Data Mining in Healthcare Information Systems: Case Study of a Veterans? Administration Spinal Cord Injury Population.

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Abstract

In the following paper the process of knowledge generation from the Veterans Administration healthcare information system is explored. This inquiry is concerned with predicting length of stay of a subset of the total patient population, specifically those with spinal cord injuries (SCI). Although SCI patients do not present large numbers, they are outliers in the healthcare system due to extended hospital stays and high costs for treatment. Predicting length of stay can increase efficiencies and effectiveness in resource allocation thus lowering cost. The following research is the first of its kind to use nursing diagnosis and neural networks to predict length of stay. Background material on SCI and the knowledge discovery process is introduced. The entire data mining process is described beginning with data gathering followed by cleaning, aggregation, and integration. Issues faced while conducting the research are discussed. Results of artificial neural networks used to predict length of stay are presented.

KEYWORDS: Hospital Information Systems; Data Mining; Knowledge Discovery in Databases; Veterans Administration; Spinal Cord Injury; Artificial Neural Networks

INTRODUCTION

The healthcare field faces strong pressures to reduce costs while increasing quality of services delivered [1,2,3,10,11,21]. One strategy that can be used to address these issues is the utilization of healthcare information systems for decision support and knowledge management [5,6,10,11,21]. Healthcare facilities have at their disposal vast amounts of data. Thorough analysis of available data on a given problem can lead to more efficient decision-making [5,21]. The challenge is to extract relevant knowledge from this data and act upon it in a timely manner. The generation of information and knowledge calls for data organized into a useful form.

Knowledge discovery in databases using data mining techniques is an approach to extracting patterns from large data sets and deducing knowledge insights from those patterns [6]. This knowledge discovery process has several distinct steps or sub-processes that begin with data gathering, followed by data cleaning, then aggregation and integration. At this point the data is ready to be utilized for data visualization and finally data mining. Rather than being sequential, sub-processes in the data mining process are iterative i.e. movement from data visualization back to data cleaning if irregularities are discovered in the data set [6,16]. In this paper the knowledge discovery process as it pertains to prediction of length of stay (LOS) of patients with spinal cord injury (SCI) in a VHA Hospital is presented. SCI nursing data elements are explored as a mechanism useful in the prediction of patient length of stay (LOS). To the best of our knowledge the following research is the first of its kind to use nursing diagnosis to predict length of stay and is hence novel and insightful.

The setting for this study is a large tertiary care Veteran's Health Administration (VHA) Hospital located on a 62-acre campus within the metropolitan Chicago area. The VHA is involved in the full continuum of SCI care and has the largest single network of SCI care in the nation [4]. This particular hospital has two acute rehabilitation /continuing care inpatient SCI units with a total of 68 beds, a hospital-based SCI home care program, and a 30 bed residential SCI unit. At any one time, 500 to 800 patients are on the VA SCI service rolls from a referral/catchment area of service that includes Illinois, Michigan, Indiana, Iowa, Montana, Wyoming, and South Dakota. The hospital uses the national VA Hospital Information System (HIS) known as the Veterans Health Information Systems and Technology Architecture (VistA). VistA, one of the most extensive hospital information systems in the world, is an internally developed comprehensive integrated system that provides for both administrative and clinical support and documentation of care. Permission to use this VHA SCI database for this study was obtained from the facility's institutional review board (IRB). Since there were no interventions and no direct contact with patients, the facility IRB gave an expedited review approval. IRB approval for the study was also obtained from the Institutional Review Board of Loyola University. Confidentiality of the patient data in this study was maintained by using the internal VA patient coding to download data that was immediately re-recoded by the investigator and all possibility of patient identification was removed.

In the following section background material on SCI and artificial neural networks is presented. Next, a process framework is presented for looking at knowledge discovery in databases. Each stage in the knowledge discovery process is then presented and issues faced when carrying the study are articulated. Concluding the paper limitations of the study and areas for future research are discussed.

