Application of Neural Networks Techniques to Military Pharmaceutical Ordering Problems

by

John J. Novak, Jr.

Submitted to the Department of Electrical Engineering and Computer Science

in Partial Fulfillment of the Requirements for the Degree of

Master of Engineering in Electrical Engineering and Computer Science

at the Massachusetts Institute of Technology

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Author____
Department of Electrical Engineering and Computer Science

Certified by____
Amar Gupta
Thesis Supervisor

Accepted by____
Arthur C. Smith
Chairman, Department Committee on Graduate Theses

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ABSTRACT

The military is one of the largest pharmaceutical distributors in the country. In order to minimize the amount of inventory held, and hence warehousing and expired drug costs, data mining techniques can be applied to old transaction records to predict future needs. One powerful method of data mining is the use of neural networks. Neural networks have the ability to learn inventory needs based on past situations which are expected to occur again. Using neural networks to data mine government pharmaceutical supply necessities will enable the reduction of inventory levels as well as improve customer satisfaction by increasing the chance the needed prescriptions will be in stock. This thesis introduces inventory methods, data mining methods, and explores the application of data mining and neural network methods to actual inventory optimization problems. Limits and future direction suggestions are included at the end of the document.

Thesis Supervisor: Amar Gupta
Title: Co-Director, Productivity from Information Technology (PROFIT) Initiative. MIT School of Management

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1.0 INTRODUCTION

1.1 THE NEEDS OF A SUCCESSFUL BUSINESS

Businesses require many conditions to be successful. When a business starts, these needs are simple and survival-oriented. As months, then years pass, the needs change and mature. The business becomes more concerned with keeping their customers and streamlining their operation to reach their optimum potential. Two very important aspects of these evolved needs are minimizing loss and continuously matching demand.

1.1.1 MINIMIZING LOSS

A well-organized business makes use of every dollar to maximize their profit. When a company releases its year-end summary, a *balance sheet* is often included. Such a report keeps track of every loss, such as payments, purchases, debts, and depreciation, and every gain, including sales and stock purchases, so that an investor in the company can see what the company does with the money it gets. One thing people outside the business world may find confusing is that at the bottom of the balance sheet, the assets often equal the liabilities. If so, if the gains equal the losses, where was the profit? This brings up the point: every dollar that does not work for the business is a loss. If the company made a profit, having that money sitting in the bank means it is not being used to help the business along. Consider this: if the company is experiencing 20% growth per year, and there is $1 million dollars being held in the bank, that $1 million is not being employed in that 20% gain. Hence, if that money was instead used to help sustain business growth, it is reasonable to assume it would be subject to the same growth rate, or total $1.2 million at the end of the year. If the manager of the company does not make use of every dollar available, he or she will have just lost $200,000. Clearly, making every dollar work is of the utmost importance.

Another part of minimizing loss is to make sure no expenditures work against the business. In other words, bad investments must be minimized. One such bad investment, the topic of this paper, is buying only what will be used. Everything bought should be used: be it machinery, personnel, land, or products. This streamlining is consistent with any kind of operation, be it the management of a home or multi-billion dollar corporation: buy only what is needed. This paper will address one aspect one aspect of minimizing loss: reducing surplus inventory. This will be examined later, though suffice it to say for the moment that buying more than one can sell means the difference between the two is money spent that is not aiding the company in making a profit.

1.1.2 MATCHING DEMAND

Another need of a maturing business is to keep the customers they have. This is done only one way: keeping the customer satisfied. Satisfaction results from of having the lowest reasonable price and having what the customer wants available. Having the lowest price results from making the minimal purchases required to produce a good product, while having what the customer wants is a question of matching demand. One could assert that this is a part of minimizing losses by buying only what is sold, but the decision on how much will be sold is a separate entity by itself. The customer is not directly concerned with the supplying company having an overstock—that often means a reduced-price sale. However, if the supplier's stores run out before the demand for that period does, some customers will have to wait for their orders or go to another store.

1.2 INVENTORY MANAGEMENT

1.2.1 PRINCIPLES OF INVENTORY MANAGEMENT

As stated, the importance of accurate inventory management is of utmost concern for any product-oriented business. Order too many raw materials or commercial products to be re-distributed and anything not sold represents lost money for that ordering period. Consider the case many people have experienced: going to the video store. Often, one has heard that a movie was good, was just released, etc., and goes to their favored video store to rent the movie. If one goes looking for a popular movie, it is probably a fair statement that that person has discovered all copies of that movie have been rented out, and there are none left for them. Now envision the same emotions times 10,000, all of whom are customers, who came to the store looking for something but could not find it. Some may just leave, marking a loss in potential profit. Others may wander the store looking for something else. Still others may try a different store, which may or may not be part of the same chain.

All situations share a common thread: they produce an unhappy customer. Every time such an event occurs, it mars the company's reputation in the eyes of the consumer. While one or two such instances may not matter much to a business owner, one must bear in mind that people tend to be loyal to one store at a time: one video store, one grocery store, one drug store, one clothing store per type of clothing, etc. Often, these loyalties are the result of several factors, including location, accessibility, quality, price, environment, and, most importantly, customer satisfaction. Disturb that satisfaction—disappoint the customer—too many times, and the customer may change loyalties. In other words, not satisfying them at the moment and losing a few dollars can potentially translate into driving them off as a customer. Doing so loses all future dollars that customer might spend at the business over the duration of their stay in the area, or maybe even their life. Thus, the risk run by undershooting on the inventory predictions, while perhaps saving the company considerable money in reduced inventory overstock, may result in pushing customers away from the store and starting a self-sufficient loop. The store underestimates consumer need, and drives customers away. The market base shrinks, so the predictions shrink. Unless the prediction model has changed, this will underestimate the market need again, driving even more customers away, etc.

1.2.2 COST OF INVENTORY

In addition to the worries of overstock and stockouts, an inventory manager must also content with the fact that inventories cost money. Storage space, personnel, and upkeep all must be paid for, and scale linearly with inventory size. One estimate sets every dollar of inventory costing at least 25 cents per year to maintain [21]. Thus, while holding a large stock to satisfy all customers may seem like a good idea, one must remember storing and maintaining that inventory costs money.

The way to minimize inventory, and hence maintenance costs, is data mining. Using analytical methods including neural networks, decision trees, rule induction, and data visualization software [22], inventory managers are capable of predicting upcoming need. Using this information to place their order, the managers minimize the level of new inventory coming in, thus keeping storage costs to a minimum while ordering the minimum inventory necessary.

1.2.3 JUST-IN-TIME

The idea of just-in-time delivery has been gaining popularity recently, thanks to the increased use of computers. Just-in-time is a method of inventory delivery that promotes the lowest possible inventory by having a refill order arrive just as the current stock is empty or very close to it [11]. The concept is that exercising ordering patterns in this way will minimize the standing inventory, thus reducing waste from any inventory expiring.

There are two main necessities that need to be fulfilled before such a program can be implemented. First, there must be enough of a history on the goods being ordered to be able to make a justifiable decision on how often the reorder points should occur. Second, and more importantly, the market demands the just-in-time concept is trying to satisfy should be a steady one. If the demand surges and slows inconsistently, the inventory will not be consumed at a steady pace, which will result in stockouts and overstocks, neither of which is preferable when dealing with perishable goods, such as medicine.

1.3 MEDICINE

Medical inventories have extra considerations that need to be given to them that other inventory management schemes may not. At the forefront of these differences is the simple fact that the inventory is *medicine*, and hence it is very important that the customer get it promptly. Typically, a patient who goes to the doctor and gets a prescription needs the medicine to start the healing process. Such drugs are grouped into a class of *acute* drugs: drugs for the treatment of temporary conditions that require immediate attention. This is in contrast to *maintenance* drugs: medicines people need to take on a regular basis for a condition that either occurs often or never goes away (i.e., allergy or blood pressure medication) [2]. In the case of acute medicine, it is of vital importance to the pharmaceutical supplier that to maintain customer satisfaction (and in some cases, safety), the necessary drugs need to be in stock. The penalties for being out of stock can be severe, for both the patient (who now must go to another store) and the store.

Medical inventories have another consideration that needs to be attended to while anticipating the next ordering cycle's need: drugs expire. Like food products, medicine is not stocked indefinitely, as it most often loses its strength and sometimes its chemical composition. While expiration dates may be on the order of months or years, any inventory that expires before sold becomes shrinkage: inventory that cannot be sold and incurring a financial loss. If a business wishes to succeed and grow, such events must be minimized.

1.4 OPTIMIZING OVERALL DELIVERY STRUCTURE

Bearing in mind all ideas encountered thus far, there seem to be two competing necessities regarding the management of medical inventories. While one cannot understock without losing customers, overstocking produces a financial loss, which may in turn end up having to be passed on to the consumer in product price increases. Some method needs to be implemented to attempt to split the difference between the two, and allow a company to order just the right amount of medicine every ordering cycle. This is especially important now and in the future, where HMOs and government agencies, who both have needs of streamlining pharmaceutical deliveries, must cut back their expenditures while increasing service.

The solution gaining popularity recently is the previously mentioned concept of data mining. Given the amount of information stored in computer databases, and the ready accessibility often enjoyed in these systems, the idea has caught on that by looking for patterns in this data one can learn vital information for the support of their business. Hence the term *data mining*: looking for new data in a collection of old. One form of data mining, the form of which this paper is about, uses neural networks to make predictions based upon previous terms' order patterns. Given their ability to recognize input patterns better than statistical analysis and ability to derive patterns too complicated for the human mind to decipher, neural networks are an appropriate tool. Given the rise in available computing power at reasonable costs, the use of neural networks to predict need appears an excellent decision in many areas.

1.5 THESIS OUTLINE

This thesis will proceed in such a manner that builds the reader's knowledge in a logical order, starting first with the principle target of this paper, medical inventories. Following a thorough description of medical inventory history, current state, and problems, neural networks will be introduced, allowing the reader to think about them with the medical inventory needs freshly implanted in mind. Neural network origins, types, implementation, and use will be discussed at a level pertinent to data mining. Following that chapter, a pair of actual case studies using neural networks will be presented: one regarding a major pharmaceutical supplier and the other regarding a large pharmaceutical consumer: the US government. Finally, a set of conclusions and recommendations for further neural network study will conclude this document.

