NEURAL NET BASED BUSINESS FORECASTING: AN APPLICATION TO THE MUSIC INDUSTRY

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One of the major problems facing the music industry today concerns returned product. Predicting product return rates and quantities has been a challenge. The total industry wide estimate for product return exceeds $1 billion annually. A significant portion of this waste can be traced to relatively poor product forecasting. Recent developments in artificial intelligence (AI) techniques suggest that there is an opportunity to improve the predictive ability of business forecasts. The primary purposes of this study are twofold: 1) to introduce the use of neural nets as a simple and user friendly forecasting system and 2) to develop a prototype model for estimating product return and sales. The preliminary results show that a neural network can accurately predict product return over a wide range of sales and initial return volumes. The reported R-squares exceed 95%. The new generation in AI technologies holds considerable promise for improving forecasting in this dynamic business.

One of the major problems facing the music industry today concerns returned product. Typically, record distributors, as opposed to retailers, must take the brunt of the risk associated with new releases. Such programs under which this risk is shifted to the distributor will remain in place. The distributor, therefore, must find a way to manage this risk. Whether through advanced distribution systems, revamping of returns policy, or reducing the costs associated with returned product, distributors must take action. The music industry is making a shift toward advanced distribution systems that allow quick response product replenishment (Jeffrey, 1995). Under this type of system, product manufacturers are responsible for automatically replenishing inventory for their retail accounts, where they base their decisions on fast-moving computerized sales trend data. As a result of these trends and policies the amount of product that will ultimately be returned will diminish.

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Recently, Universal Music and Video Distribution set in motion a "groundbreaking new policy of supplying accounts a credit for unsold goods without requiring the physical return of the product.", (Christman, 1998). Universal is making all singles configurations, except for the CD-5, non-returnable. Accounts will now get a credit on such items from invoiced orders for the first 15 weeks of availability. Universal will charge accounts 18 cents for each unit processed for credit. This system is advantageous for Universal because it allows the company to avoid dealing with actual returned singles product.

Another way music distributors can deal with the onerous task of returns management is to construct a system under which the costs of returns handling are minimized. Such a system would reduce the amount of product that is refurbished and placed in inventory and increase the amount of product that is scrapped upon receipt. Record companies tend to be very conservative about scrapping product, not wanting to scrap something that may be in demand later. But what if later demand could be accurately forecasted? Record distributors could then scrap upon receipt that product which is not projected to sell, thus reducing the costs associated with refurbishing and storage. By what method could record distributors determine future demand for its releases?

Operations management decision support systems (DSS) encompass computer programs designed to help improve the decision-making process. Typically, the problem-solving strategy differs between systems which necessitates different methodologies. Artificial neural nets (ANNs), Bayesian nets, decision trees, statistical based models, pattern recognition, rule-based and hybrid systems are some examples of methodologies (Slater, 1993).. These models are used in conjunction with historical data to identify and evaluate decision options and to predict future performance.

Specific benefits associated with computer based DSSs, as related to product forecasting applications, include:

- Improving the accuracy of sales forecasting.
- Enhancing the reliability of product return decision-making.
- Designing optimal inventory and replacement policies.
- Strengthening the use of modern management systems throughout the organization.

Artificial neural nets (ANNs) have found widespread acceptance throughout business and government (Perry, 1994). In the arena of forecasting, ANNs have emerged as a significant forecasting tool (Poli, 1995; Annsuj, 1996). More specifically, ANNs are being used extensively in improving market targeting at all levels (King, 1992; Venugopal ,1994). ANNs are a branch of artificial intelligence that address the problem of forecasting by simulating the biological neural network found in the human brain (Hample 1996). This study evaluated the effectiveness of an ANN for generating accurate product sales and return forecasts.

DISCUSSION

Problem Statement

The problem of unnecessary product refurbishment can be addressed by using ANNs to analyze a database of unit sales and returns information. The pilot database consists of approximately 150 CD selections released in 1996 from a major distributor. For each product selection, 12 months of sales and returns data has been collected. The primary focus of the analysis was to develop forecasts for:

- Annual sales based on data from the first few months of product release.
- Annual product returns levels based on data from the first few months of release.