BACKGROUND

Spinal Cord Injury (SCI)

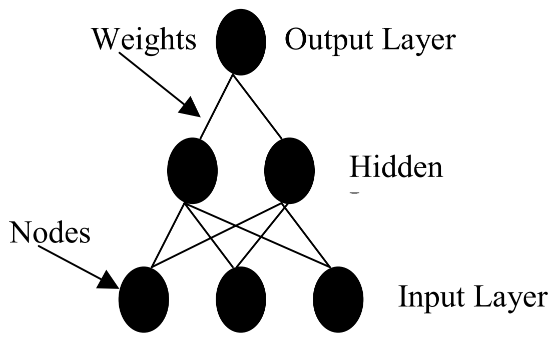
National concern about patients with SCI has led to the development of dedicated care centers in both private and federal health care systems. Although SCI occurs much less frequently than other types of injury and debilitating disease and represents a small population within the total healthcare system, it is a population with significant care costs at time of injury, throughout the lifespan, and across the continuum of care. There are approximately 200,000 SCI persons in the United States and approximately 78,000 (45%) are veterans [2]. 10,000 cases of SCI are added annually [15]. Predominant causes of SCI are vehicular accidents (48%), sports/recreation injuries (14%), violence and falls (20%) [2]. Demographics of SCI indicate that those affected are most likely to be white, male (82.2%), younger, and to have served in the armed forces. The peak incidence of injury occurs between the ages of 16 and 30 although there does appear to be an increasing incidence of SCI among older adults related to life style. Between 1994 and 1998, 50% of new enrollees in the National SCI Model Projects database were older than 60 [15]. SCI persons documented in the National SCI database represent 52.9% classified as quadriplegic while 46.2% are classified as paraplegic [15].

Berkowitz et al [2] estimate that SCI costs to individuals and to society are more than $9.7 billion per year. Direct care costs within the first year of injury average over $223,000 with an additional annual cost for SCI care of $26,000. Equipment, supplies, medications, and environmental modification costs increase both figures. Indirect costs related to loss of income and productivity are difficult to compute as consideration must be given to age at injury and earning potential, but indirect cost estimates can be projected as significant. The aggregate annual direct and indirect costs of new cases of SCI may be between $7.2 and $9.5 billion [2,7]. Hence efforts to lower the cost of treatment are beneficial.

Artificial Neural Networks

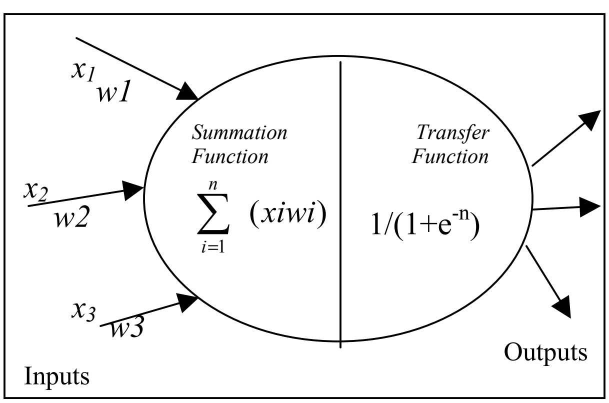
Artificial neural networks (ANNs) attempt to capture the brains' problem solving ability and apply them to information systems. Computers are faster than humans in performing a variety of mathematical computations, but humans still are better performing complex tasks such as speech and image recognition/processing. This strength is due to the methodology used by the brain to solve problems. The brain solves problems by breaking them into smaller components and through the use of massive parallel processing. ANNs try to capture these two important concepts in computer models [6]. Lippman [14] defines them as a statistical information processing mechanism composed of numerous distributed processing units or nodes that perform simultaneous computations and communicate using adaptable interconnections called "weights".

