054
2	10:43-11-6:1	0.644845	0.612613	0.619984	1.209903	1.328039	0.1181	1.366026	BP4b	4886	63.0577
3	10:43-11-6:1	0.646003	0.632653	0.626939	1.178242	1.306432	0.1282	1.276601	BP5b	4902	63.7903
4	**10:43-11-6:1**	**0.673993**	**0.631107**	**0.644951**	**1.210112**	**1.358705**	**0.1486**	**1.275316**	**BP15b**	**4913**	**65.6015**
5	10:43-11-6:1	0.645057	0.619125	0.618314	1.203516	1.251923	0.0484	1.354522	BP13b	4936	63.1888
6	10:42-11-6:1	0.599595	0.602429	0.616194	1.316863	1.325552	0.0087	1.343181	BP0b	4940	60.4453
7	10:43-11-6:1	0.651284	0.622793	0.639647	1.197370	1.299749	0.1024	1.252197	BP4b	4984	64.1252
8	10:42-11-6:1	0.619334	0.609952	0.614767	1.284385	1.311999	0.0276	1.334912	BP0b	4985	61.5848
9	10:43-11-6:1	0.637129	0.610754	0.617978	1.179016	1.241749	0.0627	1.323408	BP9b	4986	62.5752
10	10:43-11-6:1	0.622846	0.612360	0.632424	1.227485	1.329968	0.1025	1.284810	BP0b	4987	62.2619
11	10:43-11-6:1	0.656914	0.631917	0.617482	1.197645	1.331840	0.1342	1.345926	BP10b	4989	64.0810
12	10:43-11-6:1	0.644516	0.631410	0.629808	1.235755	1.220243	0.0155	1.299866	BP1b	4994	63.7565
13	10:42-11-6:1	0.626651	0.608487	0.631705	1.215027	1.324128	0.1091	1.310840	BP11b	4997	62.3374
14	10:42-11-6:1	0.636907	0.605746	0.631285	1.257879	1.333182	0.0753	1.317157	BP2b	5015	62.7717
15	10:43-11-6:1	0.637849	0.636364	0.606061	1.178189	1.339249	0.1611	1.410013	BP8b	5018	62.9534
16	10:43-11-6:1	0.647831	0.602707	0.648089	1.246830	1.290353	0.0435	1.298354	BP11b	5025	63.6617
17	10:43-11-6:1	0.638999	0.623211	0.611288	1.227058	1.295425	0.0684	1.313262	BP3b	5034	62.8129
18	10:43-11-6:1	0.646593	0.620444	0.634707	1.193569	1.283510	0.0899	1.364505	BP4b	5048	63.7084
19	10:43-11-6:1	0.645326	0.611155	0.622152	1.206086	1.284922	0.0788	1.326349	BP4b	5092	63.0990
20	10:43-11-6:1	0.659558	0.633825	0.665632	1.189969	1.303166	0.1132	1.295629	BP10b	5157	65.4644

Table 7.7

Classification Matrix for Best Model (**no. 4**) - (BP) Valid N = 4913

	Fall	Miscellaneous	Burn	Assault	Transport	Unknown	Total
Total	1999	1407	455	166	791	95	4913
Correct	1530	661	424	53	546	9	3223
Wrong	469	746	31	113	245	86	1690
Unknown	0	0	0	0	0	0	0
Correct(%)	76.54	46.98	93.19	31.93	69.03	9.47	65.6015
Wrong(%)	23.46	53.02	6.81	68.07	30.97	90.53	34.3985

7.2.4 A Summary of the Performance of the Probabilistic Neural Network

Table 7.8 below is a summary of the best performing probabilistic neural network architectures (refer to Appendix J for the classifications of each group on the individual classification matrices for each sample, and to Appendix K for the confusion matrices, which provide a detailed breakdown of the misclassifications of cases for each sample).

From the table, the architecture for all the networks is similar – ten input variables were presented to the network, there were forty-three nodes (one network had forty-two nodes) in the first layer, pattern layer nodes ranged from two thousand four hundred and nineteen, to two thousand five hundred and seventy-nine (increases as sample size increases), six nodes in the output layer corresponding to the number of groups in the dependent variable, and one output variable. The lowest selection performance is 0.59069 (model no.9) and the highest selection performance is 0.637417 (model no. 1). Looking at the absolute difference between the selection- and test-errors, it is evident that the network that gives the best classification results for the probabilistic neural network is also not the one that generalises successfully.

Of the twenty samples generated, the minimum overall percentage of correct classifications is 65.5836% (model no. 9) and the maximum overall percentage of correct classifications is 68.1982% (model no. 7). On average the probabilistic neural network correctly classified 66.8530% cases (averaged over all the 20 samples).

Examining the model that gives the best classification results (model no.7 – refer to Table 7.9 below), we can see that the probabilistic neural network is also better at predicting group membership for the 'Burn' and 'Fall' groups (91.13% and 86.17% of cases are correctly classified respectively) than for the 'Unknown' group (15.27% of the cases are correctly classified). The 'Assault' and 'Miscellaneous' groups are also weakly classified (26.98% and 49.00% of the cases are correctly classified respectively), and the model moderately classified the 'Transport' group.

Table 7.8

Model Summary Report - PNN

Model no.	Profile	Train Perf.	Select Perf.	Test Perf.	Train Error	Select Error	Absolute diff. (Select error – Test error)	Test Error	Valid N	Overall Percent Correctly Classified
1	10:43-2419-6:1	0.722199	0.637417	0.629139	0.254230	0.287929	0.0337	0.285182	4835	67.7766
2	10:42-2444-6:1	0.714812	0.601966	0.629812	0.255824	0.294385	0.0386	0.284768	4886	66.5370
3	10:43-2452-6:1	0.722675	0.591020	0.613878	0.252363	0.296313	0.0440	0.289184	4902	66.2587
4	10:43-2457-6:1	0.723647	0.635993	0.618893	0.251888	0.288748	0.0369	0.289080	4913	67.5555
5	10:43-2468-6:1	0.709481	0.608590	0.622366	0.256676	0.289725	0.0330	0.286488	4936	66.2480
6	10:43-2470-6:1	0.710121	0.637247	0.629960	0.255041	0.285777	0.0307	0.289770	4940	67.1862
7	**10:43-2492-6:1**	**0.730337**	**0.607544**	**0.659711**	**0.249753**	**0.290356**	**0.0406**	**0.282860**	**4984**	**68.1982**
8	10:43-2493-6:1	0.716005	0.608347	0.601124	0.255976	0.288622	0.0326	0.293226	4985	66.0381
9	10:43-2494-6:1	0.711307	0.590690	0.609952	0.257133	0.297934	0.0408	0.289702	4986	65.5836
10	10:43-2495-6:1	0.710621	0.610754	0.624398	0.255852	0.290202	0.0344	0.285088	4987	66.4127
11	10:43-2495-6:1	0.705010	0.599840	0.617482	0.259337	0.294624	0.0353	0.288518	4989	65.6845
12	10:42-2498-6:1	0.726581	0.637019	0.629006	0.251752	0.287868	0.0361	0.286319	4994	67.9816
13	10:43-2499-6:1	0.712285	0.630905	0.614892	0.256507	0.284456	0.0279	0.292220	4997	66.7601
14	10:43-2509-6:1	0.721802	0.628093	0.627294	0.255215	0.289479	0.0343	0.287516	5015	67.4776
15	10:43-2510-6:1	0.708765	0.617225	0.618022	0.257233	0.289787	0.0326	0.288249	5018	66.3212
16	10:43-2513-6:1	0.709113	0.634554	0.617038	0.254640	0.286427	0.0318	0.290994	5025	66.7463
17	10:43-2518-6:1	0.724384	0.624006	0.605723	0.253326	0.285966	0.0326	0.298623	5034	66.9646
18	10:43-2524-6:1	0.715135	0.610935	0.648970	0.253371	0.293084	0.0397	0.279698	5048	67.2544
19	10:43-2546-6:1	0.713668	0.608013	0.625295	0.257174	0.290442	0.0333	0.283570	5092	66.5161
20	10:43-2579-6:1	0.725863	0.618309	0.632273	0.251754	0.286433	0.0347	0.285358	5157	67.5587

Table 7.9

Classification Matrix for Best Model (**no.7**) - (PNN) Valid N = 4984

	Miscellaneous	Transport	Fall	Unknown	Assault	Burn	Total
Total	1398	761	2054	131	189	451	4984
Correct	685	462	1770	20	51	411	3399
Wrong	713	299	284	111	138	40	1585
Unknown	0	0	0	0	0	0	0
Correct(%)	49.00	60.71	86.17	15.27	26.98	91.13	68.1982
Wrong(%)	51.00	39.29	13.83	84.73	73.02	8.87	31.8018

7.2.5 A Summary of the Performance of the Radial Basis Function Neural Network

Table 7.10 below is a summary of the best performing radial basis function neural network architectures trained by employing a *K*-means (KM) clustering algorithm in the unsupervised phase to select an optimal set of points that are placed at the centroids of clusters of training data. Once the centres are obtained, the deviation of the individual observations are set to be the average distance to its *K*-nearest neighbours (KN)), and the output layer weights are then optimised using singular value decomposing (known also as pseudo-inverse (PI)). Refer to Appendix L for the classifications of each group on the individual classification matrices for each sample, and to Appendix M for the confusion matrices, which provide a detailed breakdown of the misclassifications of cases for each sample.

From the table, the architecture for all the networks differs in the following manner – ten input variables were presented to the network, there were forty-three nodes (one network had forty-one and two networks has forty-two nodes) in the first layer, the number of radial nodes (or cluster centres) in the hidden layer varied between nine and twelve, six nodes in the output layer corresponding to the number of groups in the dependent variable, and one output variable. The lowest selection performance is 0.561134 (model no. 6) and the highest selection performance is 0.631623 (model no. 1). Looking at the absolute difference between the selection- and test-errors, it is evident for the RBF as well, that the network that gives the best classification results for the probabilistic neural network is also not the one that generalises successfully.

Of the twenty samples generated, the minimum overall percentage of correct classifications is 58.0322% (model no. 19) and the maximum overall percentage of correct classifications is 60.9928% (model no. 1). On average the radial basis function neural network correctly classified 59.3691% cases (averaged over all the 20 samples).

Examining the model that gives the best classification results (model no.1 – refer to Table 7.11 below), we can see that the radial basis function network is also better at predicting group membership for the 'Burn' and 'Fall' groups (91.90% and 76.18% of cases are correctly classified respectively) than for the 'Unknown' and 'Assault' groups (none of the cases are correctly classified). The 'Transport' and 'Miscellaneous' groups are weakly classified.

Table 7.10

Model Summary Report - RBF (KM,KN,PI)

Model no.	Profile	Train Perf.	Select Perf.	Test Perf.	Train Error	Select Error	Absolute diff. (Select error – Test error)	Test Error	Valid N	Overall Percent Correctly Classified
1	**10:43-12-6:1**	**0.610583**	**0.631623**	**0.586921**	**0.298366**	**0.294540**	**0.0038**	**0.299798**	**4835**	**60.9928**
2	10:43-12-6:1	0.584697	0.598690	0.583129	0.301468	0.303731	0.0023	0.304160	4886	58.7802
3	10:43-12-6:1	0.585644	0.613878	0.600816	0.303260	0.297561	0.0057	0.298290	4902	59.6491
4	10:43-12-6:1	0.587709	0.600163	0.579805	0.299069	0.296633	0.0024	0.300780	4913	58.8846
5	10:43-12-6:1	0.611831	0.606969	0.605348	0.296399	0.296145	0.0003	0.300873	4936	60.8995
6	10:43-12-6:1	0.593117	0.561134	0.581377	0.299820	0.306627	0.0068	0.298713	4940	58.2186
7	10:43-12-6:1	0.599518	0.597111	0.619583	0.297424	0.299854	0.0024	0.298555	4984	60.3933
8	10:42-12-6:1	0.608103	0.580257	0.597913	0.297362	0.302980	0.0056	0.303164	4985	59.8596
9	10:43-10-6:1	0.566961	0.595506	0.600321	0.307286	0.305615	0.0017	0.299820	4986	58.2431
10	10:43-12-6:1	0.598397	0.585072	0.573034	0.298694	0.300835	0.0021	0.303594	4987	58.8731
11	10:42-12-6:1	0.589980	0.583801	0.581395	0.301490	0.301661	0.0002	0.304305	4989	58.6290
12	10:41-9-6:1	0.578863	0.605769	0.621795	0.306651	0.300096	0.0066	0.299348	4994	59.6316
13	10:43-12-6:1	0.599040	0.600480	0.599680	0.299977	0.299357	0.0006	0.297115	4997	59.9560
14	10:43-12-6:1	0.604225	0.581804	0.578611	0.300003	0.301826	0.0018	0.306382	5015	59.2223
15	10:43-12-6:1	0.572510	0.585327	0.605263	0.306635	0.304192	0.0024	0.299020	5018	58.3898
16	10:43-12-6:1	0.579785	0.611465	0.574841	0.304908	0.298837	0.0061	0.308257	5025	58.6468
17	10:43-12-6:1	0.590151	0.612878	0.595390	0.298872	0.297626	0.0012	0.297769	5034	59.7139
18	10:43-12-6:1	0.593502	0.614897	0.595880	0.299569	0.295976	0.0036	0.299216	5048	59.9445
19	10:43-10-6:1	0.569128	0.607227	0.575805	0.304420	0.295223	0.0092	0.298688	5092	58.0322
20	10:43-12-6:1	0.595967	0.612878	0.612102	0.299784	0.302247	0.0025	0.297615	5157	60.4227

Table 7.11

Classification Matrix for Best Model (no. 1) - (RBF) Valid N = 4835

	Fall	Transport	Miscellaneous	Assault	Burn	Unknown	Total
Total	2057	732	1390	152	420	84	4835
Correct	1567	340	656	0	386	0	2949
Wrong	490	392	734	152	34	84	1886
Unknown	0	0	0	0	0	0	0
Correct(%)	76.18	46.45	47.19	0.00	91.90	0.00	60.9928
Wrong(%)	23.82	53.55	52.81	100.00	8.10	100.00	39.0072
Unknown(%)	0.00	0.00	0.00	0.00	0.00	0.00	0.0000

7.3 Summary

Table 7.12 below gives a summary of the overall percent of correctly classified cases as discussed above.

Table 7.12

Summary of Results
(Overall Percent of Correctly Classified Cases)

	Mean	Minimum	Model no:	Maximum	Model no:
CART	63.2271	61.0566	13	64.2308	6
DA	63.6128	62.0365	11	65.0184	20
BP	63.2841	60.4453	6	65.6015	4
PNN	66.8530	65.5836	9	68.1982	7
RBF	59.3691	58.0322	19	60.9928	1

Various data mining classification techniques were analysed using the trauma unit data from the Red Cross war Memorial Children's Hospital to determine the technique that most accurately re-classified cases based on cause of injury. Of the five techniques investigated, the probabilistic neural network performed the best, the average predictive accuracy across all twenty samples being 66.8530%. The average performance for decision trees using the CART algorithm, discriminant analysis, and the backpropagation network are comparable at 63-plus%, and the radial basis function network gave the lowest average performance at 59.3691%.

When we examined the classification matrices for the models that gave the best classification results (refer to Table 7.13 below), we saw how well all the five techniques correctly classified cases in the 'Burn' group, followed in some instances by the cases in the 'Fall' group. Cases in the 'Unknown' group were either not classified at all, or were poorly classified on balance by some of the techniques. Apart from the 'Unknown' group, the CART decision tree algorithm was able to classify the other groups better than the other techniques on balance.

Table 7.13

Summary of Results
(Percent of Correctly Classified Cases per Group)

	Miscellaneous	Fall	Transport	Burn	Assault	Unknown
CART	62.12	63.90	55.48	96.05	70.83	0.00
DA	50.48	75.12	65.46	91.96	33.14	8.74
BP	46.98	76.54	69.03	93.19	31.93	9.47
PNN	49.00	86.17	60.71	91.13	26.98	15.27
RBF	47.19	76.18	46.45	91.90	0.00	0.00

In the next chapter, we will compare and contrast the performance and usefulness of the five techniques.

CHAPTER 8 DISCUSSION OF FINDINGS

We have seen the extent to which the five data mining classification techniques are able to re-classify the outcomes of medical child trauma injuries, and how the overall classification performance differs according to the classification technique used. In this chapter, we will look at the usefulness and problems encountered when we applied the medical child trauma data to the various classification techniques, in order to determine the technique that is most useful in providing accurate and reliable confirmation of the classifications of a known outcome measure.

8.1 Data Requirements

The input data for the neural network techniques (that is, the backpropagation network, the probabilistic neural network, and the radial basis function network) has to be transformed as it needs to be in a particular range for the analysis to run, whereas input data for the decision tree and discriminant analysis techniques does not need to be transformed in any way.

8.2 Clarity

It is not possible to explain how the outcome is determined from the neural network weights and other parameters, since there is no method of setting the parameters. A combination of the parameter values are tried until the network that generalizes well or gives the most accurate result is found, hence the term 'black box' given to neural network models, because of the difficulties encountered when trying to interpret the neural network techniques.

Decision trees on the other hand are understandable as a set of rules. Cases are partitioned into different groups, and at the same time important variables can easily be seen from the tree generated, since these variables will be closer to the top of the tree (see later).

Discriminant analysis is also a technique that is easy to understand since the classification functions can be used to classify unknown cases into the group in which they are most likely to belong.

8.3 Performance of the Techniques

In our findings, the highest percentage of correctly classified cases across all the various techniques (e.g. 66.8530% for the PNN network) is not ideal, though moderate for practical purposes. One would hope that the technique used is able to re-classify the categories of the known outcome measure as accurately as possible (i.e. a classification rate close to 100%).

Our overall findings suggest that the predictive ability of the PNN is superior in terms of the overall classification, though it requires a lot of CPU time and memory space to train. The predictive ability of the backpropagation network, decision tree, and discriminant analysis techniques is comparable, though of the three techniques, the backpropagation requires a lot of CPU time and memory space to train, similar to that of the PNN. The RBF gave the poorest classification results of the five classification techniques, though the time required to train the network was very short, similar to that of the decision trees and discriminant analysis techniques.

8.4 Distributional Assumptions

All the five classification techniques except discriminant analysis embody no distributional assumptions. However in order to apply the technique, we ignored the conditions of optimality in the hope that the technique will yield useful results.

8.5 Software Limitations

The software package imposed a limitation on the size of the data file for the PNN network. Without this limitation, different results may occur. However, all classification techniques were analysed under the same limitation for consistency of comparison of results.

8.6 Appropriate Technique

We have seen the predictive ability and some of the disadvantages of the five data mining classification techniques when applied to the child trauma data. The neural network techniques are difficult to interpret, and whilst discriminant analysis is an easy technique to use, with functions that can be used to classify new cases, it embodies distributional assumptions which are violated by the medical trauma data. According to Olaru & Wehenkel (2003) "data mining techniques should simultaneously be able to manage large amounts of data, be accurate, be interpretable and comprehensible". To stay in line with this idea of data mining techniques, we would therefore recommend decision tree analysis as the technique that could be used to confirm the assignment of known outcomes from a given set of input variables.

8.7 Decision Framework

The tree structure and layout of responses derived from the model (model no: **6**) that gave the highest classification results (out of all twenty models) are shown in Appendix N. The tree structure shows (Statsoft, 2001):

- The left branch and right branch child nodes to which cases are sent if they satisfy (left), or do not satisfy (right), respectively, the split condition at a split node.
- The number of cases in each observed group that are sent to the node.
- The predicted group to which cases sent to the node are assigned.
- Information detailing the split condition for a split node. Note that no child nodes or split conditions are displayed for the terminal nodes of the tree.

We will provide below, a short illustration of how to interpret the output from the decision tree (refer to Appendix N for the tree structure and layout of responses).

For *Burn* (terminal node 2), the decision rule is:

- Pathology – category: 'burns'.

For *Fall* (terminal node 6), the decision rule is:

- Anatomy – category: 'Upper Extremeties'
- Place - category: 'Public Place'
- Pathology – all other categories except 'burns'.

For *Transport* (terminal node 8), the decision rule is:

- Pathology – all other categories except 'burns'
- Place - category: 'Public Place'
- Anatomy – all other categories except 'Upper Extremeties'
- Admission – category: 'not admitted'.

For *Miscellaneous* (terminal node 37), the decision rule is:

- Place - all other categories except 'Public Place'
- Pathology – none, other, lacerations, vascular injury
- Anatomy –category 'Head/Neck/Face'
- Age all children $\geq$ 6.5 years
- Abuse – 'no'
- Treatment – all other categories except 'other', 'cleanSuture', 'EUA/MUA' and 'operation'.

For *Assault* (terminal node 41), the decision rule is:

- Place - all other categories except 'Public Place'
- Pathology – none, other, lacerations, vascular injury
- Anatomy – all other categories except 'Head/Neck/Face'
- Treatment – all other categories except 'observation', 'cleanSuture', and 'operation'
- Abuse – 'possibly', 'yes'.

The output generated by the decision tree is important, since it shows the questions (that is, variables) that are important on the Trauma Unit Record for classifying the outcomes of child trauma injuries. Looking at the predictor importance table (Table 8.1), we can see the order of importance of the independent variables in partitioning cases (100 indicates the most important variable) for the model that gave the best classification results.

Table 8.1

Predictor Importance
Responses: Causes

Variable	**Importance**
Age	48
Race/Gender	27
Place	45
Admission	39
Resuscitation	25
Anaesthetic	49
Abuse	51
Anatomy	61
Pathology	100
Treatment	82

In the next chapter, conclusions and recommendations will be made.

CHAPTER 9 CONCLUSIONS AND RECOMMENDATIONS

9.1 CONCLUSIONS

In this research, we looked at the performance of five data mining classification techniques (decision tree, discriminant analysis, backpropagation neural network, probabilistic neural network, and the radial basis function neural network), in re-classifying (i.e. replicating) the outcomes of child trauma injuries. Based on the findings of this research, the following conclusions may be drawn:

- **Only a few of the questions/variables from the Trauma Record form are important for predicting child trauma injuries.**

It was important to try and reduce the number of input variables, especially for the neural network techniques in order to improve the performance (in terms of predictive accuracy and training times) of the techniques.

Of the twenty-two questions that have to be completed on the Trauma Record form, only ten were found to give optimal results for all the classification techniques. The ten questions that were used for all the techniques were: 'Abuse', 'Admission', 'Age', 'Anaesthetic', 'Anatomy', 'Pathology', 'Place', 'Race/Gender', 'Resuscitation', 'Year of birth', and 'Treatment'.

- **The primary finding for all the twenty samples is that the probabilistic neural network is superior to all the other techniques.**

Using the variables mentioned above, the probabilistic neural network correctly classified 68.20% of the cases. This result is given by the best model from the twenty samples. On average (of the correctly classified cases by all twenty models), the PNN outperforms all the other data mining classification techniques as well.

- **The backpropagation network, discriminant analysis and decision trees trained using the CART algorithm differ marginally with respect to the overall classification accuracy.**

On average (of the correctly classified cases by all twenty models), the backpropagation neural network correctly classified 63.28% of the cases, discriminant analysis correctly classified 63.61% of the cases, and the CART decision tree correctly classified 63.23% of the cases. Thus we can conclude that the performance of the data on the same data is comparable.

- **The radial basis function network gives the lowest classification performance of the five data mining classification techniques.**

Given the variables like those mentioned above, the predictive accuracy of the radial basis function network is reasonable, but lower than that of the other techniques.

- **The decision tree trained using the CART algorithm is superior in classifying the different category outcomes of child trauma injuries.**

Analysis of the classification matrices of the best models suggests that on balance, the CART decision tree is able to predict the outcomes of child trauma injuries better that the other techniques.

- **The neural network techniques are difficult to interpret compared to the decision tree and discriminant analysis techniques.**

Trying to understand how the outcome is determined by the neural network techniques is impossible, since setting the network parameters is more an art than a technique. On the other hand, both the decision tree and discriminant analysis techniques are easy to understand, though for discriminant analysis, there are conditions of optimality that need to be met. Even though we ignored the conditions of optimality in the hope that the technique will yield useful results, the results obtained from this techniques were comparable to the other techniques as mentioned above.

- **The data mining process is can be applied successfully to the child trauma data.**

Through this research, we have demonstrated how the data mining process can be applied successfully to the medical child trauma data.

9.2 RECOMMENDATIONS

Based on the findings and conclusions of this research, the following recommendations can be made to management at the Red Cross War Memorial Children's Hospital:

- **Variables like those in this data set could be used to confirm the outcomes of child trauma injuries reasonably well.**

This research demonstrates that the following variables: 'Abuse', 'Admission', 'Age', 'Anaesthetic', 'Anatomy', 'Pathology', 'Place', 'Race/Gender', 'Resuscitation', 'Year of birth', and 'Treatment' can be used in the model to confirm the outcomes of child trauma injuries.

- **Other potential variables (questions) related to the cause of child trauma injuries should be considered for the Trauma Record form.**

Management at the Red Cross War Memorial Children's Hospital should consider including other questions on the trauma Record form since the ones used in the research only attained a moderate performance classification rate.

An in-depth discussion with medical authorities at the Red Cross War Memorial Children's Hospital would be needed to help identify these potential variables so they can be included on the Trauma Unit Record for future analysis.

- **The decision tree trained using the CART algorithm should be used to ahead of other classification techniques to confirm the assignment of categories of a known outcome measure.**

The overall predictive accuracy of all the techniques is moderate. Nevertheless the probabilistic neural network is superior to all the other techniques, though as we have seen, the only technique that is able to simultaneously manage large amounts of data, is accurate, interpretable and comprehensible, is the decision tree trained using the CART algorithm.

- **The data mining process should be applied to the child trauma data.**

We have demonstrated how data mining process can be applied to the child trauma data, and therefore recommend to management at the Red Cross War Memorial Children's Hospital to apply the seven step model when confirming the outcomes of child trauma injuries.

BIBLIOGRAPHY

Adya, M., Werts, N. (2001). *Data Mining in the Healthcare: Issues regarding a Research Agenda,* Department of Information Systems, University of Maryland Baltimore County.

Anderson, D., McNeil G. (1992). *Artificial Neural Networks Technology.* [Online]. Available: http://www.dacs.dtic.mil/techs/neural/neural.title.html.

Anderson, J. A. (1995). *An Introduction to Neural Network.* MIT Press, London.

Andree, H. M. A., Lourens, W., Taal, A., Vermeulen, J. C. (1995). *Feed-forward Neural Networks for Shower Recognition: Construction and Generalisation.* Nuclear Instruments and Methods in Physics Research [Online], vol. 355, p 589-599. Available: http:// www.elsevier.com.

Apte, C., Weiss, S. (1997). *Data Mining with Decision Trees and Decision Rules.* Future Generation Computer Systems [Online], vol. 13, p 197–210. Available: http:// www.elsevier.com.

Basheer, I., Hajmeer, M. (2003). *Comparison of Logistic Regression and Neural Network-based Classifiers for Bacterial Growth.* Food Microbiology [Online], vol. 20, p 43–55. Available: http:// www.elsevier.com/locate/jnlabr/yfmic.

Becerra-Fernandez, I., Walczak, S., Zanakis, S.H. (2002). *Knowledge Discovery Techniques for Predicting Country Investment Risk.* Computer and Industrial Engineering, [Online], vol. 43, p 787-800. Available: http:// www.elsevier.com/locate/dsw.

Bejou, D., Palmer, A., Wray, B. (1993). *Using Neural Network Analysis to Evaluate Buyer-Seller Relationships.* European Journal of Marketing, vol. 28, no. 10. MCB University Press.

Berry, M. J. A., Linoff, G. S. (2000). *Mastering Data Mining: The Art and* Science of *Customer Relationship Management.* John Wiley & Sons Inc., New York.

Berson, A., Smith, S., Thearling, K. (1999). *Building Data Mining Applications for CRM.* McGraw-Hill Companies, USA.

Bigus, J., P. (1996). *Data Mining with Neural Networks: Solving Business Problems – from Application Development to Decision Support.* McGraw-Hill Companies, USA.

Blasius, J., Greenacre, M. (1998). *Visualization of Categorical Data.* Academic Press, USA.

Breiman, L., Friedman, J. H., Olshen, R. A., Stone, C. J. (1984). *Classification and Regression Trees.* Chapman & Hall, USA.

Butler, C., Caudill, M. (1992). *Understanding Neural Networks Computer Explorations.* MIT Press, UK.

Burgess, M., Callum, I., Enright, P., Goel, P. K., Madramootoo, C., Prasher, S. O., Yang, C. (2003). *Application of Decision Tree Technology for Image Classification using Remote Sensing Data.* Agricultural Systems [Online], vol. 76, p 1101-1117. Available: http:// www.elsevier.com/locate/agsy.