2.0 MEDICAL INVENTORIES

2.1 CONVENTIONAL ORDERING CHAIN

The structure of medical delivery systems, as well as for other types of inventory, is fairly consistent. At the top of the chain is the manufacturer that makes and stores some quantity of the medicine. Next in the chain some sort of distributor channel, such as an organization or government agency. Next, some localized distribution branch of the organization is found, where warehousing and distribution of products from multiple manufacturers occurs. This is the point where the final customer accesses the supply chain. By minimizing loss, and hence maximizing profit, at each point on the delivery chain, price to the final consumer can be minimized while at the same time generating just enough product to meet demand. Given that the consumers have the broadest range of needed products, the middleman in the chain is the one that has the most diverse needs to fill, and hence most inventory to store. This storage warehouse may take the form of an actual warehouse, or of a store if the delivery system represents a commercial drug distributorship.

2.2 INVENTORY MANAGEMENT

The type of inventory control discussed here deals mainly with storage of finished products for later dispersal to the public or other agency. Entities using this type of storage include stores, warehouses, restaurants, and other finished-goods distribution facilities.

2.2.1 DEFINITION

Inventory control is the management of a supply of goods that must both satisfy a demand (outflow) and needs to be refilled (inflow). The goal of effective inventory management is to hold both inflow and outflow as close as possible to each other so that the storage space required to hold the goods is minimized while still satisfying some majority of the customers.

Consider the ideal case: the warehouse holds exactly one of each item a customer expects to find there. When a customer comes in and buys one of those items, a request to the warehouse's supplier goes out and a replacement item is sent to fill the void before the next customer gets there. This would conceivably minimize inventory and satisfy 100% of the customers (presuming they did not want multiples of the same product). Unfortunately, this is not a system that can be implemented in real life, particularly because the inflow to restock purchases takes a potentially unknown time to occur. Inflow may only be capable of being executed at daily, weekly, or monthly intervals. For this reason, some sort of estimate needs to happen to predict how much of an item will be needed between restock times. Satisfying these constraints while pleasing the customer are the principles of inventory management.

2.2.2 FACTORS INFLUENCING INVENTORY

There are several factors to be vigilant about in managing inventory outflow and inflow. Several layers of inventory must be maintained to account for several potential situations. For more detailed explanations on these safeguards, refer to the Production and Inventory Control Handbook[8].

The most basic inventory need most people realize is the need for some sort of *buffer* or *safety* inventory to protect against the unknown. There are, however, other sorts of pre-stocking that need to be considered. For instance, one may need to build an *anticipation* inventory when expecting some future event to skew the need between deliveries in an upward direction. Such events can include an upcoming holiday preventing stock refills at the normal interval, or having a sale on an item and expecting it to sell more. Rounding out the demand-based considerations is a *hedge* inventory that attempts to provide a safeguard against sudden changes in demand, due potentially to news stories, price drops, or simple consumer randomness.

Considerations to take into account on the inflow side are just as important as those mentioned pertaining to outflow. Most of these considerations are based upon having a *reorder point*, or stock level at which the request for a stock refill takes place. Upon placing such an order, the inventory must contain a *transportation* inventory, or a supply to maintain the warehouse while the refill is being delivered. Another area to monitor is the *lot size* inventory. Most of the time, inventory cannot be ordered down to the individual dosage or package size. Cough medicine and pills come in boxes with multiple containers. Several types of pharmaceutical drugs come in very large containers of potentially 1000 doses or more. When one gets a prescription filled, the bottle they receive is not pre-packaged—it is filled from some larger container, and it is these containers that are reordered. Finally, a *lead-time* inventory may need to be maintained to provide insurance against a temporarily incapable manufacturer. Unfortunately, when a warehouse places an order, the manufacturer of that item may not always have it in stock or otherwise available. In such cases, an inventory supply is needed so that the warehouse can conduct business while the manufacturer prepares the order.

2.2.3 ACCURACY

In March 1995, Terrance Hancock and Cynthia Childress published a paper describing an attempted match between actual inventory and computer-reported inventory in an animal hospital [9]. Their results were displeasing. Their hospital medical inventory was divided into 26 categories, and an item was chosen at random from each. Of these products, the amount the computer reported was on-hand was compared to the actual amount. Summing these items in terms of cost, the computer predicted $4,134 worth of stock. The actual value was $1,646, or just shy of 40% of expected levels. The remaining 60% of stock was unaccounted for, presumably lost to treatment, employees, or theft (many drugs for animals work just as well on humans). Periodic inventory counts were used only to reset the computer's values, not to account for or discover loss. In other words, it was accepted that the actual values were below what the computer said existed, and instead of trying to discover why, numbers were adjusted to reflect reality.

This study raises an excellent point: if a company wishes to optimize their inventory delivery system, the numbers used to do the predictions must be accurate. For instance, if someone had tried to use any of the above prediction models on such data, the effects of the weekly inventory corrections, which would likely represent a loss of 60% if the discovered ratios held throughout the inventory, would horribly skew the predictions. The storage of accurate data is vital to the success of any attempt to streamline warehousing operations, because that data is what will be used to make future predictions.

2.2.4 THE DILEMMA

All the problems of inventory management reduce to one concern: price versus availability. Attempting to make sure 100% of the customers are satisfied 100% of the time means storing more merchandise than attempting to fill 90% of orders. For this reason, the person in charge of inventory management should be working with a goal: either setting the availability level and minimizing price, or setting the price and maximizing inventory. There is no overall "optimal" inventory level—it varies according to whatever needs are placed on it. In other words, like any other problem, the needs of the system must be clearly described before a solution can be presented.

2.3 MEDICAL CONSIDERATIONS

2.3.1 INVENTORY OVERSTOCK

The management of medical inventories has several facts that need to be considered before deciding how much of a product to order for the next timeframe's needs. Chief among these differences is expiration of products' usefulness. Drugs are chemicals designed for digestion: to be relatively easy for the body to break down and absorb. This same need also hurts the quality of a medicine if it sits on a shelf for too long before it can be used: the chemical inside breaks down on its own. One can verify this for hiself/herself: simply go to the medicine cabinet and look for a package of medicine. Somewhere on the package will be stamped an expiration date, whether the medicine is prescription or store-bought. Thus, this part of managing a medical inventory is much like managing a grocery store or restaurant inventory, since much like food, medicine must be used before it goes bad. One does not need to worry about such things if they are managing a stock of computer chips or shoes—they will never expire on the shelf unless technology makes them obsolete.

The problem with having inventory overstock is that anything that expires on the shelf represents spent money that goes to the trash. This loss then becomes part of the overall inventory *shrinkage*—a term usually reserved for lost, stolen, or damaged stock. Since expired overstock represents money spent by the company that it will never recover from selling the product, its grouping there is appropriate. And, as store owners know, the money that pays the difference between what was bought and what was sold must be made up for, and instead of allowing it bite into profits, the cost is usually passed on to the consumer. Thus, when a customer, be they an individual or organization, arrives to purchase what they need, they are paying both for the product and for any other products that have gone bad through no fault of their own.

Consumer demand variations play a role in producing overstock, but the fault in the situation cannot be totally assigned to the public. Doctors and pharmaceutical companies are equally to blame for prediction difficulties. Doctors, for one, are human, and subject to moods and hunches, and cannot be relied on to have the same behavior 100% of the time. Thus, a doctor may prescribe different medications to the same types of situations on something as simple as the fact they may be having a good day, and may make a more aggressive drug choice.

Doctor's choices may also be influenced by the pharmaceutical companies, who seem to constantly be releasing new and improved products. Several times a month there are news stories on the latest drugs now available to the public. It can be assumed that most drugs released are to treat conditions that are fairly common (or else a drug company would have little to gain by selling to a small audience), and that these ailments are already being treated with some sort of drug. The problem complicating the prediction situation is that medicine *replacement* will occur when a new drug is introduced into an established market. Typically, every prescription for the new drug written replaces an order for the previous drug that person had been taking, reducing the market need for that drug one doctor visit at a time. Since there is very little one can do to predict the market percentage a new drug will take, predicting how much of the old drug will be needed in that market is often little more than an educated guess. This guess goes both ways, however. Not only is it hard to estimate how much to reduce orders by to prevent inventory overshoots, when ordering the new drug, with no history to base decisions on, preventing undershoots becomes difficult too.

2.3.2 INVENTORY UNDERSTOCK

The other consideration that sets medical inventories apart from non-medical inventories is the high necessity for not being out-of-stock of an item. When a customer goes to the music store to buy a CD, very little beyond annoyance will occur if it cannot be find. However, medicine delivery is intended to fill an immediate, necessary need. While it is unlikely a doctor would send someone to a pharmacy while they were in desperate need of aid, not having an item in stock means that the customer will either have to wait for the store to get the drug or go somewhere else. With this in mind, it is highly unlikely any store wants to be responsible for aggravating an already ill person. For this reason it is in the company's best interest to try to ensure as best as possible that they not be out of stock of any item a customer needs.

Hospitals are a separate story. They are the ones responsible for *saving* lives: pharmacies need only *keep* people alive. A patient seeking aid in a hospital both has an immediate need for medicine and cannot easily go to a different hospital. Turning a patient away from a hospital due to poor inventory management would be extraordinarily bad press. Further complicating the issue is that in such cases, acute drugs are often called for, since if someone had a condition that could be fixed by a widely available pill it is unlikely they would be in the hospital. Hospitals do enjoy one benefit pharmacies do not: if something is not available, there are plenty of doctors available to think of quick and adequate substitutions using what is available. Unless someone's life is in danger, pharmacists cannot change doctor's orders.