The development of accurate annual sales and product return forecasts would significantly improve cost management, including the design of criteria under which product selections can be designated as "scrap upon receipt". Table 1 provides a summary of the input factors considered for this study.

Table 1 Summary of Input Factors

Input Factor	Variable Type	Min Value	Max Value	Mean
1^{st} Month Sales	**Continuous**	**44,258**	**2,214,393**	**175,834**
Popular Music	**Dummy**	**0**	**1**	**0.50**
Country Music	**Dummy**	**0**	**1**	**0.15**
Ratio 3^{rd} to 2^{nd} Sales	**Continuous**	**0.01**	**1.97**	**0.50**
otal Returns After 3 mo.	**Continuous**	**16**	**21,987**	**2,497**
otal Returns After 6 mo.	**Continuous**	**510**	**73,698**	**14,228**

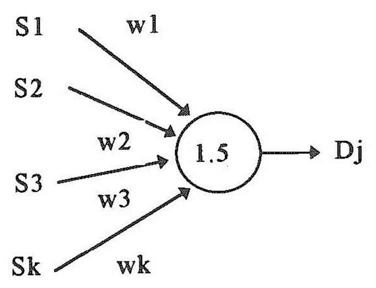
For example, this data show that the average of 1^{st} month sales was 175,834 units, which amounted to approximately two-thirds of the total unit sales for the year. This large proportion suggests the potential that highly accurate annual forecasts can be developed. Interestingly, sales declined about 50% from the second to third month. Furthermore, about 50% of the product database was popular music and 15% was country music.

NEURAL NETS

First proposed in 1947, ANNs use nonlinear equations to mimic the connections between sets of data. ANNs have been touted as the ideal model for non-linear applications (Ajlumi, 1995). Among other things, ANNs have the advantage of not requiring a prior assumptions about possible relations as is the case with standard regression analysis (Foster, 1997). The architecture of an ANN consists, at a minimum, of two layers: an input neuron or neuron layer and an output neuron. There may also be one or more intermediate or "hidden" layers of neurons. It is these hidden layers of neurons and the complexity of the interconnections that increase the computational power of ANN.

Neural networks can employ a feed-back (back propagation) or a feed-forward architecture. Several subsets of these main types are available, including: probabilistic neural network, general regression network, self organizing maps, and neural networks employing genetic algorithms. In the most common schema, each neuron in one layer is connected to each neuron in the layer above it as shown in Figure 1.

Figure 1 Example Predictive Neural Net



Sk = input states (e.g., symptoms, pre-conditions), wk = weights, Dj = Return state

In this example, the prediction of product return (Dj) is derived as a function of input states and a set of weights. The values for the input states may come from the activation of other neurons or specific environmental factors, e.g., age. The example numerical value inside the node represents the threshold value for firing or activating the neuron. In this case, if the sum of the weights exceeds 1.5 then the neuron is "fired" which suggests a certain level of product return. The values for the weights are determined through an iterative process wherein the goal is to minimize the system error. Typically, a portion of the data base is used to train the neural net and the remaining data is used for predictive or forecasting purposes. In general, the input values can be either discrete , e.g., 0=not popular music, 1=popular music, or continuous, e.g., 1st month sales. .

Compared to many other network-type DSSs, e.g., Bayesian net, an ANN approach has a distinct advantage in terms of defining the structural relationship since a complex influence diagram is not required. Furthermore, the size of the required database can be significantly smaller for an ANN especially if a large number of discrete factors are involved. ANNs also hold a similar advantage over traditional regression techniques (linear and non-linear systems) in their relative easy of use. This is particular the case for non-linear regression designs where model specifications are required. The easy of use is an important consideration when introducing analytical forecasting into the management process. However, neural nets are basically a black box and offer little if any insight into possible causal relationships which is of considerable interest in forecasting (Rodriguez, 1994).