Chae, Y. M., Ho, S. H., Kim, H. S., Park, H. J., Tark, K. C. (2003). *Analysis of Healthcare Quality Indicator using Data Mining and Decision Support.* Expert Systems with Applications [Online], vol 24, p 167-172. Available: http:// www.elsevier.com/locate/eswa.

Chen Y. (2000). An *Application of Radial Basis Function Networks in Operation of Home Appliances.* Intelligent Data Analysis [Online], vol. 4, p 531-547, IOS Press. Available: EBSCO*host* database (Business Source Premier).

Corse, S. J., Smith, M. (1998). *Reducing Substance Abuse During Pregnancy: Discriminating Among Levels of Response in a Prenatal Setting.* Journal of Substance abuse Treatment [Online], vol 5, p 457-467. Available: http:// www.elsevier.com.

Cronan, T. P., Epley, D. R., Perry, L. G. (1987). *A Procedure for Uncovering Acceptable and Nonacceptable Mortgage Applications through Discriminant Analysis using Ranked Data.* The Journal of Real Estate Research [Online], vol. 2, no. 1. Available: EBSCO*host* database (Business Source Premier).

Cronin, M. T. D., Worth, A. P. (2003). *The use of Discriminant Analysis, Logistic Regression and Classification Tree Analysis in the Development of Classification Models for Human Health Effects.* Journal of Molecular Structure (Theochem) [Online], vol. 622, p 97-111. Available: http:// www.elsevier.com/locate/theochem.

Fayyad, U., Piatesky-Shapiro, G., Smyth, P. (1996). *Advances in Knowledge Discovery and Data Mining.* MIT Press, USA.

Fausett, L. (1994). *Fundamentals of Neural Networks – Architectures, Algorithms, and Applications.* Prentice Hall, New Jersey, USA.

Grassi, M. C., Caricati A. M., Intraligi, M., Buscema, M., Nencini, P. (2002). *Artificial Neural Network Assessment of Substitutive Pharmacological Treatments in Hospitalised Intravenous Drug Users.* Artificial Intelligence in Medicine [Online], vol .24, p 37-49. Available: http:// www.elsevier.com/locate/artmed.

Gupta, J. N. D., Smith, K. A. (2000). *Neural Networks in Business: Techniques and Applications for the Operations Researcher.* Computers and Operations Research [Online], vol. 27, p 1023-1044. Available: http://www.elsevier.com/locate/dsw.

Hand, D., Mannila, H., Smyth, P. (2001). *Principles of Data Mining.* Massachusetts Institute of Technology, USA.

Haykin, S. (1994). *NEURAL NETWORKS: A Comprehensive Foundation.* MacMillan Publishing Company, Inc., USA.

Hertz, J., Krogh, A., Palmer, R. G. (1991). *Introduction to the Theory of Neural Computation.* Addison-Wesley Publishing Company, USA.

Hora, S. C., Wilcox, J. B. (1982). *Estimation of Error Rates in Several-Population Discriminant Analysis.* Journal of Marketing Research, vol. 19, p 57-61.

Hutchinson, J. M., Lo, A. W., Poggio, T. (1994). *A Nonparametric Approach to Pricing and Hedging Derivative Securities via Learning Networks*. The Journal of Finance, vol. 49, no. 3.

James, M. (1985). *Classification Algorithms*. Collins Professional and Technical Books, London.

Klecka, W. R. (1980). *Discriminant Analysis*. Quantitative Applications in the Social Sciences Series, No. 19. Sage Publications, Inc., CA

Liebich, H. M., Shan, Y., Xu, G., Zhang, Y., Zhao, R. (2002). *Application of Probabilistic Neural Network in the Clinical Diagnosis of Cancers based on Clinical Chemistry Data*. Analytica Chimica Acta [Online], vol 471, p 77–86. Available: http:// www.elsevier.com/locate/aca.

Lin, F. Y., McClean, S. (2001). *A Data Mining Approach to the Prediction of Corporate Failure*, Knowledge Based Systems [Online], vol. 14, p 189–195. Available: http:// www.elsevier.com/locate/knosys.

Manly, B. F. J. (1986). *Multivariate Statistical Methods: A Primer*. Chapman and Hall, London.

May, J. H., Spangler, W. E., Vargas, L. G. (1999). *Choosing Data-Mining Methods for Multiple Classification: Representational and Performance Measurement Implications for Decision Support.* Journal of Management Information Systems [Online], vol. 16 no. 1, p37. Available: EBSCO*host* database (Business Source Premier).

Morlini, I. (1999). *Radial Basis function Networks with Partially Classified Data*. Ecological Modelling [Online], vol. 120, p 109–118. Available: http:// www.elsevier.com/locate/ecomodel.

Mullet, G. M., Myers, J.H. (2003). *Managerial Applications of Multivariate Analysis in Marketing.* American Marketing Association, Chicago, Illinois.

Nolan, J. R. (2002). *Computer Systems that Learn: An Empirical Study of the Effect of Noise on the Performance of Three Classification Methods*. Expert Systems with Applications [Online], vol. 23, no. 1, p8. Available: http://www.elsevier.com/locate/eswa.

Olaru, C., Wehenkel, L. (2003). *A Complete Fuzzy Decision Tree Technique*. Fuzzy Sets Systems [Online], vol. 138, p 221-254. Available: http://www.elsevier.com/locate/fss.

Platt, M. B., Platt, H. D., Yang, Z. R. (1999). *Probabilistic Neural Networks in Bankruptcy Prediction.* Journal of Business Research [Online], vol. 44, p 67-74. Available: http://www.elsevier.com.

Patterson, D. W. (1996). *Artificial Neural Networks: Theory and Applications.* Simons & Schuster Pte Ltd, Asia.

Ripley, B. D. (1996). *Pattern Recognition and Neural Networks.* Cambridge University Press, UK

Siganos, D., Stergiou, C. (1996). *Neural Networks.* [Online]. Available: http://www.doc.ic.ac.uk/~nd/surprise_96/journal/vol4/csll/report.html.

Smith, M. (1996). *Neural Networks for Statistical Modelling*. International Thomson Computer Press, USA.

Singh, D., Singh, S. P. (2001). *A Self- Selecting Network for Short-Term Load Forecasting*. Electric Power Components and Systems [Online]. vol. 29, p 117-130. Available: EBSCOhost database (Business Source Premier).

Statsoft. (2001). STATISTICA Electronic manual [Online]. Available: http://www.statsoft.com.

Tarassenko, L. (1998). *A Guide to Neural Computing Applications.* John Wiley & Sons Inc., USA.

Van den Honert, R. (1997). *Intermediate Statistical Methods for Business and Economics*. UCT Press, Cape Town.

Wegner, T. (2002). *Multivariate Statistical Methods with Management Applications*. Research and Survey Statistics Handbooks, UCT, Cape Town.

West, D. (2000). *Neural Network Credit Scoring Models.* Computers & Operations Research [Online], vol. 27, p 1131-1152. Available: http://www.elsevier.com/locate/dsw.

Zirilli, J. S. (1997). *Financial Prediction using Neural Networks*. International Thomson Publishing Inc., London.

APPENDIX A BAYES' DECISION THEOREM

A.1 Bayes' Decision Theorem

Bayesian decision theory, which is to "*assign the object to the class with the highest conditional probability*" James (1985), asserts that a case x, should be placed in the group to which it has the greater value of its decision function, since it is the one that gives the optimal classification rule, and is based on perfect knowledge of all probabilities in the system (James, 1985). In a case where there are C groups, with known prior probabilities, $P(C_i)$, of a case belonging to each of the C_i groups, Bayes' rule translates into assigning a case to group i if:

$$P(C_i) > P(C_j) \qquad \text{for all } i \neq j$$

Conditional probabilities are central to classification theory. For conditional probabilities, $P(C_i | x)$, which specify the probability that a case comes from group i given that we observe a particular set of measurements, x, Bayes' rule translates into assigning a case to group i if:

$$P(C_i | x) > P(C_j | x) \qquad \text{for all } j \neq i$$

In practice, Bayes' rule is not realistic, as finding conditional probabilities such as $P(C_i | x)$ is very difficult by standard methods of estimation (James, 1985). However, the conditional probabilities $P(x | C_i)$, which specify the probability of observing a particular set of measurements x given that the case comes from group i, are simply estimated by taking a sample of cases from group i. The connection between the two conditional probabilities, known as 'Bayes' theorem' is given by:

$$P(C_i \mid x) = \frac{P(x \mid C_i)P(C_i)}{\sum_{\text{all } i} P(x \mid C_i)P(C_i)}$$

The right-hand side of the equation can easily be estimated. ($P(x \mid C_i)$ is estimated by taking a sample of cases from group *i*, and $P(C_i)$ is the proportion of group *i* in the population). Putting Bayes' theorem into Bayes' rule translates into assigning a case into group *i* if:

$$\frac{P(x \mid C_i)P(C_i)}{\sum_{\text{all } k} P(x \mid C_k)P(C_k)} > \frac{P(x \mid C_j)P(C_j)}{\sum_{\text{all } k} P(x \mid C_k)P(C_k)} \qquad \text{for all } i \neq j$$

and cancelling out the denominators on both sides of the inequality, Bayes' rule translates into assigning an case to group *i* if:

$$P(x \mid C_i)P(C_i) > P(x \mid C_j)P(C_j) \qquad \text{for all } i \neq j$$

A.2 The Normal Distribution

The normal distribution describes the probability of a variable. The multivariate normal distribution is specified by:

$$\left(\frac{1}{(2\pi)^{n/2}\left|\sum\right|^{1/2}}\right)\exp[-\frac{1}{2}(x-\mu)'\sum^{-1}(x-\mu)]$$

where μ is the mean vector, responsible for the location of the distribution, and Σ is the covariance matrix, the multivariate equivalent of the standard deviation which affects the 'shape' of the distribution (James, 1985).

A.3 Application of Bayes' Rule to the Normal Distribution

The probability of observing a case, x, given that the case comes from group i, $P(x \mid C_i)$, and assuming that it comes from a normal distribution is given by:

$$P(x \mid C_i) = \left(\frac{1}{(2\pi)^{n/2} \left| \sum_i \right|^{1/2}} \right) \exp[-\frac{1}{2}(x-\mu_i)' \sum_i^{-1} (x-\mu_i)]$$

where μ_i, the group mean vector, and $\sum_i$, the group covariance matrix, are the only parameters that need to be estimated. Hence using the normal form of $P(x \mid C_i)$, Bayes' rule translates into assigning an case x into group C_i if:

$$\left(\frac{P(C_i)}{(2\pi)^{n/2} \left| \sum_i \right|^{1/2}} \right) \exp[-\frac{1}{2}(x-\mu_i)' \sum_i^{-1} (x-\mu_i)] \; > \; \left(\frac{P(C_j)}{(2\pi)^{n/2} \left| \sum_j \right|^{1/2}} \right) \exp[-\frac{1}{2}(x-\mu_j)' \sum_j^{-1} (x-\mu_j)]$$

for all $i \neq j$

A.4 Prior Probabilities of Group Membership

The number of cases in different groups (of the dependent variable) is not always the same. There are times when there are more cases in one group than in any other, and this can affect the performance of the analysis in that the classification of a new case would be biased in favour of the group with more cases. If the unequal number of cases in different groups is a reflection of the true distribution in the population, the prior probabilities are set to be proportional to the sizes of the groups, and if they are random, the prior probabilities are specified as being equal in each group (Klecka, 1980).

APPENDIX B

COPY OF TRAUMA UNIT RECORD

RED CROSS WAR MEMORIAL CHILDREN'S HOSPITAL

TRAUMA UNIT RECORD

RX15

Sticky label

SURNAME (1–24) RACE/SEX (25)

FIRST NAME (26–37) FOLDER No. (38–45) DATE OF BIRTH (46–53)

ADDRESS:

DATE (54–59) TIME (Nearest hr, 24 hr, clock) (60–61) HOURS SINCE INJURY (62–63)

RACE/SEX: 1 = W M 3 = C M 5 = A M 7 = B M; 2 = W F 4 = C F 6 = A F 8 = B F

CAUSE (Mark one code with circle) 64-65

TRANSPORT	ASSAULT	BURN	FALL	MISCELLANEOUS	
01 MVA Pedestrian	10 Blunt	20 Flame	30 Off bed	40 Struck by/Against	47 Immersion/Drowning
02 MVA Passenger - restrained	11 Sharp	21 Fluid	31 Stairs/Steps	41 Caught between	48 Suffocation
03 MVA Passenger - unrestrained	12 Rape/sexual assault	22 Heat contact	32 Attendants arms	42 Sharp instrument	49 Food FB
04 MVA Passenger - bakkie/minibus	13 Human bite	23 Electrical	33 Playground equip.	43 Firearm	50 Other FB
05 Cycle	14 Other	24 Chemical	34 Mobiles	44 Machinery	51 Other cause
06 Motorcycle		25 Explosion	35 Other heights	45 Dog bite	
07 Other, e.g. boat, train, plane, horse		26 Other	36 Other level	46 Other bite	99 Unknown

PLACE OF OCCURRENCE 66

1 Own home inside	6 School/Creche
2 Own home outside	7 Public place*
3 Other home inside	8 Sport*
4 Other home outside	9 Other*
5 Road/Pavement*	0 Unknown

* ADDRESS WHERE ACCIDENT OCCURED (If 66 = 5, 7, 8 or 9)

ADMISSION 67

1 Not admitted
2 Admitted to Trauma Unit
3 Admitted directly to other ward/ICU

DISPOSAL FROM TRAUMA UNIT 68-69

01 Absconded	06 Ward
02 Home/GP	07 Burns unit
03 Day Hospital	08 ICU
04 Other Hospital	09 Childcare Agency
05 Out-Patients	10 Died

UNCONSCIOUS (70)	SHOCK (71)	RESUSCITATION (72)	ANAESTHETIC (73)	SELF INFLICTION (74)	ABUSE (75)
1 No	1 No	1 None	1 None	1 No	1 No
2 Yes	2 Yes	2 Simple	2 Local/Regional	2 Yes	2 Possible
		3 Complex	3 General		3 Yes

CODES FOR ANATOMY, PATHOLOGY, INJURY SCORE AND TREATMENT (ONE SET OF CODES/INJURY - MAX. 4)

	ANAT	PATH	AIS	TRT
1. (76–81)				
2. (82–87)				
3. (88–93)				
4. (94–99)				

ANATOMY

01 No Injury	15 Shoulder girdle	29 Kidney/ureter
02 Scalp	16 Shoulder joint	30 Bladder/urethra
03 Skull	17 Upper arm	31 Pelvis
04 Brain - Closed	18 Elbow (s'condylar)	32 Perineum/buttock
05 Brain - Open	19 Elbow - other	33 Vertebral column
06 Eye (s)	20 Forearm	34 Spinal cord
07 Nose	21 Wrist	35 Hip/femoral neck
08 Facial bones	22 Hand	36 Femur - shaft/thigh
09 Mouth/Orophar	23 Nerve plexus	37 Knee region
10 Mandible	24 Thorax cage	38 Tib./Fib. shaft/calf
11 Ear	25 Thorax resp.	39 Ankle region
12 Face Other	26 Thorax CVS	40 Foot
13 Neck	27 Abdominal wall	
14 Oesophagus	28 Abdominal viscus	

PATHOLOGY

01 None	14 Joint injury - open
02 Concussion	15 Fracture - pathol.
03 Abrasions	16 Fracture - closed
04 Closed tissue	17 Fracture - open
05 Laceration - supertic.	18 Fracture dislocation
06 Laceration - complic.	19 Foreign body
07 Avulsion/amputation	20 Pneumothorax
08 Burns	21 Haemothorax
09 Vascular injury	22 Haemopneumothorax
10 Nerve injury	23 CSA no injury
11 Muscle/tendon injury	24 CSA injury present
12 Dislocation	25 Other
13 Joint injury - closed	

ABBR. INJURY SCORE (AIS)

1 Minor 3 Severe
2 Moderate 4 Mortal

TREATMENT

1 Advice/Medication/HIF
2 Dressings/Simple POP
3 Clean and suture
4 Observation/Traction
5 EUA/MUA
6 Open operation
7 Amputation
8 Skin graft
9 Other

	SIGNATURE	
BP		HISTORY:
RESP		
PULSE		PMH:
TEMP		
TET TOX		EXAMINATION:
Hb		
Wt		
HIF/J88/CSA		
EMERGENCY DRUGS		

Signature: .... Print Name: ....

APPENDIX C

SPREADSHEET SAMPLE TABLE OF TRAUMA DATA

TRAUMA

	Year of Injury	Year of Birth	Age	Time	Hours Since Injury	Race/ Gender	Causes	Place	Admission	Disposal	Unconscious	Shock	Resuscitation	Anaesthetic	Self Infliction	Abuse	Anatomy	Pathology	AIS	Treatment
1	late-nineties	eighties	10	19	1	Coloured	Fall	PublicPlace	Not	Home	No	No	None	General	No	No	UpperExtre.	fractures	Minor	dressingsPOP
2	late-nineties	nineties	8	16	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	Head	foreignbody	Minor	other
3	late-nineties	eighties	11	19	1	Coloured	Burn	Home	Not	Home	No	No	None	None	No	No	Head	burns	Moderate	adviceMedication
4	late-nineties	nineties	7	22	1	Black	Fall	PublicPlace	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Minor	adviceMedication
5	millenium	nineties	3	13	0	Coloured	Unknown	Unknown	Ward	Home	No	No	None	None	No	No	Head	none	Minor	adviceMedication
6	millenium	nineties	5	15	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	dressingsPOP
7	millenium	nineties	4	14	1	Black	Miscellaneous	Home	Not	Home	No	No	None	None	No	Possible	Head	fractures	Moderate	operation
8	millenium	nineties	3	1	2	Black	Transport	PublicPlace	Not	Home	Yes	Yes	Complex	None	No	No	Head	laceration	Moderate	dressingsPOP
9	late-nineties	nineties	0	18	1	Coloured	Transport	PublicPlace	Ward	Hospital	No	No	None	None	No	No	Head	laceration	Minor	dressingsPOP
10	late-nineties	nineties	9	13	1	Black	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	adviceMedication
11	late-nineties	nineties	1	15	1	Coloured	Miscellaneous	PublicPlace	Ward	Hospital	No	No	None	None	No	No	Truncal	other	Minor	other
12	late-nineties	nineties	0	15	1	Black	Fall	PublicPlace	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	laceration	Minor	dressingsPOP
13	late-nineties	nineties	0	21	1	Black	Burn	Home	Trauma	Hospital	No	No	None	None	No	No	Head	burns	Minor	observation
14	late-nineties	nineties	0	21	1	Coloured	Transport	PublicPlace	Ward	Hospital	No	No	None	None	No	No	Head	none	Minor	adviceMedication
15	late-nineties	nineties	0	8	1	Black	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	none	Minor	adviceMedication
16	late-nineties	nineties	0	17	1	Coloured	Transport	PublicPlace	Ward	Home	No	No	Simple	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
17	millenium	nineties	4	20	1	Coloured	Fall	Home	Ward	Hospital	No	No	None	General	No	No	Head	laceration	Minor	cleanSuture
18	millenium	nineties	4	16	24	Black	Fall	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	observation
19	millenium	millenium	1	8	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
20	millenium	nineties	3	5	8	Coloured	Miscellaneous	Home	Ward	Hospital	No	No	None	None	No	No	Head	vascular	Minor	other
21	millenium	nineties	5	21	1	Black	Transport	PublicPlace	Not	Home	Yes	No	Simple	None	No	No	Head	laceration	Moderate	cleanSuture
22	millenium	nineties	2	8	0	Coloured	Transport	PublicPlace	Ward	Home	No	No	None	Local	No	No	Head	laceration	Moderate	cleanSuture
23	millenium	nineties	4	22	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	dressingsPOP
24	millenium	nineties	3	1	12	Coloured	Burn	Home	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	burns	Moderate	dressingsPOP
25	early-nineties	nineties	2	14	1	Black	Miscellaneous	Home	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	laceration	Minor	dressingsPOP
26	millenium	nineties	8	15	1	Coloured	Transport	PublicPlace	Not	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	observation
27	late-nineties	nineties	5	18	2	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
28	late-nineties	nineties	2	12	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	adviceMedication
29	late-nineties	nineties	3	20	1	Coloured	Miscellaneous	Home	Not	Home	No	No	None	None	No	No	LowerExtre.	fractures	Minor	dressingsPOP
30	late-nineties	nineties	9	18	7	Coloured	Burn	Home	Ward	Home	No	No	None	None	No	No	Truncal	burns	Moderate	other
31	late-nineties	nineties	6	14	24	Coloured	Fall	Unknown	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	none	Minor	adviceMedication

32	late-nineties	nineties	9	13	3	Black	Burn	Home	Trauma	Hospital	No	No	Simple	None	No	No	Head	burns	Moderate	dressingsPOP
33	late-nineties	nineties	2	14	1	Coloured	Miscellaneous	PublicPlace	Not	Home	No	No	None	General	No	No	UpperExtre.	fractures	Moderate	dressingsPOP
34	late-nineties	nineties	9	14	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	Head	none	Minor	adviceMedication
35	late-nineties	eighties	12	24	72	Coloured	Transport	PublicPlace	Not	Home	No	No	None	None	No	No	Head	laceration	Minor	dressingsPOP
36	millenium	eighties	12	9	1	Black	Transport	PublicPlace	Ward	Home	No	No	None	Local	No	No	UpperExtre.	laceration	Moderate	operation
37	millenium	nineties	11	15	24	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Moderate	dressingsPOP
38	millenium	nineties	10	17	5	Coloured	Transport	PublicPlace	Not	Home	Yes	No	None	None	No	No	Truncal	laceration	Minor	adviceMedication
39	late-nineties	nineties	7	13	48	Coloured	Assault	Home	Not	Home	No	No	None	Local	No	No	Head	fractures	Moderate	observation
40	millenium	nineties	8	16	2	Coloured	Fall	Home	Not	Home	No	No	None	None	No	No	UpperExtre.	fractures	Moderate	adviceMedication
41	millenium	nineties	8	18	1	Coloured	Transport	PublicPlace	Not	Home	No	No	None	General	No	No	LowerExtre.	fractures	Moderate	operation
42	millenium	nineties	9	19	6	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	None	No	No	LowerExtre.	fractures	Minor	dressingsPOP
43	millenium	nineties	8	21	4	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	adviceMedication
44	millenium	nineties	7	9	2	Black	Fall	Home	Ward	Home	No	No	None	General	No	No	UpperExtre.	fractures	Moderate	EUA/MUA
45	millenium	nineties	6	20	1	Coloured	Fall	Home	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Moderate	dressingsPOP
46	millenium	nineties	6	11	1	Coloured	Miscellaneous	Home	Ward	Hospital	No	No	None	None	Yes	No	UpperExtre.	none	Minor	dressingsPOP
47	late-nineties	nineties	3	2	1	Black	Miscellaneous	Home	Ward	Hospital	No	No	None	None	No	No	LowerExtre.	fractures	Moderate	dressingsPOP
48	late-nineties	nineties	2	20	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	Head	foreignbody	Minor	other
49	millenium	nineties	5	18	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
50	late-nineties	nineties	4	17	1	Black	Fall	Home	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
51	late-nineties	eighties	12	2	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
52	millenium	nineties	5	9	2	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Moderate	adviceMedication
53	millenium	nineties	4	19	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	cleanSuture
54	millenium	nineties	10	23	1	Coloured	Unknown	Unknown	Ward	Home	No	No	None	None	No	No	Head	none	Minor	adviceMedication
55	millenium	nineties	3	2	5	Black	Burn	Home	Trauma	Hospital	No	No	None	None	No	No	LowerExtre.	burns	Moderate	other
56	millenium	nineties	2	11	1	Black	Miscellaneous	Home	Ward	Home	No	No	Simple	None	Yes	No	Head	other	Moderate	other
57	millenium	nineties	3	23	1	Coloured	Miscellaneous	PublicPlace	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Moderate	dressingsPOP
58	millenium	nineties	5	21	1	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Moderate	dressingsPOP
59	millenium	nineties	7	24	7	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	none	Minor	other
60	early-nineties	seventies	15	11	48	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Moderate	dressingsPOP
61	early-nineties	seventies	18	13	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	fractures	Minor	dressingsPOP
62	early-nineties	seventies	15	10	30	Coloured	Burn	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	burns	Minor	dressingsPOP
63	early-nineties	seventies	16	16	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	adviceMedication
64	early-nineties	seventies	14	19	1	Coloured	Unknown	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	adviceMedication
65	late-nineties	nineties	4	17	1	Coloured	Transport	PublicPlace	Not	Home	No	No	Simple	None	No	No	Head	laceration	Minor	dressingsPOP
66	early-nineties	seventies	14	19	1	Black	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	concussion	Minor	dressingsPOP
67	early-nineties	seventies	15	15	2	White	Assault	Home	Ward	Home	No	No	None	None	No	No	Head	none	Minor	adviceMedication

68	early-nineties	seventies	14	9	12	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	None	No	No	LowerExtre.	fractures	Minor	dressingsPOP
69	early-nineties	seventies	17	16	4	Coloured	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	adviceMedication
70	early-nineties	seventies	14	14	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	concussion	Minor	adviceMedication
71	early-nineties	seventies	14	17	1	Coloured	Miscellaneous	PublicPlace	Ward	Hospital	No	No	None	Local	No	No	UpperExtre.	laceration	Moderate	cleanSuture
72	early-nineties	seventies	15	21	1	Coloured	Miscellaneous	Home	Ward	Hospital	No	No	None	Local	No	No	UpperExtre.	laceration	Minor	dressingsPOP
73	early-nineties	seventies	14	7	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Moderate	other
74	late-nineties	eighties	10	12	1	Coloured	Miscellaneous	Home	Ward	Hospital	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
75	early-nineties	eighties	9	23	2	Coloured	Assault	PublicPlace	Not	Home	No	No	None	None	No	No	Head	laceration	Minor	dressingsPOP
76	millenium	nineties	4	8	99	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	Head	foreignbody	Minor	other
77	early-nineties	seventies	18	12	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	dressingsPOP
78	early-nineties	seventies	13	17	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	Truncal	laceration	Minor	adviceMedication
79	early-nineties	seventies	13	9	1	Coloured	Assault	Home	Ward	Hospital	No	No	None	None	No	No	LowerExtre.	laceration	Minor	dressingsPOP
80	early-nineties	seventies	14	10	1	Black	Fall	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
81	early-nineties	seventies	13	11	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Moderate	dressingsPOP
82	early-nineties	seventies	13	18	1	Coloured	Transport	Home	Ward	Home	No	No	None	Local	No	No	LowerExtre.	laceration	Minor	cleanSuture
83	early-nineties	seventies	13	22	1	Coloured	Assault	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
84	early-nineties	seventies	13	11	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
85	early-nineties	seventies	17	16	1	Coloured	Fall	Home	Ward	Home	No	No	None	Local	Yes	No	Head	laceration	Minor	cleanSuture
86	early-nineties	seventies	13	22	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	dressingsPOP
87	early-nineties	seventies	15	17	1	White	Miscellaneous	Home	Ward	Home	No	No	None	Local	Yes	No	Head	laceration	Minor	cleanSuture
88	early-nineties	seventies	13	19	1	Coloured	Burn	Home	Trauma	Hospital	No	No	None	None	No	No	Head	burns	Moderate	other
89	early-nineties	seventies	13	19	1	Coloured	Transport	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	dressingsPOP
90	early-nineties	seventies	14	14	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	Truncal	foreignbody	Minor	adviceMedication
91	early-nineties	seventies	16	16	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	LowerExtre.	fractures	Minor	adviceMedication
92	early-nineties	seventies	13	19	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	dressingsPOP
93	early-nineties	seventies	13	17	1	Coloured	Assault	PublicPlace	Ward	Hospital	No	No	None	None	No	No	Truncal	laceration	Minor	cleanSuture
94	early-nineties	seventies	13	8	1	Black	Fall	PublicPlace	Ward	Hospital	No	No	None	None	No	No	LowerExtre.	laceration	Moderate	other
95	early-nineties	seventies	13	16	1	Coloured	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	other	Minor	adviceMedication
96	early-nineties	seventies	13	17	2	Coloured	Fall	PublicPlace	Not	Home	No	No	None	General	No	No	UpperExtre.	fractures	Moderate	observation
97	early-nineties	seventies	13	10	18	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	Yes	No	Head	chest	Minor	adviceMedication
98	early-nineties	seventies	13	13	1	Black	Assault	PublicPlace	Not	Home	No	No	None	None	No	No	Head	fractures	Minor	dressingsPOP
99	early-nineties	seventies	13	18	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	dressingsPOP
100	early-nineties	seventies	13	15	1	Coloured	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	Truncal	laceration	Minor	adviceMedication
101	early-nineties	seventies	14	12	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
102	early-nineties	seventies	14	11	2	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	foreignbody	Minor	adviceMedication
103	early-nineties	seventies	14	14	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	Local	No	No	Head	laceration	Moderate	cleanSuture