2.4 ENVIRONMENTAL (MILITARY) CONSIDERATIONS

The military has an even tighter problem with inventory prediction than hospitals do. During a military operation, storing the amount of medicine a pharmacy or hospital does is not an option: such size reduces mobility. There is also the possibility that any additional medicine may be remotely located, and can take a day to get there (or more if the medicine has to come all the way from the mainland United States). Not only do the doctors have to meet all patient needs, they have to do it without outside help: all needs must be met within their self-contained environment. A perfect example of this need is with the Air Force's air-transportable hospital. This mobile support service must be capable of meeting the support needs of 4000 personnel for 30 days, without replenishment. [24]

Despite having provisions stored at various bases and hospital ships, it takes time to access those provisions. Compound this with the fact that battle has a randomizing effect on ailments: certain problems are expected in the city, but in battle, anything can happen. A gunshot victim may need saline to raise their blood pressure and antibiotics to fight infection until they can get out to surgery. Someone else may be badly burned and need ointments. Someone else may have contracted an infection or fever of some sort, and their friend may have food poisoning. Conflicts are a totally different situation than what exists on the mainland, and for that reason merit their own prediction calculations. These calculations must take into account both the diversity of injuries and that the people using the inventory could be cut off from the sources and have to exist independently for a time.

Another consideration a large organization like the military has to take into account is environmental. Examining previous news-worthy military endeavors, it quickly becomes evident that the armed forces seldom go to the same place twice (something the defense department may well be proud of!). However, environment has a substantial effect on medical needs. For instance, the desert, the jungle, and the urban areas all have and cause different types of injuries and illnesses. Peacekeeping missions have different needs than combat situations. Such diversity of environmental backgrounds makes acquiring past historical knowledge of the situation (for prediction purposes) very difficult. Though, conceivably, if a situation ever arises again, an inventory model based upon the last campaign can be re-used.

The military does not only have wartime medical needs to fulfill. According to an article describing the pharmaceutical system of the Department of Veteran's Affairs, the VA is the nation's largest integrated health system [25]. In 1996 the VA expenditures for medically necessary pharmaceuticals and medical supplies was $1.1 billion dollars. The VA is but one part of the distribution channels that must be supported by the government. Additionally, the government must support public health systems, as well as the medical services of the Army, Air Force, and Navy, who each have their own infrastructure, the size of which is not negligible. As a quick example, in terms of fixed (non-mobile) facilities, the Army has:

- 76 ambulatory clinics, generating 3.3 million prescriptions/year
- 28 community hospitals, with 8.2 million prescriptions/year
- 8 medical centers, with 5 million prescriptions/year

Also, this is only for the Army—the Navy, Air Force, and Veteran's Administration have not been included in the above numbers.

3.0 PREDICTION AND DATA MINING TECHNIQUES

Considering the breadth of businesses with inventory, it is only natural that several types of prediction methods to model customer demand on inventory have been devised. The variety of inventory types, and hence requirements, does not allow the definition of a single optimization method to be the best solution for all systems. Instead, some knowledge of the inventory system must be used to provide an educated guess as to which systems to try first. Naturally, suppliers with steadily increasing or decreasing demand would prefer a simpler prediction method. Trying to provide predictions for a complex system of multiple variables of unknown importance and various surges and slumps demands a more robust prediction model. However, the price of model robustness and accuracy in these cases gets reflected in computational power required and time needed to generate models for each item to be predicted.

3.1 STANDARD STATISTICAL METHODS

All of the models to be mentioned assume the use of a computer to aid in desired predictions. Hence, when the term "complexity" is used, often what is being referred to is the difficulty of programming such a system on a computer and the effort it takes to make that program work. This section introduces some of the least complex prediction schemes available. Such methods are advised for inventories where past data is available, and suggests the inventory levels are steady, steadily increasing, steadily decreasing, or steadily cycling according to some unknown function.

3.1.1 SINGLE OUTPUT VARIABLE ANALYSIS

The most basic attempt to match inventory patterns is to assume that demand for a particular item (in our case, medicine) is consistent through time (i.e., maintenance drugs should theoretically have little variation). If this were true, and no forces were acting on the demand, next period's inventory (I_{n+1}) could simply be an average of the previous periods:

$$I_{n+1} = \sum_{x=1}^{n} I_x$$

This function, over time, would converge to a steady level enabling the user to simply order the same amount of product every cycle. In the business world, however, demand is very seldom a constant, so patterns in the fluctuation must be matched. If the demand is seasonal, as a handful of drugs is expected to be, one could simply base the average above on the previous periods in history that match the period to be predicted. However, this calls for readily identifiable seasons, which may not always exist.

Another way that attempts to capture the trend of demand is exponential smoothing. The method for prediction of this type is similar to simple averaging, except that recent data samples carry more weight in the prediction, thus making the prediction fall more in line with the immediate history rather than the overall history. In this formula, α is a smoothing constant between 0 and 1, typically 2/n+1 [8], and I_{n+1} is the next inventory cycle to be determined:

$$I_{n+1} = \alpha I_n + \sum_{x=0}^{n-1} (1-\alpha)^{n-x} I_x$$

However, there exists a problem in the methods described thus far. Only the seasonal modification to the averaging technique offers any hope of catching an upcoming market surge before it happens. If one were actually employing one of these techniques and a market surge did occur, because the inventory prediction for the term was based on the surge-less past, the prediction will be drastically less than the actual demand, resulting in an understock and loss of potential revenue, customers, and image.

3.1.2 MULTIVARIABLE PREDICTION METHODS

An alternative method of analyzing the pre-existing data attempts to flush out causal relations between the output (actual inventory needs) and inputs (circumstances) that led to those needs. Wherein the single-variable prediction studied only the amount of inventory used, multi-variable analysis takes into account several aspects of the situation before any attempts at prediction are made. Of course, this presumes that there exists a relationship in the data between the situation and the need for that period.

One popular method that attempts to predict demand is a curve-fitting method called least-squares. It attempts to calculate the function governing the output (in this case, the inventory level) with respect to time:

$$I_t = a + bt + e_t$$

where the previous data is used to calculate the equation's coefficients. However, this particular type of equation is linear in t, so while it could catch trends, it would not be able to model cyclical data well. Other flavors of least-squares offer methods for computing predictions for polynomial, exponential, or trigonometric formulae.

The least-squares method of predicting the function governing an outcome can be expanded to permit the variable being referenced against be something other than the time, t. Such techniques generate what are called causal models, since, as the name implies, they allow one to try to create a formula for one variable based on any continuous variable. If successful, such models can be tremendously helpful because of their ability to *explain*: the other models tell one only that needs are going up and down—causal models tell the user which variable is the source of, or at least an indicator of, the changes. The equation the type of causal model derived from least-squares, called linear least-squares, is very familiar:

$$Y_t = a + bX_t + e_t$$

where Y is the value to be determined and X is any continuous variable, and

$$a = \frac{\sum X^2 \sum Y - \sum X \sum XY}{n\sum X^2 - \left(\sum X\right)^2}$$

and

$$b = \frac{\sum Y - na}{\sum X}$$

The primary problem with this set of formulae is that it requires the user to select which attributes to study against, some of which may yield poor matches. There are variations that allow for Y to be based upon more than one input variable, but it still requires user (or repeated computer) selection of which variables to try.

3.2 DATA MINING TECHNIQUES

Data mining is a term referring to the process of examining data in a database for previously undiscovered relations. In other words, data is mined for new data--hopefully that can be applied to gain a business advantage [3]. Data mining is the process by which data is explored and modeled discover previously unknown patterns [12], and is the first step in a larger process called Knowledge Discovery in Databases (KDD). KDD is the process of retrieving the new data, while data mining is the actual step within KDD. The other steps in KDD are data warehousing: the storage of data in a manner facilitating easy, accurate access to the elements, and data analysis: seeing what data was produced and what is "useful."

3.2.1 DATA WAREHOUSING

Data warehousing is the first, most basic step in using KDD methods [3]. Arguably, every business has some form of a data warehouse--the main variance is the degree of usefulness for data mining. Data warehousing is simply the storage of data, usually with the intention of using it later. Obviously, paper records are a data warehouse, though they are not terribly useful to a computer simulation. They are, however, useful to someone, so the "intention of utilization" should not be judged. However, if computer simulation or prediction is the purpose of the data, then computerized records are in order.

The power of the data warehouse is just coming to fruition thanks to the rise of the hard disk drive. The reason there is such a recent surge in data mining is the decreasing price per megabyte of fast storage, which makes it available to more and more companies. It was just over 6 years ago that a 80 megabyte hard drive on a computer would have been considered excessive. During that time, storing a gigabyte of sales information would have been a costly venture on anything but tape. Now, individuals and corporations have the ability to store virtually limitless amounts of data. This being the case, businesses have been storing their transactions for years, simply as a means of record. Then, the logical question started floating around: "I have years and years of data just sitting about. Can I use it for something?" The answer was yes.

The primary condition that applies to the computer records is the manner in which they are stored, and hence retrieved. Typically, the most useful data is stored in some sort of database system, which has clear advantages over storing receipts as word-processor documents. Database systems give the user the ability to call upon information by key, which allows access to information given a certain parameter. Such parameters include item, store location, time of year, etc. There is, however, a trade-off. Deciding which pieces of information to store may be a tricky exercise. If one does not store enough transaction information, there is the chance that some fact relevant to accurate predictions may be omitted—even if at the time people in the business agree that said information can have no possible value. On the other side of the equation, attempting to store every conceivable piece of information in the database would result in massive storage requirements. Information storage has a price, and is thus subject to the same overflow and underflow problems that are trying to be resolved in this document.

3.2.2 DATA MINING

Data mining can be carried out many methods, which is what makes it an interesting topic for nearly any company. While this paper explores the application of one type of data mining technique, neural networks, to pharmacy inventories, it can be applied to a myriad of situations. Anything with data too complex for any one person to understand can benefit from it, and such examples are found extensively in the appropriate literature:

- Members of the XACT Medicare Fraud Unit used data mining methods on billing claims and discovered unusual patterns coming from an ambulance company. Investigating and discovering some of the claims were fraudulent, the ambulance company settled out-of-court for $4.5 million.[12]
- Prudential Insurance Co. used data mining on its customers to analyze which types of people have interest in annuity products. Their trial test resulted in twice the response randomly selected households would have. [23]
- The SKICAT system was used to catalog images from the Palomar Observatory Sky Survey of 3000 16-bit 23,040x23,040 pixel images with 40 attributes each into either star or galaxy classes (from a distance, a galaxy can appear as a star). Using astronomers to provide initial, training attributes, the resulting system emerged 94% accurate. [3]

Clearly, with the feats being accomplished in so many different areas, the application of data mining methods to commercial and scientific problems is a good idea.