RESULTS

The database was analyzed using NeuralShell Easy Predictor, by the Ward Group. This neural system is one of several that is currently available in the market (Machrone, 1995, Etberudge, 1994). A standard stepwise multiple regression analysis also was conducted on the data set as a basis for comparison with the neural net analysis. A more complex non-linear regression model could have been used which could have matched the performance of the neural net. However, this would have tended to negate one of the primary purposes of the paper -- namely the capacity of providing the manager with a simple and user friendly forecasting system. The testing database consisted of 133 observations. A "hold-out" group of ten observations was set aside for comparative analysis between the two analytical approaches. The two dependent variables examined were 1) annual sales (units) and 2) annual product return (units). Table 2 presents the statistically significant results of the multiple regression analysis at the 0.05 level where the dependent variable is annual sales.

Table 2 Multiple Regression Analysis of Annual Sales

Variable	Beta
1st month sales	**0.919**
Popular music	**-0.70**
Constant	**-**

Not surprisingly 1st month sales is the dominant variable in the model. Interestingly, popular music products tend to yield lower sales results compared with non-popular music products. Table 3 shows the statistically significant results of the regression analysis at the 0.05 level where annual product return is the dependent variable. Again, 1st months sales is statistically significant, however, the dominant variable, as measured by the standardized betas, is six months product return. This is not surprising since six month product returns constitute nearly 38% of total returns while three month returns account for less than 7% of total annual returns. This result suggests that, unlike the sales forecasts, more monthly observations are need to make an accurate forecast of annual product return.

Table 3 Multiple Regression Analysis of Annual Product Return

Variable	Beta
1st month sales	**0.207**
Ratio 3rd to 2nd sales	**0.091**
6th mo. Returns	**0.747**
Constant	-

The NeuralShell Easy Predictor model was run using the same database. The reported R^2 for the regression analysis are adjusted for sample size. Table 4 shows a comparison of model performance between the two methods for the sales forecast application. The neural net yielded a larger R^2 for both the "in-sample" or model case and the "hold-out" or forecast case. Again, the "hold-out" case consisted of ten observations that were randomly sampled from the original database.

Table 4 Annual Sales Forecast Comparison

Model	Model R^2	Forecast R^2
Neural Net	**0.88**	**0.97**
Regression	**0.84**	**0.94**

Similar results were also obtained for the product return analysis data as reported in Table 5. The neural net mode was based on the three-month product return while the regression model used the six-month return. Interestingly, the ANN was less efficient with variable values that were significantly outside the general trend of the data. This was particularly the case for the variable involving the ratio of 3rd month sales to 2nd month sales.

Table 5 Annual Product Return Forecast Comparison.

Model	Model R^2	Forecast R^2
Neural Net	**0.89**	**0.98**
Regression	**0.76**	**0.86**

CONCLUSION

The purpose of this paper was to examine the feasibility of using neural nets to help shape product return policies and improve cost management. The preliminary results are encouraging. The neural net "out performed" the standard regression model in both applications. The fact that the net was able to accurately predict product return levels based on only the first three months of data is extremely encouraging. Furthermore, the neural net is not constrained by the assumptions associated with regression analysis and is considerably easier to use. Ease of use is a very important factor if analytical forecasting methods are going to be effectively integrated into the management process. One downside, of course, is that the ANN appears to the user as a black box. Another concern is that ANNs are built primarily for developing point forecasts while traditional regression models can generated both point and interval estimates.

The analysis also identified several possible areas for further improving the performance of the net. These include:

- Developing several models based on segmenting the data into more homogeneous groups, e.g., in the present model annual product sales ranged from over 2.5 million units to less than 45,000 units.
- Developing models for estimating quarterly sales and returns over a two-year period.
- Designing a screening model for identifying "out of range" data sets.
- Conceptualizing an approach for allowing managers to evaluate a wide range of database ratios.
- Assessing the relative effectiveness of an ANN classifier model versus a traditional regression model.
- Formulating a training system for introducing neural nets into the management process.

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