104	early-nineties	eighties	12	17	2	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	Yes	No	LowerExtre.	fractures	Minor	dressingsPOP
105	early-nineties	seventies	13	16	1	Coloured	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	dressingsPOP
106	early-nineties	seventies	13	20	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
107	early-nineties	seventies	13	17	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	none	Minor	adviceMedication
108	early-nineties	seventies	13	12	1	Coloured	Transport	PublicPlace	Not	Home	No	No	None	None	Yes	No	Head	other	Moderate	adviceMedication
109	early-nineties	seventies	13	10	1	Coloured	Assault	Home	Ward	Home	No	No	None	None	No	Possible	Head	none	Minor	adviceMedication
110	early-nineties	seventies	13	20	1	Coloured	Assault	Home	Ward	Home	No	No	None	None	No	No	Truncal	laceration	Minor	adviceMedication
111	early-nineties	seventies	13	14	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	adviceMedication
112	early-nineties	seventies	13	11	1	Coloured	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	none	Minor	adviceMedication
113	early-nineties	seventies	13	19	1	Black	Miscellaneous	Home	Ward	Home	No	No	None	Local	No	No	Truncal	laceration	Moderate	cleanSuture
114	early-nineties	seventies	13	19	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	dressingsPOP
115	early-nineties	seventies	14	13	1	Black	Fall	Home	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Moderate	dressingsPOP
116	early-nineties	seventies	13	18	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	Local	No	No	Head	laceration	Minor	cleanSuture
117	early-nineties	seventies	13	15	1	Coloured	Transport	PublicPlace	Ward	Home	No	No	Simple	None	No	No	LowerExtre.	fractures	Minor	dressingsPOP
118	early-nineties	seventies	13	20	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	dressingsPOP
119	early-nineties	seventies	13	16	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	adviceMedication
120	early-nineties	seventies	13	11	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
121	early-nineties	seventies	13	20	1	Black	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	adviceMedication
122	early-nineties	seventies	13	19	1	Coloured	Fall	PublicPlace	Not	Home	No	No	None	General	Yes	No	UpperExtre.	fractures	Moderate	operation
123	early-nineties	seventies	14	12	1	Coloured	Assault	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
124	early-nineties	seventies	14	23	4	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	LowerExtre.	other	Minor	other
125	early-nineties	seventies	15	12	15	Coloured	Fall	Home	Ward	Home	No	No	None	None	Yes	No	UpperExtre.	laceration	Minor	adviceMedication
126	early-nineties	seventies	14	9	1	Black	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
127	early-nineties	seventies	13	11	1	White	Fall	PublicPlace	Ward	Home	No	No	None	Local	No	No	UpperExtre.	laceration	Minor	cleanSuture
128	early-nineties	seventies	13	13	2	White	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
129	early-nineties	seventies	13	18	1	Black	Assault	Home	Ward	Home	No	No	None	Local	No	No	Head	laceration	Minor	cleanSuture
130	early-nineties	seventies	12	18	1	Coloured	Miscellaneous	PublicPlace	Ward	Hospital	No	No	None	Local	No	No	LowerExtre.	laceration	Moderate	cleanSuture
131	early-nineties	seventies	12	12	1	White	Fall	Home	Not	Home	No	No	None	General	No	No	UpperExtre.	fractures	Minor	dressingsPOP
132	early-nineties	seventies	13	20	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	none	Minor	adviceMedication
133	early-nineties	seventies	14	17	1	Coloured	Miscellaneous	PublicPlace	Ward	Hospital	No	No	None	Local	No	No	UpperExtre.	laceration	Minor	cleanSuture
134	early-nineties	seventies	13	9	1	Black	Transport	PublicPlace	Not	Home	No	No	None	General	No	No	Head	fractures	Moderate	observation
135	early-nineties	seventies	14	18	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	Yes	No	LowerExtre.	laceration	Minor	dressingsPOP
136	early-nineties	seventies	14	9	12	Coloured	Fall	Home	Ward	Home	No	No	Simple	None	No	No	LowerExtre.	laceration	Minor	dressingsPOP
137	early-nineties	seventies	13	11	2	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	dressingsPOP
138	early-nineties	seventies	13	19	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	Yes	No	LowerExtre.	fractures	Minor	dressingsPOP
139	early-nineties	seventies	12	16	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication

140	early-nineties	seventies	12	15	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	other	Minor	other
141	early-nineties	seventies	13	9	2	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	dressingsPOP
142	early-nineties	seventies	14	12	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
143	early-nineties	seventies	12	14	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	dressingsPOP
144	early-nineties	seventies	12	16	2	Coloured	Fall	PublicPlace	Not	Home	No	No	None	None	No	No	Head	laceration	Moderate	adviceMedication
145	early-nineties	seventies	12	20	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	Local	No	No	Head	laceration	Minor	cleanSuture
146	early-nineties	seventies	12	23	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	dressingsPOP
147	early-nineties	seventies	13	14	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	Local	No	No	LowerExtre.	laceration	Minor	cleanSuture
148	early-nineties	seventies	12	17	1	Coloured	Fall	PublicPlace	Not	Home	No	No	None	General	No	No	UpperExtre.	fractures	Minor	other
149	early-nineties	seventies	13	23	1	Coloured	Assault	Home	Not	Hospital	No	No	None	None	No	No	Head	other	Minor	other
150	early-nineties	seventies	12	14	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	Local	No	No	Head	laceration	Minor	cleanSuture
151	early-nineties	seventies	13	10	2	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	dressingsPOP
152	early-nineties	seventies	12	20	1	Black	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	Head	none	Minor	adviceMedication
153	early-nineties	seventies	12	19	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
154	early-nineties	seventies	12	11	1	Coloured	Assault	PublicPlace	Ward	Hospital	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
155	early-nineties	seventies	13	9	2	Coloured	Unknown	Home	Ward	Home	No	No	None	None	No	No	LowerExtre.	fractures	Moderate	dressingsPOP
156	early-nineties	seventies	13	19	3	Coloured	Assault	Home	Ward	Hospital	No	No	None	None	No	No	Head	none	Minor	adviceMedication
157	early-nineties	seventies	13	18	2	Coloured	Assault	Home	Ward	Home	No	No	None	None	No	No	Truncal	other	Moderate	other
158	early-nineties	seventies	12	19	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Moderate	dressingsPOP
159	early-nineties	seventies	12	19	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	dressingsPOP
160	early-nineties	seventies	12	17	1	Coloured	Assault	PublicPlace	Ward	Hospital	No	No	None	Local	No	No	Head	laceration	Minor	cleanSuture
161	early-nineties	seventies	13	15	2	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	Local	No	No	UpperExtre.	fractures	Moderate	other
162	early-nineties	seventies	13	16	1	Coloured	Unknown	Home	Ward	Home	No	No	None	None	No	No	LowerExtre.	fractures	Minor	adviceMedication
163	early-nineties	seventies	14	10	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	dressingsPOP
164	early-nineties	seventies	19	10	1	Coloured	Unknown	Home	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
165	early-nineties	seventies	12	13	96	Coloured	Transport	PublicPlace	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	laceration	Minor	dressingsPOP
166	early-nineties	eighties	4	15	1	Coloured	Miscellaneous	Home	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	amputations	Minor	cleanSuture
167	millenium	eighties	13	19	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	adviceMedication
168	late-nineties	eighties	10	9	24	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
169	early-nineties	eighties	7	17	1	Coloured	Fall	Home	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
170	early-nineties	eighties	7	10	48	Black	Miscellaneous	PublicPlace	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	other	Minor	dressingsPOP
171	early-nineties	seventies	12	15	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
172	early-nineties	seventies	12	20	1	Coloured	Transport	PublicPlace	Not	Home	No	No	None	None	No	No	LowerExtre.	fractures	Moderate	operation
173	early-nineties	seventies	13	23	2	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
174	early-nineties	seventies	13	13	1	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
175	early-nineties	seventies	12	9	1	Coloured	Burn	Home	Trauma	Hospital	No	No	None	None	No	No	Truncal	burns	Moderate	dressingsPOP

176	early-nineties	seventies	12	18	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	dressingsPOP
177	millenium	nineties	6	16	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	Yes	No	Head	none	Minor	adviceMedication
178	early-nineties	seventies	13	19	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
179	early-nineties	seventies	13	10	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	adviceMedication
180	early-nineties	seventies	12	12	12	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	adviceMedication
181	early-nineties	seventies	12	22	1	Coloured	Assault	PublicPlace	Ward	Home	No	No	None	Local	No	No	UpperExtre.	laceration	Minor	cleanSuture
182	early-nineties	seventies	12	19	2	Coloured	Assault	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
183	early-nineties	seventies	12	20	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	Local	No	No	UpperExtre.	amputations	Minor	cleanSuture
184	late-nineties	seventies	17	18	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	Head	fractures	Minor	adviceMedication
185	early-nineties	seventies	12	17	1	Coloured	Miscellaneous	PublicPlace	Ward	Hospital	No	No	None	None	No	No	LowerExtre.	laceration	Minor	adviceMedication
186	early-nineties	seventies	13	17	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
187	early-nineties	eighties	3	18	1	Coloured	Fall	Home	Ward	Home	No	No	None	Local	No	No	Head	laceration	Minor	cleanSuture
188	early-nineties	eighties	5	18	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	Yes	Possible	UpperExtre.	fractures	Minor	dressingsPOP
189	late-nineties	eighties	11	14	1	Coloured	Fall	Home	Not	Home	No	No	None	Local	No	No	UpperExtre.	fractures	Minor	dressingsPOP
190	early-nineties	seventies	12	19	1	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	None	No	No	LowerExtre.	fractures	Minor	dressingsPOP
191	early-nineties	seventies	13	12	1	Coloured	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
192	early-nineties	seventies	13	18	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	Local	No	No	Head	laceration	Minor	cleanSuture
193	early-nineties	seventies	12	21	1	Coloured	Fall	PublicPlace	Not	Home	No	No	None	General	No	No	UpperExtre.	fractures	Minor	dressingsPOP
194	early-nineties	seventies	14	12	1	Black	Fall	PublicPlace	Not	Hospital	No	No	None	General	No	No	LowerExtre.	fractures	Moderate	other
195	early-nineties	seventies	13	21	1	Coloured	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	other	Minor	other
196	early-nineties	seventies	12	17	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	dressingsPOP
197	early-nineties	seventies	13	16	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	dressingsPOP
198	early-nineties	seventies	12	23	6	Black	Fall	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Moderate	dressingsPOP
199	early-nineties	seventies	12	12	1	Coloured	Miscellaneous	PublicPlace	Ward	Hospital	No	No	None	Local	No	No	LowerExtre.	laceration	Moderate	cleanSuture
200	early-nineties	seventies	15	19	2	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
201	early-nineties	seventies	12	21	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	adviceMedication
202	early-nineties	seventies	12	13	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	Local	No	No	UpperExtre.	laceration	Moderate	cleanSuture
203	early-nineties	seventies	13	22	1	Coloured	Assault	Home	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
204	early-nineties	seventies	16	18	1	Coloured	Fall	Home	Ward	Home	No	No	None	Local	Yes	No	Head	laceration	Minor	cleanSuture
205	early-nineties	seventies	13	19	1	Coloured	Miscellaneous	PublicPlace	Ward	Hospital	No	No	None	None	No	No	Truncal	fractures	Minor	other
206	early-nineties	seventies	13	14	1	Black	Assault	Home	Ward	Hospital	No	No	None	None	No	No	LowerExtre.	laceration	Minor	adviceMedication
207	early-nineties	seventies	13	19	1	Coloured	Miscellaneous	PublicPlace	Ward	Hospital	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
208	early-nineties	seventies	12	17	1	Coloured	Miscellaneous	PublicPlace	Ward	Hospital	No	No	None	Local	No	No	LowerExtre.	laceration	Minor	cleanSuture
209	early-nineties	seventies	12	12	1	Coloured	Burn	PublicPlace	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	burns	Minor	dressingsPOP
210	early-nineties	seventies	13	16	1	White	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Moderate	adviceMedication
211	early-nineties	seventies	13	22	1	Black	Transport	PublicPlace	Not	Hospital	No	No	None	None	No	No	Truncal	laceration	Moderate	adviceMedication

212	early-nineties	seventies	14	11	1	Black	Fall	PublicPlace	Ward	Home	No	No	None	None	Yes	No	UpperExtre.	fractures	Moderate	dressingsPOP
213	early-nineties	seventies	13	11	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	Head	fractures	Minor	dressingsPOP
214	early-nineties	seventies	13	19	1	Coloured	Fall	Home	Not	Home	No	No	None	None	No	No	Head	other	Minor	other
215	early-nineties	seventies	12	13	4	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
216	early-nineties	seventies	13	21	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	Possible	LowerExtre.	laceration	Minor	dressingsPOP
217	early-nineties	seventies	12	10	1	Black	Assault	Home	Ward	Hospital	No	No	None	None	No	Yes	Truncal	laceration	Minor	adviceMedication
218	early-nineties	seventies	13	13	1	Coloured	Transport	PublicPlace	Ward	Hospital	No	No	None	Local	Yes	No	Head	laceration	Minor	cleanSuture
219	early-nineties	seventies	12	19	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
220	early-nineties	seventies	13	17	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Moderate	dressingsPOP
221	early-nineties	seventies	13	22	1	Black	Transport	PublicPlace	Not	Hospital	No	No	None	None	No	No	Head	laceration	Moderate	dressingsPOP
222	early-nineties	seventies	12	22	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
223	early-nineties	seventies	12	18	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	dressingsPOP
224	early-nineties	seventies	12	14	2	Coloured	Miscellaneous	Home	Not	Home	No	No	None	General	No	No	LowerExtre.	fractures	Moderate	operation
225	early-nineties	seventies	12	19	2	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	Local	No	No	Head	laceration	Minor	cleanSuture
226	early-nineties	seventies	13	19	1	Coloured	Fall	Home	Ward	Hospital	No	No	None	None	No	No	LowerExtre.	fractures	Moderate	dressingsPOP
227	early-nineties	seventies	12	10	1	Coloured	Assault	Home	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
228	early-nineties	seventies	12	21	2	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
229	early-nineties	seventies	12	23	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
230	early-nineties	seventies	12	19	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	LowerExtre.	fractures	Minor	dressingsPOP
231	early-nineties	seventies	12	19	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	dressingsPOP
232	early-nineties	seventies	12	15	1	Coloured	Burn	PublicPlace	Trauma	Hospital	No	No	None	None	No	No	Head	burns	Moderate	dressingsPOP
233	early-nineties	seventies	13	17	1	Coloured	Miscellaneous	Home	Ward	Hospital	No	No	None	Local	No	No	Head	laceration	Minor	cleanSuture
234	early-nineties	seventies	13	9	1	Coloured	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	adviceMedication
235	early-nineties	seventies	13	14	1	Coloured	Transport	PublicPlace	Not	Home	Yes	No	Simple	None	No	No	Head	laceration	severeMortal	other
236	early-nineties	seventies	12	1	1	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	None	No	No	LowerExtre.	fractures	Minor	dressingsPOP
237	early-nineties	seventies	13	10	1	Black	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	adviceMedication
238	early-nineties	seventies	13	19	1	Coloured	Transport	PublicPlace	Not	Home	No	No	None	None	No	No	Head	laceration	Minor	dressingsPOP
239	early-nineties	seventies	12	14	48	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	dressingsPOP
240	early-nineties	seventies	14	11	1	Black	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	dressingsPOP
241	early-nineties	seventies	12	9	1	Black	Transport	PublicPlace	Not	Hospital	No	No	None	General	No	No	UpperExtre.	fractures	Moderate	dressingsPOP
242	early-nineties	seventies	12	16	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	fractures	Minor	dressingsPOP
243	early-nineties	seventies	13	9	1	Coloured	Burn	Home	Ward	Home	No	No	None	None	Yes	No	UpperExtre.	burns	Minor	dressingsPOP
244	early-nineties	seventies	13	20	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	dressingsPOP
245	early-nineties	seventies	12	13	1	Coloured	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	adviceMedication
246	late-nineties	seventies	17	15	24	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	LowerExtre.	fractures	Minor	dressingsPOP
247	early-nineties	seventies	13	20	1	Coloured	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	fractures	Minor	dressingsPOP

248	early-nineties	seventies	13	1	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	Local	No	No	LowerExtre.	laceration	Moderate	cleanSuture
249	early-nineties	seventies	12	13	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	dressingsPOP
250	early-nineties	seventies	12	15	1	Coloured	Fall	Home	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
251	early-nineties	seventies	16	9	1	Coloured	Miscellaneous	Home	Ward	Hospital	No	No	None	None	No	No	LowerExtre.	fractures	Minor	dressingsPOP
252	early-nineties	seventies	12	21	1	Coloured	Fall	Home	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	laceration	Minor	adviceMedication
253	early-nineties	seventies	12	15	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
254	early-nineties	seventies	14	20	1	Coloured	Transport	Home	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
255	early-nineties	seventies	14	18	1	Black	Fall	Home	Ward	Home	No	No	None	Local	No	No	Head	laceration	Minor	cleanSuture
256	early-nineties	seventies	12	19	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	dressingsPOP
257	early-nineties	seventies	12	12	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
258	early-nineties	seventies	12	20	1	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Moderate	dressingsPOP
259	early-nineties	seventies	12	16	2	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
260	early-nineties	seventies	14	9	12	Coloured	Transport	PublicPlace	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	laceration	Minor	dressingsPOP
261	early-nineties	seventies	13	12	1	Coloured	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	adviceMedication
262	early-nineties	seventies	12	13	1	Coloured	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
263	early-nineties	seventies	13	19	1	Black	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	adviceMedication
264	early-nineties	seventies	13	17	2	Coloured	Assault	PublicPlace	Not	Home	No	No	Simple	General	No	No	Truncal	laceration	Minor	cleanSuture
265	early-nineties	seventies	12	17	1	Coloured	Transport	PublicPlace	Not	Home	No	No	None	None	No	No	Head	laceration	Minor	other
266	early-nineties	seventies	12	21	1	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	None	Yes	No	LowerExtre.	fractures	Moderate	dressingsPOP
267	early-nineties	seventies	14	9	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	adviceMedication
268	early-nineties	eighties	6	21	1	Coloured	Miscellaneous	PublicPlace	Ward	Hospital	No	No	None	None	No	No	Head	none	Minor	adviceMedication
269	early-nineties	eighties	5	20	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Moderate	cleanSuture
270	early-nineties	seventies	13	20	1	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Moderate	dressingsPOP
271	early-nineties	seventies	12	21	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	Local	No	No	Head	laceration	Minor	cleanSuture
272	early-nineties	seventies	14	1	1	Black	Assault	Home	Ward	Home	No	No	None	None	No	Yes	Truncal	laceration	Moderate	adviceMedication
273	early-nineties	seventies	13	13	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
274	early-nineties	seventies	12	19	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	dressingsPOP
275	early-nineties	seventies	13	17	2	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	Local	No	No	UpperExtre.	laceration	Moderate	cleanSuture
276	early-nineties	seventies	13	21	1	Coloured	Fall	Home	Not	Home	No	No	None	None	No	No	Head	laceration	Minor	dressingsPOP
277	early-nineties	seventies	13	16	2	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
278	early-nineties	seventies	13	9	1	Coloured	Fall	Home	Ward	Home	Yes	Yes	None	None	No	No	UpperExtre.	fractures	Moderate	dressingsPOP
279	early-nineties	seventies	13	15	4	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	fractures	Minor	dressingsPOP
280	early-nineties	seventies	14	21	2	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	Yes	UpperExtre.	laceration	Minor	dressingsPOP
281	early-nineties	seventies	12	11	1	Coloured	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	adviceMedication
282	early-nineties	eighties	7	16	1	Coloured	Fall	PublicPlace	Not	Home	No	No	None	None	No	No	Head	concussion	Minor	observation
283	early-nineties	seventies	12	20	1	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	None	No	No	LowerExtre.	fractures	Minor	dressingsPOP

284	early-nineties	seventies	12	23	1	Coloured	Miscellaneous	Home	Ward	Hospital	No	No	None	Local	No	No	Head	laceration	Minor	cleanSuture
285	early-nineties	seventies	14	16	48	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	Yes	No	LowerExtre.	fractures	Moderate	dressingsPOP
286	early-nineties	seventies	14	14	1	White	Transport	Home	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
287	early-nineties	seventies	12	12	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	fractures	Minor	cleanSuture
288	early-nineties	seventies	12	11	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	Yes	No	Truncal	foreignbody	Minor	adviceMedication
289	early-nineties	seventies	13	16	2	Coloured	Miscellaneous	Home	Not	Hospital	No	No	None	Local	No	No	UpperExtre.	vascular	severeMortal	operation
290	early-nineties	seventies	12	20	1	Coloured	Fall	Home	Not	Hospital	No	No	None	General	No	No	UpperExtre.	fractures	Moderate	operation
291	early-nineties	seventies	13	15	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	Yes	No	LowerExtre.	laceration	Minor	adviceMedication
292	early-nineties	seventies	12	15	1	Black	Burn	Home	Ward	Hospital	No	No	None	None	No	No	LowerExtre.	burns	Minor	adviceMedication
293	early-nineties	seventies	13	21	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	Local	No	No	Truncal	laceration	Minor	cleanSuture
294	early-nineties	seventies	13	18	1	Coloured	Transport	PublicPlace	Ward	Hospital	No	No	None	None	Yes	No	Head	laceration	Moderate	cleanSuture
295	early-nineties	seventies	12	10	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
296	early-nineties	seventies	12	19	1	Coloured	Transport	PublicPlace	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Minor	adviceMedication
297	early-nineties	seventies	13	9	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	adviceMedication
298	early-nineties	seventies	13	22	1	Coloured	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	dressingsPOP
299	early-nineties	seventies	12	19	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	dressingsPOP
300	early-nineties	seventies	13	14	1	Coloured	Fall	Home	Ward	Hospital	No	No	None	None	No	No	LowerExtre.	fractures	Minor	dressingsPOP
301	early-nineties	eighties	3	9	1	Black	Fall	Home	Ward	Hospital	No	No	None	None	No	No	Head	other	Moderate	adviceMedication
302	early-nineties	eighties	5	8	48	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	concussion	Minor	adviceMedication
303	late-nineties	eighties	8	10	48	Coloured	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
304	early-nineties	eighties	5	19	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	adviceMedication
305	early-nineties	eighties	6	20	1	Coloured	Fall	PublicPlace	Not	Home	No	No	None	None	No	No	Head	none	Minor	adviceMedication
306	late-nineties	eighties	10	16	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	laceration	Moderate	adviceMedication
307	early-nineties	eighties	4	19	2	Coloured	Fall	Home	Ward	Home	No	No	None	Local	Yes	No	Head	laceration	Moderate	dressingsPOP
308	early-nineties	seventies	12	23	2	Coloured	Assault	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	dressingsPOP
309	early-nineties	seventies	12	24	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
310	early-nineties	seventies	12	14	1	Coloured	Assault	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
311	early-nineties	seventies	13	13	1	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	None	No	No	LowerExtre.	fractures	Moderate	dressingsPOP
312	early-nineties	seventies	12	14	1	Coloured	Transport	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	adviceMedication
313	early-nineties	seventies	13	21	1	Coloured	Miscellaneous	PublicPlace	Ward	Hospital	No	No	None	None	No	No	Head	laceration	Moderate	cleanSuture
314	early-nineties	seventies	12	12	1	Coloured	Miscellaneous	Home	Trauma	Hospital	No	No	None	None	No	No	Head	none	Minor	adviceMedication
315	early-nineties	seventies	14	22	48	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
316	early-nineties	seventies	12	17	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Moderate	dressingsPOP
317	early-nineties	seventies	14	9	1	Coloured	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	none	Minor	adviceMedication
318	early-nineties	seventies	13	10	14	Coloured	Assault	Home	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	adviceMedication
319	early-nineties	seventies	12	13	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	Local	Yes	No	Head	other	Minor	adviceMedication

320	early-nineties	seventies	13	15	1	Coloured	Assault	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	adviceMedication
321	early-nineties	seventies	12	20	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	adviceMedication
322	early-nineties	seventies	13	15	1	Coloured	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	dressingsPOP
323	early-nineties	seventies	14	17	2	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	dressingsPOP
324	early-nineties	seventies	13	22	1	Coloured	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	adviceMedication
325	early-nineties	seventies	13	18	1	Coloured	Transport	PublicPlace	Not	Home	No	No	None	None	No	No	Head	laceration	Minor	dressingsPOP
326	early-nineties	seventies	12	11	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	dressingsPOP
327	early-nineties	seventies	12	16	1	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	Local	No	No	Head	laceration	Minor	cleanSuture
328	early-nineties	seventies	13	21	2	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
329	early-nineties	seventies	12	14	1	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
330	early-nineties	seventies	12	19	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	Local	No	No	LowerExtre.	laceration	Moderate	cleanSuture
331	early-nineties	seventies	13	23	1	Black	Miscellaneous	Home	Ward	Hospital	No	No	None	Local	No	No	Truncal	laceration	Minor	cleanSuture
332	early-nineties	seventies	12	17	1	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Moderate	dressingsPOP
333	early-nineties	seventies	13	17	1	Coloured	Assault	Home	Ward	Home	No	No	None	None	No	No	Head	none	Minor	adviceMedication
334	early-nineties	eighties	11	16	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	dressingsPOP
335	early-nineties	eighties	12	24	1	Coloured	Fall	Home	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
336	early-nineties	eighties	11	12	1	Coloured	Miscellaneous	Home	Ward	Hospital	No	No	None	Local	No	No	UpperExtre.	laceration	Minor	other
337	early-nineties	seventies	12	19	2	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	laceration	Minor	dressingsPOP
338	early-nineties	seventies	13	12	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Moderate	dressingsPOP
339	early-nineties	seventies	13	20	1	Coloured	Assault	PublicPlace	Ward	Home	No	No	None	Local	No	No	LowerExtre.	laceration	Minor	cleanSuture
340	early-nineties	seventies	12	17	1	Coloured	Miscellaneous	Home	Ward	Hospital	No	No	None	None	No	No	LowerExtre.	fractures	Moderate	dressingsPOP
341	early-nineties	seventies	12	15	1	Coloured	Miscellaneous	PublicPlace	Ward	Hospital	No	No	None	Local	No	No	LowerExtre.	laceration	Moderate	cleanSuture
342	early-nineties	seventies	12	20	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	fractures	Minor	dressingsPOP
343	late-nineties	seventies	18	10	2	Black	Assault	Home	Ward	Home	No	No	None	Local	No	No	Head	laceration	Moderate	cleanSuture
344	early-nineties	seventies	12	17	1	Coloured	Transport	PublicPlace	Ward	Home	No	No	None	Local	No	No	Head	laceration	Minor	cleanSuture
345	early-nineties	seventies	12	21	4	Coloured	Transport	PublicPlace	Ward	Home	No	No	None	None	Yes	No	Head	concussion	Moderate	dressingsPOP
346	early-nineties	seventies	12	17	28	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	None	Yes	No	UpperExtre.	fractures	Moderate	dressingsPOP
347	early-nineties	seventies	12	17	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	adviceMedication
348	early-nineties	seventies	13	12	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	adviceMedication
349	early-nineties	seventies	12	19	1	Black	Assault	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
350	early-nineties	seventies	12	15	1	Black	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	adviceMedication
351	early-nineties	seventies	12	19	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	Local	No	No	UpperExtre.	laceration	Minor	cleanSuture
352	early-nineties	seventies	13	18	1	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
353	early-nineties	seventies	12	19	3	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	observation
354	early-nineties	eighties	12	23	1	Coloured	Transport	PublicPlace	Not	Home	No	No	None	Local	No	No	Head	laceration	Minor	cleanSuture
355	early-nineties	seventies	13	16	2	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	dressingsPOP