3.2.3 DATA VALIDATION

Data validation is the last step of knowledge discovery in databases. Virtually all forms of data mining require the user not to use all available data for creating the model, whatever it may be. There is, however, a step that precludes the use of the entire dataset. Before a scientist or inventory manager or sales representative goes before their superiors and reveals the newfound ability given to them thanks to data mining, the technology developed must be proven. Typically, a chunk of data, usually the most recent piece, is withheld from the creation of the prediction model. Instead, once the model is created, it is compared with the actual data reserved.

The way to measure the accuracy of a given data mining technique is to compare its predictive capacity against reality. All forms of data-mining oriented prediction require model inputs of some sort. In the case of the validation step, the model is fed the same inputs that "reality" was fed, and the results of the model are compared to what occurred in actuality. Naturally, the more accurately the model mimics reality, the more credibility it has as a business or analytical tool.

Following validation of the model, it is often found that the previous data used to train the data is no longer needed (though never should be destroyed). Instead, the knowledge contained in the data now also resides in the model. This is useful for two reasons. First, a model is always much smaller than the data used to train it, or else creating such a prediction device would be moot. Smaller sizes without loss of accuracy means that instead of placing the data on the server and flooding the network and host computer with requests for such a large transmission, the smaller, simpler model can be transmitted. Second, the model is typically much more useful than raw data. Assuming that people requesting the data are looking at it for references of potential future occurrences, the model is already prepared to do predictions. If one wanted to run a prediction against raw data, the data mining process would have to begin anew every time the data was requested.

3.3 RULE-BASED SYSTEMS

Unless the data to be modeled follows some sort of regular mathematical equation, it is hard to say statistical analysis truly generates any new knowledge about the dataset. Since it is likely demand does not follow a simple equation, some means of describing that data must exist in the model than humans can understand. One such way utilizes rule-based systems to describe the data. Rules are things people are used to using every day, so any system that presents the knowledge gained from exploring a data system in such a manner is immediately useful.

Rule-based systems traverse data looking for interrelations between various elements with respect to the variable trying to be modeled as the outcome of the input event. Often, rule-based systems require a discrete output, so if one were to use it for modeling pharmaceutical need, instead of predicting the order amount needed, it would be more suitable to predict the level needed. For instance, instead of having continuous output values on all the training data, they could all be replaced with which range they fell into (if the value was 74 and the range of the outputs was evenly distributed from 50 to 100, it could be put into a "middle" category covering 70-80).

Having trained itself on the training data, a rule-based system software then presents the user with rules governing the output of the system, as well as the accuracy of those rules. A possible rule governing inventory requirements for a drug could be:

if ((winter) and (last_month > 100) and (sale)) then need=high_demand (90%)

What such a rule states is that 90% of the time, if it is winter, more than 100 units were sold last month, and there is a sale on the item, the demand level on the item will be high (as opposed to medium, low, medium-high, etc.). The reading of such a rule requires minimal training, and only a fundamental knowledge of probability to exploit. It also potentially presents the user with new knowledge. For the prediction of this item, there may have been a dozen inputs, but the only real factors affecting the sales level of the item is whether or not it is winter and it is on sale. Such information can be used to gain a business advantage: if it is winter and sales have been on an upswing lately, putting the item on sale will likely result in more people buying it, thus creating more profits.

4.0 NEURAL NETWORKS

Another data mining tool to create more accurate prediction models of the needs of pharmaceutical ordering systems, a tool called Artificial Neural Networks is gaining popularity. This chapter explores the origins, operation, and application of neural networks to predict the inventory needs of a system—in particular, pharmaceuticals.

4.1 NEURAL NETWORKS PROPER

Neural networks derive their name from the nervous system found in all vertebrate animals. Composed of *neurons*, the system's primary function is communication of information from sensory areas to the brain. In addition to simply transmitting information, neurons also have decision-making properties that may play a role in human decisions. Their organization through the body resembles a relay system, where each neuron represents a stop on that system. However, instead of transmitting the entirety of the signals received at each neuron, the signals are summed. If (and only if) the sum of the signals is above a certain level, a new signal is created and sent up the relay. By doing this, neurons are able to filter out presumably unnecessary input from the system, which eventually converges at various decision centers in the brain. In the brain, even more of these neurons exist, connected into patterns to aid in recognition (as opposed to passing information from touch, vision, etc.). There, it is believed the neurons form a more defined system, where neurons represent certain concepts or ideas. If enough clues are passed into the brain triggering a neuron to fire, that neuron can mean "car" or "house," or in our case, "surge" or "decline."

The neuron, being a communication and analysis component, has the requisite parts one would expect to find on a such device even if it were not on a cellular level. The first of these, the neuron inputs, are called *dendrites*. These dendrites spider out to receive inputs from other neighboring neurons or sensory receptors, via knobs at the ends of the dendrites that connect to the other cells through synaptic gaps. Sodium and potassium transmission across the synapse change the electric potential of that branch of the dendrite, and that potential travels up the dendrites to the cell body. The cell body then sums the potentials, which can be both excitatory and inhibitory, at the second part of the communication device, the *axon hillock*. This part of the neuron has been conditioned over time to learn which level of summed inputs is important enough to pass up the network—which level "means" something.

The final part of the neuron, corresponding to the output of a communication device, is called the axon. If the axon hillock gets senses enough of a potential in the cell membrane, the hillock will send its own potential up the axon to other neurons further up the chain [Figure 1]. It is important to also note that the dendrites form synaptic connections with more than one axon. This way, each neuron receives input from a wider set of inputs than a single-pipeline connection into the brain would need, and thus reduces the complexity of transmission and analysis [Figure 2]. By constructing a tree of neurons and reducing the information to a set of patterns instead of distinct signals, neurons are capable of guiding people through their lives.

