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Static models
All of the models we have discussed so far are 'snap shots in time'. The models assume that the process under consideration is static. For instance, when we considered the response surface, we assumed that the model based on the information contained in the database was applicable to the future. Static models are generally assumed to hold for an extended period of time.

Dynamic systems
But it is possible to look upon the system, itself, as evolving over time. This means that the model should not only account for the current state of affairs but should incorporate changes in the system itself over a period of time. This sounds logical, but dynamic systems are not easy to model. There are two types of problems that make modelling a dynamic system difficult. First, unpredictable external events create 'noise' in the system. Second, even when the underlying dynamic is simple, it can lead to highly complex outcomes. As a simple example, a bridge may be able to bear x tons of weight before collapsing. But this capacity declines over a period of time. After being used for several decades, the bridge can collapse bearing only a fraction of the weight it is supposed to bear. But it is difficult to predict this will happen and how much stress will be required. The mathematics of Chaos Theory deals with such sytems. Complexity theory, another new branch of dynamic systems theory that deals with complex systems, shows that in very complex systems, ordered patterns of behaviour can emerge spontan-eously. This 'anti-chaos' approach of complexity theory enables us to predict dynamic systems, even as chaos introduces uncertainty into such systems.

Standard modelling approaches
We need to predict the future, even when we know that our predictions are likely to be off-target due to partly or totally unforeseen events and conditions. We need to make the sales forecasting projections, advertising response forecasts, and price elasticity assumptions which are essential to business planning.

Traditionally we use two approaches - time series and causal modelling. In using time series modelling we take into account such factors as past sales patterns, cycles, and seasonality. When we use causal modelling, we model the effect of extraneous factors such as GDP and inflation. Unfortunately, we do not know the precise effect of different variables on variables such as sales. We simply rely on empirical data to provide us with an estimate of these relationships. Because we dealt with these models in my earlier articles, I would like to move on in this article to discuss chaos and complexity theories.

Chaos theory
Let us return to our earlier example of the collapse of a bridge after a few decades. From a scientific (deterministic) point of view, if we know how much weight the bridge carried over the years, if we know and can calculate the effect of weather, and if we know how the bridge was built, we should be able to predict when exactly the bridge will collapse. But in fact we are not able to do so. It is not possible to predict when the bridge will collapse even if we have extensive data. We cannot predict when a crack will appear on a wall. We cannot predict very precisely what the weather will be 72 hours from now.

How so? According to chaos theory, even when we know everything about a system, there is some error attached to our knowledge at the beginning. This error could be tiny. Yet it may have unpredictable consequences. The initial error can grow rapidly and can lead to radically different outcomes than the one predicted. Since it is impossible to know the exact condition of a system at the beginning, chaotic systems will always be unpredictable in the long run.

The butterfly effect
This concept of unexpected outcomes is commonly referred to as the 'butterfly effect'. If a butterfly flapped its

wings in Africa today, will it change the weather in Winnipeg next week? Chaos theory would suggest that it is quite possible.

Linear models and chaos theory

For chaos theory to hold, the underlying system should be non-linear. Even more importantly, the non-linearity has some permanence attached to it, meaning that we cannot get rid of the non-linearity by applying a mathematical transformation of the data.

The implication of this requirement is that the traditional forecasting models cannot be applied to chaotic systems. Trad-itional time series and causal models are linear in nature. In these models, when the data are not linear, we apply some mathematical transformation to make them linear. Since chaotic systems include permanent non-linearity, trad-itional forecasting models cannot be used for understanding chaotic systems.