356	early-nineties	eighties	5	17	1	Coloured	Miscellaneous	Home	Not	Home	No	No	None	General	No	No	UpperExtre.	laceration	Minor	operation
357	late-nineties	eighties	10	23	1	Black	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	Truncal	laceration	Minor	adviceMedication
358	early-nineties	seventies	13	9	72	Black	Fall	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
359	early-nineties	seventies	13	22	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	other
360	early-nineties	seventies	15	19	2	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	Truncal	laceration	Minor	adviceMedication
361	early-nineties	seventies	13	15	1	Coloured	Fall	Home	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
362	early-nineties	seventies	12	20	1	Coloured	Burn	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	amputations	Minor	adviceMedication
363	early-nineties	seventies	13	16	1	Coloured	Burn	Home	Ward	Home	No	No	None	None	No	No	LowerExtre.	burns	Minor	dressingsPOP
364	early-nineties	seventies	12	20	1	Coloured	Assault	Home	Ward	Hospital	No	No	None	Local	No	No	Head	laceration	Moderate	cleanSuture
365	early-nineties	seventies	13	14	2	Coloured	Fall	PublicPlace	Not	Hospital	No	No	None	None	No	No	LowerExtre.	fractures	Minor	dressingsPOP
366	early-nineties	seventies	13	21	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	Head	foreignbody	Minor	dressingsPOP
367	early-nineties	seventies	13	21	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	Head	foreignbody	Minor	dressingsPOP
368	early-nineties	seventies	13	16	1	Coloured	Burn	Home	Ward	Hospital	No	No	None	None	Yes	No	Head	burns	Minor	adviceMedication
369	early-nineties	eighties	12	18	1	Coloured	Miscellaneous	PublicPlace	Not	Home	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
370	early-nineties	eighties	11	18	1	Coloured	Transport	PublicPlace	Ward	Hospital	No	No	None	None	No	No	LowerExtre.	laceration	Minor	adviceMedication
371	early-nineties	eighties	11	10	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	fractures	Minor	adviceMedication
372	early-nineties	eighties	11	9	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	dressingsPOP
373	early-nineties	eighties	11	1	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	Local	No	No	Head	laceration	Minor	cleanSuture
374	early-nineties	seventies	13	22	1	Coloured	Burn	Home	Trauma	Hospital	No	No	None	None	No	No	UpperExtre.	burns	Moderate	other
375	early-nineties	seventies	12	13	10	Black	Fall	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	burns	Minor	dressingsPOP
376	early-nineties	seventies	12	11	1	Coloured	Fall	Home	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Minor	adviceMedication
377	early-nineties	seventies	13	14	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	Local	Yes	No	Head	laceration	Moderate	cleanSuture
378	early-nineties	seventies	12	13	1	Black	Fall	Home	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
379	early-nineties	seventies	12	21	1	Coloured	Fall	Home	Not	Home	No	No	None	None	No	No	UpperExtre.	laceration	Moderate	cleanSuture
380	early-nineties	seventies	13	17	1	Coloured	Fall	PublicPlace	Not	Home	Yes	Yes	Simple	None	No	No	Head	laceration	Minor	dressingsPOP
381	early-nineties	seventies	13	13	1	Coloured	Transport	PublicPlace	Not	Home	No	No	None	None	No	No	UpperExtre.	fractures	Moderate	dressingsPOP
382	early-nineties	seventies	12	11	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	adviceMedication
383	early-nineties	seventies	12	13	1	Coloured	Assault	PublicPlace	Ward	Home	No	No	None	Local	No	No	Truncal	laceration	Minor	cleanSuture
384	early-nineties	eighties	12	15	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	Head	none	Minor	adviceMedication
385	early-nineties	seventies	13	10	1	Coloured	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	Truncal	laceration	Minor	adviceMedication
386	early-nineties	seventies	15	21	1	White	Miscellaneous	PublicPlace	Ward	Hospital	No	No	None	None	No	No	LowerExtre.	fractures	Moderate	dressingsPOP
387	early-nineties	seventies	12	18	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	adviceMedication
388	early-nineties	seventies	12	17	1	Coloured	Miscellaneous	PublicPlace	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	nerve injury	Minor	adviceMedication
389	early-nineties	seventies	16	16	1	White	Fall	Home	Ward	Home	No	No	None	Local	No	No	Head	laceration	Moderate	cleanSuture
390	early-nineties	seventies	14	19	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	dressingsPOP
391	early-nineties	seventies	13	14	4	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	fractures	Minor	dressingsPOP

392	early-nineties	seventies	13	12	1	Coloured	Miscellaneous	PublicPlace	Ward	Hospital	No	No	None	None	No	No	Head	other	Moderate	other
393	early-nineties	eighties	11	17	1	Coloured	Fall	PublicPlace	Not	Home	No	No	None	Local	No	No	UpperExtre.	laceration	Moderate	operation
394	early-nineties	eighties	12	11	1	Coloured	Assault	PublicPlace	Ward	Home	No	No	None	None	No	No	Truncal	laceration	Minor	dressingsPOP
395	early-nineties	eighties	13	21	2	Coloured	Miscellaneous	PublicPlace	Ward	Hospital	No	No	None	None	No	No	LowerExtre.	laceration	Minor	adviceMedication
396	early-nineties	seventies	13	20	1	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	Local	No	No	Head	fractures	Moderate	other
397	early-nineties	seventies	12	18	1	Coloured	Fall	PublicPlace	Not	Home	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
398	early-nineties	eighties	11	11	1	Coloured	Assault	PublicPlace	Ward	Home	No	No	None	None	No	Possible	Head	none	Minor	adviceMedication
399	early-nineties	eighties	11	16	2	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	fractures	Moderate	dressingsPOP
400	early-nineties	seventies	12	12	1	Black	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
401	early-nineties	eighties	12	20	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	adviceMedication
402	early-nineties	seventies	12	10	99	Black	Fall	Home	Ward	Hospital	No	No	None	None	Yes	No	UpperExtre.	fractures	Minor	dressingsPOP
403	early-nineties	eighties	7	19	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
404	early-nineties	eighties	13	19	1	Coloured	Miscellaneous	Home	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
405	early-nineties	eighties	12	17	4	Coloured	Assault	PublicPlace	Not	Home	No	No	None	None	No	No	Head	laceration	Minor	dressingsPOP
406	early-nineties	eighties	11	15	1	Coloured	Assault	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	cleanSuture
407	early-nineties	eighties	11	11	1	Coloured	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	Truncal	concussion	Minor	adviceMedication
408	early-nineties	eighties	12	20	1	Coloured	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Moderate	adviceMedication
409	early-nineties	eighties	11	18	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	adviceMedication
410	early-nineties	eighties	12	18	1	Coloured	Miscellaneous	Home	Not	Home	No	No	None	General	No	No	UpperExtre.	foreignbody	Minor	other
411	early-nineties	seventies	13	19	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	Local	No	No	UpperExtre.	laceration	Minor	cleanSuture
412	early-nineties	eighties	13	9	14	Black	Fall	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
413	early-nineties	seventies	13	22	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	Yes	No	Head	laceration	Minor	adviceMedication
414	early-nineties	eighties	11	22	1	Coloured	Assault	Home	Not	Hospital	No	Yes	Simple	General	No	No	Head	laceration	Minor	other
415	early-nineties	eighties	13	21	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
416	early-nineties	seventies	13	23	2	Black	Miscellaneous	Home	Trauma	Hospital	Yes	Yes	Simple	None	No	Possible	Head	other	Moderate	other
417	early-nineties	eighties	11	9	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
418	early-nineties	eighties	12	13	24	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	Yes	No	Head	laceration	Moderate	other
419	early-nineties	seventies	13	21	1	Coloured	Miscellaneous	PublicPlace	Ward	Hospital	No	No	None	None	No	No	Head	laceration	Moderate	dressingsPOP
420	early-nineties	seventies	13	19	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
421	early-nineties	eighties	12	13	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	severeMortal	dressingsPOP
422	early-nineties	eighties	11	22	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	adviceMedication
423	early-nineties	eighties	14	10	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
424	early-nineties	eighties	12	20	1	Coloured	Transport	PublicPlace	Ward	Hospital	No	No	None	Local	No	No	LowerExtre.	laceration	Minor	cleanSuture
425	early-nineties	eighties	11	21	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
426	early-nineties	eighties	11	21	1	Black	Transport	PublicPlace	Not	Home	Yes	Yes	Simple	Local	Yes	Yes	Head	laceration	Minor	adviceMedication
427	early-nineties	eighties	11	17	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	Local	No	No	LowerExtre.	laceration	Minor	cleanSuture

428	early-nineties	seventies	13	10	48	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	Yes	No	UpperExtre.	fractures	Minor	dressingsPOP
429	early-nineties	eighties	11	19	1	Coloured	Miscellaneous	Home	Ward	Hospital	No	No	None	Local	No	No	UpperExtre.	laceration	Moderate	cleanSuture
430	early-nineties	seventies	12	13	1	Coloured	Fall	Home	Ward	Hospital	No	No	None	None	No	No	LowerExtre.	laceration	Minor	dressingsPOP
431	early-nineties	seventies	14	11	1	Coloured	Fall	Home	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
432	early-nineties	eighties	11	19	1	Coloured	Assault	Home	Ward	Home	No	No	None	None	No	No	Head	concussion	Minor	adviceMedication
433	early-nineties	seventies	12	12	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	Local	No	No	Head	laceration	Minor	adviceMedication
434	early-nineties	eighties	12	9	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Moderate	dressingsPOP
435	early-nineties	eighties	12	16	1	Coloured	Assault	Home	Not	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
436	early-nineties	seventies	13	10	20	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	None	Yes	No	UpperExtre.	fractures	Moderate	dressingsPOP
437	early-nineties	eighties	13	14	1	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Moderate	dressingsPOP
438	early-nineties	eighties	12	20	1	Coloured	Miscellaneous	PublicPlace	Ward	Hospital	No	No	None	Local	No	No	UpperExtre.	laceration	Minor	cleanSuture
439	early-nineties	eighties	11	22	1	Coloured	Transport	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Moderate	dressingsPOP
440	early-nineties	seventies	13	20	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	Local	Yes	No	UpperExtre.	fractures	Moderate	cleanSuture
441	early-nineties	seventies	13	16	1	Coloured	Miscellaneous	PublicPlace	Ward	Hospital	No	No	None	None	No	No	Truncal	foreignbody	Minor	adviceMedication
442	early-nineties	eighties	13	19	1	Coloured	Assault	PublicPlace	Ward	Hospital	No	No	None	Local	No	No	UpperExtre.	laceration	Minor	cleanSuture
443	early-nineties	eighties	12	15	1	Coloured	Assault	PublicPlace	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
444	early-nineties	eighties	12	14	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	laceration	Minor	cleanSuture
445	early-nineties	eighties	12	20	28	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	dressingsPOP
446	early-nineties	eighties	11	20	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	adviceMedication
447	early-nineties	eighties	11	12	1	Coloured	Miscellaneous	PublicPlace	Not	Home	No	No	None	General	No	No	UpperExtre.	fractures	Minor	observation
448	early-nineties	eighties	12	17	1	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	None	No	No	Head	laceration	Minor	cleanSuture
449	early-nineties	seventies	12	20	1	Coloured	Miscellaneous	Home	Ward	Hospital	No	No	None	Local	No	No	UpperExtre.	fractures	Minor	dressingsPOP
450	early-nineties	eighties	12	12	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	Yes	No	LowerExtre.	laceration	Moderate	EUA/MUA
451	early-nineties	seventies	13	9	1	Coloured	Assault	Home	Ward	Home	No	No	None	None	No	Yes	Truncal	none	Minor	adviceMedication
452	early-nineties	eighties	12	15	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	Local	No	No	LowerExtre.	laceration	Minor	cleanSuture
453	early-nineties	seventies	12	19	1	Coloured	Burn	PublicPlace	Ward	Home	No	No	None	None	No	No	Head	burns	Minor	dressingsPOP
454	early-nineties	seventies	12	20	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	foreignbody	Minor	adviceMedication
455	early-nineties	seventies	12	13	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	Truncal	laceration	Minor	adviceMedication
456	early-nineties	eighties	11	14	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
457	early-nineties	eighties	13	22	1	Coloured	Miscellaneous	Home	Trauma	Hospital	No	No	None	None	No	No	Head	laceration	Minor	other
458	early-nineties	eighties	12	11	1	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	None	No	No	LowerExtre.	laceration	Minor	adviceMedication
459	early-nineties	eighties	12	16	1	Coloured	Fall	Home	Ward	Home	No	No	None	Local	No	No	Head	laceration	Minor	cleanSuture
460	early-nineties	eighties	11	19	2	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	dressingsPOP
461	early-nineties	seventies	12	10	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	Yes	No	LowerExtre.	laceration	Minor	dressingsPOP
462	early-nineties	eighties	11	1	1	Coloured	Assault	PublicPlace	Ward	Hospital	No	No	None	Local	No	No	Head	laceration	Moderate	cleanSuture
463	early-nineties	eighties	13	22	1	Coloured	Fall	PublicPlace	Not	Home	No	No	None	None	No	No	UpperExtre.	fractures	Moderate	EUA/MUA

464	early-nineties	eighties	11	12	1	Coloured	Assault	Home	Ward	Home	No	No	None	None	No	Possible	Head	laceration	Minor	dressingsPOP
465	early-nineties	eighties	11	9	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	Local	Yes	No	LowerExtre.	foreignbody	Minor	operation
466	early-nineties	eighties	13	11	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
467	early-nineties	eighties	11	17	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	Local	No	No	Truncal	laceration	Minor	cleanSuture
468	early-nineties	eighties	11	19	1	Coloured	Transport	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	concussion	Minor	adviceMedication
469	early-nineties	eighties	12	10	48	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	None	Yes	No	Head	other	Moderate	adviceMedication
470	early-nineties	eighties	11	14	2	Black	Transport	PublicPlace	Not	Home	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
471	early-nineties	eighties	13	21	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	Local	No	No	Head	laceration	Moderate	adviceMedication
472	early-nineties	eighties	11	23	1	Coloured	Miscellaneous	PublicPlace	Ward	Hospital	No	No	None	Local	No	No	Head	laceration	Minor	cleanSuture
473	early-nineties	eighties	14	12	1	White	Fall	PublicPlace	Not	Home	No	No	None	None	Yes	No	Head	concussion	Moderate	observation
474	early-nineties	eighties	12	14	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	dressingsPOP
475	early-nineties	seventies	14	19	2	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	LowerExtre.	burns	Minor	adviceMedication
476	early-nineties	seventies	13	14	1	Coloured	Fall	PublicPlace	Not	Home	No	No	None	None	No	No	Head	laceration	Minor	dressingsPOP
477	early-nineties	seventies	13	15	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Moderate	dressingsPOP
478	early-nineties	eighties	12	19	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	fractures	Minor	dressingsPOP
479	early-nineties	eighties	11	11	1	Black	Unknown	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	fractures	Minor	dressingsPOP
480	early-nineties	eighties	12	10	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	Local	No	No	UpperExtre.	amputations	Moderate	cleanSuture
481	early-nineties	seventies	13	18	1	Coloured	Fall	PublicPlace	Ward	Hospital	No	No	None	None	No	No	UpperExtre.	fractures	Moderate	dressingsPOP
482	early-nineties	eighties	12	12	1	Black	Assault	Home	Ward	Hospital	No	No	None	Local	No	No	Head	laceration	Minor	cleanSuture
483	early-nineties	eighties	11	18	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	Local	No	No	UpperExtre.	laceration	Minor	cleanSuture
484	early-nineties	eighties	12	15	1	Coloured	Miscellaneous	PublicPlace	Ward	Hospital	No	No	None	None	No	No	LowerExtre.	laceration	Minor	dressingsPOP
485	early-nineties	eighties	11	9	1	Black	Assault	Home	Ward	Hospital	No	No	None	None	No	No	Head	laceration	Minor	adviceMedication
486	early-nineties	eighties	12	17	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	adviceMedication
487	early-nineties	eighties	11	9	1	Coloured	Assault	Home	Ward	Hospital	No	No	None	None	No	No	Truncal	laceration	Minor	adviceMedication
488	early-nineties	eighties	13	18	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	Truncal	laceration	Moderate	adviceMedication
489	early-nineties	eighties	11	17	1	Coloured	Assault	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	fractures	Minor	dressingsPOP
490	early-nineties	eighties	11	17	1	Coloured	Fall	PublicPlace	Ward	Home	No	No	None	None	No	No	LowerExtre.	laceration	Minor	dressingsPOP
491	early-nineties	eighties	14	12	24	Coloured	Unknown	PublicPlace	Ward	Hospital	No	No	None	None	No	No	Truncal	other	Minor	adviceMedication
492	early-nineties	eighties	12	11	1	Coloured	Fall	PublicPlace	Not	Home	No	No	None	General	No	No	UpperExtre.	fractures	Minor	EUA/MUA
493	early-nineties	eighties	12	15	1	Coloured	Assault	PublicPlace	Ward	Hospital	No	No	None	Local	No	No	Head	laceration	Minor	cleanSuture
494	early-nineties	eighties	11	12	1	Coloured	Transport	Home	Ward	Home	No	No	None	None	No	No	LowerExtre.	fractures	Minor	dressingsPOP
495	early-nineties	eighties	11	12	1	Coloured	Fall	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	adviceMedication
496	early-nineties	eighties	13	24	1	Coloured	Miscellaneous	PublicPlace	Ward	Home	No	No	None	None	No	No	Truncal	laceration	Minor	adviceMedication
497	early-nineties	seventies	13	13	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	foreignbody	Minor	other
498	early-nineties	eighties	12	19	1	Coloured	Burn	PublicPlace	Trauma	Hospital	No	No	Simple	None	No	No	LowerExtre.	burns	Moderate	dressingsPOP
499	early-nineties	seventies	14	9	1	Black	Miscellaneous	Home	Ward	Hospital	No	No	None	Local	Yes	No	LowerExtre.	laceration	Minor	cleanSuture

500	early-nineties	eighties	11	9	1	Coloured	Miscellaneous	Home	Ward	Home	No	No	None	None	No	No	UpperExtre.	laceration	Minor	dressingsPOP

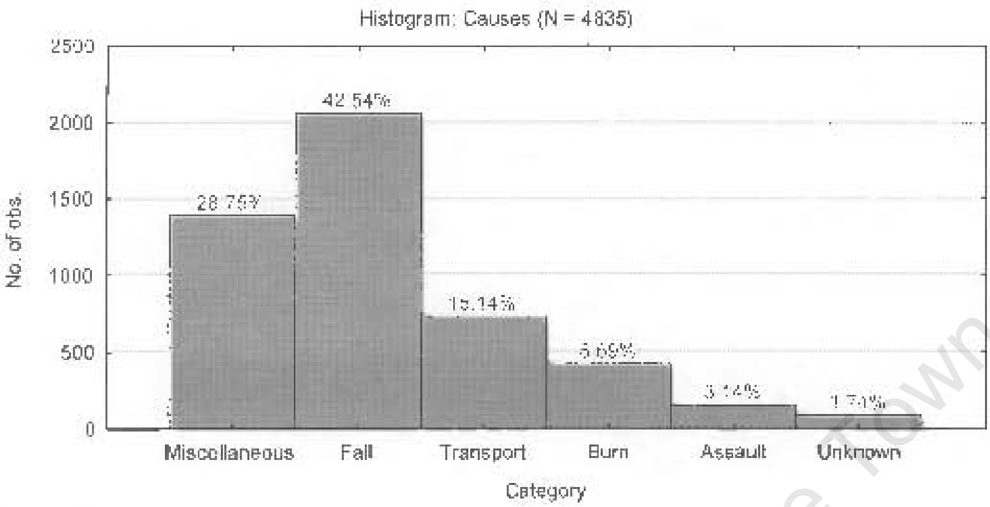


Figure D.1

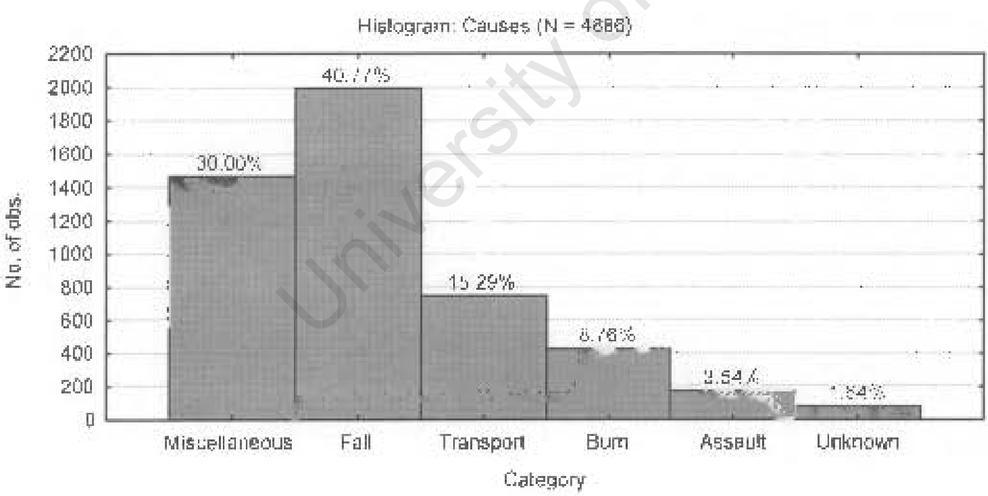
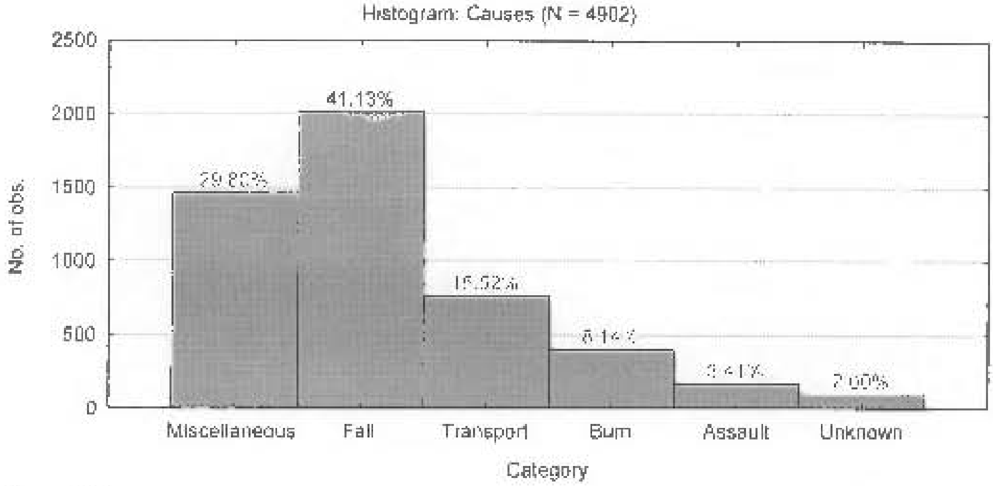


Figure D.2



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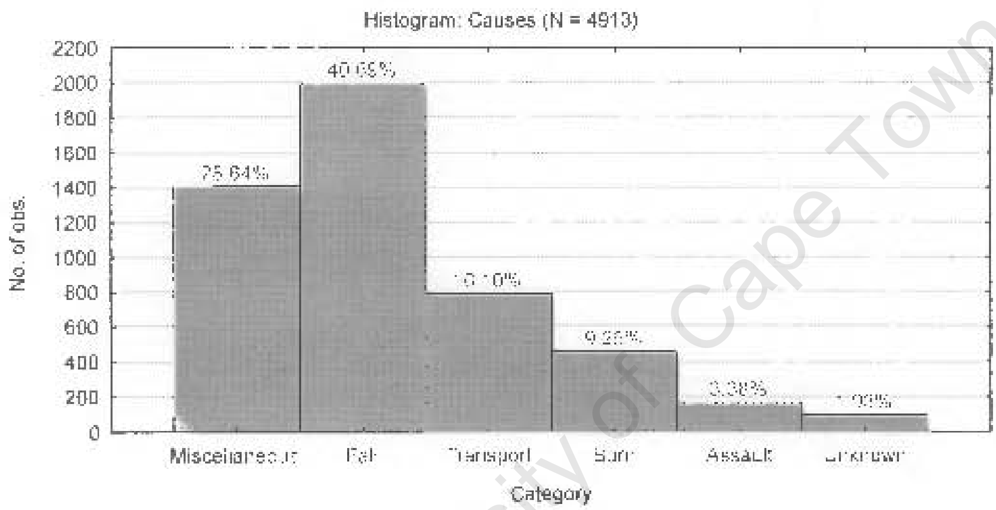

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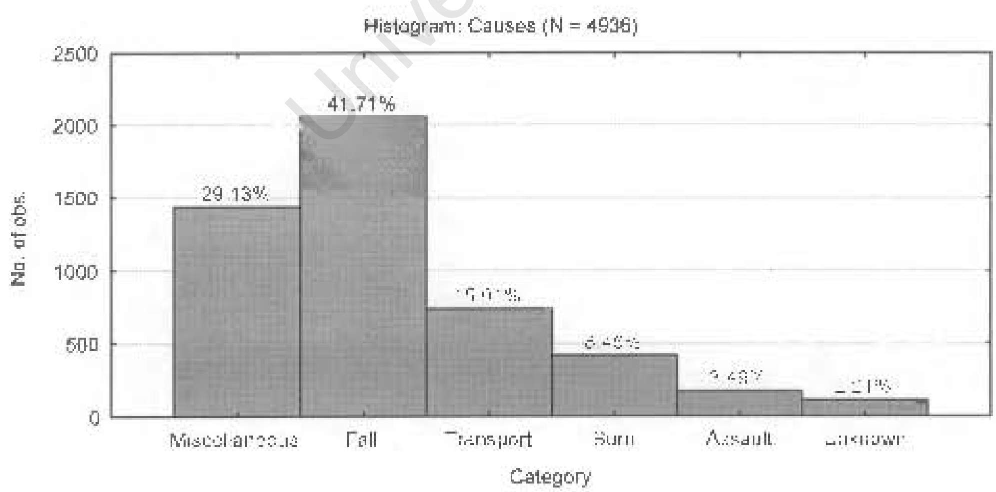

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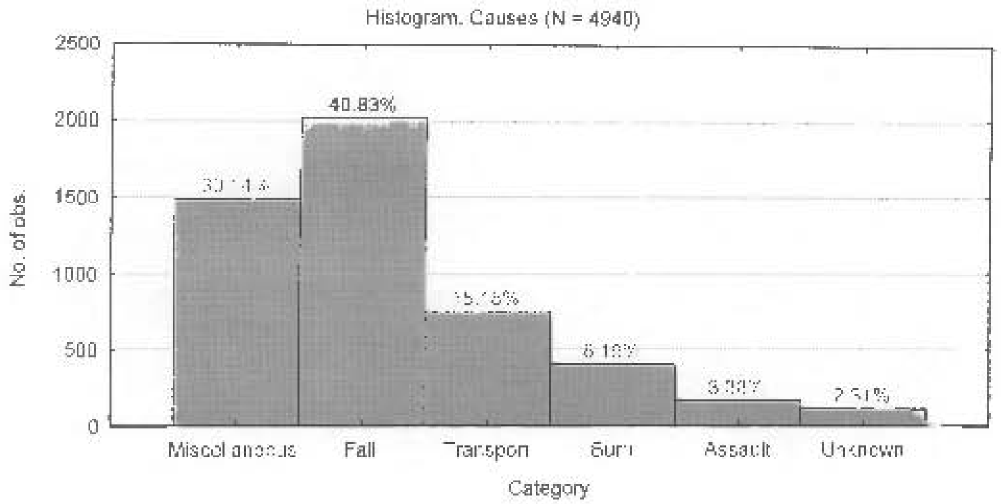
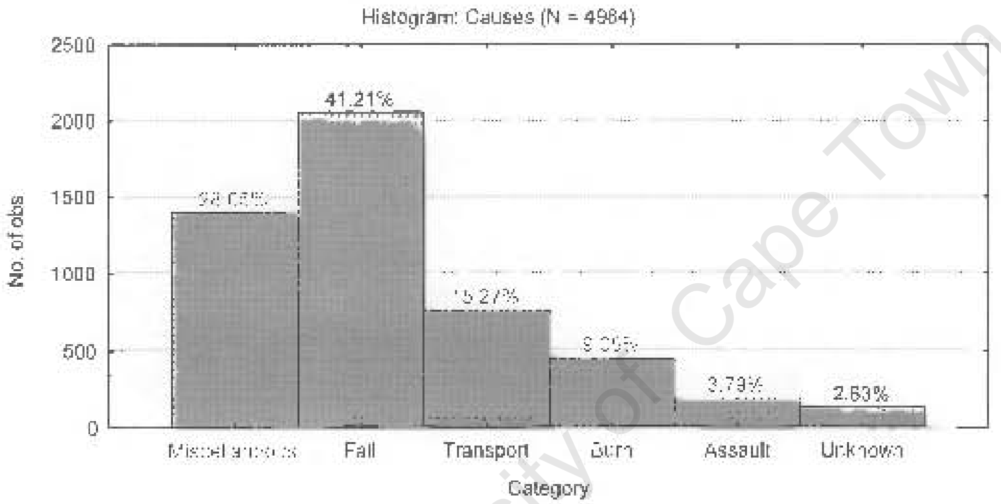