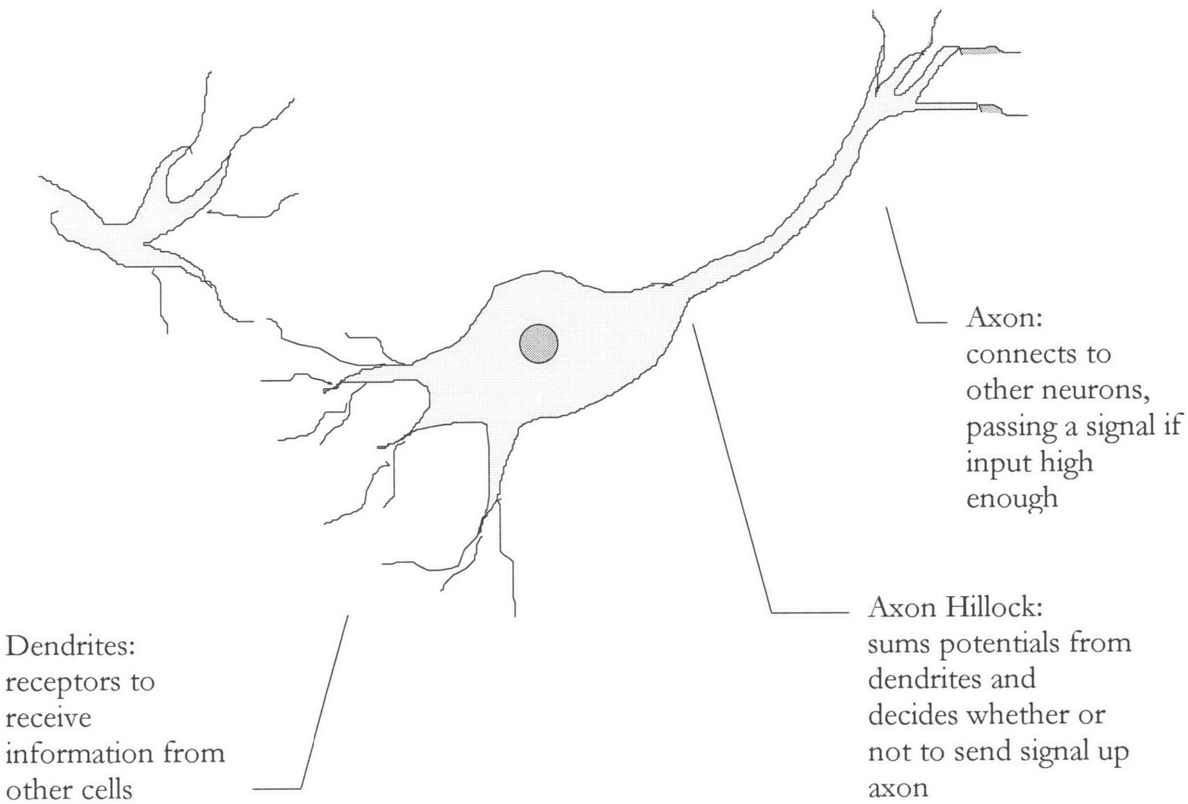


Figure 1: A Neuron

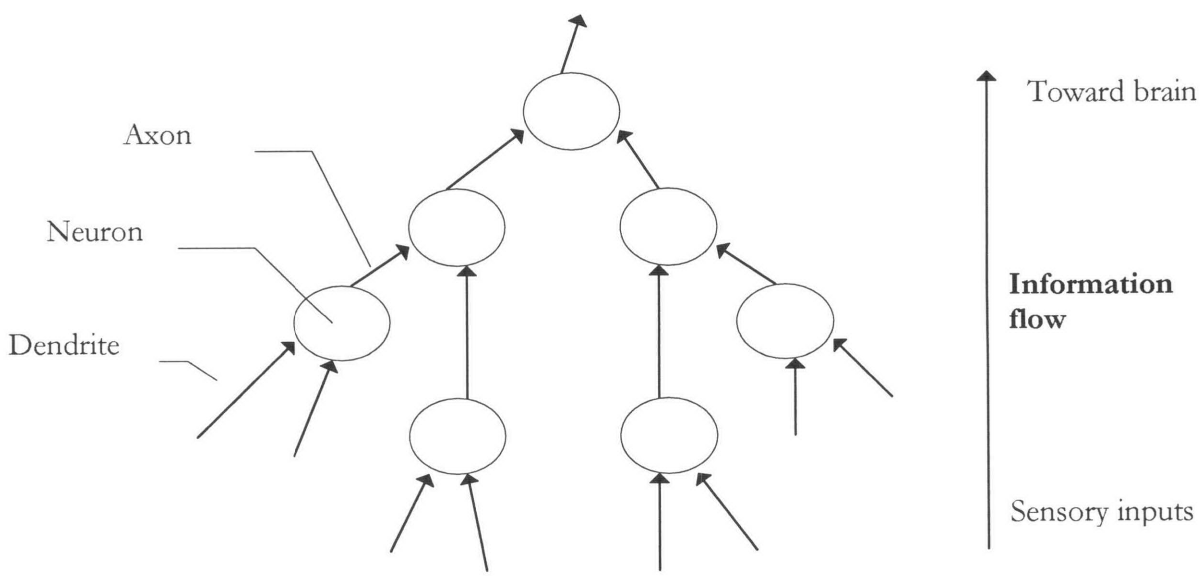


Figure 2: Idealized version of neural connections

4.2 ARTIFICIAL NEURAL NETWORKS

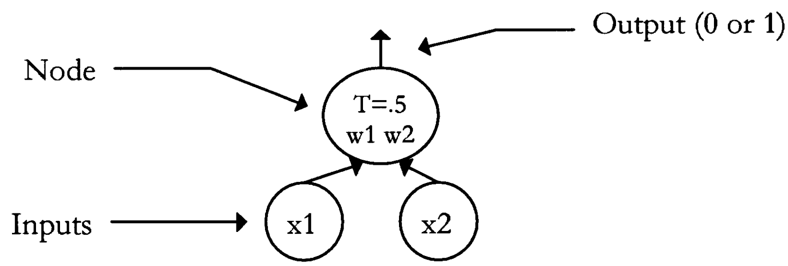
4.2.1 NETWORK DESCRIPTION

The artificial, or computer-based neural network began as a result of a paper written in 1943 by Warren McCulloch and Walter Pitts. The topic of the paper was a new kind of reasoning system, one that consisted of units that turn their output on (1) or off (0) based upon whether or not the sum of the inputs was beyond a certain threshold level. Such a system, they claimed, would be able to model literally any function, provided it had enough of these *nodes* [6]. The nodes were to be arranged in tree fashion, where the data to be fed the network entered through lines at the "bottom," or wide unconnected end, of the system, and some sort of decision based on that data would emerge from one or more nodes at the top of the structure.

The power of the neural networks comes from the adjustment of the *thresholds* and *weights* of each node's input. The threshold, as already described, is the point at which the node "turns on." It is also important to note the output of a node is a binary decision—it is either turned on or off, with no in-between. Likewise, the strength or intensity of the output of a node does not vary—just like a real neuron. However, these outputs have operations performed on them by other nodes. Each node, in addition to bearing a threshold, also assigns a weight to every input before the threshold level is calculated, a process that imparts an importance to particular inputs. This permits the neural network to look for patterns in the data, rather than the values of each variable trying to be analyzed. By examining the node values in a successful network, one can conceivably recover which values in the input are the most important, and perhaps use that information for a business advantage.

Consider the task of trying to reproduce the Boolean AND function. Such a function has a direct application to the business world: if two inputs are true, then a certain condition registers as true. That is, the function returns true if and only if both inputs are true. The modification here is that in the real world (as opposed to a mathematical world on paper), there are seldom 1's and 0's. Instead, there are threshold values: a value that defines the border between true or false. For demonstration purposes, the threshold will be set to 0.5—anything above or equal to 0.5 is construed as true, and anything below is false. In this case, a single neural network node is capable of simulating the function [Figure 3].

In addition to setting thresholds capable of mimicking functions, the structure of the neural network also serves prediction. In more complicated functions, the network must be more complex, bearing extra nodes and connections. Within the network will lie what is referred to as a *hidden layer*: a layer of nodes not connected to either the inputs or the outputs of the network. Instead, their connections are to other nodes exclusively. Often, the nodes in the hidden layer are connected to all the input nodes, with their purpose being monitoring the input data for patterns [Figure 4]. Conceivably, a particular node or set of nodes will fire only when a particular situation in the input data presents itself, and hence inform the output node(s) of the network that the situation is occurring and the predictions for output should be modified as such. If one were to go overboard with hidden nodes in the network, it is possible to have a hidden layer node per piece of input data that correctly stores the



Need: x1*w1 + x2*w2 < T for 00, 01, 10 and
x1*w1 + x2*w2 > T for 11
Potential values (w1, w2):
(.25, .25), (.3, .4), (.1, .45)

Or, if x1 and x2 are continuous, the potential weights still work, as long as x1,x2>.5 is a 1, x1,x2<.5 is a 0.

Figure 3

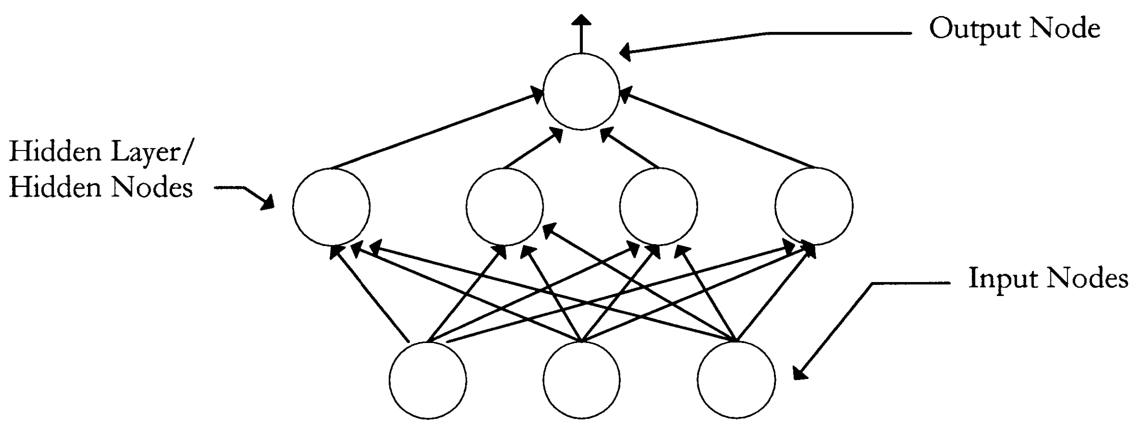


Figure 4

output of that case of data, thus reproducing the training data perfectly. However, given the computing power needed to run neural networks and that many networks are trained with several hundreds or thousands of test data, adding a node per input data would make the network excessively large.

4.2.2 TRAINING

While McCulloch's paper described a seemingly excellent pattern recognition system, it offered little advice on how to obtain the weights and thresholds of the nodes. For a time, neural network theorists were constrained to simple algorithms (for simple networks) or hand-tweaking, until the backpropagation algorithm found its way into the field. Backpropagation is a training algorithm readily implemented on neural networks that seeks to minimize the error between the input to the network, the network's output, and what the output should be [6]. This error is then distributed across the network to form corrections that both keep the pre-existing underlying numerical structure of the network and minimize the network's error in classifying the system inputs.

Foregoing in-depth discussion of the various learning algorithms available since the topic of this paper is the application of neural networks, it still remains clear that neural networks do not work spontaneously. Learning in neural networks has the same need people trying to learn need: history. When a person goes into a classroom, they are presented with the basics of a topic, how the topic can be applied, and some actual examples of application. Following this, the student is trusted to go out into the world and apply what they learned. The difference between people and neural networks is that neural networks skips right to the examples for its learning. For this reason, neural networks do not as much "learn" knowledge as much as they "store" knowledge. By being presented with several dozen or even thousands of pieces of data, and running a learning algorithm to minimize the error between the network's predictions and what occurred in real life, the system is expected to acquire the ability to categorize data it has never been presented with before. This is the goal of the neural network: to learn all it can from previous examples so that it can be used to make new guesses. Thus, one of the strengths of the neural network is defined: the network predictions are based on reality. It is easy for a sales manager to say sales will increase 10% if an action is taken, but by incorporating that action into the neural network's predictions, history-supported evidence to that assertion can be presented. Even more importantly, a complete understanding of whatever system is being modeled is not necessary. The neural network does not care if the predictions are a function of a single variable or many variables in differing patterns—it only predicts.

The training of neural networks requires two things. First, there must be a reasonable data-to-prediction ratio. A neural network, like any system, cannot be expected to produce respectable results unless sufficient training data is presented. Most training inventory data sets can be divided into some sort of discrete unit in time, and it is this data element that must have more than one training data element to its period. For instance, if the data given in weeks, and one wishes to make a prediction for week 42, it would be beneficial if there were other week 42 predictions from earlier years in the training data. There is also a greater advantage to using more training data: predicting week 42 would conceivably be easier if there were more than 1 or 2 week 42's included in the training data. While a neural network *can* make a prediction about a time period it has not been trained with, it is akin to asking a person what will happen next in a series without letting them know what happened the last time the period happened.

Second, the data presented to the neural network must be accurate. As seen previously in the veterinary hospital example, having data stored on the computer does not mean the numbers are an accurate representation of what actually happens. For this reason, it is beneficial some sort of *data validation* take place. For instance, if a warehouse inventory computer says it shipped 10,000 units of product in the last month, obtaining invoices from each of the groups the warehouse distributed to and adding the totals up would be one way to verify the truth of the data. If the two numbers do not agree, then there is clearly some force other than consumer demand driving the inventory reduction. With that in mind, the error of attempting to model inventory needs based on an incomplete set of needs fulfillment quickly becomes evident. The need for accurate data has a very simple human parallel: if someone is taught with the wrong information, they cannot be trusted to make extrapolations with their learning.