Figure 1: General Structure of an Artificial Neural Network



The basic architecture for an ANN is depicted in Figure 1. Each node receives inputs, does processing, and generates output. Whether this output will be transferred to other nodes will depend on its strength. As illustrated there are three types of layers in the network: input, hidden, and output. A network can have multiple hidden layers depending on the complexity of the problem [5,6,14]. In the diagram each node is connected layer are connected to one node in the hidden layer, the node with a heavier weight influences the hidden layer to a greater degree. The output layer of the network can send information either directly to the user or to another information system.

Figure 2: Structure of a Node in an Artificial Neural Network



A node consists of two parts: a summation function and a transfer function (see figure 2). Each node receives multiple inputs with different weights from other nodes or from an outside source if it is in the input layer. The summation function aggregates the value of all inputs based on their respective weights. This function can perform a simple summation or calculate the average, find min or max etc. For illustration lets say that a node has inputs x_1, x_2, x_3 with weights of $w_1,\ w_2,\ w_3$. A simple summation output would be as follows: $x_1 w_1 + x_2 w_2 + x_3 w_3$ A generalized formula for n inputs will be: $\sum_{i=1}^{n} (xiwi)$.

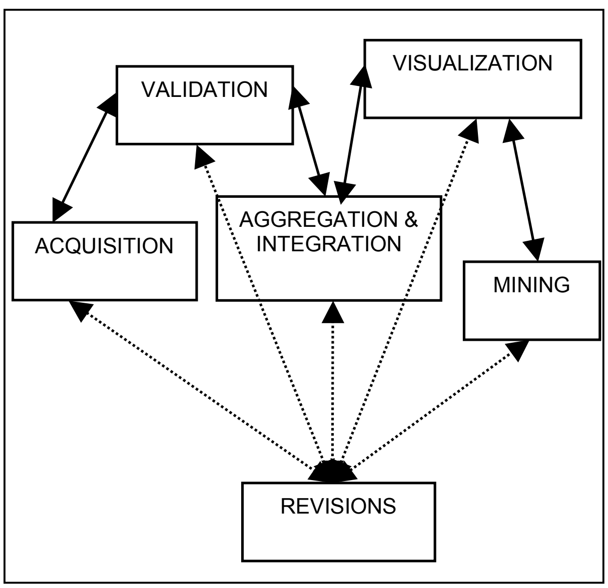
After processing is complete the node has to decide whether or not to transfer a signal to the next node in the hierarchy. The transfer function as the name implies determines if the output from one node is significant enough, for it to be transferred to the next layer. Use of a sigmoidal function is common when designing transfer functions [5,6]. However there are other alternatives such as thresholds, hard-limits, sine, etc (see [6] for more details). The Sigmoidal curve gives us a value between 0 and 1 depending on the summation value. This value is calculated using the following formula: $\dfrac{1}{1+e^{-n}}$

If the value is1 or close to one the output is passed to the next node in the network, if 0, there is no reaction. Hence for a data to move from one node to another the weighted sum of all the nodes inputs should be large enough so as to generate a number close to 1 from the transfer function. Networks learn through training from data sets. They can be trained through supervised or unsupervised learning methods. Vast majority of current neural applications learn through supervised learning, where the network is given both test data and the desired output. Errors between network output and desired output are then routed back into the network. Interested readers are referred to [5,6,14,17,18] for more details on neural networks.

KNOWLEDGE DISCOVERY IN DATABASES

Data mining and knowledge discovery in databases relate to the process of extracting valid, previously unknown and potentially useful patterns and information from raw data in large databases. "The analogy of "mining" suggests the sifting through of large amounts of low grade ore (data) to find something valuable. It is a multi- step, iterative inductive process [16]. It includes such tasks as problem analysis, data extraction, data preparation and cleaning, data reduction, rule development, output analysis and review. Generally, data mining and knowledge discovery in databases are treated as synonyms and refer to the whole process in moving from data to knowledge [6]. A small number of published studies address the value of data mining within the healthcare industry (see [5] for a survey). ANNs have been used to predict transfusion needs [21], identify myocardial infarctions [1], estimate drug and plasma concentrations levels of pharmaceutical drugs [20], and predict the risk of coronary artery disease [12]. All studies assert that a key strength of ANNs compared to traditional statistical models is their ability to deal with non-linearities in data sets while not worrying about the underlining distribution of data [5]. Other popular data mining techniques applied to healthcare are Bayesian models, association rules, case-based reasoning, genetic algorithms, and fuzzy systems (see [5,6] for applications).