Figure D.6



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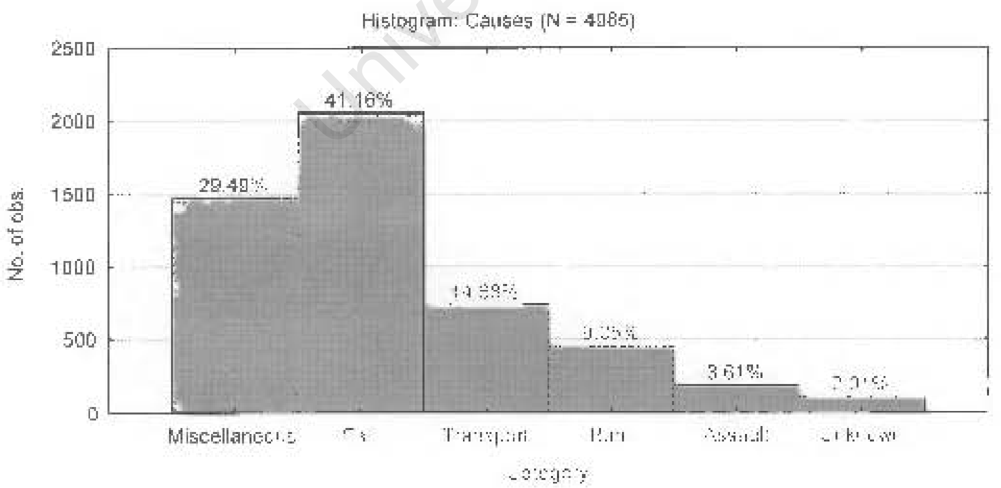
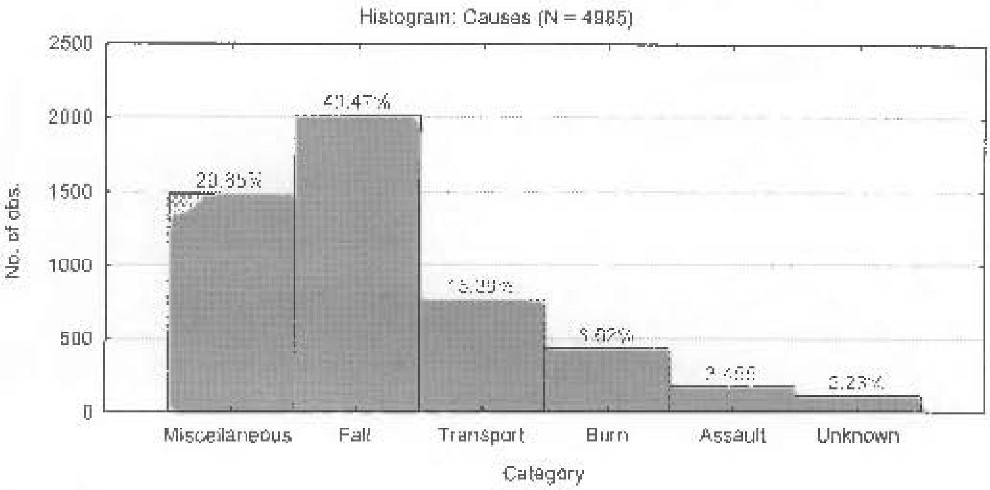


Figure D.8



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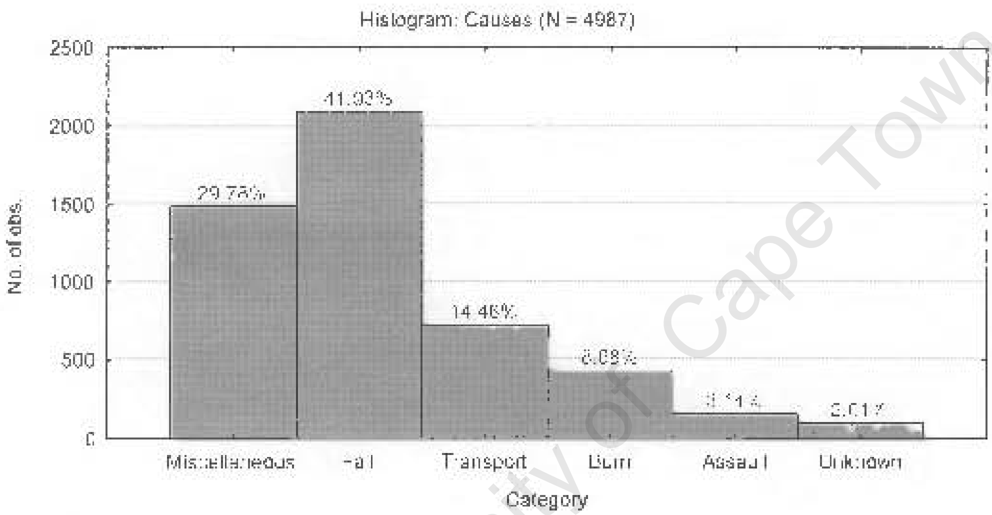
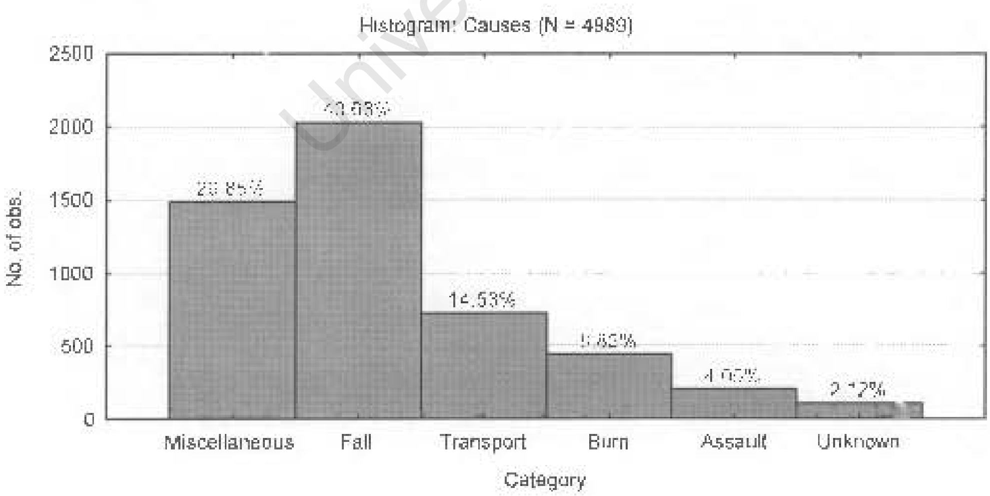


Figure D.10



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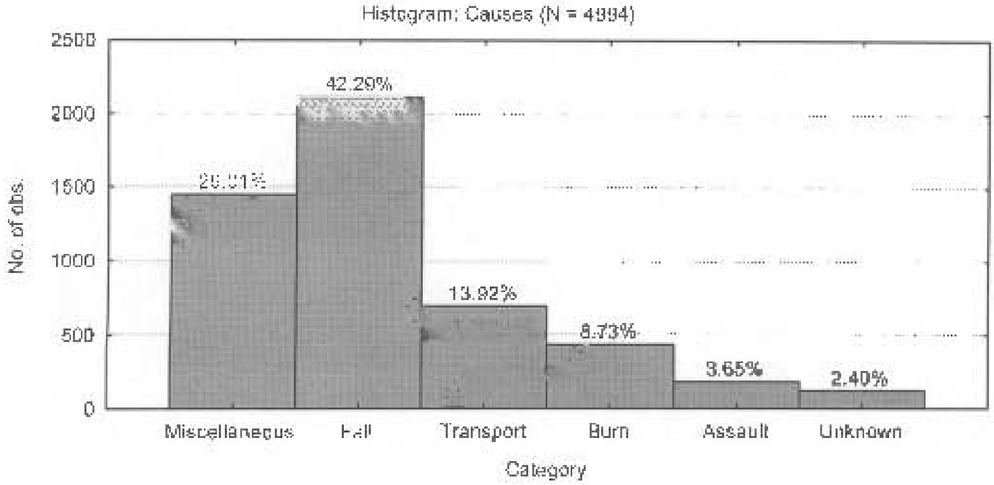

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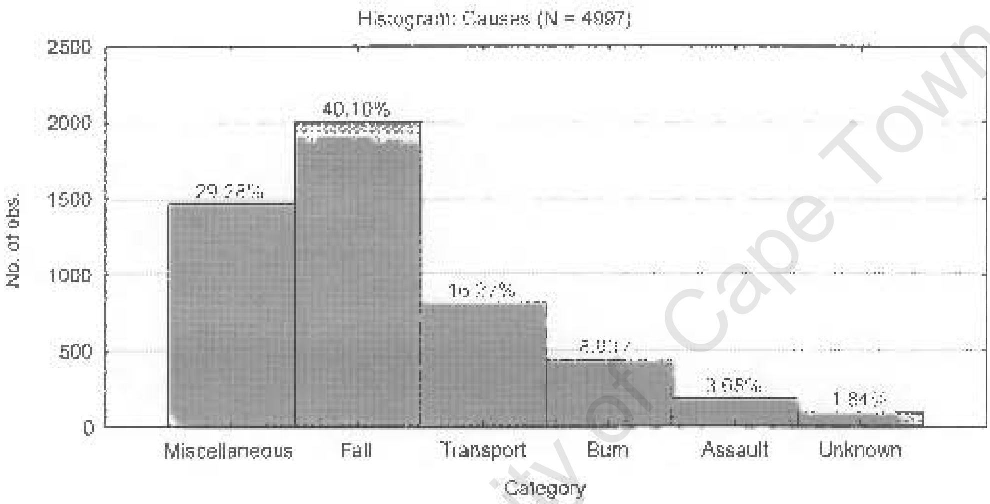


Figure D.13

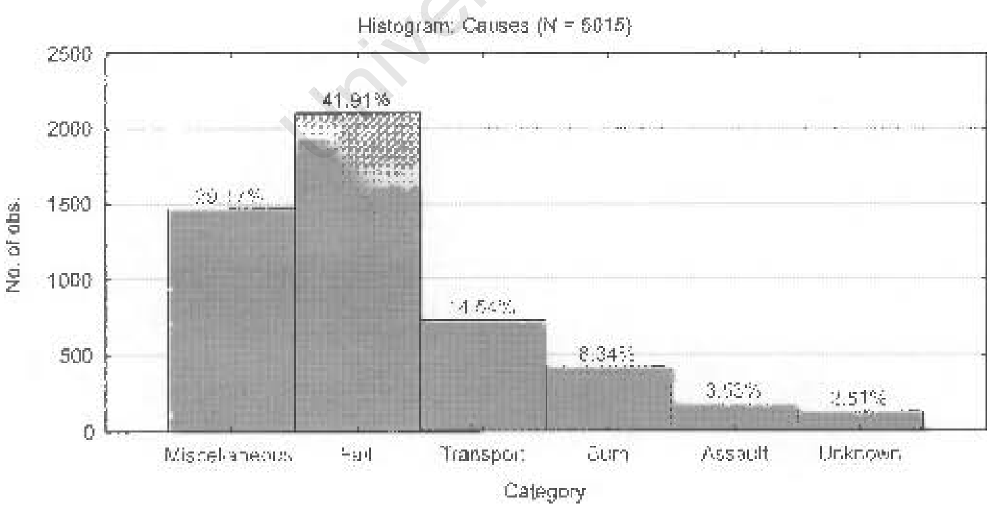


Figure D.14

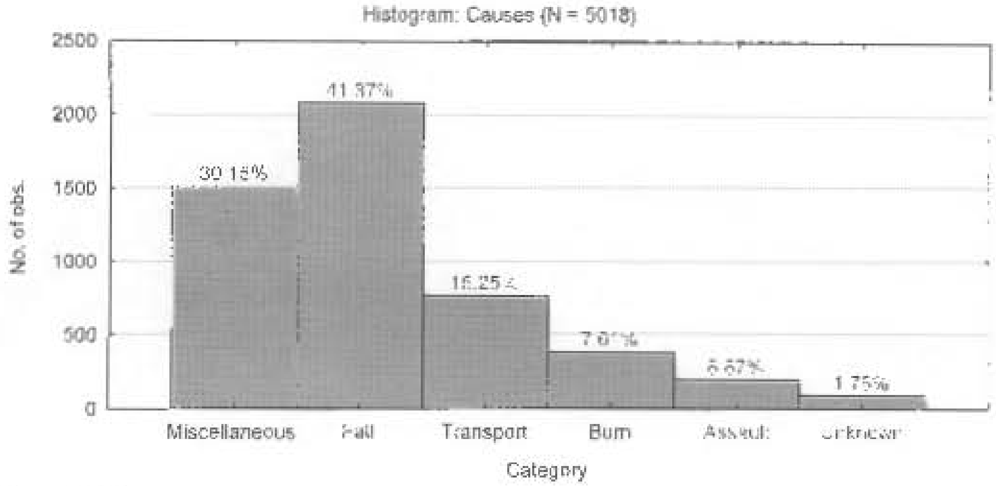
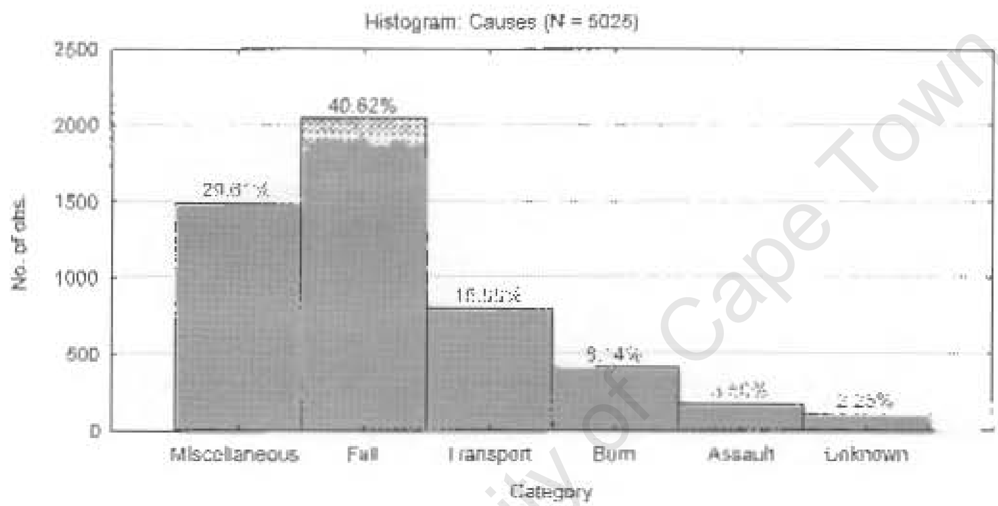


Figure D.15



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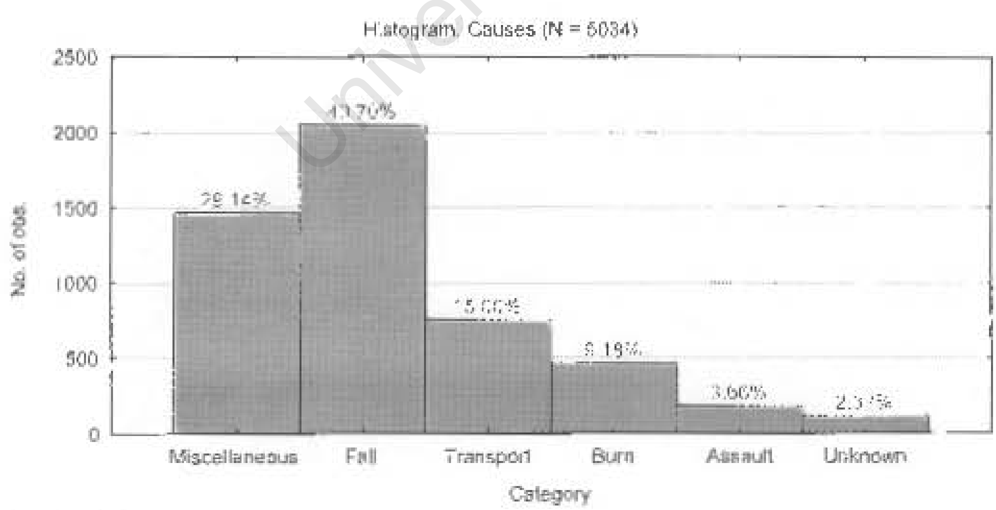

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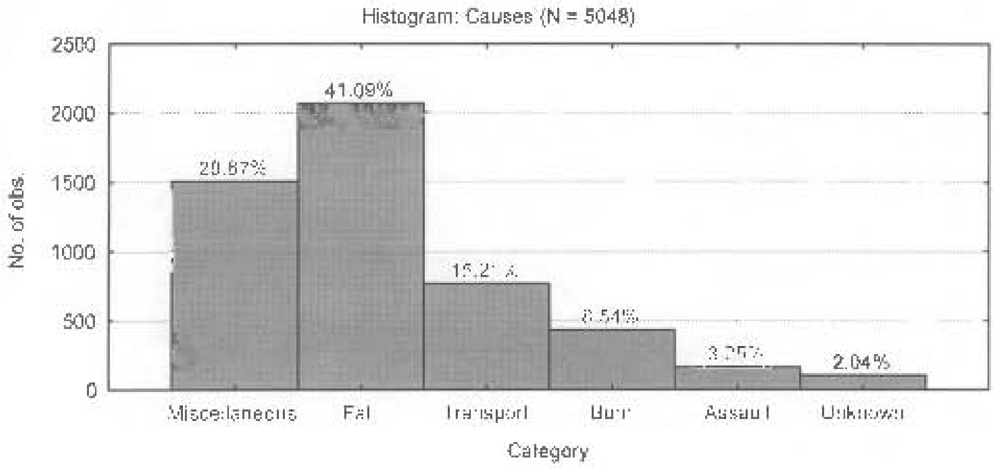

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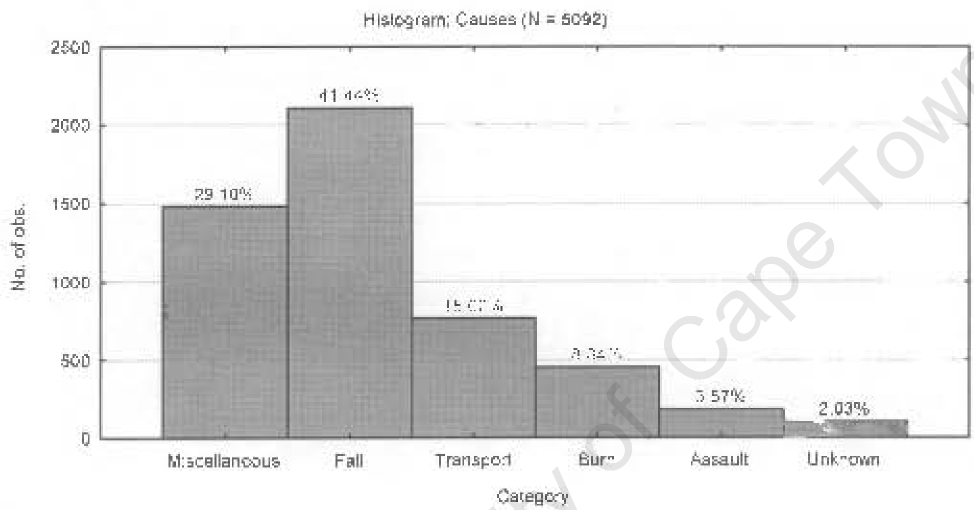

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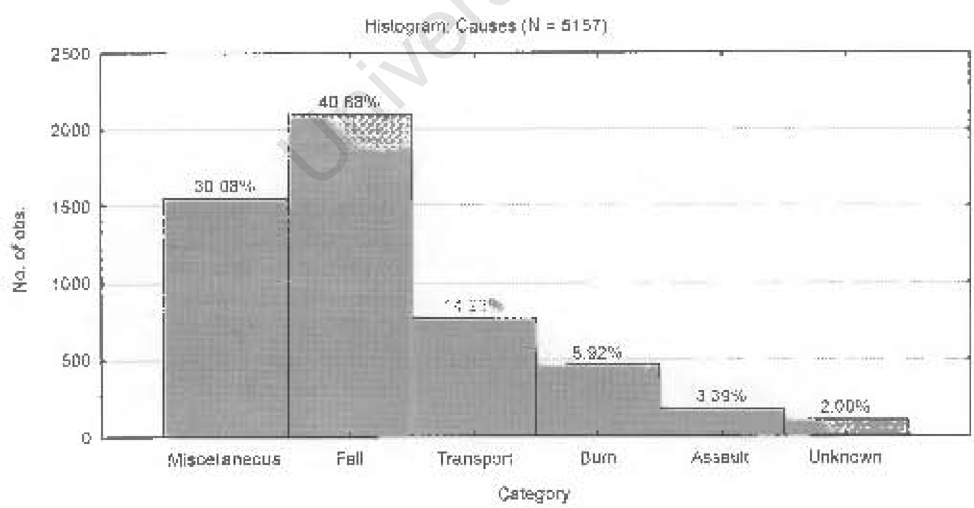

Figure D.20

APPENDIX E.1

SENSITIVITY ANALYSIS

Table E.1.1 Sensitivity Analysis (Marked values have ratios ≤ 1.0000)

	Year of Injury	Year of Birth	Age	Time	Hours Since Injury	Race/ Gender	Place	Admission	Disposal	Unconscious	Shock	Resuscitation	Anaesthetic	Self Infliction	Abuse	Anatomy	Pathology	AIS	Treatment
Ratio (BP-1)	**0.9983**	1.0064	1.0023	1.0003	**0.9999**	1.0028	1.0738	1.0149	1.0039	**1.0000**	1.0001	1.0011	0.9987	1.0007	1.0193	1.0184	1.6039	**0.9999**	1.0207
Ratio (BP-2)	1.0022	1.0021	1.0008	**0.9990**	1.0001	1.0055	1.0676	1.0088	1.0028	1.0007	1.0005	1.0008	**0.9986**	1.0021	1.0161	1.0243	1.4458	1.0014	1.0054
Ratio (BP-3)	1.0006	1.0027	1.0016	1.0002	**0.9998**	1.0047	1.0498	1.0008	1.0034	1.0021	1.0007	**0.9969**	1.0034	**0.9997**	1.0132	1.0351	1.3901	1.0016	1.0027
Ratio (BP-4)	**0.9976**	1.0094	1.0050	1.0009	**0.9999**	1.0019	1.0917	1.0057	1.0005	1.0004	**0.9998**	1.0016	**0.9997**	1.0022	1.0122	1.0336	1.3029	1.0012	1.0140
Ratio (BP-5)	**0.9980**	1.0049	1.0022	1.0001	**1.0000**	1.0019	1.0884	1.0138	**0.9997**	1.0001	1.0001	1.0004	1.0021	1.0005	1.0128	1.0132	1.3861	1.0033	1.0023
Ratio (PNN-1)	1.0275	1.0242	1.0023	1.0042	1.0001	1.0301	1.0506	1.0232	1.0321	1.0006	1.0002	1.0036	1.0159	1.0050	1.0072	1.0581	1.1070	1.0194	1.0499
Ratio (PNN-2)	1.0293	1.0236	1.0026	1.004	1.0002	1.0304	1.0629	1.0257	1.0307	1.0009	1.0001	1.0046	1.0171	1.0054	1.0083	1.0624	1.1099	1.0205	1.0525
Ratio (PNN-3)	1.0305	1.0232	1.0034	1.0050	1.0002	1.0364	1.0641	1.0247	1.0303	1.0008	1.0005	1.0038	1.0201	1.0061	1.0076	1.0618	1.1165	1.0232	1.0478
Ratio (PNN-4)	1.0302	1.0270	1.0029	1.0040	1.0001	1.0374	1.0614	1.0243	1.0316	1.0004	**0.9999**	1.0054	1.0219	1.0048	1.0081	1.0697	1.1157	1.0240	1.0540
Ratio (PNN-5)	1.0292	1.0264	1.0036	1.0043	1.0001	1.0355	1.0567	1.0226	1.0275	1.0007	**1.0000**	1.0046	1.0194	1.0054	1.0062	1.0608	1.1058	1.0234	1.0508
Ratio (RBF-1)	1.0036	1.0017	1.0002	**0.9998**	**0.9999**	1.0006	1.0191	1.0036	1.0017	**0.9998**	**0.9998**	**0.9995**	1.0022	**0.9983**	1.0024	1.0116	1.0533	**0.9956**	1.0115
Ratio (RBF-2)	**0.9980**	1.0016	**1.0000**	**1.0000**	**1.0000**	1.0009	1.0307	1.0050	1.0040	**0.9995**	**0.9997**	**0.9986**	1.0022	**0.9992**	1.0011	1.0153	1.0484	**0.9992**	1.0111
Ratio (RBF-3)	1.0029	1.0032	**1.0000**	**0.9999**	**1.0000**	**0.9981**	1.0276	1.0022	1.0022	**0.9999**	**0.9999**	**0.9994**	1.0025	**0.9990**	1.0013	1.0106	1.0522	**0.9986**	1.0093
Ratio (RBF-4)	1.0035	1.0017	1.0001	**0.9999**	**0.9997**	1.0020	1.0237	1.0049	1.0036	**0.9997**	**0.9997**	**0.9989**	1.0035	**0.9989**	1.0007	1.0160	1.0512	**0.9971**	1.0111
Ratio (RBF-5)	1.0010	1.0034	1.0003	**0.9999**	**0.9999**	**0.9994**	1.0218	1.0044	1.0013	**0.9999**	**0.9999**	**0.9995**	1.0001	**0.9995**	1.0015	1.0101	1.0373	1.0001	1.0138

APPENDIX E.2

DECISION TREES

PREDICTOR IMPORTANCE

Table E.2.1 Decision Trees

Predictor importance: Causes
Sample 1
(Marked values have values ≤ 20)

Variable	Importance (Rank)
Age	34
Time	21
Hours Since Injury	**19**
Year of Injury	**9**
Year of Birth	**12**
Race/Gender	30
Place	30
Admission	41
Disposal	37
Unconscious	**10**
Shock	**9**
Resuscitation	21
Anaesthetic	29
Self Infliction	23
Abuse	56
Anatomy	67
Pathology	100
AIS	**12**
Treatment	57

Table E.2.2 Decision Trees

Predictor importance: Causes
Sample 2
(Marked values have values ≤ 20)

Variable	Importance (Rank)
Age	50
Time	20
Hours Since Injury	27
Year of Injury	**8**
Year of Birth	**16**
Race/Gender	38
Place	43
Admission	42
Disposal	24
Unconscious	**15**
Shock	**8**
Resuscitation	27
Anaesthetic	35
Self Infliction	21
Abuse	44
Anatomy	51
Pathology	100
AIS	**12**
Treatment	66

Table E.2.3 Decision Trees

Predictor importance: Causes
Sample 3
(Marked values have values ≤ 20)

Variable	Importance (Rank)
Age	55
Time	**19**
Hours Since Injury	**17**
Year of Injury	**14**
Year of Birth	**15**
Race/Gender	35
Place	51
Admission	43
Disposal	28
Unconscious	**13**
Shock	**8**
Resuscitation	26
Anaesthetic	58
Self Infliction	**9**
Abuse	64
Anatomy	61
Pathology	100
AIS	14
Treatment	83

Table E.2.4 Decision Trees

Predictor importance: Causes
Sample 4
(Marked values have values ≤ 20)

Variable	Importance (Rank)
Age	44
Time	24
Hours Since Injury	27
Year of Injury	**13**
Year of Birth	**19**
Race/Gender	24
Place	41
Admission	42
Disposal	21
Unconscious	**18**
Shock	**7**
Resuscitation	30
Anaesthetic	42
Self Infliction	**12**
Abuse	43
Anatomy	86
Pathology	100
AIS	21
Treatment	69

Table E.2.5 Decision Trees

Predictor importance: Causes
Sample 5
(Marked values have values ≤ 20)

Variable	**Importance (Rank)**
Age	40
Time	23
Hours Since Injury	**18**
Year of Injury	**6**
Year of Birth	22
Race/Gender	**19**
Place	25
Admission	35
Disposal	**19**
Unconscious	**9**
Shock	**8**
Resuscitation	26
Anaesthetic	34
Self Infliction	**5**
Abuse	46
Anatomy	76
Pathology	100
AIS	**18**
Treatment	73

APPENDIX E.3

DISCRIMINANT ANALYSIS

TESTS OF SIGNIFICANCE

Table E.3.1 Discriminant Analysis

Multivariate Tests of Significance
Sample 1
(Marked values have p-values ≥ 0.05)

Variable	p-value
Age	0.000000
Time	**0.245504**
Hours Since Injury	0.004176
Year of Injury	**0.309357**
Year of Birth	**0.107515**
Race/Gender	0.000000
Place	0.000000
Admission	0.000000
Disposal	0.000000
Unconscious	**0.337375**
Shock	**0.290307**
Resuscitation	0.000000
Anaesthetic	0.004742
Self Infliction	0.000000
Abuse	0.000000
Anatomy	0.000000
Pathology	0.000000
AIS	**0.734403**
Treatment	0.000000

Table E.3.2 Discriminant Analysis

Multivariate Tests of Significance
Sample 2
(Marked values have p-values ≥ 0.05)

Variable	p-value
Age	0.000012
Time	**0.476822**
Hours Since Injury	**0.404443**
Year of Injury	**0.292220**
Year of Birth	**0.399173**
Race/Gender	0.000000
Place	0.000000
Admission	0.000000
Disposal	0.012646
Unconscious	0.000002
Shock	0.006433
Resuscitation	0.000004
Anaesthetic	**0.142406**
Self Infliction	0.000005
Abuse	0.000000
Anatomy	0.000000
Pathology	0.000000
AIS	**0.100125**
Treatment	0.000000