4.2.3 ACCURACY

The accuracy of a neural network's evaluations can be readily analyzed with three techniques [2]. The first, the Pearson Correlation Coefficient measures how accurately the predicted outcome for a dataset matches the actual values, in terms of fit (i.e. bumps and valleys matching). Second, the Normalized Mean Square Error measures the accuracy of the means of the validation data versus the predicted means. Third, and finally, the Absolute Error measures the difference between the actual and expected value of the outputs in terms of a percentage of the actual value.

4.2.4 APPLICATION TO DATA MINING

A key element trying to be accomplished with data mining is the universality of the prediction model being created. A neural network, while trainable to recognize an event that occurs rarely, is not always optimal. By storing information about infrequent events, the neural network has extraneous information in it regarding only a very tiny percentage of its training scenarios. Such information can often lead to erroneous results (since said event occurs so infrequently). There is, however, a technique that attempts to remedy the over-storage problem. By carrying through the tree metaphor on the neural network, one can employ pruning. By training the network with what appears to be an excess of information, one can then observe the weights assigned to various inputs by the various nodes, looking for input information that is frequently given lower-than-average weight. Since these pieces of information appear to produce little more than noise in the output, one can simply eliminate them altogether. This pruning of the weak branch reduces the complexity of the tree, reduces the training data necessary to create the weights and thresholds, and reduces training time since many nodes will have less information to process.

Once preliminary tree pruning has taken place, and the data desired to be trained upon has been acquired, one can begin the actual data mining. Data mining is a computer process, as humans would find it difficult to understand the underlying complexities of such a large system [3]. In the case of this paper, this step will be implemented with artificial neural network technology, since sequential and temporal problems are well-suited for neural network analysis [4]. The final consideration to take into account before network training begins is the decision on which type of neural network to use. There are several dozen varieties, but three types stand out in their applicability to inventory states. The first is the Multi-Layer Perceptron (MLP) network. This is one of the simplest and most elegant ways to construct a neural network. In fact, when one sees a picture of a neural network, it is generally an MLP [as in Figure 4]. It consists simply of layers of nodes, with one or more inputs and one or more outputs, and some number of hidden layers in between. Most importantly, information only flows in one direction: output information of a node always goes to another node above it in the tree, and never back into itself or one of its predecessors.

The second type of neural network, the recurrent network, shows promise at catch inventory trends. The contrast between a MLP and recurrent networks is that recurrent networks are allowed to have information propagate backwards in the tree, often back into the node the output came from, thus creating a feedback loop. The usefulness of this kind of network is that if a node, via looking at its own previous output value, sees that the value was higher than normal, it can construe that an upward trend is taking place, and should adjust this training cycle's output accordingly.

The third network that shows promise for inventory problems is the time-delay neural network. In essence, this type of network runs on a clock, and either presumes all the input data is coming in the order it actually occurred, or makes its predictions based upon some user-defined time cycle (for instance, a user can tell the network that every six inputs represents a new cycle). The strength of this system is that it is specifically designed for picking up temporal patterns in the data, and therefore make more accurate predictions because of them (presuming they exist). Time-lag neural networks may also resemble recurrent networks on a timer. Instead of a feedback node getting the information about its previous state right away, data can be held in a buffer until some user- or computer-defined wait period has passed, allowing the node to look not at the data that just occurred, but at the data that happened last month or last year.

It may take several attempts to find the optimal network type and variations that best model the data, but once this decision has been made, one can start training the chosen network. This is easily implemented by some batch training system, where one programs the computer to take the first data set, train the first network, save it, and move on to the next network, etc. Post-network creation, it would also be wise to have the batch running process run some validation data through the network.

5.0 CASE STUDIES

5.1 SUPPLY SIDE

5.1.1 MEDICORP BACKGROUND

Medicorp is a chain of retail stores that exists in several states and grosses several billions of dollars a year. However, the cost of producing that much income comes at the price of maintaining a billion dollar inventory. The need was justified, since as a retail store, they have a very diverse group of consumers (the general public), and if they wished to be able to satisfy the majority of that group, large inventories are required. Also, Medicorp is a distributor with many competitors, so not having someone's needs in stock means lost business to another store, since if a consumer needed a drug it is not likely they would wait a few days for it to be in stock. Also, as stated in the description of medical inventory problems, Medicorp realized the losses it suffered when merchandise expired on store or warehouse shelves.

The medical inventory of Medicorp provides an excellent model to exercise neural network experimentation on. Not only do they market and sell pharmaceutical services, but they also sell over-the-counter medicines This permits analysis of their inventory needs in two ways.

First, in selling over-the-counter medications Medicorp resembles other typical retail stores in that it is simply reselling a manufacturer's product to the masses. As stated, since pharmaceutical inventory is subject to expiration, it must be replaced periodically, as would a grocery store with its food. Serving the public introduces an element of needing to supply random need, which raises the amount of inventory. Also, from a practical angle, one element of just-in-time (JIT) delivery of drugs is that retail stores, for display purposes, have to put more stock out on the shelves than will be sold that period. For instance, if the expectation for Brand X of cough medicine is three bottles that cycle, more will likely be put on the shelves since a mere three bottles is not very aesthetically pleasing. Putting too few of an item on a shelf gives the appearance that a store is almost out of the product, not that they only expect 3 bottles to be sold. So, in the case of retail stores with on-the-shelf merchandise, there will always be discrepancy between how many units are orders versus how many were actually purchased (as traceable through bar-codes, etc.). As further evidence of this point, one of the discoveries of this investigation will be mentioned here early: using neural network technology, Medicorp would be able to halve its standing inventory. Such facts do not translate well to the retail store arena. A half-full store lacks visual appeal. Moving to a smaller store and putting only the necessary inventory on shelves would be too crowded. Such factors must be considered when supplying a retail store.

In the second form of possible analysis, one exploits that Medicorp is also a pharmacy and must fill prescriptions. Where a consumer at the retail level has a variety of OTC choices per ailment, a pharmacy must stock the exact drug the doctor prescribed. Failure to do so will result in the pharmaceutical order being sent to another store, and thus representing lost income. There is also a tendency to receive follow-up refills from the same store that filled the original prescription, meaning that income is lost as well, not even mentioning whatever other items the customer may purchase in the store as a simple matter of convenience. The high need to match specific prescription orders places a burden on the pharmacy to have extensive supplies of many types of drugs if they wish to satisfy the majority of the clients that request service. There is, however, the benefit that the medicines are stored behind the counter, where the customer can never see what the pharmacy's stock levels look like, and thus cannot draw any negative conclusions JIT delivery of drugs might lead one to form.

5.1.2 SETUP

The project group constructed the neural network analysis using a freeware product called SNNS 4.0, a choice likely made because of its free status and its ability to run on the UNIX platform. As there is no standard way to determine which network type is best suited to a particular input situation, several dozen networks need to be produced per prediction item so that the best network type can be evaluated. Instead of coding each one of these network types and variations of such by hand, SNNS includes a feature called *batchman*, which automates the generation of neural networks.

The next issue to be dealt with was the decision on how big of a time slice to use for training and how much will be predicted. There were several factors to consider in this decision, both from a business perspective and from an analytical one. Having few datapoints, such as would be the case if training and predictions were in terms of months (only twelve points per year) means there are fewer cases to train on, which in turn affects the accuracy of the network. Using too many datapoints, as with daily inputs, introduces a considerable amount of noise into the training of the neural network, and is illogical from a business standpoint since having drugs being delivered daily is not always possible. Bearing this in mind, Medicorp asked for the prediction data to be oriented for a weekly delivery system. Their decision was also based on the observation that totals for longer periods of time tend to have increased accuracy than do short periods due to their increased sampling of input noise, which decreases the variability overall. Also, initial attempts to use multi-layer perceptron neural networks to predict daily need proved unsatisfactory [2].

The next situation to be dealt with involved which type of neural network to use, and which training algorithms to use in them. The three major network types tried were:

Multi-Layer Perceptron (MLP, or feed-forward): The most basic type of neural network. Consists simply of network inputs, hidden nodes, and an output layer. All information in an MLP network flows in one direction: from input to output.

Time Delay Neural Networks (TDNN): Networks of this type function the same way as MLP networks, except that the data is fed in sequentially and computed in a manner that preserves the temporal history of the data, thus adding "time" as an additional input parameter to compute with [2].

Recurrent Neural Networks (RNN): RNNs feature information flowing in both directions inside the neural network. During computation, some nodes store their output state and pass it back into themselves to be used the next time that node is trained, allowing a node to capture trends in that it knows what its previous answer was. Essentially, some nodes have information feedback[4].

Due to the sequential and potentially time-oriented nature of customer data, MLPs and TDNNs were the networks of primary analysis. Beyond network selection, several training algorithms were tried: Hebbian learning, backpropagation, momentum learning, time delay network learning, and topographic learning [2]. Exploration into Hebbian and topographic learning were discontinued due to poor initial results.

5.1.3 RESULTS

In a business application such as Medicorp, there is one way to evaluate the performance of a research endeavor: test it against the models currently in use. Medicorp's supply rules were simple: minimize overshoot of stock while being able to satisfy 95% of the customers. At the time of the article's writing, Medicorp used an easy-to-implement 3 week supply rule to keep its stores and warehouses stocked. This, however, is not an optimal method to minimize inventory.

The advantages of the neural network were pitted against the predictive capacities of a flat-sales model as a means of determining neural networks' strengths. To be effective, both models had to introduce the concept of days-of-supply [2]. Needing a universal language to put the inventory levels, measured in grams, pills, and milliliters does not lend itself well to either analysis or prediction. What is more important to the drug supplier is how many often a customer will come into the store to buy their medicine, which in turn is determined by how many days pass between initial purchase and secondary purchase—hence, days of supply. As planned, days-of-supply let the details of measurement units take a back seat to the real information Medicorp wanted: how often will people come back to the store, which in turn answers how much supply to keep on-hand.

