Forecasting Methods

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Introduction

Background

The Party City franchise stores of San Diego and Northern Riverside Counties were founded in 1995, with a store in Mission Valley. There are fourteen Party City stores in San Diego; eight are owned by the parent corporation, six are owned by a single franchisee, who owns the rights to any additional franchise additions to San Diego or Riverside counties. Worldwide, the company has over 500 locations, with approximately half owned by franchisees. The company has become successful marketing itself as the "Halloween Superstore". Twenty-five percent of annual sales are made in the month of October nationwide; however, the stores also have strong foundations in other events such as Easter, Christmas, Graduation and Wedding planning (The A Team, February 5, 2004). The customers of a Party City store in San Diego County are typically young adults and families with young children from moderate and working class incomes. (The demographic does vary some by location however. For example in Carmel Mountain, the average income is higher for a typical shopper than in Lemon Grove.) The suppliers to Party City range from small, local vendors such as Party Star, a local piñata maker, to Amscan and Hallmark, some of the largest distributors of party supplies in the United States.

This paper intends to identify the existing gross sales or demand-forecasting methods used by Party City and provide suggestions on ways to improve these forecasting techniques.

Decision Making Under Uncertainty

The term *uncertainty* is not the same as the term *risk.* Risk is the likelihood or probability of each state of nature and thus could be estimated. (Bowerman, 2003). On the other hand, uncertainty refers to having no information about the likelihood of the various state of nature. Therefore, decision making under uncertainty requires methodically analysis of the existing information and making a good prediction about the future; in short *forecasting.*

The database of most organizations contains a wealth of information for the decision makers to perform good forecasting. However, lot of the time either the data are not used or very little of it used to make decisions. The reasons being sometimes the managers do not know what to look for and the other times they simply do not know how to use those data.

In the article, “The Balanced Scorecard--Measures that Drive Performance” the authors Kaplan and Norton (1992) talked about several financial and operational measurement systems that can clearly identify an organization’s future performance. The authors discussed a balanced scorecard for senior management that helps them to gain critical information from all perspectives (i.e., customer, internal, innovation, learning and financial) without suboptimization or information overload. They also suggested that the only way management could create this balanced scorecard is to employ the best forecasting model and make continuous effort to improve it.

Forecasting Models

In order to predict the uncertain future, it is important to choose the right forecasting techniques and design a good model. The major forecasting techniques are classified in the following table:

Qualitative	Time Series Analysis	Causal	Simulation Models
✓Grass Roots ✓Market Research ✓Panel Consensus ✓Historical Analogy ✓Delphi Method	✓Simple Moving Average ✓Weighted Moving Average ✓Exponential Smoothing ✓Regression Analysis ✓Box Jenkins Technique ✓Shiskin Time Series ✓Trend Time Series	✓Regression Analysis ✓Econometric Models ✓Input/Output Models ✓Leading Indicators	

Source: Chase, R. B (2004) p. 468.

The qualitative forecasting methods are subjective and judgmental; it is based on estimate and opinion. Since forecasting is a predictor of what will happen in the future and it is an uncertain process, it is important to use more systematic methods of forecasting. Therefore, most managers prefer time series analysis over qualitative methods.

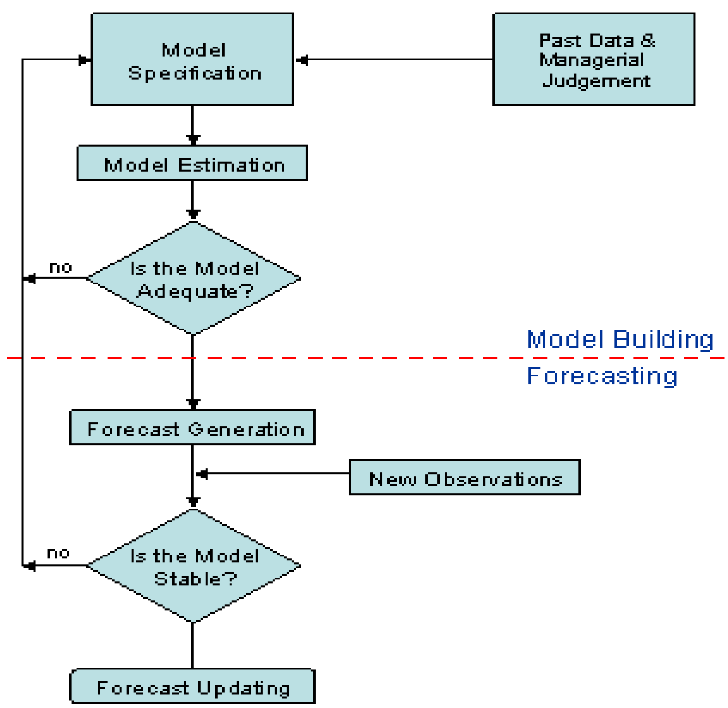
Time series methods analyze the history of occurrences over time to predict the future. A time series is a set of numbers that measures the historical records of some activity, with measurement taken at equally spaced intervals with a consistency in the activity of the method and measurement (Arsham, 2002).