Table E.3.3 Discriminant Analysis

Multivariate Tests of Significance
Sample 3
(Marked values have p-values ≥ 0.05)

Variable	p-value
Age	0.000000
Time	0.018383
Hours Since Injury	**0.474947**
Year of Injury	**0.255743**
Year of Birth	**0.174634**
Race/Gender	0.000000
Place	0.000000
Admission	0.000000
Disposal	0.000122
Unconscious	**0.493649**
Shock	**0.491425**
Resuscitation	0.000000
Anaesthetic	0.000047
Self Infliction	0.000479
Abuse	0.000000
Anatomy	0.000000
Pathology	0.000000
AIS	0.043233
Treatment	0.000000

Table E.3.4 Discriminant Analysis

Multivariate Tests of Significance
Sample 4
(Marked values have p-values ≥ 0.05)

Variable	p-value
Age	0.000031
Time	0.007684
Hours Since Injury	**0.065881**
Year of Injury	**0.335888**
Year of Birth	0.000016
Race/Gender	0.000000
Place	0.000000
Admission	0.000000
Disposal	**0.204913**
Unconscious	0.000136
Shock	**0.151581**
Resuscitation	0.000000
Anaesthetic	0.000010
Self Infliction	0.000007
Abuse	0.000000
Anatomy	0.000000
Pathology	0.000000
AIS	0.020709
Treatment	0.000000

Table E.3.5 Discriminant Analysis

Multivariate Tests of Significance
Sample 5
(Marked values have p-values ≥ 0.05)

Variable	p-value
Age	0.000000
Time	0.004487
Hours Since Injury	**0.601247**
Year of Injury	**0.701817**
Year of Birth	**0.283077**
Race/Gender	0.000000
Place	0.000000
Admission	0.000000
Disposal	**0.376919**
Unconscious	**0.151718**
Shock	**0.138025**
Resuscitation	0.000000
Anaesthetic	**0.354377**
Self Infliction	0.001083
Abuse	0.000000
Anatomy	0.000000
Pathology	0.000000
AIS	0.007492
Treatment	0.000000

APPENDIX F CLASSIFICATION MATRICES OF CLASSIFICATION TREES

Table F.1

Classification matrix Tree Valid N = 4835

	% Correct	Fall	Transport	Miscellaneous	Assault	Burn	Unknown
Fall	61.8354	1570	280	562	55	17	55
Transport	58.1395	136	375	99	31	1	3
Miscellaneous	58.9786	339	76	716	42	17	24
Assault	72.7273	5	0	2	24	1	1
Burn	95.0495	7	1	11	0	384	1
Unknown	0.0000	0	0	0	0	0	0
Total	63.4747	2057	732	1390	152	420	84

Table F.2

Classification matrix Tree Valid N = 4886

	% Correct	Transport	Miscellaneous	Fall	Assault	Unknown	Burn
Transport	55.9140	468	102	226	33	6	2
Miscellaneous	62.6448	98	649	209	43	20	17
Fall	60.2579	180	697	1542	72	51	17
Assault	61.5385	1	4	8	24	2	0
Unknown	0.0000	0	0	0	0	0	0
Burn	94.4578	0	14	7	1	1	392
Total	62.9349	747	1466	1992	173	80	428

Table F.3

Classification matrix Tree Valid N = 4902

	% Correct	Burn	Transport	Fall	Assault	Miscellaneous	Unknown
Burn	96.2264	357	1	3	1	8	1
Transport	53.2556	1	548	269	29	168	14
Fall	64.7352	19	132	1430	52	532	44
Assault	56.8966	1	0	9	33	11	4
Miscellaneous	60.5565	21	80	302	52	740	27
Unknown	61.5384	0	0	3	0	2	8
Total	63.5659	399	761	2016	167	1461	98

Table F.4

Classification matrix Tree Valid N = 4913

	% Correct	Fall	Miscellaneous	Burn	Assault	Transport	Unknown
Fall	67.9173	1249	358	13	37	131	51
Miscellaneous	57.3315	425	825	15	56	82	36
Burn	91.0064	11	25	425	3	3	0
Assault	73.8095	4	3	1	31	1	2
Transport	50.9769	310	196	1	39	574	6
Unknown	0.0000	0	0	0	0	0	0
Total	63.1793	1999	1407	455	166	791	95

Table F.5

Classification matrix Tree Valid N = 4936

	% Correct	Transport	Fall	Assault	Miscellaneous	Unknown	Burn
Transport	61.6580	357	104	29	81	7	1
Fall	59.0845	342	1678	94	640	74	12
Assault	100.0000	0	0	9	0	0	0
Miscellaneous	63.9589	38	270	40	685	28	10
Unknown	0.0000	0	0	0	0	0	0
Burn	90.1602	4	7	0	32	0	394
Total	63.2699	741	2059	172	1438	109	417

Table F.6

Classification matrix Tree Valid N = 4940

	% Correct	Transport	Miscellaneous	Fall	Assault	Unknown	Burn
Transport	55.4767	547	145	247	27	18	2
Miscellaneous	62.1199	87	712	246	51	30	25
Fall	63.8947	114	620	1515	53	62	11
Assault	70.8333	1	4	6	34	3	0
Unknown	0.0000	0	0	0	0	0	0
Burn	96.0526	1	8	3	2	1	365
Total	64.2308	750	1489	2017	167	114	403

Table F.7

Classification matrix Tree Valid N = 4984

	% Correct	Miscellaneous	Transport	Fall	Unknown	Assault	Burn
Miscellaneous	61.1062	696	69	273	45	36	20
Transport	53.7525	148	530	253	11	43	1
Fall	63.9932	540	158	1516	74	75	6
Unknown	0.0000	0	0	0	0	0	0
Assault	76.0870	2	1	7	1	35	0
Burn	95.4955	12	3	5	0	0	424
Total	64.2255	1398	761	2054	131	189	451

Table F.8

Classification matrix Tree Valid N = 4985

	% Correct	Fall	Burn	Miscellaneous	Transport	Assault	Unknown
Fall	57.9329	1760	20	766	339	84	69
Burn	95.8140	5	412	11	0	1	1
Miscellaneous	65.4206	188	18	630	70	38	19
Transport	64.6586	90	1	60	322	18	7
Assault	69.6429	9	0	3	1	39	4
Unknown	0.0000	0	0	0	0	0	0
Total	63.4504	2052	451	1470	732	180	100

Table F.9

Classification matrix Tree Valid N = 4986

	% Correct	Transport	Miscellaneous	Fall	Unknown	Burn	Assault
Transport	54.6943	501	133	239	6	2	35
Miscellaneous	62.5988	83	713	240	36	28	39
Fall	61.2890	180	635	1531	65	20	67
Unknown	100.0000	0	0	0	2	0	0
Burn	97.4359	2	4	3	0	380	1
Assault	73.1707	1	3	5	2	0	30
Total	63.3172	767	1488	2018	111	430	172

Table F.10

Classification matrix Tree Valid N = 4987

	% Correct	Miscellaneous	Fall	Transport	Assault	Unknown	Burn
Miscellaneous	59.1821	767	343	101	42	33	10
Fall	65.3725	532	1448	118	51	49	17
Transport	49.7012	170	293	499	29	11	2
Assault	80.0000	6	0	2	32	0	0
Unknown	54.5455	3	2	0	0	6	0
Burn	95.9620	7	5	1	3	1	404
Total	63.2845	1485	2091	721	157	100	433

Table F.11

Classification matrix Tree Valid N = 4989

	% Correct	Transport	Miscellaneous	Fall	Unknown	Assault	Burn
Transport	50.5528	503	180	248	11	52	1
Miscellaneous	57.7548	83	782	372	41	50	26
Fall	64.5236	134	508	1395	50	64	11
Unknown	60.0000	0	2	0	3	0	0
Assault	72.9167	3	4	5	1	35	0
Burn	94.5882	2	13	7	0	1	402
Total	62.5376	725	1489	2027	106	202	440

Table F.12

Classification matrix Tree Valid N = 4994

	% Correct	Miscellaneous	Transport	Fall	Assault	Unknown	Burn
Miscellaneous	56.8688	741	144	302	59	42	15
Transport	58.7859	73	368	148	30	7	0
Fall	64.0589	605	182	1654	59	67	15
Assault	62.2642	14	0	4	33	2	0
Unknown	0.0000	0	0	0	0	0	0
Burn	94.4186	16	1	4	1	2	406
Total	64.1169	1449	695	2112	182	120	436

Table F.13

Classification matrix Tree Valid N = 4997

	% Correct	Miscellaneous	Fall	Transport	Assault	Unknown	Burn
Miscellaneous	53.7313	864	423	181	82	38	20
Fall	58.6761	552	1498	363	68	52	20
Transport	69.4517	34	72	266	10	1	0
Assault	66.6667	3	6	1	22	1	0
Unknown	0.0000	0	0	0	0	0	0
Burn	95.4762	10	5	2	2	0	401
Total	61.0566	1463	2004	813	184	92	441

Table F.14

Classification matrix Tree Valid N = 5015

	% Correct	Miscellaneous	Fall	Burn	Transport	Unknown	Assault
Miscellaneous	60.3122	734	261	13	121	33	55
Fall	61.9847	640	1624	23	177	75	81
Burn	93.8272	9	11	380	3	2	0
Transport	56.9907	79	204	2	428	14	24
Unknown	0.0000	0	0	0	0	0	0
Assault	77.2727	1	2	0	0	2	17
Total	63.4696	1463	2102	418	729	126	177

Table F.15

Classification matrix Tree Valid N = 5018

	% Correct	Fall	Transport	Miscellaneous	Assault	Unknown	Burn
Fall	64.2991	1376	152	498	60	45	9
Transport	52.5128	269	512	141	43	9	1
Miscellaneous	57.7926	425	99	864	52	34	21
Assault	92.6829	2	0	1	38	0	0
Unknown	0.0000	0	0	0	0	0	0
Burn	95.6403	4	2	9	1		351
Total	62.5947	2076	765	1513	194	88	367

Table F.16

Classification matrix Tree Valid N = 5025

	% Correct	Transport	Assault	Miscellaneous	Fall	Unknown	Burn
Transport	54.5364	547	33	151	250	22	0
Assault	67.8571	1	19	4	4	0	0
Miscellaneous	57.1027	96	72	812	401	26	15
Fall	63.8042	153	52	504	1382	56	19
Unknown	50.0000	0	0	7	1	8	0
Burn	96.1538	1	0	10	3	1	375
Total	62.5473	798	176	1488	2041	113	409

Table F.17

Classification matrix Tree Valid N = 5034

	% Correct	Transport	Fall	Miscellaneous	Assault	Unknown	Burn
Transport	55.1378	440	168	146	32	12	0
Fall	60.2131	278	1639	616	90	79	20
Miscellaneous	67.0600	36	233	682	33	20	13
Assault	68.2927	0	5	7	28	0	1
Unknown	45.4545	1	1	4	0	5	0
Burn	96.1798	0	3	12	1	1	428
Total	64.0047	755	2049	1467	184	117	462

Table F.18

Classification matrix Tree Valid N = 5048

	% Correct	Transport	Fall	Unknown	Miscellaneous	Assault	Burn
Transport	65.3846	357	100	7	62	20	0
Fall	61.6976	281	1461	37	524	52	13
Unknown	0.0000	0	0	0	0	0	0
Miscellaneous	54.4365	129	500	55	908	57	19
Assault	60.7143	1	9	2	9	34	1
Burn	97.0732	0	4	2	5	1	398
Total	62.5594	768	2074	103	1508	164	431

Table F.19

Classification matrix Tree Valid N = 5092

	% Correct	Transport	Miscellaneous	Fall	Assault	Unknown	Burn
Transport	52.1869	525	156	270	40	12	3
Miscellaneous	55.3817	111	885	465	64	47	26
Fall	67.5382	129	424	1369	53	41	11
Assault	80.0000	0	1	2	24	2	1
Unknown	0.0000	0	0	0	0	0	0
Burn	94.8956	0	16	4	1	1	409
Total	63.0793	765	1482	2110	182	103	450

Table F.20

Classification matrix Tree Valid N = 5157

	% Correct	Fall	Transport	Miscellaneous	Unknown	Assault	Burn
Fall	62.4799	1552	156	644	63	58	11
Transport	52.4330	272	528	152	17	37	1
Miscellaneous	62.8281	264	85	742	23	42	25
Unknown	0.0000	0	0	0	0	0	0
Assault	74.0000	8	0	5	0	37	0
Burn	97.2414	2	1	8	0	1	423
Total	63.6417	2098	770	1551	103	175	460

APPENDIX G

CLASSIFICATION MATRICES OF DISCRIMINANT ANALYSIS

Table G.1

Classification Matrix Valid N = 4835 Rows: Observed, Columns: Predicted classifications

	% Correct	Miscellaneous	Fall	Transport	Burn	Assault	Unknown
Miscellaneous	48.3453	672	559	127	11	11	10
Fall	76.2275	249	1568	206	7	23	4
Transport	59.8361	60	228	438	1	3	2
Burn	91.4286	14	19	2	384	1	0
Assault	31.5789	25	52	27	0	48	0
Unknown	13.0952	15	50	3	1	4	11
Total	64.5502	1035	2476	803	404	90	27

Table G.2

Classification Matrix Valid N = 4886 Rows: Observed, Columns: Predicted classifications

	% Correct	Miscellaneous	Fall	Transport	Burn	Assault	Unknown
Miscellaneous	50.1364	735	559	139	14	10	9
Fall	72.7410	288	1449	226	7	15	7
Transport	65.3280	71	184	488	0	3	1
Burn	91.5888	14	21	1	392	0	0
Assault	24.2775	30	62	36	1	42	2
Unknown	11.2500	19	44	4	1	3	9
Total	63.7536	1157	2319	894	415	73	28

Table G.3

Classification Matrix Valid N = 4902 Rows: Observed, Columns: Predicted classifications

	% Correct	Miscellaneous	Fall	Transport	Burn	Assault	Unknown
Miscellaneous	49.4867	723	543	163	8	18	6
Fall	73.6607	286	1485	224	3	14	4
Transport	66.3601	55	194	505	1	4	2
Burn	89.4737	20	20	0	357	2	0
Assault	28.7425	31	65	22	1	48	0
Unknown	12.2449	20	53	8	1	4	12
Total	63.8515	1135	2360	922	371	90	24

Table G.4

Classification Matrix Valid N = 4913 Rows: Observed, Columns: Predicted classifications

	% Correct	Miscellaneous	Fall	Transport	Burn	Assault	Unknown
Miscellaneous	49.1827	692	540	142	12	12	9
Fall	73.9870	286	1479	189	9	23	13
Transport	60.9355	65	236	482	2	5	1
Burn	92.9670	9	20	2	423	1	0
Assault	27.7108	26	62	27	3	46	2
Unknown	12.6316	13	62	5	0	3	12
Total	63.7899	1091	2399	847	449	90	37

Table G.5

Classification Matrix Valid N = 4936 Rows: Observed, Columns: Predicted classifications

	% Correct	Miscellaneous	Fall	Transport	Burn	Assault	Unknown
Miscellaneous	46.3839	667	589	141	15	12	14
Fall	76.5420	248	1576	215	7	8	5
Transport	66.1269	51	195	490	2	1	2
Burn	93.2854	11	16	1	389	0	0
Assault	24.4186	34	67	29	0	42	0
Unknown	10.0917	16	70	6	0	6	11
Total	64.3233	1027	2513	882	413	69	32

Table G.6

Classification Matrix Valid N = 4940 Rows: Observed, Columns: Predicted classifications

	% Correct	Miscellaneous	Fall	Transport	Burn	Assault	Unknown
Miscellaneous	48.8919	728	566	162	8	9	16
Fall	71.0957	323	1434	235	3	15	7
Transport	70.6667	63	150	530	1	5	1
Burn	90.5707	16	17	5	365	0	0
Assault	28.1437	37	56	24	2	47	1
Unknown	14.9123	24	56	13	1	3	17
Total	63.1781	1191	2279	969	380	79	42

Table G.7

Classification Matrix Valid N = 4984 Rows: Observed, Columns: Predicted classifications

	% Correct	Miscellaneous	Fall	Transport	Burn	Assault	Unknown
Miscellaneous	46.4950	650	588	119	12	13	16
Fall	78.1889	232	1606	188	5	19	4
Transport	60.4468	63	229	460	3	4	2
Burn	94.0133	18	8	1	424	0	0
Assault	31.7460	25	74	30	0	60	0
Unknown	11.4504	19	84	7	0	6	15
Total	64.5064	1007	2589	805	444	102	37

Table G.8

Classification Matrix Valid N = 4985 Rows: Observed, Columns: Predicted classifications

	% Correct	Miscellaneous	Fall	Transport	Burn	Assault	Unknown
Miscellaneous	47.8912	704	600	132	11	10	13
Fall	75.2437	283	1544	199	5	19	2
Transport	59.9727	71	219	439	0	2	1
Burn	91.3525	17	20	1	412	1	0
Assault	28.8889	38	65	23	1	52	1
Unknown	11.0000	20	55	7	1	6	11
Total	63.4303	1133	2503	801	430	90	28

Table G.9

Classification Matrix Valid N = 4986 Rows: Observed, Columns: Predicted classifications

	% Correct	Miscellaneous	Fall	Transport	Burn	Assault	Unknown
Miscellaneous	50.0672	745	583	128	4	21	7
Fall	71.3578	293	1440	247	3	25	10
Transport	63.8853	77	195	490	2	2	1
Burn	90.6977	13	22	3	390	2	0
Assault	28.4884	29	63	28	1	49	2
Unknown	14.4144	24	66	3	0	2	16
Total	62.7758	1181	2369	899	400	101	36

Table G.10

Classification Matrix Valid N = 4987 Rows: Observed, Columns: Predicted classifications

	% Correct	Miscellaneous	Fall	Transport	Burn	Assault	Unknown
Miscellaneous	47.4747	705	617	134	7	13	9
Fall	75.0359	291	1569	201	5	18	7
Transport	56.1720	65	242	405	1	7	1
Burn	93.3025	10	18	0	404	1	0
Assault	26.7516	34	57	21	3	42	0
Unknown	21.0000	14	54	8	1	2	21
Total	63.0840	1119	2557	769	421	83	38

Table G.11

Classification Matrix Valid N = 4989 Rows: Observed, Columns: Predicted classifications

	% Correct	Miscellaneous	Fall	Transport	Burn	Assault	Unknown
Miscellaneous	45.6011	679	630	127	13	17	23
Fall	75.1850	280	1524	190	7	19	7
Transport	58.8966	67	222	427	2	6	1
Burn	91.3636	24	13	1	402	0	0
Assault	24.2574	39	69	42	1	49	2
Unknown	13.2075	17	62	7	0	6	14
Total	62.0365	1106	2520	794	425	97	47

Table G.12

Classification Matrix Valid N = 4994 Rows: Observed, Columns: Predicted classifications

	% Correct	Miscellaneous	Fall	Transport	Burn	Assault	Unknown
Miscellaneous	46.4458	673	619	106	16	25	10
Fall	79.5455	253	1680	157	4	11	7
Transport	55.3957	63	240	385	1	3	3
Burn	93.1193	14	16	0	406	0	0
Assault	28.5714	32	73	23	1	52	1
Unknown	16.6667	20	71	4	2	3	20
Total	64.3973	1055	2699	675	430	94	41

Table G.13

Classification Matrix Valid N = 4997 Rows: Observed, Columns: Predicted classifications

	% Correct	Miscellaneous	Fall	Transport	Burn	Assault	Unknown
Miscellaneous	50.5126	739	553	134	10	11	16
Fall	73.9022	304	1481	186	5	18	10
Transport	54.7355	95	263	445	2	3	5
Burn	90.9297	22	17	0	401	0	1
Assault	28.2609	39	69	22	2	52	0
Unknown	10.8696	25	52	3	0	2	10
Total	62.5976	1224	2435	790	420	86	42

Table G.14

Classification Matrix Valid N = 5015 Rows: Observed, Columns: Predicted classifications

	% Correct	Miscellaneous	Fall	Transport	Burn	Assault	Unknown
Miscellaneous	48.1203	704	594	135	9	9	12
Fall	74.3102	276	1562	229	11	17	7
Transport	64.8834	57	190	473	3	6	0
Burn	90.9091	13	23	1	380	1	0
Assault	23.1638	38	62	33	0	41	3
Unknown	12.6984	24	70	9	2	5	16
Total	63.3300	1112	2501	880	405	79	38

Table G.15

Classification Matrix Valid N = 5015 Rows: Observed, Columns: Predicted classifications

	% Correct	Miscellaneous	Fall	Transport	Burn	Assault	Unknown
Miscellaneous	47.5215	719	619	139	9	12	15
Fall	72.6397	298	1508	242	4	18	6
Transport	63.0065	66	214	482	2	1	0
Burn	91.8848	14	17	0	351	0	0
Assault	31.4433	36	52	44	1	61	0
Unknown	9.0909	14	55	7	0	4	8
Total	62.3555	1147	2465	914	367	96	29

Table G.16

Classification Matrix Valid N = 5025 Rows: Observed, Columns: Predicted classifications

	% Correct	Miscellaneous	Fall	Transport	Burn	Assault	Unknown
Miscellaneous	48.1183	716	582	152	10	12	16
Fall	75.2572	280	1536	200	3	16	6
Transport	64.7870	63	207	517	1	5	5
Burn	91.6870	18	15	1	375	0	0
Assault	25.5682	33	70	27	0	45	1
Unknown	14.1593	24	53	15	1	4	16
Total	63.7811	1134	2463	912	390	82	44

Table G.17

Classification Matrix Valid N = 5034 Rows: Observed, Columns: Predicted classifications

	% Correct	Miscellaneous	Fall	Transport	Burn	Assault	Unknown
Miscellaneous	50.1022	735	552	139	12	15	14
Fall	72.7184	319	1490	219	3	13	5
Transport	65.5629	67	191	495	0	1	1
Burn	92.6407	9	22	1	428	2	0
Assault	24.4565	35	80	23	1	45	0
Unknown	12.8205	24	70	6	1	1	15
Total	63.7267	1189	2405	883	445	77	35

Table G.18

Classification Matrix Valid N = 5048 Rows: Observed, Columns: Predicted classifications

	% Correct	Miscellaneous	Fall	Transport	Burn	Assault	Unknown
Miscellaneous	48.1432	726	614	129	5	18	16
Fall	75.6509	281	1569	202	4	16	2
Transport	59.5052	71	233	457	0	6	1
Burn	92.3434	17	14	1	398	1	0
Assault	33.5366	31	59	17	1	55	1
Unknown	15.5340	22	56	4	2	3	16
Total	63.8074	1148	2545	810	410	99	36

Table G.19

Classification Matrix Valid N = 5092 Rows: Observed, Columns: Predicted classifications

	% Correct	Miscellaneous	Fall	Transport	Burn	Assault	Unknown
Miscellaneous	48.7854	723	579	142	16	10	12
Fall	74.9763	298	1582	209	4	12	5
Transport	63.0065	77	200	482	0	5	1
Burn	90.8889	19	18	3	409	1	0
Assault	28.5714	33	66	29	1	52	1
Unknown	8.7379	16	68	6	1	3	9
Total	63.9631	1166	2513	871	431	83	28

Table G.20

Classification Matrix Valid N = 5157 Rows: Observed, Columns: Predicted classifications

	% Correct	Miscellaneous	Fall	Transport	Burn	Assault	Unknown
Miscellaneous	50.4836	783	592	134	8	16	18
Fall	75.1192	263	1576	227	2	23	7
Transport	65.4545	67	191	504	1	6	1
Burn	91.9565	25	11	1	423	0	0
Assault	33.1429	32	54	27	1	58	3
Unknown	8.7379	20	58	13	0	3	9
Total	65.0184	1190	2482	906	435	106	38

APPENDIX H CLASSIFICATION MATRICES OF THE BACKPROPAGATION NEURAL NETWORK

Table H.1

Classification - (BP) Valid N = 4835

	Fall	Transport	Miscellaneous	Assault	Burn	Unknown	Total
Total	2057	732	1390	152	420	84	4835
Correct	1531	504	638	53	388	0	3114
Wrong	526	228	752	99	32	84	1721
Unknown	0	0	0	0	0	0	0
Correct(%)	74.43	68.85	45.90	34.87	92.38	0.00	64.4054
Wrong(%)	25.57	31.15	54.10	65.13	7.62	100.00	35.5946

Table H.2

Classification - (BP) Valid N = 4886

	Transport	Miscellaneous	Fall	Assault	Unknown	Burn	Total
Total	747	1466	1992	173	80	428	4886
Correct	514	795	1338	42	0	392	3081
Wrong	233	671	654	131	80	36	1805
Unknown	0	0	0	0	0	0	0
Correct(%)	68.81	54.23	67.17	24.28	0.00	91.59	63.0577
Wrong(%)	31.19	45.77	32.83	75.72	100.00	8.41	36.9423

Table H.3

Classification - (BP) Valid N = 4902

	Burn	Transport	Fall	Assault	Miscellaneous	Unknown	Total
Total	399	761	2016	167	1461	98	4902
Correct	370	534	1432	39	748	4	3127
Wrong	29	227	584	128	713	94	1775
Unknown	0	0	0	0	0	0	0
Correct(%)	92.73	70.17	71.03	23.35	51.20	4.08	63.7903
Wrong(%)	7.27	29.83	28.97	76.65	48.80	95.92	36.2097

Table H.4

Classification - (BP) Valid N = 4913

	Fall	Miscellaneous	Burn	Assault	Transport	Unknown	Total
Total	1999	1407	455	166	791	95	4913
Correct	1530	661	424	53	546	9	3223
Wrong	469	746	31	113	245	86	1690
Unknown	0	0	0	0	0	0	0
Correct(%)	76.54	46.98	93.19	31.93	69.03	9.47	65.6015
Wrong(%)	23.46	53.02	6.81	68.07	30.97	90.53	34.3985

Table H.5

Classification - (BP) Valid N = 4936

	Transport	Fall	Assault	Miscellaneous	Unknown	Burn	Total
Total	741	2059	172	1438	109	417	4936
Correct	326	1895	51	445	9	393	3119
Wrong	415	164	121	993	100	24	1817
Unknown	0	0	0	0	0	0	0
Correct(%)	43.99	92.03	29.65	30.95	8.26	94.24	63.1888
Wrong(%)	56.01	7.97	70.35	69.05	91.74	5.76	36.8112

Table H.6

Classification - (BP) Valid N = 4940

	Transport	Miscellaneous	Fall	Assault	Unknown	Burn	Total
Total	750	1489	2017	167	114	403	4940
Correct	574	474	1533	37	0	368	2986
Wrong	176	1015	484	130	114	35	1954
Unknown	0	0	0	0	0	0	0
Correct(%)	76.53	31.83	76.00	22.16	0.00	91.32	60.4453
Wrong(%)	23.47	68.17	24.00	77.84	100.00	8.68	39.5547

Table H.7

Classification - (BP) Valid N = 4984

	Miscellaneous	Transport	Fall	Unknown	Assault	Burn	Total
Total	1398	761	2054	131	189	451	4984
Correct	842	485	1376	0	64	429	3196
Wrong	556	276	678	131	125	22	1788
Unknown	0	0	0	0	0	0	0
Correct(%)	60.23	63.73	66.99	0.00	33.86	95.12	64.1252
Wrong(%)	39.77	36.27	33.01	100.00	66.14	4.88	35.8748

Table H.8

Classification - (BP) Valid N = 4985

	Fall	Burn	Miscellaneous	Transport	Assault	Unknown	Total
Total	2052	451	1470	732	180	100	4985
Correct	1382	421	746	517	4	0	3070
Wrong	670	30	724	215	176	100	1915
Unknown	0	0	0	0	0	0	0
Correct(%)	67.35	93.35	50.75	70.63	2.22	0.00	61.5848
Wrong(%)	32.65	6.65	49.25	29.37	97.78	100.00	38.4152

Table H.9

Classification - (BP) Valid N = 4986

	Transport	Miscellaneous	Fall	Unknown	Burn	Assault	Total
Total	767	1488	2018	111	430	172	4986
Correct	519	738	1428	10	408	17	3120
Wrong	248	750	590	101	22	155	1866
Unknown	0	0	0	0	0	0	0
Correct(%)	67.67	49.60	70.76	9.01	94.88	9.88	62.5752
Wrong(%)	32.33	50.40	29.24	90.99	5.12	90.12	37.4248

Table H.10

Classification - (BP) Valid N = 4987

	Miscellaneous	Fall	Transport	Assault	Unknown	Burn	Total
Total	1485	2091	721	157	100	433	4987
Correct	709	1575	422	6	1	392	3105
Wrong	776	516	299	151	99	41	1882
Unknown	0	0	0	0	0	0	0
Correct(%)	47.74	75.32	58.53	3.82	1.00	90.53	62.2619
Wrong(%)	52.26	24.68	41.47	96.18	99.00	9.47	37.7381