The results for prediction capacities of both models on slow-moving drugs showed MLP neural networks the winner, suggesting that the forecasting ability of the neural network to be much more powerful and diverse than the flat inventory model. The potential problem in the flat inventory model is that it overgeneralizes the data from the year used to train it, expecting the testing year's data to resemble the training year's, and expecting the distribution of that expectation to be equal within the timeframe computed. A neural network's capacity for identifying patterns in the input allowed it to generate inventory requirements within the 95% customer satisfaction rate required, as well as lowering the standing inventory (in terms of days-of-supply) by 66%.

5.2 DEMAND SIDE

5.2.1 PROJECT DESCRIPTION

Whereas the first example presented dealt with meeting the supplier-side demands of Medicorp, a consumer-oriented example is now explored. Where Medicorp had to supply the general public with pharmaceutical inventory and model the data, a consumer of Medicorp's goods had to model their need for goods from all vendors. This organization was the United States government, perhaps the largest single consumer organization in the US. A group at the Productivity from Information Technology Initiative at the Sloan School of Management at MIT was charged with analyzing the pharmaceutical needs of the government, including Medicare distributions, VA hospitals, and the military. The goal of the project was to produce ways in which the government could optimize it drug delivery to customers while at the same time streamlining the delivery system and minimizing inventory.

5.2.2 PROJECT BACKGROUND

The United States government has its own medical procurement and distribution system, as do retail drug stores. However, whereas commercial retail distributors have to market to the general public, the government has very specific target audiences. Namely, the government has the responsibility of supplying its agencies, including the Medicare health system, Veterans' Administration (VA) hospitals, and the various military organizations. Each of these are consumers and suppliers of medical necessities, with the emphasis placed on consumerism. Since the agencies are meant to have the medicine locally, they can best be thought of as a consumer—much like an individual buying drugs for home, so that they are immediately on hand when needed. A major agency in this field is the Defense Personnel Supply Center (DPSC), which serves primarily the military, but also serves other agencies since it already has the type of infrastructure needed for medicine dispersal.

The primary thrust of this exercise was to develop a needs model for various military contingencies, so that the Defense Department would be better able to serve their forces. Each type of military operation has its own variables which increase the complexity of trying to model the situation. The Vietnam war, Korean war, Desert Storm, and the missions to Croatia and Somalia all have different medical needs since they all occurred in different environments and for different missions. For instance, the Somalia mission was a peacekeeping and humanitarian mission, which should mean a lower occurrence of combat injuries and greater use of vaccinations (since aiding health was part of the humanitarian mission) and non-combat medical treatment. Desert Storm and the Vietnam war have the difference of the first taking place in a desert and the second in a jungle. Environmental and mission variations are responsible for the unique medical needs of every mission, and if optimum field support is to be provided, these factors must be considered when planning how much medicine will be needed. This is where the plausibility of neural network technology came into play. By including environmental and mission parameters in the training data, the neural network would learn not only how much medicine is needed between reorder points, but also tailor those predictions to the specific case being examined. Should another desert/attack military situation arise, if the neural network training had included data from Desert Storm, a viable need prediction could be made.

In addition to anticipating the neural network analysis to aid in needs prediction, the government was hoping for inventory modeling optimizations of the nature Medicorp experienced. The government is a consumer of medical inventory, and has to hold its own inventory in its warehouses. Government operations have a set of vendors from which they order their supplies on a periodic basis, either on time-based ordering (ordering x items every y weeks) or by the achievement of a reorder point. In either case, the government is responsible both in peacetime and war in supplying their people with medicine. In peacetime, the government resembles any other large retail distributor, though with a somewhat less broad consumer group than the general public. In war, however, the normal importance of not undershooting a medical inventory gets increased several times. When a soldier is injured on the battlefield, making sure that they get the treatment they need is in everyone's best interest—the soldier's, of course, and the military since a soldier could be fighting if not ill or may be a liability unless they can take care of themselves. If there is not the proper amount of medicine available to the injured person, their life genuinely hangs in the balance. In a pharmacy, the patient has the opportunity, however inconvenient, to go to another store. Such is not the case in a battleship, bivouac, or even some bases.

5.2.3 RESULTS

The data available to train the neural networks with turned out to be sparse, and provides a good example of what happens when this is the case. The data received contained monthly information for only 24 months, which raises two kinds of problems. First, a month is long time for variables to affect an inventory. There was no information available about how many patients were served in this month, if the numbers were simply monthly inventory levels, whether 30 days had actually passed between readings, etc. All the Initiative was provided with were drug numbers, names, and 24 monthly readings of unknown parameters.

In an attempt to continue and see what could be observed from these numbers, MLP and TD neural networks were produced. Neither method with the data in the form it was could produce a Normalized Mean Standard Error (NMSE) significantly less than 1.0. A NMSE of 0 means on average, the network perfectly matched the actual data, while a 1.0 or more means the data and predictions did not match, as though one were comparing the predictions to random numbers. Ideally, the closer to 0 the validation tests get, the better the network is. Initially, neither network could produce quality results.

To demonstrate the effects of more detailed input information, some liberties were taken with the data. First, there was data with duplicate drug names and numbers in it, but different inventory levels. These were assumed to be cumulative, as though the measurements came from different government warehouses and the task was to predict the total need of the drug to the entire system. Second, instead of using the supplied month information, which ranged from Month 1 to Month 24, the assumption was made that the information represented contiguous months. On that assumption, the month input was rewritten to vary from 1 to 12, and a year input was added, which ranged from 1 to 2. The first 20 months in this fashion were used to train a time-delay neural network, in the hopes that it could pick up any temporal patterns that existed in the data. These assumption yielded some improvement, generating a NMSE of .7-.8, which meant the neural network was producing somewhat better than random matches to the actual data.

5.3 BENEFITS TO MILITARY ORDERING PROBLEMS

5.3.1 SIMILARITIES TO RETAIL DISTRIBUTIONS

The military pharmaceutical distribution system bears a striking similarity to retail distribution systems. The Defense Logistics Agency (DLA) is the military's combat support backbone, whose purpose is to make sure military personnel around the world have the resources they need. This highest level of supplying goods is analogous to a parent company owning one of the many popular pharmaceutical retailers. Continuing the analogy to a civilian retail organization, if the DLA is a parent company, then the Defense Supply Center Philadelphia (DSCP, formerly known as DPSC) is the company of interest. The DSCP in this analogy is the pharmaceutical distribution agency, such as Walgreens, CVS, Rite Aid, Medicine Shoppe, or Drug Emporium. Each of these companies, and the DSCP is a distributor of pharmaceutical goods to a customer.

Carrying the metaphor further, it does not make sense to have a single agency location attempting to fill the needs of a customer. Thus, various distribution channels are needed. In the case of the retail organizations, each of these channels would be a store. For the DSCP, the channels, or outlets, are domestically and internationally dispersed warehouses that fill needs in the region. At this point, consumers of the goods in the outlets (or stores) finally are able to purchase goods. Where the retail stores have to fill orders from doctors and the public in general, the DSCP outlets have to fill the needs of VA hospitals, Medicare recipients, and field soldiers. In peacetime, the DLA-DSCP-outlet-customer chain resembles a retail distribution almost perfectly. However, in times of war, the needs of the system quickly need to be remodeled to fill the new variety of injuries expected.

5.3.2 INVENTORY TURNOVER

The similarity of the military pharmaceutical distribution chain in peacetime resembles the retail chain so much that it makes sense to model it in the same manner. This includes subjecting it to the same modifications that are improving the performance in retail distributors of the same goods. The DSCP annually purchases over $3.4 billion worth of inventory [15], and sells $1.03 billion worth of medical supplies and equipment [16]. A more important indicator of inventory management practices than yearly sales is the *turnover ratio*. Also called a sales to inventory ratio, it is a number that represents the number of times per year are bought and sold out. The ratio is computed by dividing the sales for a year by the inventory dollar amount. The higher the number, the more times the inventory is being sold out and replenished. Thus, in the world of pharmaceuticals, having a turnover rate as high as possible reduces the potential of a drug expiring on the shelf. The reported turnover ratio for fiscal year 1996 of the DSCP's medical goods was 4.2.

As a simple comparison of the improvements brought about by better inventory management, Schein Pharmaceutical Inc. boosted the turnover ratios of the pharmacies at H.E.B Grocery Co. and Giant Food Inc. from 5.9 and 16, respectively, to ~25 and 23 [17]. Walgreen's turnover ratio in 1997 was:

$$\frac{\text{Cost of sales (millions): } 9682}{\text{Inventories(millions): } 1733} = 5.6 \text{ [18]}$$

For Drug Emporium, the cost of sales was not available, but an upper bound on their turnover ratio can be computed by dividing their net sales by the cost of inventory:

$$\frac{\$855016 \text{ (thousand)}}{\$208991} = 4.1 \text{ [19]}$$

Rite Aid's cost of sales and inventory on-hand were both available:

$$\frac{\$5113047 \text{ (thousand)}}{\$2336659} = 2.2 \text{ [20]}$$

Comparing the DSCP's inventory turnover ratio to those of the leading drug stores in the country, the government is doing well. However, doing well is not an excuse for not doing better. If the DLA used the neural networks techniques implemented by the group studying Medicorp, and met with the same success (50% reduction of inventory), the 4.2 turnover ratio would quickly rise to 8.4, ideally. Assuming even a 30% reduction of inventory would place its ratio at the top of this list (5.7). Should the application of data mining and neural networks techniques raise the turnover ratio to the levels now enjoyed by the clients of Schein Pharmaceuticals, the military's drug distribution chain could easily be the largest, most effective in the nation. Some areas of the military are already implementing plans to optimize their inventories to market demand. For instance, the Air Force's optimizations have decreased inventories at certain distribution facility warehouses by more than $1 million, and is generating inventory turnover rates in excess of 24 per year [24].

Part of the optimization implemented by the Air Force and other government distribution channels is the use of the Prime Vendor Program. One of the targets of the Prime Vendor program inventory replenishment. The government sets up agreements with wholesale pharmaceutical distributors in the region being serviced to supply orders of certain drugs quickly—next day service in the case of the Air Force. Having next-day refill available allows a pharmacy to carry minimal inventory, as anything that runs out can be replenished the next day.