Figure 3: Stage Model for Knowledge Discovery in Databases



This study purposes the knowledge discovery process is viewed in multiple stages. Ramaprasad's [16] staged model that consisted of data acquisition, integration, mining, and revisions of requirements is expanded to a model that consists of the following: acquisition, validation, aggregation and integration, visualization, mining, and revision of objectives (see figure 3). A knowledge discovery assignment must begin with clear objectives in mind. These objectives will not be in the form of pre-conceived hypothesis, but must state clearly the scope of the study and potential goals. The process begins with data gathering in which relevant data is sought after for analysis, followed by cleaning and validation. Next disparate data sources will need to be aggregated and visualized to gain preliminary insights. Following this we apply algorithms to mine the data and extract or deduce relevant patterns - knowledge. At each stage of the data mining process questions and goals may be revised. This staged framework is used to describe our case study in healthcare data mining.

DATA ACQUISITION

The first stage of the process is data acquisition in which data elements of interest are located and extracted. The study sample included all patient episodes of care (patient admissions) in the computerized VistA SCI clinical database from one inpatient SCI unit during the period of study. The list of admissions to the study unit was downloaded from an archived ORACLE mainframe database built through nightly data extracts from VistA. 597 SCI patients with 1107 admissions to the study unit between July, 1989 and June, 2000 became the study sample. Next, nursing diagnoses and interventions selected for these patient encounters were extracted using an identification and ranking query that is part of the VistA nursing software. Since the nursing data elements of interest in this study are not included in the VA national data warehouse, this data was downloaded directly from the operational database.

DATA VALIDATION

Validation and cleaning of data elements ensures that accurate elements are being incorporated in the study. It is estimated that 80% of the time spent in a data mining project is spent in data preparation and cleaning [5]. Data preparation includes data selection (identification and extraction of data); data preprocessing (sampling and quality testing); and data transformation (conversion into an analytical model) [3]. Goodwin et al [9] identify the issues obstructing progress in data mining for improved health outcomes as "data quality, data redundancy, data inconsistency, repeated measures, temporal (time-contextual) measures, and data volume" (p.291). Computerization of data does not make up for bad data but once data has been cleaned, the analysis of vast amounts of data may identify potentially important relationships that do not emerge from sparse data. Invariably, routinely collected clinical data is full of errors and incompleteness.

Much of the data collected from this computerized database was found to be non-standardized and at a nominal level of measurement. As a result, data elements were visually inspected, structured, and checked for accuracy, reliability, and redundancy. Data "noise" included redundant, insignificant, erroneous, and missing data. Differences in punctuation and case or changes in word sequence were recognized by the computer software as new terms, new labels, or new variables. This required the researcher to make a visual inspection of all diagnostic and interventional labels and create a structure of labels that represent label clusters with a common or shared meaning [11].

Missing data elements were inspected to determine if they are random. If missing data were infrequent and appeared to be random, pair-wise deletion was applied and the case with missing data was dropped from specific statistical analysis. List-wise deletion was planned for use if there is an indication in this study that a specific variable has significant amounts of missing data in 50% or more of the cases. This means that the specific variable would be dropped from the study. No variables were dropped because of missing data. Patients seen in the early years of the study period who did not return for further care and follow-up were not entered into the SCI Registry database. This database was commissioned during the latter two-thirds of the study period. Since the registry was the source of year and level of injury as well as service connected status, this meant that a group of patients seen in the early years of the study period had these data elements missing. In order to clarify the difference between missing data from non-entry into the SCI Registry from other missing data, these elements were coded as Not in Registry (NIR). Except for the NIR elements, all other missing data appeared to be random. Four patients were identified as facility employees. Because of the additional security attached to employee records, these cases representing 8 admissions were eliminated from the study set. Since the study focus is on the SCI population, patients on the study unit with medical diagnoses of Multiple Sclerosis and Gullian Barre Syndrome were also deleted from the study population. This process eliminated an additional 34 patients. The remaining 525 patients with 1107 admissions became the study population.