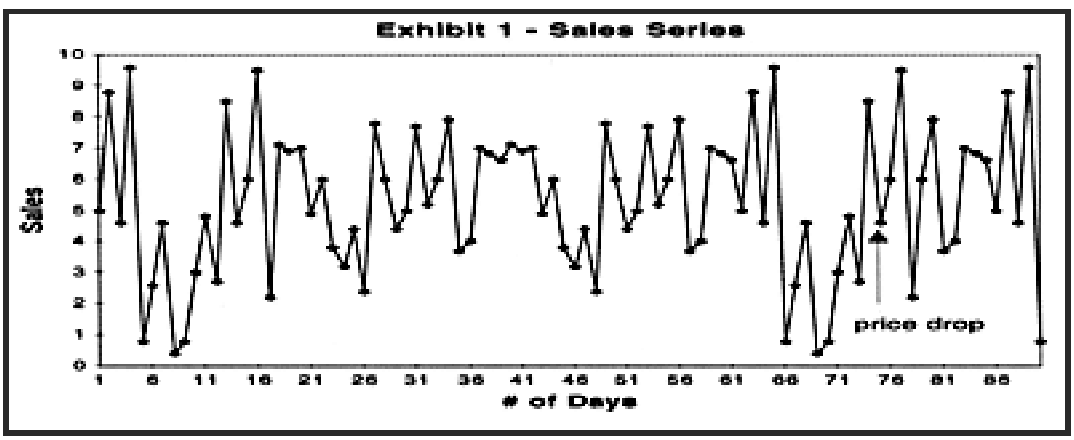
An example

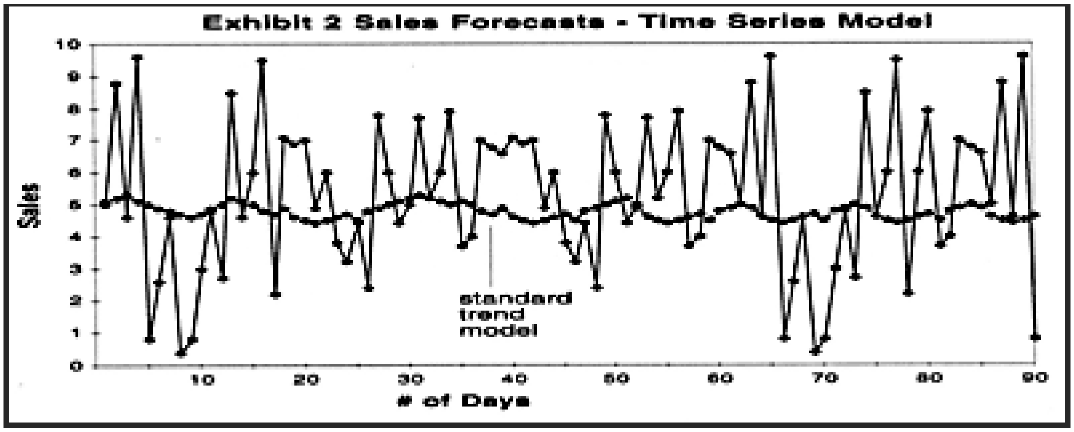
Let us consider the sales of Brand X. Exhibit 1 shows the sales for 90 days. During this period, the price of the product was dropped 20% (also shown in Exhibit 1). Just by scanning the data in the chart it appears that the price drop did not have any effect on sales. Applying regular time-series models did not identify any patterns either (see Exhibit 2). This means either that price had no effect on sales or that standard linear models are not suitable for identifying the underlying relationships.

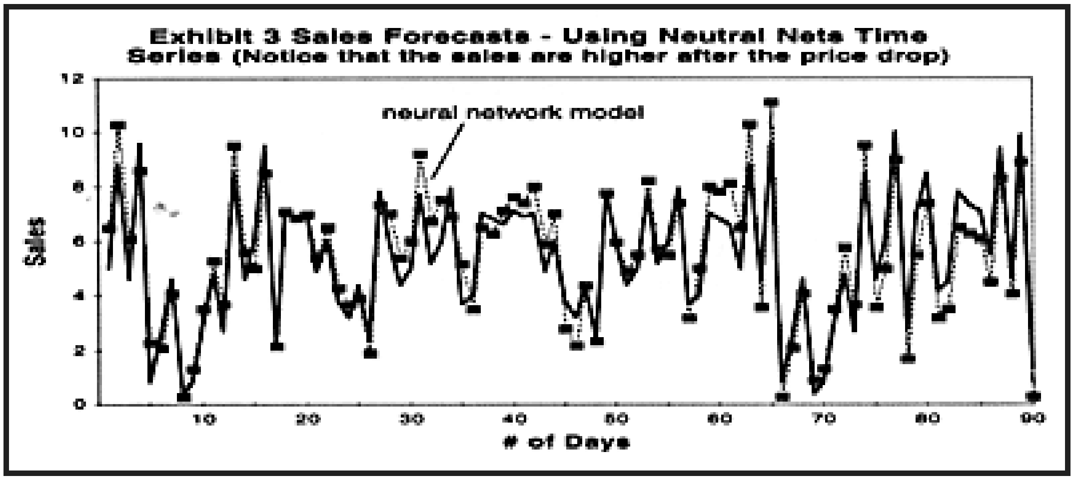
We can apply non-linear techniques in cases like these. For instance, a neural net can be trained to predict each day's sales based on the previous day's sales. Or a neural net can be trained on the previous year's data and the model can then be applied to the period under consideration.