6.0 CONCLUSIONS

6.1 USEFULNESS

In available literature neural networks have proven their ability time and time again. They excel at picking up difficult patterns, classifying events, making predictions based on historical patterns, and routinely beat numerical analysis. The weaknesses of other prediction methods comes from their limitations in terms of number of variables to base their calculations on. Their rigidity and simplicity of explanation curtails their ability to match the power of the neural networks. Neural networks are a fluid computation device—they simply model the data without question as to linear and exponential elements, continuous or discrete elements, or time and history. Neural networks do not "know" nor care if a simple function models the input, it merely observes the data and produces something that works.

This document only shows the latest example of how the benefits of neural networks can be applied to a specialized field. Areas of expansion of the topics presented are numerous: grocery stores have to keep a perishable supply of goods on-hand, and be in-stock with what their customers need. Doctor scheduling is also sensitive to over- and under-staffing concerns: have too few doctors available and people will have to wait longer for care. Having too many doctors present in a lost investment, as they are being paid to wait.

Neural networks have the potential to be applied to any problem having large amounts of previous data to examine and no reasonable way for a person to visualize that data in a way that can be useful to a company. As stated, neural networks excel in areas the mind has difficulty with. Given the ready and cost-effective storage that has been available the past several years, nearly any business based on transactions of goods for money falls into this category. The existence of regular transactions means there is a customer, and in most cases the customer is human, subject to the unpredictable variables that control the life of a human. Given that the customer is human, then it is reasonable to assume that demand for whatever service caused the transaction is not a constant, and therefore must be predicted if the supplier of that service wishes to minimize their costs. Thus, nearly all retail stores, grocery stores, manufacturers, distributors, and rental services all fit this need. Among people who frequent video rental stores, who has not gone to the store only to find their desired movie not there? If the customer satisfaction rate could be brought to the levels Medicorp was, people may be more inclined to go.

6.2 LIMITATIONS

Neural networks are not without their faults, despite what this paper, commercial products, and data mining companies might lead a business owner to believe. Unfortunately, their main strength is also their primary weakness: they rely on history. Training neural networks with historical data is a great concept, unless there is no data to train with. Thus, the weakness of neural networks is revealed: they have great difficulty predicting anything new. Neural networks are machines that model the past, meaning without a past, they are helpless. The analogy to human learning holds: a human being can learn English and use it perfectly for a great deal of time, but when someone is presented with a word that has no context or roots they recognize, they are helpless to use it effectively. The analogue in the medical inventory world would be the introduction of a new product. Without adequate history to train the neural network with, accurate predictions will not be possible. The best one could achieve would involve some sort of analysis of the introduction of a similar product to market, market surveys, and media popularity.

Neural networks are also limited by their need for computational power. Given the time it takes to configure and run several dozen neural network simulations, and the effort that goes into the tuning of each one, producing a neural network for each of the 10,000+ potential drugs a distributor may have to supply may prove too daunting a task. The computational cycles and storage requirements may also not be available either, as the overwhelming majority of the world does not have the latest machinery. This limits use of neural networks only to those with money to invest or already invested in high-powered computer if they want the job done in a reasonable amount of time. However, for companies whose inventories are only a few dozen or possibly hundred items, neural network analysis of inventory needs may be a wise idea.

6.3 FUTURE OF NEURAL NETWORKS

The future of neural networks appears excellent thanks to the increasing storage capacities and speeds of hard drives, as well as the ever-increasing processor and bus speeds. These two elements of technological development allow more information to be processed in less time. Given the storage and computing power needed to create neural networks, every step in computer evolution makes neural networks increasingly practical. In fact, the computer industry may even profit from utilizing neural network training speeds as benchmarks—a true test of a computer's power. Computers spend most of their time waiting for their users to give them input, so despite all the increasing power, users are not necessarily taking advantage of all of it. Neural networks, on the other hand, are programs that are computationally heavy by design, and can benefit greatly. Advances in processor power, memory speed and size, and motherboard bus design will all aid in getting the calculations completed sooner.

Another boon to the neural network market is the hard drive industry, both in terms of permanent and portable drives. The bottleneck in the processor's performance is that the hard drive only delivers information to the memory at a much slower speed than the processor is capable of analyzing. Advances in hard drive technology are increasing this transfer speed on a continual basis, even hitting 80MB/s in Ultra SCSI-2 drives. This is still considerably slower than the processor can handle, but every speedup through that bottleneck makes neural network technologies more useful. Even drives with transportable disks are getting faster in their transmission to the computer they are attached to. The portability also adds a dynamic degree to the neural network system, as it provides an easy way to bring a neural network program more information to train with. And as mentioned several times before, more information can make a network more accurate.

6.4 FUTURE PROJECTS RECOMMENDATIONS

6.4.1 DATA FORMATS

There are two factors largely inhibiting the usage of neural networks in business on a day-to-day basis. The first of these has to do with the software implementation of the neural network training. Most commercial applications want the training data to be presented to it in a particular way, and this way may not always be the way the data was stored in the archives. For instance, it is not unusual for a neural network to desire each of its training elements to be complete data "concepts" within themselves—that is, each row of a spreadsheet represents an occurrence rather than a list of occurrences. Consider the case of the data received by MIT about the government's pharmaceutical needs. The data came in spreadsheet form, with multiple lines of the format (type 1):

Drug Number/Location/Month 1/Month 2/Month 3/...

If each line of data were to represent an occurrence rather than a list of occurrences, a more appropriate row would be (type 2):

Drug Number/Location/Week/Year/Inventory Level

with the line repeated per inventory level recorded. This, however, is not the most optimal listing in terms of disk storage. Whereas type 1 data needs only store d + n elements (d = number of describing attributes, n = number of inventory levels), type 2 needs to store (d+1 or more) * n elements. This case is worsened when one actually has an appropriate amount of data to train a neural network with—if one had two years' worth of weekly inventory data, the transition would have to be made from storing 2+104=106 elements to storing 5*104=520 elements, or nearly a 5-fold increase. Storing data in such a manner is clearly not optimal, though it is the way some neural networks would like to receive it.

The only way around this problem is with programming skill, either on the part of the artificial neural network software developer or a team whose job it is to make the conversions. Neural network programs written to take advantage of the way data is typically stored in files would give that software and the neural network industry a key advantage in generating more useful products. Otherwise, if software that matches the way an establishment already stored their data is not available, the people doing the neural network project will have to write programs that do the conversions for them, with the drawback of needing enough disk space to store the newly formatted data. The drawback to this approach, obviously, is the price of disk space and the extra work the firm that purchased the neural network software has to put into using it.

6.4.2 REDUCING COST OF COMPUTING

The other major factor preventing the widespread use of neural networks is they are computationally expensive, and in order to get them done in a reasonable amount of time, the latest in computing technology is often needed. This, of course, requires investment in new hardware as well as the investments in the neural network software and manpower to use them. There may, however, be a potential method of neural network computation that would involve almost no investment on the part of a business owner, and may perhaps be able to generate networks even faster and more robustly than the latest chip designs.

Neural networks are ideal for multiprocessor implementation. The calculations for each node in the hidden layers of network are independent of each other, and thus could conceivably each be assigned to a different processor to calculate. This way, a single processor would not need to traverse each node of the network, and each implementation of the backpropagation algorithm could be done in a few computation cycles rather than waiting for it do run those cycles for every node in the network. Thus the problem of running neural networks quickly becomes an issue of having access to a multiprocessor computer. Not every company has the money to invest in such an item. However, with a little creativity, they would not have to.

For the past few years there have been Internet-wide collaborative code-breaking efforts. People write programs that run during spare computing cycles (such as when a screensaver is running, or overnight, etc.) that attempt to find the key to unlock a DES, RC5, or other cryptographically encoded message. If one does, they win a cash prize. Since the use of only one computer is unlikely to find the key in the huge keyspace in one's lifetime, people have wrote collaborative programs. Instead of trying to find the key on their own, the programs check with some central Internet server to determine which keys have been checked thus far. Of the remaining keys available, the program then randomly picks a starting place and starts checking the keys from there on forward. When the program has completed checking a sequence of keys, it reports back to the central keyserver to mark the processed keys as checked, so that nobody else will waste their time on them. With this system, everyone working from the same keyserver is doing valuable work and not wasting time.

This model of operation can be implemented on a much smaller scale. A multiprocessor computer is a computer with more than one processor where each processor is in communication with the others and can perform calculations concurrently with each other. There is hence no need for these processors to all be in the same machine. In other words, any networked office can be considered a giant multiprocessor computer. There are as many processors as there are computers turned on, and all are in communication via Ethernet or whatever other protocol connects them together. Typically, in such systems, there is also some sort of central file server, where all common knowledge is stored, rather than each computer having to maintain copies of the same data. Not coincidentally, this is also the same place the records that would be used to train a neural network are stored: the fastest computer available with the most storage space.

Hence, a new potential model for neural network processing emerges. With zero hardware investment, a company can turn an existing office network into a multiprocessor neural network simulator. Each computer in the office would be responsible for computing the values for a single node, which would make each training epoch of the network get done considerably faster. The central file server would be "in charge," since it not only is (typically) the most powerful, but it also has the training data. In addition to completing neural network calculations considerably faster, following this method would also produce a higher return on investment in the computers. Being an office, the employees go home at night, during which time their computers are not being used. This time represents lost computational power that can never be recovered. By implementing this idea, the computers are working for the company *all the time*, not just when the user is there.

The strength of this idea is its fluidity. As a company grows, it will need more workers, and those workers will need more computers. Obviously, the more computers available, the neural network software would be able to produce more complex simulations quicker. This concept also cares little about what sorts of computers are in the office. If each computer is doing the calculations for only one node, the difference between an older Pentium-100 and a new Pentium-400 is negligible—they are only performing simple math functions and sending the results out on a network that can only run from 10-100 Megabits per second. As more and more newer computers and faster networks are introduced, the faster the network can be pushed. Thus, the use of the office network as a multiprocessor computer not only offers legacy value to the older computers in a company, but also will be valid in the future by its very nature.

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