DATA AGGREGATION AND INTEGRATION

There were 4750 different nursing diagnoses labels in the cumulative eleven-year database that after visual inspection were determined to represent 161 unique nursing diagnoses. Through further inspection, these were clustered into 20 diagnostic categories. Two domain experts with significant SCI knowledge and experience reviewed the categories to reach a consensus on the labels for the diagnostic categories. The selected diagnostic categories for the cumulative data were: Skin Care; Elimination; Self Care Deficit; Infection Prevention/Control; Mobility; Respiratory Function; Psychosocial Adaptation; Community Reintegration; Pain Management; Knowledge Deficit; Nutrition; Fluid Volume Maintenance; Acute Problem Management; Safety/Prevention of Injury; Activity/Rest; Cognitive Functioning; Temperature Control; Sexual Health; Communication, and Miscellaneous. Any diagnostic label within the cumulative database that did not appear at least eleven times during the eleven-year study period was assigned to the category of “Miscellaneous.” The decision was made to focus on whether diagnostic patterns had any relationship to LOS. The relationship between nursing diagnoses and the Diagnostic Related Group (DRG) system seemed apparent and the DRG system already had a LOS element. If nursing diagnoses could be predictors of LOS, those same diagnoses could be predictors of resource consumption and resource allocation. The 20 nursing diagnoses clusters became the input variables for the data mining software and the development of the ANN models predicting LOS.

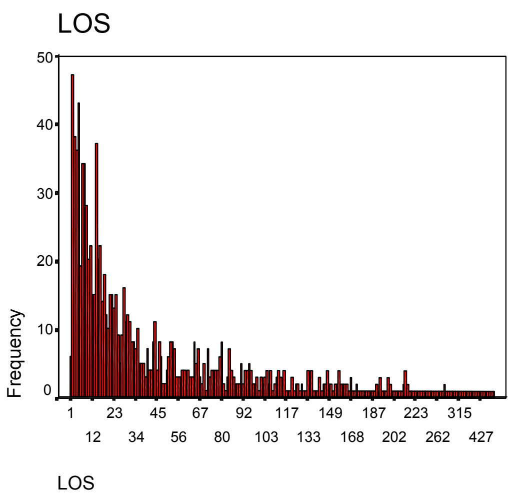
DATA VISUALIZATION

Data visualization is an invaluable counterpart to data mining. Visualization includes displays of trends, clusters, and differences. The visual review of all eleven years of data in this study took approximately 500 hours of time. A map of the annual diagnostic rankings for each of the eleven years in the study was developed to determine if there were significant changes in nursing diagnosis over the study time frame It quickly became apparent that the diagnostic categories of skin care, elimination, self-care deficit, infection prevention/control, and respiratory function remained in the top ranked categories over the entire eleven-year study period.

The length of stay for the episodes of care within the study database ranged from one day to 770+ days. The mean length of stay was 55.76 days with a standard deviation of 77.39 days. It is noted that the LOS curve is skewed significantly to the left and that there are outliers to the right indicating those cases in which LOS was extremely extended (see Figure 4). Observing the dispersion in the data, a decision was made to focus initial model development on patiients whose length of stay was between 1-40 days. Following the standards for ANN development, all lengths of stay in the study database were normalized to move values to a finite space [6]. This was accomplished by applying the following Formula:

$x_i = \left(\frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \right) (H_i - L_i) + L_i$ Where X_i is the un-normalized value, $X_{\max}$ and $X_{\min}$ are the largest and smallest value of the variable vector; H_i and L_i are the upper and lower limits of the normalized range in our case 0 and 1 respectively.