The causal techniques try to explain multiple cause and effects. The most popular causal technique is the regression analysis. Sometimes operations managers use multiple regression analysis to determine the effect of two or more independent factors (advertising, quality and competitors) on a dependent factor (sales).

Finally, Simulation Models are computer aided dynamic models, that allow the forecaster to make assumptions about the internal variables and external environment in the model (Chase, 2004).

Although detailed discussion of the different methods are outside the scope of this paper; one method requires special attention, which is Box-Jenkins Techniques. Box-Jenkins Techniques can model a wide spectrum of time-series behaviors. It has a large class of models to choose from and a systematic approach to identifying the correct model. The underlying goal is to find an appropriate formula so that the residuals are as small as possible and exhibit no pattern. According to Chase et al., Box-Jenkins is the most accurate statistical technique available.

Following is the flowchart of a typical forecasting system:



Forecasting System:
The Model-Building and The Forecasting Phases

Source: Arsham, H. (2002)

Forecasting Methods Being Used Currently at Party City

Currently Party City is forecasting its demand or net sales based on the percentage increase or decrease of the past sales. In order to determine any positive or negative bias in the forecast a simple Mean Absolute Deviation (MAD) method is being used (see Appendix 1). The result of the analysis is as follows:

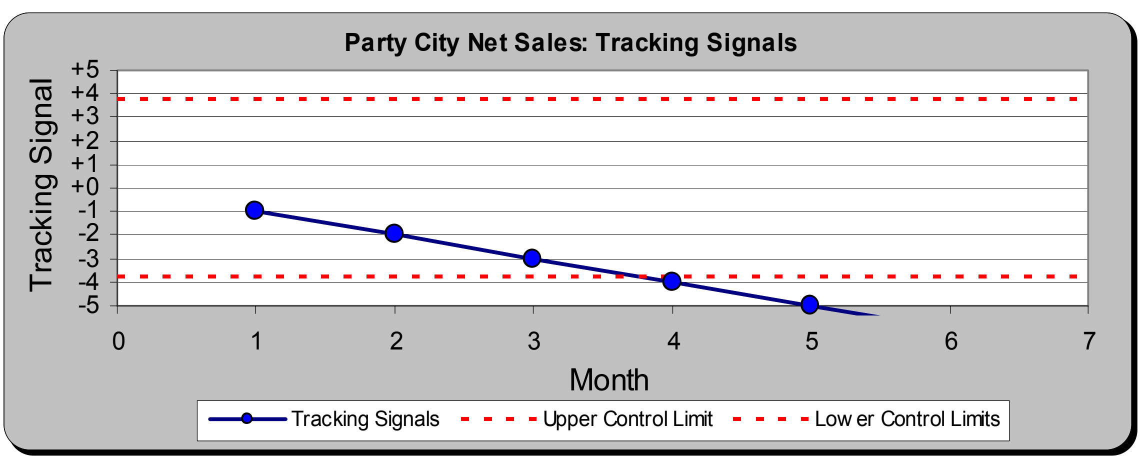
Mean Absolute Deviation = 29,555.8

Tracking Signal = -5.9933

3-sigma Upper Control Limit = 3.75

3-sigma Lower Control Limit = -3.75

Here, MAD = 29,555.8, indicates on average the forecast was off by $29,556 and the tracking signal was equal to 5.9933 MAD. The 3-Sigma upper and lower control limit is calculated based on the formula 1 MAD = 0.8 standard deviation. Therefore, ± 3.75 MAD means approximately 90% of the points are lying within control limits and considered as good forecasting.



Source: Author's own construction

The downward tracking signal indicates that the forecasted demand was greater than the actual demand and in October 2003, the tracking signal crossed the lower control limit and thus indicates unreliable forecasting for November and December.