To apply a model like this, we may want to begin with last year's sales data for each day. Each day's sales can be thought of as a function of the previous day's, the previous two days' or the previous n-th days' sales. In building the model, we usually do not know how many days we have to go back to predict today's sales.

Let us assume that the 'day-before sales' turned out to be the best predictor of any given day's sales. If we use that model to predict our sales data, we see that the model is very close to the data on hand except when the price dropped. In days following the price drop, the actual sales are higher than the predicted sales (Exhibit 3). Using the non-linear model it is clear that the price decrease did have an impact on sales.







Complexity theory
Complexity theory (also known as adaptive systems) is the reverse of chaos theory and is sometimes called 'anti-chaos' theory. While chaos theory holds that simple rules can result in complex results, complexity theory holds that complex rules can result in organized behaviour. Complexity theory does not attempt to build a model from the 'bottom-up' i.e. from layers of detailed information. Rather it models a system of interacting attributes. An advantage of such a system is that it can identify emerging macro patterns. Such patterns cannot be identified when we look at each individual attribute separately.

A basic hypothesis of complexity theory is that there are patterns that are common to many systems and regularities often arise when we look at systems. We start with known local rules about how the attributes within the system interact. Then we can carry out a series of simulation exercises under different conditions.

A number of researchers are applying complexity theory to different areas of human endeavour. Work in this area has been done in fields as diverse as economics and ecological systems. Santa Fe Institute, Carnegie-Mellon and the University of Delaware are examples of institutions where work on complexity theory is in progress.

Complexity systems are said to 'self-evolve critically'. While chaotic systems make outcomes less and less predictable, complexity theory attempts to identify common patterns and the attribute interactions that give rise to them.

Complexity theory and marketing
Complexity theory can be highly relevant in marketing contexts. We can view the market as a huge collection of interacting units such as consumers. Promotional efforts can be viewed as the 'global effect' which might be followed by undefined channels of com-munication such as 'word-of-mouth' which results in local interaction of units involved in the system. We are still in the early stages of applying these models to marketing and it is too early to tell whether they will prove to be more useful than the traditional models.

The future of data mining models
The data mining models we have discussed so far - classification tree, chaos theory and time series using chaos

theory - are being used increasingly in marketing as well as in other disciplines. Classification trees have been known for over 30 years and neural networks for over 50 years. Why the renewed use and interest now?

The simple answer is that the universal accessibility to high powered computers and the inexpensiveness of computer time has brought computer-based modelling within the reach of most of us. Because computer time these days is practically free (if you have a computer), large scale exper-imentation with complex modelling involves no monetary risk. Even in terms of time, the investment is only a fraction what it would have been about 10 years ago.

The other reason for the increasing popularity of these models is the availability of computer programs. About 20 years ago, the only reasonable program that was available to carry out classification tree analysis was the Automatic Interaction Detector, a program with cumbersome input and output features. The program also had several restrictions. Now, programs like CHAID and KnowledgeSeeker are on the market. These programs are more sophisticated and in many cases, self-explanatory. They are com-mercially marketed and widely available.

Similarly, neural nets have been made widely available through programs such as the one marketed by SPSS and Catpac. Availability of easy-to-use programs increases experimentation, and that is what seems to be happening now.

Given the rapid growth in technology, this trend is likely to accelerate. If what has been happening in the past 5 years is any guide, we can look forward to seeing more and more complex modelling techniques being used in the next few years. Paradoxically, less and less technical knowledge will be needed to use these new models.

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