Figure 4: Length of Stay



LENGTH OF STAY

LOS is frequently used in health care as an indicator of resource utilization and cost. The Health Care Finance Administration (HCFA) Medicare reimbursement system uses length of stay for the Diagnostic Related Group (DRG) payment system. A DRG represents a valid group that classifies patients into a clinically cohesive group with the expectation of similar consumption of resources and similar patters in LOS [19]. Payment is based on a geographical average for each DRG category and the expected LOS. The concept of diagnostic groups from the medical perspective is closely related to nursing diagnostic clusters and utilization of the nursing diagnostic information may be a means of bringing more focused and appropriate resource allocation to the care of SCI individuals who, as consumers of significant care resources, are 'outliers' in the healthcare system [13]. Patients identified as outliers are those whose annual care costs far exceed normally expected healthcare costs. The potential for predicting LOS with associated resource utilization using nursing diagnoses and ANNs became of interest as database elements were visualized, cleaned, and explored.

DATA MINING

ANNs were chosen for building predictive models for length of stay. Four types of ANNs were developed: dynamic network, prune network, the multilayer perceptron, and the radial basis function network. These ANN models all represent "supervised learning" models with a known output used for comparison of the model output. The targeted output in this study is the known LOS. The dynamic model creates an initial network topology that is modified by adding and/or removing hidden units as the training progresses. The prune neural net method is most similar to a decision tree. It in fact, 'prunes' away certain input variables based on their significance and weight for prediction of the output. It is considered a slow model but one that can yield good results. The multilayer perceptron (MLP) is a type of in which each hidden layer contains weighted combinations of neurons that produce an output that is compared to actual and the difference between the predicted and actual goes back into the network. The feeding of the error rate back to the network is "back propagation" and this process adjusts weights until the correct response is learned. The Radical basis function (RBF) neural net is similar to a feed-forward network. It has a rapid training time that is usually much faster than the MLP net but the RBF net model may be slower when implemented because it uses more computation than the MLP [17].

After models were developed, an automated script computed and reviewed 800 iterations for each of the four models to identify the best one for each model style based on an evaluation of the prediction accuracy score and the mean square error (MSE). The results of optimal neural net models are presented in Table 1. The variables ND1…ND20 represent the 20 diagnostic variables found in the database. As expected, the Prune model had the longest training time and the RBF model was trained in the shortest time period. In the training process, the predicted accuracy scores which indicate the proportion of LOS correctly predicted based on nursing diagnoses ranged from 77.58% to 78.34%. The dynamic and MLP models had two hidden layers each but the dynamic model had three and five neurons in these layers while the MLP had 27 neurons in hidden layer one and two neurons in hidden layer two. The Prune and RBF models each had one hidden layer with 16 and 20 neurons respectively. Weights were assigned across the four models. The Dynamic Model ranked self-care, miscellaneous, and respiratory function as the heaviest weighted variables. The MLP Model assigned self-care, pain management, and fluid volume maintenance the heaviest weights. The Prune Model weighted cognitive functioning, knowledge deficit, respiratory function, and self-care deficit in descending order. The RBF Model weighted respiratory function twice as heavy as the second and third heaviest weighted variables of psychosocial adaptation and knowledge deficit.

The mean square error (MSE) rate for the four models ranged from 0.772 to 0.0813 in the validation run. Selecting the best model through the MSE process reduces the overall error dispersion around the actual LOS. Based on both MSE and predicted accuracy, the RFB model was selected as the best ANN model. In the selection of the RBF as the 'best' model, one can remain confident that the model will provide reliable information when it is applied to real up-coming data to define the LOS of future patients. As noted in figure 5, most of the observations of the predicted normalized LOS and the actual normalized LOS fall between 0.2 and 0.4 points indicating that the model is predictive.

In a later run of data, the one day length of stays were eliminated since it was known by the domain expert that these stays were an accommodation made to allow for annual physical exams [10]. After the elimination of the one day stays, the neural net models identified skin care as the heaviest weighted node. This was the expected weighting.