Exponential Smoothing Technique

Exponential techniques are an averaging technique that uses unequal weights and the weights applied to the past observations declines in an exponential manner. This is a relatively simple technique that requires less data and useful for short to medium term forecasting. Following is the basic model for exponential smoothing method:

$F_{t+1} = \alpha D_t + (1-\alpha) F_t$

Where,

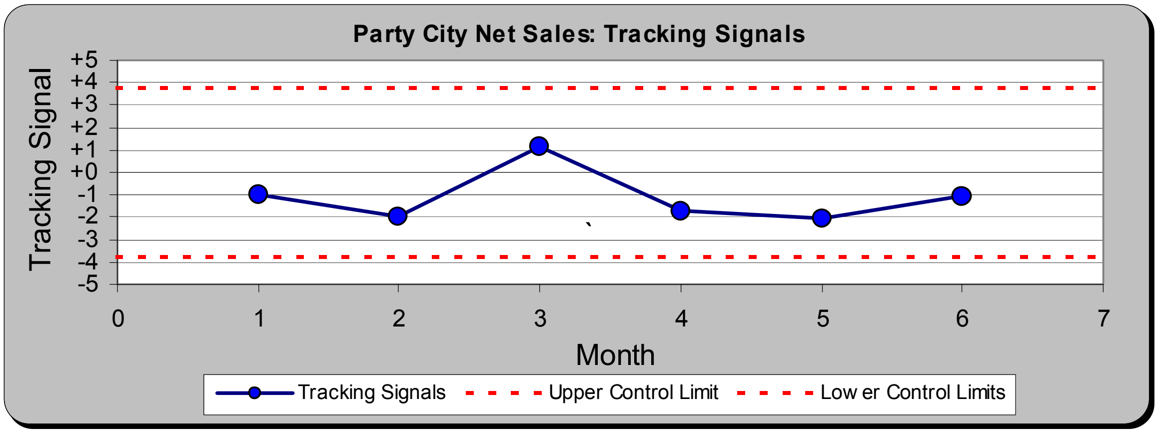
F_{t+1} = Forecasted value for next period

α = The weighting factor which ranges from 0 to 1

D_t = The actual demand

F_t = Forecasted value for this period

A small α provides a detectable, and visible smoothing. While a large α provides a fast response to the recent changes in the time series and a smaller amount of smoothing. The following tracking signal is for the forecasted demand after employing exponential smoothing technique (see Appendix 2), which is well within the upper and lower control limits.



Source: Author's own construction

Analysis

For the purpose of this forecasting, different weighting were used for the months of October and November. According to an internal source, 25% of Party city's annual sales occur in the month of October nationwide. The following month, November, the company sales drop sharply before beginning to rise again. Therefore, some adjustments are made in the smoothing technique to accommodate these two unusual months. Although the tracking signal of the new forecasting method is well within the 3 standard deviation or acceptable range of forecasting, the data and the graphs (see Appendix 3) does not show any significant improvement from the existing method.

There could be several reasons for this. First, only six months of data are being used for this analysis and among them two months had to be filtered for anomaly. For any time series analysis four months of data cannot produce a good prediction. Second, the forecasting was done based on only one variable and the other variables that might influence results were not being considered.

Conclusion and Final Thoughts

Most managerial decisions are based on forecasts. Every decision becomes operational at some point in the future, and the success of that decision depends on how well it was forecasted. Forecasting is also a dynamic process and requires continuous improvement and review, based on the changing internal and external environment of the organization.

Large organizations with large operations and technical staffs usually undertake expensive forecasting techniques, to become industry leaders and beat the competitors. However, in order to control cash flow and stay in business, small organizations also need to implement better forecasting techniques. Although sophisticated long term forecasting is still out of reach for small to midsize firms, short and intermediate term forecasting techniques are available for companies of every size. Forecasting techniques like exponential smoothing is an inexpensive and easy way to forecast small company's demand. This paper has shown that even with limited data, a good forecasting could be done. Therefore, it is recommended that the accountants of Party City consider exponential smoothing method for their forecasting. With few years of data and careful modeling they will be able to predict future sales more accurately. However, they also need to remember that the forecasting success with any time series analysis depends on only good, uninterrupted and low noise data set.