Table H.11

Classification - (BP) Valid N = 4989

	Transport	Miscellaneous	Fall	Unknown	Assault	Burn	Total
Total	725	1489	2027	106	202	440	4989
Correct	492	860	1367	12	47	419	3197
Wrong	233	629	660	94	155	21	1792
Unknown	0	0	0	0	0	0	0
Correct(%)	67.86	57.76	67.44	11.32	23.27	95.23	64.0810
Wrong(%)	32.14	42.24	32.56	88.68	76.73	4.77	35.9190

Table H.12

Classification - (BP) Valid N = 4994

	Miscellaneous	Transport	Fall	Assault	Unknown	Burn	Total
Total	1449	695	2112	182	120	436	4994
Correct	705	366	1664	36	0	413	3184
Wrong	744	329	448	146	120	23	1810
Unknown	0	0	0	0	0	0	0
Correct(%)	48.65	52.66	78.79	19.78	0.00	94.72	63.7565
Wrong(%)	51.35	47.34	21.21	80.22	100.00	5.28	36.2435

Table H.13

Classification - (BP) Valid N = 4997

	Miscellaneous	Fall	Transport	Assault	Unknown	Burn	Total
Total	1463	2004	813	184	92	441	4997
Correct	872	1205	579	41	0	418	3115
Wrong	591	799	234	143	92	23	1882
Unknown	0	0	0	0	0	0	0
Correct(%)	59.60	60.13	71.22	22.28	0.00	94.78	62.3374
Wrong(%)	40.40	39.87	28.78	77.72	100.00	5.22	37.6626

Table H.14

Classification - (BP) Valid N = 5015

	Miscellaneous	Fall	Burn	Transport	Unknown	Assault	Total
Total	1463	2102	418	729	126	177	5015
Correct	775	1459	387	510	3	14	3148
Wrong	688	643	31	219	123	163	1867
Unknown	0	0	0	0	0	0	0
Correct(%)	52.97	69.41	92.58	69.96	2.38	7.91	62.7717
Wrong(%)	47.03	30.59	7.42	30.04	97.62	92.09	37.2283

Table H.15

Classification - (BP) Valid N = 5018

	Fall	Transport	Miscellaneous	Assault	Unknown	Burn	Total
Total	2076	765	1513	194	88	382	5018
Correct	1482	585	699	40	0	353	3159
Wrong	594	180	814	154	88	29	1859
Unknown	0	0	0	0	0	0	0
Correct(%)	71.39	76.47	46.20	20.62	0.00	92.41	62.9534
Wrong(%)	28.61	23.53	53.80	79.38	100.00	7.59	37.0466

Table H.16

Classification - (BP) Valid N = 5025

	Transport	Assault	Miscellaneous	Fall	Unknown	Burn	Total
Total	798	176	1488	2041	113	409	5025
Correct	435	29	761	1574	12	388	3199
Wrong	363	147	727	467	101	21	1826
Unknown	0	0	0	0	0	0	0
Correct(%)	54.51	16.48	51.14	77.12	10.62	94.87	63.6617
Wrong(%)	45.49	83.52	48.86	22.88	89.38	5.13	36.3383

Table H.17

Classification - (BP) Valid N = 5034

	Transport	Fall	Miscellaneous	Assault	Unknown	Burn	Total
Total	755	2049	1467	184	117	462	5034
Correct	456	1389	847	43	0	427	3162
Wrong	299	660	620	141	117	35	1872
Unknown	0	0	0	0	0	0	0
Correct(%)	60.40	67.79	57.74	23.37	0.00	92.42	62.8129
Wrong(%)	39.60	32.21	42.26	76.63	100.00	7.58	37.1871

Table H.18

Classification - (BP) Valid N = 5048

	Transport	Fall	Unknown	Miscellaneous	Assault	Burn	Total
Total	768	2074	103	1508	164	431	5048
Correct	504	1561	0	686	51	414	3216
Wrong	264	513	103	822	113	17	1832
Unknown	0	0	0	0	0	0	0
Correct(%)	65.63	75.27	0.00	45.49	31.10	96.06	63.7084
Wrong(%)	34.38	24.73	100.00	54.51	68.90	3.94	36.2916

Table H.19

Classification - (BP) Valid N = 5092

	Transport	Miscellaneous	Fall	Assault	Unknown	Burn	Total
Total	765	1482	2110	182	103	450	5092
Correct	577	829	1386	8	0	413	3213
Wrong	188	653	724	174	103	37	1879
Unknown	0	0	0	0	0	0	0
Correct(%)	75.42	55.94	65.69	4.40	0.00	91.78	63.0990
Wrong(%)	24.58	44.06	34.31	95.60	100.00	8.22	36.9010

Table H.20

Classification - (BP) Valid N = 5157

	Fall	Transport	Miscellaneous	Unknown	Assault	Burn	Total
Total	2098	770	1551	103	175	460	5157
Correct	1492	583	814	1	55	431	3376
Wrong	606	187	737	102	120	29	1781
Unknown	0	0	0	0	0	0	0
Correct(%)	71.12	75.71	52.48	0.97	31.43	93.70	65.4644
Wrong(%)	28.88	24.29	47.52	99.03	68.57	6.30	34.5356

APPENDIX I CONFUSION MATRICES OF THE BACKPROPAGATION NEURAL NETWORK

Note: for the confusion matrices below, numbers on the diagonal represent correct classifications, and off-diagonal numbers represent misclassifications.

Table I.1

Confusion Matrix - (BP) Valid N = 4835

	Fall	Transport	Miscellaneous	Assault	Burn	Unknown
Fall	1531	148	557	41	16	49
Transport	292	504	163	29	3	4
Miscellaneous	200	58	638	29	11	24
Assault	26	20	20	53	2	6
Burn	7	2	11	0	388	1
Unknown	1	0	1	0	0	0

Table I.2

Confusion Matrix - (BP) Valid N = 4886

	Transport	Miscellaneous	Fall	Assault	Unknown	Burn
Transport	514	144	248	48	7	1
Miscellaneous	58	795	373	45	25	15
Fall	164	483	1338	36	44	16
Assault	11	30	26	42	4	4
Unknown	0	0	0	0	0	0
Burn	0	14	7	2	0	392

Table I.3

Confusion Matrix - (BP) Valid N = 4902

	Burn	Transport	Fall	Assault	Miscellaneous	Unknown
Burn	370	1	4	3	16	1
Transport	0	534	277	21	148	12
Fall	18	137	1432	69	541	42
Assault	2	2	2	39	7	1
Miscellaneous	9	87	301	35	748	38
Unknown	0	0	0	0	1	4

Table I.4

Confusion Matrix - (BP) Valid N = 4913C

	Fall	Miscellaneous	Burn	Assault	Transport	Unknown
Fall	1530	567	22	60	178	61
Miscellaneous	192	661	6	23	62	16
Burn	8	10	424	3	1	0
Assault	18	12	1	53	4	3
Transport	251	154	2	27	546	6
Unknown	0	3	0	0	0	9

Table I.5

Confusion Matrix - (BP) Valid N = 4936

	Transport	Fall	Assault	Miscellaneous	Unknown	Burn
Transport	326	92	16	57	6	0
Fall	371	1895	95	885	80	19
Assault	31	12	51	31	6	0
Miscellaneous	9	52	10	445	8	5
Unknown	2	1	0	7	9	0
Burn	2	7	0	13	0	393

Table I.6

Confusion Matrix - (BP) Valid N = 4940

	Transport	Miscellaneous	Fall	Assault	Unknown	Burn
Transport	574	229	299	34	25	3
Miscellaneous	13	474	174	15	18	6
Fall	161	769	1533	79	66	25
Assault	2	3	8	37	2	1
Unknown	0	0	0	0	0	0
Burn	0	14	3	2	3	368

Table I.7

Confusion Matrix - (BP) Valid N = 4984

	Miscellaneous	Transport	Fall	Unknown	Assault	Burn
Miscellaneous	842	132	419	67	41	12
Transport	115	485	214	9	37	2
Fall	404	129	1376	47	47	7
Unknown	1	0	0	0	0	0
Assault	24	13	40	8	64	1
Burn	12	2	5	0	0	429

Table I.8

Confusion Matrix – (BP) Valid N = 4985

	Fall	Burn	Miscellaneous	Transport	Assault	Unknown
Fall	1382	16	522	164	80	53
Burn	7	421	16	1	2	1
Miscellaneous	341	10	746	49	54	31
Transport	322	4	185	517	40	15
Assault	0	0	1	1	4	0
Unknown	0	0	0	0	0	0

Table I.9

Confusion Matrix - (BP) Valid N = 4986

	Transport	Miscellaneous	Fall	Unknown	Burn	Assault
Transport	519	143	271	8	3	32
Miscellaneous	99	738	301	26	0	56
Fall	145	573	1428	64	19	61
Unknown	0	5	2	10	0	0
Burn	3	22	9	2	408	6
Assault	1	7	7	1	0	17

Table I.10

Confusion Matrix - (BP) Valid N = 4987

	Miscellaneous	Fall	Transport	Assault	Unknown	Burn
Miscellaneous	709	276	107	44	17	4
Fall	648	1575	191	77	71	32
Transport	120	236	422	26	10	5
Assault	1	0	0	6	0	0
Unknown	1	0	0	0	1	0
Burn	6	4	1	4	1	392

Table I.11

Confusion Matrix - (BP) Valid N = 4989

	Transport	Miscellaneous	Fall	Unknown	Assault	Burn
Transport	492	156	233	11	40	0
Miscellaneous	75	860	414	32	67	13
Fall	150	429	1367	46	45	8
Unknown	0	8	1	12	1	0
Assault	6	13	5	1	47	0
Burn	2	23	7	4	2	419

Table I.12

Confusion Matrix - (BP) Valid N = 4994

	Miscellaneous	Transport	Fall	Assault	Unknown	Burn
Miscellaneous	705	144	293	43	47	11
Transport	100	366	148	38	8	0
Fall	616	184	1664	64	60	12
Assault	5	0	1	36	3	0
Unknown	0	0	0	0	0	0
Burn	23	1	6	1	2	413

Table I.13

Confusion Matrix - (BP) Valid N = 4997

	Miscellaneous	Fall	Transport	Assault	Unknown	Burn
Miscellaneous	872	474	104	66	35	11
Fall	361	1205	121	37	45	9
Transport	200	312	579	36	10	3
Assault	8	4	3	41	1	0
Unknown	0	2	1	1	0	0
Burn	22	7	5	3	1	418

Table I.14

Confusion Matrix - (BP) Valid N = 5015

	Miscellaneous	Fall	Burn	Transport	Unknown	Assault
Miscellaneous	775	343	16	73	39	71
Fall	499	1459	14	143	71	54
Burn	11	10	387	3	2	0
Transport	175	289	1	510	11	38
Unknown	1	1	0	0	3	0
Assault	2	0	0	0	0	14

Table I.15

Confusion Matrix - (BP) Valid N = 5018

	Fall	Transport	Miscellaneous	Assault	Unknown	Burn
Fall	1482	132	585	59	62	11
Transport	378	585	215	59	10	1
Miscellaneous	212	46	699	35	16	17
Assault	0	1	4	40	0	0
Unknown	0	0	0	0	0	0
Burn	4	1	10	1	0	353

Table I.16

Confusion Matrix - (BP) Valid N = 5025

	Transport	Assault	Miscellaneous	Fall	Unknown	Burn
Transport	435	34	100	139	21	0
Assault	3	29	6	4	0	0
Miscellaneous	61	41	761	317	30	9
Fall	295	70	594	1574	47	12
Unknown	1	1	9	2	12	0
Burn	3	1	18	5	3	388

Table I.17

Confusion Matrix - (BP) Valid N = 5034

	Transport	Fall	Miscellaneous	Assault	Unknown	Burn
Transport	456	192	124	20	10	1
Fall	200	1389	470	60	69	11
Miscellaneous	98	457	847	59	33	20
Assault	1	8	16	43	4	3
Unknown	0	0	0	0	0	0
Burn	0	3	10	2	1	427

Table I.18

Confusion Matrix - (BP) Valid N = 5048

	Transport	Fall	Unknown	Miscellaneous	Assault	Burn
Transport	504	263	5	145	24	0
Fall	158	1561	57	642	53	9
Unknown	0	0	0	0	0	0
Miscellaneous	102	235	32	686	36	7
Assault	4	10	7	24	51	1
Burn	0	5	2	11	0	414

Table I.19

Confusion Matrix - (BP) Valid N = 5092

	Transport	Miscellaneous	Fall	Assault	Unknown	Burn
Transport	577	212	322	54	14	3
Miscellaneous	60	829	398	72	44	24
Fall	128	427	1386	47	44	10
Assault	0	0	0	8	0	0
Unknown	0	0	0	0	0	0
Burn	0	14	4	1	1	413

Table I.20

Confusion Matrix - (BP) Valid N = 5157

	Fall	Transport	Miscellaneous	Unknown	Assault	Burn
Fall	1492	125	525	55	48	10
Transport	318	583	192	25	35	3
Miscellaneous	272	58	814	21	36	16
Unknown	0	0	0	1	0	0
Assault	14	3	13	1	55	0
Burn	2	1	7	0	1	431

APPENDIX J CLASSIFICATION MATRICES OF THE PROBABILISTIC NEURAL NETWORK

Table J.1

Classification - (PNN) Valid N = 4835

	Fall	Transport	Miscellaneous	Assault	Burn	Unknown	Total
Total	2057	732	1390	152	420	84	4835
Correct	1734	444	694	30	370	5	3277
Wrong	323	288	696	122	50	79	1558
Unknown	0	0	0	0	0	0	0
Correct(%)	84.30	60.66	49.93	19.74	88.10	5.95	67.7766
Wrong(%)	15.70	39.34	50.07	80.26	11.90	94.05	32.2234

Table J.2

Classification - (PNN) Valid N = 4886

	Transport	Miscellaneous	Fall	Assault	Unknown	Burn	Total
Total	747	1466	1992	173	80	428	4886
Correct	480	789	1569	31	14	368	3251
Wrong	267	677	423	142	66	60	1635
Unknown	0	0	0	0	0	0	0
Correct(%)	64.26	53.82	78.77	17.92	17.50	85.98	66.5370
Wrong(%)	35.74	46.18	21.23	82.08	82.50	14.02	33.4630

Table J.3

Classification - (PNN) Valid N = 4902

	Burn	Transport	Fall	Assault	Miscellaneous	Unknown	Total
Total	399	761	2016	167	1461	98	4902
Correct	342	483	1679	36	698	10	3248
Wrong	57	278	337	131	763	88	1654
Unknown	0	0	0	0	0	0	0
Correct(%)	85.71	63.47	83.28	21.56	47.78	10.20	66.2587
Wrong(%)	14.29	36.53	16.72	78.44	52.22	89.80	33.7413

Table J.4

Classification - (PNN) Valid N = 4913

	Fall	Miscellaneous	Burn	Assault	Transport	Unknown	Total
Total	1999	1407	455	166	791	95	4913
Correct	1745	705	402	24	434	9	3319
Wrong	254	702	53	142	357	86	1594
Unknown	0	0	0	0	0	0	0
Correct(%)	87.29	50.11	88.35	14.46	54.87	9.47	67.5555
Wrong(%)	12.71	49.89	11.65	85.54	45.13	90.53	32.4445

Table J.5

Classification - (PNN) Valid N = 4936

	Transport	Fall	Assault	Miscellaneous	Unknown	Burn	Total
Total	741	2059	172	1438	109	417	4936
Correct	424	1826	24	611	13	372	3270
Wrong	317	233	148	827	96	45	1666
Unknown	0	0	0	0	0	0	0
Correct(%)	57.22	88.68	13.95	42.49	11.93	89.21	66.2480
Wrong(%)	42.78	11.32	86.05	57.51	88.07	10.79	33.7520

Table J.6

Classification - (PNN) Valid N = 4940

	Transport	Miscellaneous	Fall	Assault	Unknown	Burn	Total
Total	750	1489	2017	167	114	403	4940
Correct	488	672	1747	40	16	356	3319
Wrong	262	817	270	127	98	47	1621
Unknown	0	0	0	0	0	0	0
Correct(%)	65.07	45.13	86.61	23.95	14.04	88.34	67.1862
Wrong(%)	34.93	54.87	13.39	76.05	85.96	11.66	32.8138

Table J.7

Classification - (PNN) Valid N = 4984

	Miscellaneous	Transport	Fall	Unknown	Assault	Burn	Total
Total	1398	761	2054	131	189	451	4984
Correct	685	462	1770	20	51	411	3399
Wrong	713	299	284	111	138	40	1585
Unknown	0	0	0	0	0	0	0
Correct(%)	49.00	60.71	86.17	15.27	26.98	91.13	68.1982
Wrong(%)	51.00	39.29	13.83	84.73	73.02	8.87	31.8018

Table J.8

Classification - (PNN) Valid N = 4985

	Fall	Burn	Miscellaneous	Transport	Assault	Unknown	Total
Total	2052	451	1470	732	180	100	4985
Correct	1734	409	719	396	28	6	3292
Wrong	318	42	751	336	152	94	1693
Unknown	0	0	0	0	0	0	0
Correct(%)	84.50	90.69	48.91	54.10	15.56	6.00	66.0381
Wrong(%)	15.50	9.31	51.09	45.90	84.44	94.00	33.9619

Table J.9

Classification - (PNN) Valid N = 4986

	Transport	Miscellaneous	Fall	Unknown	Burn	Assault	Total
Total	767	1488	2018	111	430	172	4986
Correct	410	717	1719	9	375	40	3270
Wrong	357	771	299	102	55	132	1716
Unknown	0	0	0	0	0	0	0
Correct(%)	53.46	48.19	85.18	8.11	87.21	23.26	65.5836
Wrong(%)	46.54	51.81	14.82	91.89	12.79	76.74	34.4164

Table J.10

Classification - (PNN) Valid N = 4987

	Miscellaneous	Fall	Transport	Assault	Unknown	Burn	Total
Total	1485	2091	721	157	100	433	4987
Correct	679	1789	401	34	11	398	3312
Wrong	806	302	320	123	89	35	1675
Unknown	0	0	0	0	0	0	0
Correct(%)	45.72	85.56	55.62	21.66	11.00	91.92	66.4127
Wrong(%)	54.28	14.44	44.38	78.34	89.00	8.08	33.5873

Table J.11

Classification - (PNN) Valid N = 4989

	Transport	Miscellaneous	Fall	Unknown	Assault	Burn	Total
Total	725	1489	2027	106	202	440	4989
Correct	417	682	1729	5	45	399	3277
Wrong	308	807	298	101	157	41	1712
Unknown	0	0	0	0	0	0	0
Correct(%)	57.52	45.80	85.30	4.72	22.28	90.68	65.6845
Wrong(%)	42.48	54.20	14.70	95.28	77.72	9.32	34.3155

Table J.12

Classification - (PNN) Valid N = 4994

	Miscellaneous	Transport	Fall	Assault	Unknown	Burn	Total
Total	1449	695	2112	182	120	436	4994
Correct	654	363	1916	45	18	399	3395
Wrong	795	332	196	137	102	37	1599
Unknown	0	0	0	0	0	0	0
Correct(%)	45.13	52.23	90.72	24.73	15.00	91.51	67.9816
Wrong(%)	54.87	47.77	9.28	75.27	85.00	8.49	32.0184

Table J.13

Classification - (PNN) Valid N = 4997

	Miscellaneous	Fall	Transport	Assault	Unknown	Burn	Total
Total	1463	2004	813	184	92	441	4997
Correct	655	1686	555	39	8	393	3336
Wrong	808	318	258	145	84	48	1661
Unknown	0	0	0	0	0	0	0
Correct(%)	44.77	84.13	68.27	21.20	8.70	89.12	66.7601
Wrong(%)	55.23	15.87	31.73	78.80	91.30	10.88	33.2399

Table J.14

Classification - (PNN) Valid N = 5015

	Miscellaneous	Fall	Burn	Transport	Unknown	Assault	Total
Total	1463	2102	418	729	126	177	5015
Correct	707	1830	382	409	21	35	3384
Wrong	756	272	36	320	105	142	1631
Unknown	0	0	0	0	0	0	0
Correct(%)	48.33	87.06	91.39	56.10	16.67	19.77	67.4776
Wrong(%)	51.67	12.94	8.61	43.90	83.33	80.23	32.5224

Table J.15

Classification - (PNN) Valid N = 5018

	Fall	Transport	Miscellaneous	Assault	Unknown	Burn	Total
Total	2076	765	1513	194	88	382	5018
Correct	1727	421	770	57	2	351	3328
Wrong	349	344	743	137	86	31	1690
Unknown	0	0	0	0	0	0	0
Correct(%)	83.19	55.03	50.89	29.38	2.27	91.88	66.3212
Wrong(%)	16.81	44.97	49.11	70.62	97.73	8.12	33.6788

Table J.16

Classification - (PNN) Valid N = 5025

	Transport	Assault	Miscellaneous	Fall	Unknown	Burn	Total
Total	798	176	1488	2041	113	409	5025
Correct	518	37	707	1723	5	364	3354
Wrong	280	139	781	318	108	45	1671
Unknown	0	0	0	0	0	0	0
Correct(%)	64.91	21.02	47.51	84.42	4.42	89.00	66.7463
Wrong(%)	35.09	78.98	52.49	15.58	95.58	11.00	33.2537

Table J.17

Classification - (PNN) Valid N = 5034

	Transport	Fall	Miscellaneous	Assault	Unknown	Burn	Total
Total	755	2049	1467	184	117	462	5034
Correct	379	1724	807	34	10	417	3371
Wrong	376	325	660	150	107	45	1663
Unknown	0	0	0	0	0	0	0
Correct(%)	50.20	84.14	55.01	18.48	8.55	90.26	66.9646
Wrong(%)	49.80	15.86	44.99	81.52	91.45	9.74	33.0354

Table J.18

Classification - (PNN) Valid N = 5048

	Transport	Fall	Unknown	Miscellaneous	Assault	Burn	Total
Total	768	2074	103	1508	164	431	5048
Correct	435	1797	15	722	33	393	3395
Wrong	333	277	88	786	131	38	1653
Unknown	0	0	0	0	0	0	0
Correct(%)	56.64	86.64	14.56	47.88	20.12	91.18	67.2544
Wrong(%)	43.36	13.36	85.44	52.12	79.88	8.82	32.7456

Table J.19

Classification - (PNN) Valid N = 5092

	Transport	Miscellaneous	Fall	Assault	Unknown	Burn	Total
Total	765	1482	2110	182	103	450	5092
Correct	377	690	1867	44	6	403	3387
Wrong	388	792	243	138	97	47	1705
Unknown	0	0	0	0	0	0	0
Correct(%)	49.28	46.56	88.48	24.18	5.83	89.56	66.5161
Wrong(%)	50.72	53.44	11.52	75.82	94.17	10.44	33.4839

Table J.20

Classification - (PNN) Valid N = 5157

	Fall	Transport	Miscellaneous	Unknown	Assault	Burn	Total
Total	2098	770	1551	103	175	460	5157
Correct	1809	420	792	17	42	404	3484
Wrong	289	350	759	86	133	56	1673
Unknown	0	0	0	0	0	0	0
Correct(%)	86.22	54.55	51.06	16.50	24.00	87.83	67.5587
Wrong(%)	13.78	45.45	48.94	83.50	76.00	12.17	32.4413

APPENDIX K CONFUSION MATRICES OF THE PROBABILISTIC NEURAL NETWORK

Note: for the confusion matrices below, numbers on the diagonal represent correct classifications, and off-diagonal numbers represent misclassifications.

Table K.1

Confusion Matrix (PNN) Valid N = 4835

	Fall	Transport	Miscellaneous	Assault	Burn	Unknown
Fall	1734	247	594	73	41	53
Transport	148	444	95	25	1	4
Miscellaneous	170	40	694	24	8	20
Assault	1	0	2	30	0	0
Burn	4	1	5	0	370	2
Unknown	0	0	0	0	0	5

Table K.2

Confusion Matrix (PNN) Valid N = 4886

	Transport	Miscellaneous	Fall	Assault	Unknown	Burn
Transport	480	100	182	38	5	2
Miscellaneous	50	789	233	24	12	14
Fall	214	568	1569	79	49	44
Assault	1	3	3	31	0	0
Unknown	1	2	0	0	14	0
Burn	1	4	5	1	0	368

Table K.3

Confusion Matrix (PNN) Valid N = 4902

	Burn	Transport	Fall	Assault	Miscellaneous	Unknown
Burn	342	1	4	2	7	1
Transport	3	483	177	15	112	8
Fall	43	219	1679	87	640	57
Assault	0	1	2	36	2	2
Miscellaneous	11	57	154	27	698	20
Unknown	0	0	0	0	2	10

Table K.4

Confusion Matrix (PNN) Valid N = 4913

	Fall	Miscellaneous	Burn	Assault	Transport	Unknown
Fall	1745	636	39	108	280	64
Miscellaneous	138	705	11	20	75	15
Burn	5	3	402	3	1	1
Assault	2	0	0	24	1	0
Transport	108	63	3	11	434	6
Unknown	1	0	0	0	0	9

Table K.5

Confusion Matrix (PNN) Valid N = 4936						
	Transport	**Fall**	**Assault**	**Miscellaneous**	**Unknown**	**Burn**
Transport	424	124	17	109	6	1
Fall	279	1826	110	707	82	39
Assault	2	1	24	3	0	0
Miscellaneous	34	103	20	611	8	5
Unknown	0	0	0	1	13	0
Burn	2	5	1	7	0	372

Table K.6

Confusion Matrix (PNN) Valid N = 4940						
	Transport	**Miscellaneous**	**Fall**	**Assault**	**Unknown**	**Burn**
Transport	488	98	146	19	10	3
Miscellaneous	44	672	118	27	19	19
Fall	216	717	1747	79	67	25
Assault	0	1	1	40	0	0
Unknown	2	1	3	0	16	0
Burn	0	0	2	2	2	356

Table K.7

Confusion Matrix (PNN) Valid N = 4984						
	Miscellaneous	**Transport**	**Fall**	**Unknown**	**Assault**	**Burn**
Miscellaneous	685	40	156	20	24	5
Transport	70	462	119	12	29	2
Fall	633	256	1770	78	84	33
Unknown	1	0	2	20	1	0
Assault	2	1	4	1	51	0
Burn	7	2	3	0	0	411

Table K.8

Confusion Matrix (PNN) Valid N = 4985						
	Fall	**Burn**	**Miscellaneous**	**Transport**	**Assault**	**Unknown**
Fall	1734	37	643	292	101	66
Burn	5	409	10	0	1	1
Miscellaneous	192	3	719	44	31	22
Transport	119	2	91	396	19	5
Assault	0	0	6	0	28	0
Unknown	2	0	1	0	0	6

Table K.9

Confusion Matrix (PNN) Valid N = 4986

	Transport	Miscellaneous	Fall	Unknown	Burn	Assault
Transport	410	78	143	3	3	21
Miscellaneous	70	717	153	25	11	20
Fall	285	686	1719	74	41	91
Unknown	0	0	0	9	0	0
Burn	1	4	2	0	375	0
Assault	1	3	1	0	0	40

Table K.10

Confusion Matrix (PNN) Valid N = 4987

	Miscellaneous	Fall	Transport	Assault	Unknown	Burn
Miscellaneous	679	171	39	26	13	3
Fall	691	1789	278	79	65	31
Transport	107	127	401	17	10	1
Assault	2	0	3	34	0	0
Unknown	2	1	0	0	11	0
Burn	4	3	0	1	1	398

Table K.11

Confusion Matrix (PNN) Valid N = 4989

	Transport	Miscellaneous	Fall	Unknown	Assault	Burn
Transport	417	96	120	8	28	2
Miscellaneous	55	682	170	19	32	13
Fall	250	696	1729	72	96	26
Unknown	0	3	0	5	0	0
Assault	1	3	1	0	45	0
Burn	2	9	7	2	1	399

Table K.12

Confusion Matrix (PNN) Valid N = 4994

	Miscellaneous	Transport	Fall	Assault	Unknown	Burn
Miscellaneous	654	53	95	18	20	7
Transport	52	363	93	13	6	1
Fall	732	272	1916	103	73	29
Assault	1	4	0	45	0	0
Unknown	2	3	5	2	18	0
Burn	8	0	3	1	3	399

Table K.13

Confusion Matrix (PNN) Valid N = 4997

	Miscellaneous	Fall	Transport	Assault	Unknown	Burn
Miscellaneous	655	90	35	23	18	5
Fall	653	1686	219	93	58	39
Transport	142	222	555	27	7	3
Assault	8	2	2	39	0	1
Unknown	0	1	0	0	8	0
Burn	5	3	2	2	1	393