CONCLUSIONS

After acknowledging a personal and professional bias that in-patient hospital days are for the benefits of nursing care, the data reviewed in this study does indicate support for that thesis since 77^{+}% of hospital days were predictable based on the identified patient problems that do respond to nursing interventions. Although skin care problems ranked number one for nursing diagnosis across all eleven years of the study and was a major medical problem associated with hospital admissions, it did not prove to be the most significant factor in LOS. No one diagnostic cluster was found to be the critical factor in the prediction models. Instead, the data indicated that significant collinearity existed between the diagnostic clusters. According to Ferketich & Verran [8], healthcare is multi-variant. It is almost to each of the nursing diagnoses variables and vary impossible to select variables that affect patient outcomes but are unrelated to one another. The multi-variant problems known to be associated with SCI are evident in the study data.

In conclusion, this paper has presented a case study in knowledge discovery in clinical databases. Key issues in mining healthcare databases which are applicable both to researchers and practitioners are presented. Further examination of the episodes of care that are significant outliers in LOS is needed but since there were no specific differences in terms of nursing diagnoses or interventions, additional data elements may need to be studied. There are obviously other variables that also affect LOS. In the study location, it is known that many patients have an extended LOS not only because of medical problems but also because of financial or psychosocial problems that may include caregiver issues. Respite admissions that are planned to allow the caregiver to have a break in care responsibilities are known to support continued community placement but do impact the frequency of admissions and LOS. The VA has some degree of flexibility in allowing time to recognize psychosocial problems and initiate beginning steps to problem resolution. Community based long-term care placement is also difficult to find because of the demanding care needs of SCI patients.

The main constraint to this type of study using data mining is the availability of accessible and usable data/databases. The VA does have a large warehouse of data which includes ICD9 and CPT coding structures but the nursing variables of interest in this study are not included in the warehouse. This meant that nursing variables were obtained from the local transactional data files. Computerization of nursing data is best accomplished with the use of standardized nomenclature. The study data required many hours of cleaning because the language was not standardized and the data was not warehoused so it had not been filtered in any way to improve its usability. The decision of what data should be warehoused becomes very important if warehouses are built to support knowledge discovery.

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Table 1 Neural Net Model Statistics

	Dynamic	Multiple	Prune	RBF
Input Layer	20 neurons	20 neurons	4 neurons	20 neurons
Hidden Layer #1	3 neurons	27 neurons	16 neurons	20 neurons
Hidden Layer #2	5 neurons	2 neurons		
Output Layer	1 neurons	1 neurons	1 neurons	1 neurons
Predicted Accuracy	77.94%	78.00%	78.34%	77.58%
NDV1	0.02147	0.02634		0.01771
NDV2	0.01239	0.01956		0.01674
NDV3	0.07272	0.0814	0.04647	0.03504
NDV4	0.01804	0.04907		0.02176
NDV5	0.03	0.04727		0.01219
NDV6	0.03325	0.04405	0.06415	0.11021
NDV7	0.01657	0.01128		0.05276
NDV8	0.01701	0.03716		0.02495
NDV9	0.02293	0.06172		0.04316
NDV10	0.02495	0.03626	0.09545	0.05068
NDV11	0.0031	0.00139		0.03189
NDV12	0.0226	0.05541		0.03251
NDV13	0.02629	0.01279		0.03951
NDV14	0.01915	0.03597		0.01768
NDV15	0.02461	0.0085		0.02601
NDV16	0.03717	0.01874		0.03927
NDV17	0.01803	0.01238	0.16575	0.02046
NDV18	0.00246	0.01985		0.02075
NDV19	0.01756	0.01286		0.01894
NDV20	0.02795	0.00366		0.01906
Validation (MSE)	0.079000345	0.079866185	0.08133353	0.077281928
Out-of-Sample (MSE)	0.068067937	0.068211532	0.069028075	0.069616426