References

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Appendix 1

Party City Demand Forecasting

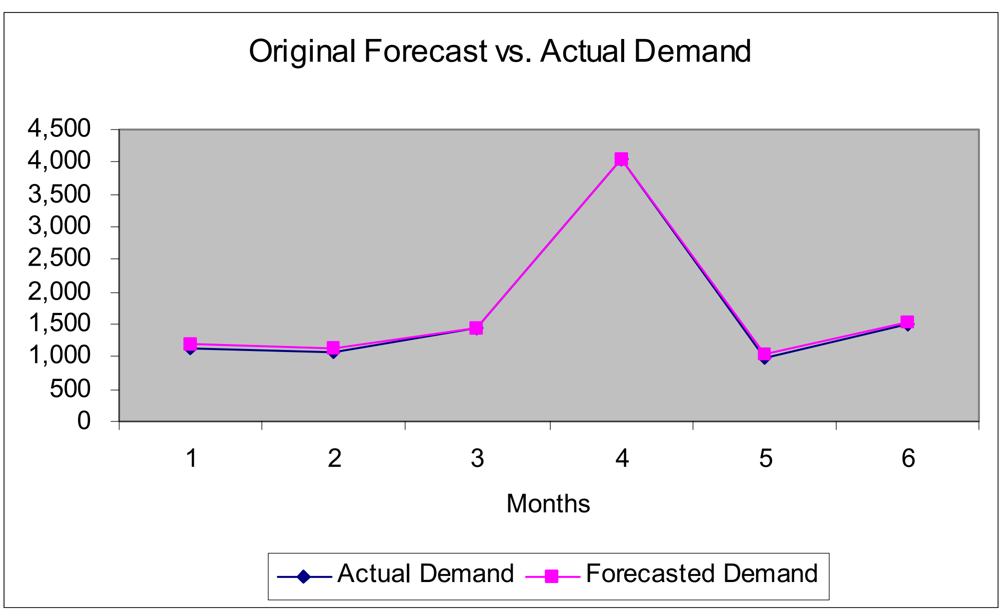
Month	Demand (Net Sales)Forecast	Actual	Deviation (Error)	RSFE	Abs. Dev.	Sum of Abs. Dev.	MAD	TS=RSFE /MAD
July	1,182,000	1,139,680	(42,320)	(42,320)	42,320	42,320	42,320	(1.00)
August	1,128,000	1,080,957	(47,043)	(89,363)	47,043	89,363	44,682	(2.00)
September	1,425,000	1,424,692	(308)	(89,671)	308	89,671	29,890	(3.00)
October	4,047,000	4,047,098	98	(89,573)	98	89,769	22,442	(3.99)
November	1,031,000	983,470	(47,530)	(137,103)	47,530	137,299	27,460	(4.99)
December	1,529,000	1,488,964	(40,036)	(177,139)	40,036	177,335	29,556	(5.99)

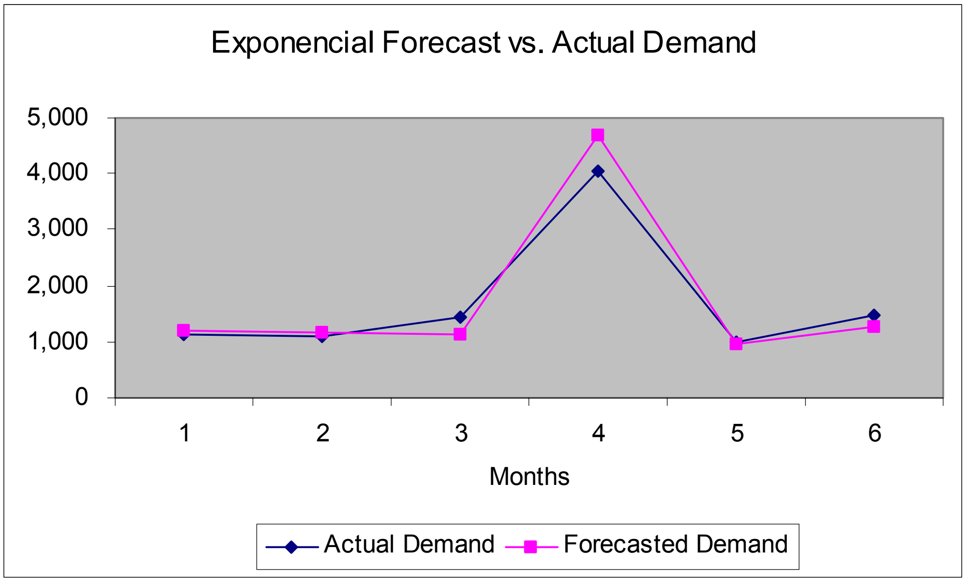
Appendix 2

Party City Demand Forecasting

Month	Demand Forecast (Exponential Smoothing)	Actual	Deviation (Error)	RSFE	Abs. Dev.	Sum of Abs. Dev.	MAD*	TS=RSFE/MAD
July	1,182,000	1,139,680	(42,320)	(42,320)	42,320	42,320	42,320	(1)
August	1,171,420	1,080,957	(90,463)	(132,783)	90,463	132,783	66,392	(2)
September	1,126,189	1,424,692	298,504	165,721	298,504	431,287	143,762	1
October	4,676,614	4,047,098	(629,516)	(463,796)	629,516	1,060,803	265,201	(2)
November	956,580	983,470	26,890	(436,906)	26,890	1,087,693	217,539	(2)
December	1,275,440	1,488,964	213,524	(223,382)	213,524	1,301,216	216,869	(1)

Appendix 3




Exponencial Forecast vs. Actual Demand
5,000
4,000
3,000
2,000
1,000
0
1
2
3
4
5
6
Months
Actual Demand
Forecasted Demand