Table K.14

Confusion Matrix (PNN) Valid N = 5015

	Miscellaneous	Fall	Burn	Transport	Unknown	Assault
Miscellaneous	707	143	6	60	15	21
Fall	683	1830	30	256	79	96
Burn	6	8	382	0	2	1
Transport	61	116	0	409	9	24
Unknown	3	1	0	1	21	0
Assault	3	4	0	3	0	35

Table K.15

Confusion Matrix (PNN) Valid N = 5018

	Fall	Transport	Miscellaneous	Assault	Unknown	Burn
Fall	1727	291	638	71	67	20
Transport	143	421	97	32	6	0
Miscellaneous	197	48	770	34	12	10
Assault	5	4	3	57	1	1
Unknown	0	0	0	0	2	0
Burn	4	1	5	0	0	351

Table K.16

Confusion Matrix (PNN) Valid N = 5025

	Transport	Assault	Miscellaneous	Fall	Unknown	Burn
Transport	518	21	99	158	13	1
Assault	1	37	1	1	0	0
Miscellaneous	63	30	707	158	18	16
Fall	215	87	674	1723	76	28
Unknown	0	1	0	0	5	0
Burn	1	0	7	1	1	364

Table K.17

Confusion Matrix (PNN) Valid N = 5034

	Transport	Fall	Miscellaneous	Assault	Unknown	Burn
Transport	379	82	58	17	9	0
Fall	296	1724	591	103	77	38
Miscellaneous	80	237	807	30	18	7
Assault	0	1	3	34	0	0
Unknown	0	0	1	0	10	0
Burn	0	5	7	0	3	417

Table K.18

Confusion Matrix (PNN) Valid N = 5048

	Transport	Fall	Unknown	Miscellaneous	Assault	Burn
Transport	435	110	4	80	17	0
Fall	264	1797	64	691	88	32
Unknown	5	1	15	7	0	0
Miscellaneous	64	163	19	722	26	6
Assault	0	1	0	1	33	0
Burn	0	2	1	7	0	393

Table K.19

Confusion Matrix (PNN) Valid N = 5092

	Transport	Miscellaneous	Fall	Assault	Unknown	Burn
Transport	377	67	77	12	2	2
Miscellaneous	60	690	158	24	30	13
Fall	327	714	1867	101	65	32
Assault	1	1	2	44	0	0
Unknown	0	0	2	0	6	0
Burn	0	10	4	1	0	403

Table K.20

Confusion Matrix (PNN) Valid N = 5157

	Fall	Transport	Miscellaneous	Unknown	Assault	Burn
Fall	1809	288	670	61	85	45
Transport	124	420	76	8	18	1
Miscellaneous	159	59	792	16	28	10
Unknown	1	0	2	17	1	0
Assault	2	2	6	0	42	0
Burn	3	1	5	1	1	404

APPENDIX L CLASSIFICATION MATRICES OF THE RADIAL BASIS FUNCTION NEURAL NETWORK

Table L.1

Classification - (RBF) Valid N = 4835

	Fall	Transport	Miscellaneous	Assault	Burn	Unknown	Total
Total	2057	732	1390	152	420	84	4835
Correct	1567	340	656	0	386	0	2949
Wrong	490	392	734	152	34	84	1886
Unknown	0	0	0	0	0	0	0
Correct(%)	76.18	46.45	47.19	0.00	91.90	0.00	60.9928
Wrong(%)	23.82	53.55	52.81	100.00	8.10	100.00	39.0072

Table L.2

Classification - (RBF) Valid N = 4886

	Transport	Miscellaneous	Fall	Assault	Unknown	Burn	Total
Total	747	1466	1992	173	80	428	4886
Correct	424	666	1391	0	0	391	2872
Wrong	323	800	601	173	80	37	2014
Unknown	0	0	0	0	0	0	0
Correct(%)	56.76	45.43	69.83	0.00	0.00	91.36	58.7802
Wrong(%)	43.24	54.57	30.17	100.00	100.00	8.64	41.2198

Table L.3

Classification - (RBF) Valid N = 4902

	Burn	Transport	Fall	Assault	Miscellaneous	Unknown	Total
Total	399	761	2016	167	1461	98	4902
Correct	362	466	1519	0	577	0	2924
Wrong	37	295	497	167	884	98	1978
Unknown	0	0	0	0	0	0	0
Correct(%)	90.73	61.24	75.35	0.00	39.49	0.00	59.6491
Wrong(%)	9.27	38.76	24.65	100.00	60.51	100.00	40.3509

Table L.4

Classification - (RBF) Valid N = 4913

	Fall	Miscellaneous	Burn	Assault	Transport	Unknown	Total
Total	1999	1407	455	166	791	95	4913
Correct	1369	681	406	0	437	0	2893
Wrong	630	726	49	166	354	95	2020
Unknown	0	0	0	0	0	0	0
Correct(%)	68.48	48.40	89.23	0.00	55.25	0.00	58.8846
Wrong(%)	31.52	51.60	10.77	100.00	44.75	100.00	41.1154

Table L.5

Classification - (RBF) Valid N = 4936

	Transport	Fall	Assault	Miscellaneous	Unknown	Burn	Total
Total	741	2059	172	1438	109	417	4936
Correct	328	1568	0	729	0	381	3006
Wrong	413	491	172	709	109	36	1930
Unknown	0	0	0	0	0	0	0
Correct(%)	44.26	76.15	0.00	50.70	0.00	91.37	60.8995
Wrong(%)	55.74	23.85	100.00	49.30	100.00	8.63	39.1005

Table L.6

Classification - (RBF) Valid N = 4940

	Transport	Miscellaneous	Fall	Assault	Unknown	Burn	Total
Total	750	1489	2017	167	114	403	4940
Correct	443	736	1331	0	0	366	2876
Wrong	307	753	686	167	114	37	2064
Unknown	0	0	0	0	0	0	0
Correct(%)	59.07	49.43	65.99	0.00	0.00	90.82	58.2186
Wrong(%)	40.93	50.57	34.01	100.00	100.00	9.18	41.7814
Unknown(%)	0.00	0.00	0.00	0.00	0.00	0.00	0.0000

Table L.7

Classification - (RBF) Valid N = 4984

	Miscellaneous	Transport	Fall	Unknown	Assault	Burn	Total
Total	1398	761	2054	131	189	451	4984
Correct	605	399	1580	0	0	426	3010
Wrong	793	362	474	131	189	25	1974
Unknown	0	0	0	0	0	0	0
Correct(%)	43.28	52.43	76.92	0.00	0.00	94.46	60.3933
Wrong(%)	56.72	47.57	23.08	100.00	100.00	5.54	39.6067

Table L.8

Classification - (RBF) Valid N = 4985

	Fall	Burn	Miscellaneous	Transport	Assault	Unknown	Total
Total	2052	451	1470	732	180	100	4985
Correct	1569	408	727	280	0	0	2984
Wrong	483	43	743	452	180	100	2001
Unknown	0	0	0	0	0	0	0
Correct(%)	76.46	90.47	49.46	38.25	0.00	0.00	59.8596
Wrong(%)	23.54	9.53	50.54	61.75	100.00	100.00	40.1404

Table L. 9

Classification - (RBF) Valid N = 4986							
	Transport	**Miscellaneous**	**Fall**	**Unknown**	**Burn**	**Assault**	**Total**
Total	767	1488	2018	111	430	172	4986
Correct	382	692	1439	0	391	0	2904
Wrong	385	796	579	111	39	172	2082
Unknown	0	0	0	0	0	0	0
Correct(%)	49.80	46.51	71.31	0.00	90.93	0.00	58.2431
Wrong(%)	50.20	53.49	28.69	100.00	9.07	100.00	41.7569

Table L.10

Classification - (RBF) Valid N = 4987							
	Miscellaneous	**Fall**	**Transport**	**Assault**	**Unknown**	**Burn**	**Total**
Total	1485	2091	721	157	100	433	4987
Correct	705	1466	359	0	0	406	2936
Wrong	780	625	362	157	100	27	2051
Unknown	0	0	0	0	0	0	0
Correct(%)	47.47	70.11	49.79	0.00	0.00	93.76	58.8731
Wrong(%)	52.53	29.89	50.21	100.00	100.00	6.24	41.1269

Table L.11

Classification - (RBF) Valid N = 4989							
	Transport	**Miscellaneous**	**Fall**	**Unknown**	**Assault**	**Burn**	**Total**
Total	725	1489	2027	106	202	440	4989
Correct	307	745	1460	0	0	413	2925
Wrong	418	744	567	106	202	27	2064
Unknown	0	0	0	0	0	0	0
Correct(%)	42.34	50.03	72.03	0.00	0.00	93.86	58.6290
Wrong(%)	57.66	49.97	27.97	100.00	100.00	6.14	41.3710

Table L.12

Classification - (RBF) Valid N = 4994							
	Miscellaneous	**Transport**	**Fall**	**Assault**	**Unknown**	**Burn**	**Total**
Total	1449	695	2112	182	120	436	4994
Correct	579	343	1649	0	0	407	2978
Wrong	870	352	463	182	120	29	2016
Unknown	0	0	0	0	0	0	0
Correct(%)	39.96	49.35	78.08	0.00	0.00	93.35	59.6316
Wrong(%)	60.04	50.65	21.92	100.00	100.00	6.65	40.3684

Table L.13

Classification - (RBF) Valid N = 4997

	Miscellaneous	Fall	Transport	Assault	Unknown	Burn	Total
Total	1463	2004	813	184	92	441	4997
Correct	653	1509	431	0	0	403	2996
Wrong	810	495	382	184	92	38	2001
Unknown	0	0	0	0	0	0	0
Correct(%)	44.63	75.30	53.01	0.00	0.00	91.38	59.9560
Wrong(%)	55.37	24.70	46.99	100.00	100.00	8.62	40.0440

Table L.14

Classification - (RBF) Valid N = 5015

	Miscellaneous	Fall	Burn	Transport	Unknown	Assault	Total
Total	1463	2102	418	729	126	177	5015
Correct	625	1633	383	329	0	0	2970
Wrong	838	469	35	400	126	177	2045
Unknown	0	0	0	0	0	0	0
Correct(%)	42.72	77.69	91.63	45.13	0.00	0.00	59.2223
Wrong(%)	57.28	22.31	8.37	54.87	100.00	100.00	40.7777

Table L.15

Classification - (RBF) Valid N = 5018

	Fall	Transport	Miscellaneous	Assault	Unknown	Burn	Total
Total	2076	765	1513	194	88	382	5018
Correct	1495	398	685	0	0	352	2930
Wrong	581	367	828	194	88	30	2088
Unknown	0	0	0	0	0	0	0
Correct(%)	72.01	52.03	45.27	0.00	0.00	92.15	58.3898
Wrong(%)	27.99	47.97	54.73	100.00	100.00	7.85	41.6102

Table L.16

Classification - (RBF) Valid N = 5025

	Transport	Assault	Miscellaneous	Fall	Unknown	Burn	Total
Total	798	176	1488	2041	113	409	5025
Correct	407	0	787	1415	0	338	2947
Wrong	391	176	701	626	113	71	2078
Unknown	0	0	0	0	0	0	0
Correct(%)	51.00	0.00	52.89	69.33	0.00	82.64	58.6468
Wrong(%)	49.00	100.00	47.11	30.67	100.00	17.36	41.3532
Unknown(%)	0.00	0.00	0.00	0.00	0.00	0.00	0.0000

Table L.17

Classification - (RBF) Valid N = 5034

	Transport	Fall	Miscellaneous	Assault	Unknown	Burn	Total
Total	755	2049	1467	184	117	462	5034
Correct	355	1432	786	2	0	431	3006
Wrong	400	617	681	182	117	31	2028
Unknown	0	0	0	0	0	0	0
Correct(%)	47.02	69.89	53.58	1.09	0.00	93.29	59.7139
Wrong(%)	52.98	30.11	46.42	98.91	100.00	6.71	40.2861

Table L.18

Classification - (RBF) Valid N = 5048

	Transport	Fall	Unknown	Miscellaneous	Assault	Burn	Total
Total	768	2074	103	1508	164	431	5048
Correct	375	1508	0	741	0	402	3026
Wrong	393	566	103	767	164	29	2022
Unknown	0	0	0	0	0	0	0
Correct(%)	48.83	72.71	0.00	49.14	0.00	93.27	59.9445
Wrong(%)	51.17	27.29	100.00	50.86	100.00	6.73	40.0555

Table L.19

Classification - (RBF) Valid N = 5092

	Transport	Miscellaneous	Fall	Assault	Unknown	Burn	Total
Total	765	1482	2110	182	103	450	5092
Correct	340	609	1592	0	0	414	2955
Wrong	425	873	518	182	103	36	2137
Unknown	0	0	0	0	0	0	0
Correct(%)	44.44	41.09	75.45	0.00	0.00	92.00	58.0322
Wrong(%)	55.56	58.91	24.55	100.00	100.00	8.00	41.9678

Table L.20

Classification - (RBF) Valid N = 5157

	Fall	Transport	Miscellaneous	Unknown	Assault	Burn	Total
Total	2098	770	1551	103	175	460	5157
Correct	1479	383	834	0	0	420	3116
Wrong	619	387	717	103	175	40	2041
Unknown	0	0	0	0	0	0	0
Correct(%)	70.50	49.74	53.77	0.00	0.00	91.30	60.4227
Wrong(%)	29.50	50.26	46.23	100.00	100.00	8.70	39.5773

APPENDIX M CONFUSION MATRICES OF THE RADIAL BASIS FUNCTION NEURAL NETWORK

Note: for the confusion matrices below, numbers on the diagonal represent correct classifications, and off-diagonal numbers represent misclassifications.

Table M.1

Confusion Matrix - (RBF) Valid N =4835

	Fall	Transport	Miscellaneous	Assault	Burn	Unknown
Fall	1567	306	597	63	14	52
Transport	189	340	115	40	2	8
Miscellaneous	290	83	656	47	18	23
Assault	0	0	0	0	0	0
Burn	11	3	22	2	386	1
Unknown	0	0	0	0	0	0

Table M.2

Confusion Matrix - (RBF) Valid N =4886

	Transport	Miscellaneous	Fall	Assault	Unknown	Burn
Transport	424	135	248	43	8	2
Miscellaneous	95	666	342	77	34	11
Fall	228	650	1391	52	38	24
Assault	0	0	0	0	0	0
Unknown	0	0	0	0	0	0
Burn	0	15	11	1	0	391

Table M.3

Confusion Matrix - (RBF) Valid N = 4902

	Burn	Transport	Fall	Assault	Miscellaneous	Unknown
Burn	362	1	5	1	13	0
Transport	2	466	221	24	135	9
Fall	26	233	1519	84	736	56
Assault	0	0	0	0	0	0
Miscellaneous	9	61	271	58	577	33
Unknown	0	0	0	0	0	0

Table M.4

Confusion Matrix N(RBF) Valid N = 4913

	Fall	Miscellaneous	Burn	Assault	Transport	Unknown
Fall	1369	535	31	71	256	50
Miscellaneous	348	681	17	54	95	35
Burn	7	21	406	4	3	0
Assault	0	0	0	0	0	0
Transport	275	170	1	37	437	10
Unknown	0	0	0	0	0	0

Table M.5

Confusion Matrix - (RBF) Valid N =4936

	Transport	Fall	Assault	Miscellaneous	Unknown	Burn
Transport	328	120	27	110	8	1
Fall	343	1568	76	585	62	23
Assault	0	0	0	0	0	0
Miscellaneous	68	364	69	729	38	12
Unknown	0	0	0	0	0	0
Burn	2	7	0	14	1	381

Table M.6

Confusion Matrix - (RBF) Valid N = 4940

	Transport	Miscellaneous	Fall	Assault	Unknown	Burn
Transport	443	137	195	22	13	4
Miscellaneous	176	736	487	79	63	15
Fall	129	603	1331	64	36	18
Assault	0	0	0	0	0	0
Unknown	0	0	0	0	0	0
Burn	2	13	4	2	2	366

Table M.7

Confusion Matrix - (RBF) Valid N = 4984

	Miscellaneous	Transport	Fall	Unknown	Assault	Burn
Miscellaneous	605	81	266	34	58	11
Transport	116	399	201	7	55	0
Fall	663	278	1580	88	75	14
Unknown	0	0	0	0	0	0
Assault	0	0	0	0	0	0
Burn	14	3	7	2	1	426

Table M.8

Confusion Matrix N(RBF) Valid N = 4985

	Fall	Burn	Miscellaneous	Transport	Assault	Unknown
Fall	1569	22	661	343	58	57
Burn	14	408	19	1	4	1
Miscellaneous	377	20	727	108	98	35
Transport	92	1	63	280	20	7
Assault	0	0	0	0	0	0
Unknown	0	0	0	0	0	0

Table M.9

Confusion Matrix - (RBF) Valid N = 4986

	Transport	Miscellaneous	Fall	Unknown	Burn	Assault
Transport	382	147	241	11	2	27
Miscellaneous	106	692	334	47	16	77
Fall	277	641	1439	52	21	67
Unknown	0	0	0	0	0	0
Burn	2	8	4	1	391	1
Assault	0	0	0	0	0	0

Table M.10

Confusion Matrix - (RBF) Valid N =4987

	Miscellaneous	Fall	Transport	Assault	Unknown	Burn
Miscellaneous	705	384	125	76	39	7
Fall	611	1466	237	53	52	18
Transport	156	233	359	27	8	2
Assault	0	0	0	0	0	0
Unknown	0	0	0	0	0	0
Burn	13	8	0	1	1	406

Table M.11

Confusion Matrix - (RBF) Valid N = 4989

	Transport	Miscellaneous	Fall	Unknown	Assault	Burn
Transport	307	90	140	8	33	0
Miscellaneous	126	745	417	34	101	15
Fall	290	637	1460	63	67	12
Unknown	0	0	0	0	0	0
Assault	0	0	0	0	0	0
Burn	2	17	10	1	1	413

Table M.12

Confusion Matrix - (RBF) Valid N = 4994

	Miscellaneous	Transport	Fall	Assault	Unknown	Burn
Miscellaneous	579	89	266	66	39	12
Transport	118	343	187	26	6	1
Fall	710	258	1649	86	71	16
Assault	0	0	0	0	0	0
Unknown	0	0	0	0	0	0
Burn	42	5	10	4	4	407

Table M.13

Confusion Matrix - (RBF) Valid N = 4997

	Miscellaneous	Fall	Transport	Assault	Unknown	Burn
Miscellaneous	653	253	89	60	42	8
Fall	623	1509	291	69	42	26
Transport	170	238	431	51	8	4
Assault	0	0	0	0	0	0
Unknown	0	0	0	0	0	0
Burn	17	4	2	4	0	403

Table M.14

Confusion Matrix - (RBF) Valid N =5015

	Miscellaneous	Fall	Burn	Transport	Unknown	Assault
Miscellaneous	625	313	12	87	38	68
Fall	711	1633	20	310	79	67
Burn	12	14	383	3	2	0
Transport	115	142	3	329	7	42
Unknown	0	0	0	0	0	0
Assault	0	0	0	0	0	0

Table M.15

Confusion Matrix N(RBF) Valid N =5018

	Fall	Transport	Miscellaneous	Assault	Unknown	Burn
Fall	1495	262	662	53	59	17
Transport	217	398	135	50	9	1
Miscellaneous	341	104	685	87	19	12
Assault	0	0	0	0	0	0
Unknown	0	0	0	0	0	0
Burn	23	1	31	4	1	352

Table M.16

Confusion Matrix - (RBF) Valid N = 5025

	Transport	Assault	Miscellaneous	Fall	Unknown	Burn
Transport	407	27	131	204	14	3
Assault	0	0	0	0	0	0
Miscellaneous	137	83	787	418	44	52
Fall	252	66	560	1415	54	16
Unknown	0	0	0	0	0	0
Burn	2	0	10	4	1	338

Table M.17

Confusion Matrix - (RBF) Valid N =5034

	Transport	Fall	Miscellaneous	Assault	Unknown	Burn
Transport	355	116	113	24	12	1
Fall	296	1432	551	88	44	15
Miscellaneous	104	494	786	69	58	15
Assault	0	0	0	2	0	0
Unknown	0	0	0	0	0	0
Burn	0	7	17	1	3	431

Table M.18

Confusion Matrix - (RBF) Valid N = 5048

	Transport	Fall	Unknown	Miscellaneous	Assault	Burn
Transport	375	202	5	153	32	1
Fall	288	1508	55	600	57	21
Unknown	0	0	0	0	0	0
Miscellaneous	104	358	41	741	74	7
Assault	0	0	0	0	0	0
Burn	1	6	2	14	1	402

Table M.19

Confusion Matrix - (RBF) Valid N = 5092

	Transport	Miscellaneous	Fall	Assault	Unknown	Burn
Transport	340	100	117	23	7	2
Miscellaneous	131	609	392	91	40	18
Fall	292	751	1592	67	55	16
Assault	0	0	0	0	0	0
Unknown	0	0	0	0	0	0
Burn	2	22	9	1	1	414

Table M.20

Confusion Matrix - (RBF) Valid N = 5157

	Fall	Transport	Miscellaneous	Unknown	Assault	Burn
Fall	1479	245	585	52	54	19
Transport	184	383	113	15	16	2
Miscellaneous	428	139	834	35	104	19
Unknown	0	0	0	0	0	0
Assault	0	0	0	0	0	0
Burn	7	3	19	1	1	420

APPENDIX N

Tree Structure and Layout of Responses

Table N.1

Tree structure Responses: Causes

	Left branch	Right branch	Size of Node	N in class Transport	N in class Miscellaneous	N in class Fall	N in class Assault	N in class Unknown	N in class Burn	Selected Category	Split Variable	Split Constant	Split Category	Split Category	Split Category	Split Category
1	2	3	4940	750	1489	2017	167	114	403	Fall	Pathology		burns			
2			380	1	8	3	2	1	365	Burn						
3	4	5	4560	749	1481	2014	165	113	38	Fall	Place		PublicPlace			
4	6	7	1665	642	355	588	47	28	5	Transport	Anatomy		Upper Extremities			
6			438	42	107	279	4	5	1	Fall						
7	8	9	1227	600	248	309	43	23	4	Transport	Admission		NotAdmitted			
8			338	237	35	56	8	2	0	Transport						
9	10	11	889	363	213	253	35	21	4	Transport	Treatment		other	cleanSuture	EUA/MUA	operation
10			213	52	91	55	11	3	1	Miscellaneous						
11	12	13	676	311	122	198	24	18	3	Transport	Pathology		foreign body	other		
12			20	1	11	7	0	0	1	Miscellaneous						
13	14	15	656	310	111	191	24	18	2	Transport	Abuse		Possible	Yes		
14			8	0	1	0	5	2	0	Assault						
15	16	17	648	310	110	191	19	16	2	Transport	Race/Gender		Black	Asian		
16			169	98	17	40	5	7	2	Transport						
17	18	19	479	212	93	151	14	9	0	Transport	Age	7.5				
18			285	131	40	101	6	7	0	Transport						
19			194	81	53	50	8	2	0	Transport						
5	20	21	2895	107	1126	1426	118	85	33	Fall	Pathology		foreign body	chest	amputations	
20			228	2	205	2	0	5	14	Miscellaneous						
21	22	23	2667	105	921	1424	118	80	19	Fall	Pathology		fractures	concussion	nerve injury	CSA
22	24	25	730	28	124	545	18	12	3	Fall	Treatment		other	adviceMedication	cleanSuture	operation
24			197	10	57	115	9	5	1	Fall						
25			533	18	67	430	9	7	2	Fall						
23	26	27	1937	77	797	879	100	68	16	Fall	Anatomy		HeadNeckFace			
26	28	29	1198	48	402	651	61	25	11	Fall	Age	1.5				
28			309	3	59	228	9	7	3	Fall						
29	30	31	889	45	343	423	52	18	8	Fall	Abuse		Possible	Yes		

30			22	0	2	4	15	1	0	Assault						
31	32	33	867	45	341	419	37	17	8	Fall	Age	6.5				
32	34	35	628	28	226	337	23	11	3	Fall	Pathology		laceration			
34			481	24	157	278	16	5	1	Fall						
35			147	4	69	59	7	6	2	Miscellaneous						
33	36	37	239	17	115	82	14	6	5	Miscellaneous	Treatment		other	cleanSuture	EUA/MUA	operation
36			87	4	51	24	5	1	2	Miscellaneous						
37			152	13	64	58	9	5	3	Miscellaneous						
27	38	39	739	29	395	228	39	43	5	Miscellaneous	Treatment		observation	cleanSuture	operation	
38			191	4	158	19	6	4	0	Miscellaneous						
39	40	41	548	25	237	209	33	39	5	Miscellaneous	Abuse		No			
40	42	43	530	24	236	207	19	39	5	Miscellaneous	Anaesthetic		LocalRegional	General		
42			24	1	21	0	1	1	0	Miscellaneous						
43	44	45	506	23	215	207	18	38	5	Miscellaneous	Anatomy		Upper Extremities	Lower Extremities		
44			417	17	173	185	6	33	3	Fall						
45			89	6	42	22	12	5	2	Miscellaneous						
41			18	1	1	2	14	0	0	Assault						

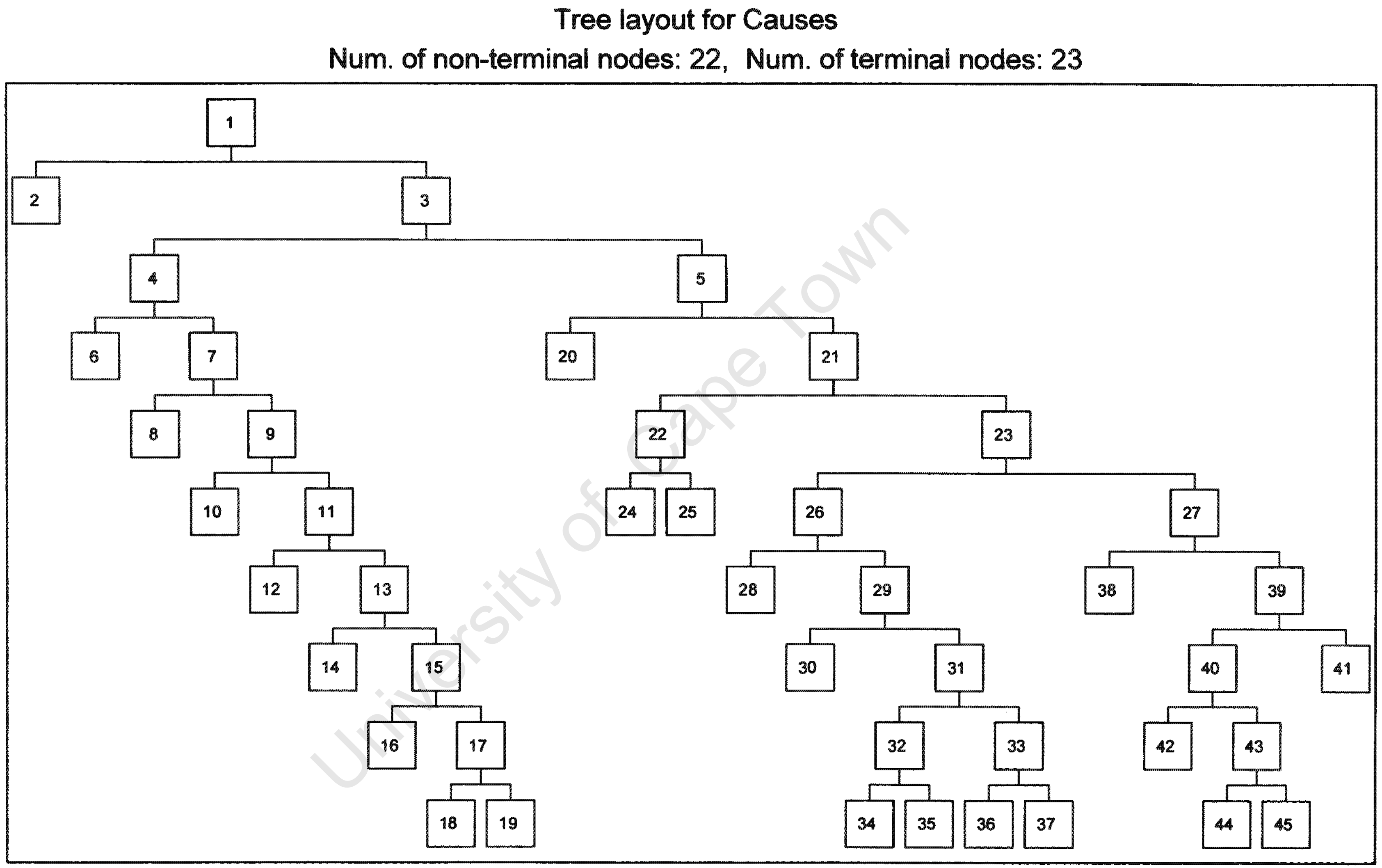
Tree layout for Causes
Num. of non-terminal nodes: 22, Num. of terminal nodes: 23
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Figure N.1