In this 35th issue of *Foresight*, we revisit a topic that always generates lively and entertaining discourse, one where business experience has been far more enlightening than academic research: the question of the proper **Role of the Sales Force in Sales Forecasting**. Our feature article by **Mike Gilliland** formulates the key aspects of the issue with three questions: Do salespeople have the ability to accurately predict their customers’ future buying behavior, as many assume they do? Will salespeople provide an honest forecast? And does improving customer-level forecasts improve company performance? Incisive commentaries follow Mike’s piece, contributed by forecast directors at three companies.

As *Foresight* Editor, I welcome continued discussion from our readers on your experiences and lessons learned at your own organizations.

**Paul Goodwin’s Hot New Research** column addresses a promising new method for properly representing the uncertainty behind a forecast. Called **SPIES** (Subjective Probability Interval Estimates), it offers a more intuitive way (than standard statistical approaches) for forecasters to determine and present the probability distribution of their forecast errors. I think you’ll find it provocative.

Our section on **Forecasting Support Systems** features the article **Data-Cube Forecasting for the Forecasting Support System**. Noted Russian consultant **Igor Gusakov** draws on his many years at CPG companies to show how we can achieve the best of what are now two distinct worlds, by synthesizing statistical forecasting capabilities with the OLAP (online analytical processing) tools now commonly used for business intelligence and reporting. **Data cubes** provide the requisite infrastructure.

Igor is also the subject of our **Forecaster in the Field** interview on page 33.

Our Summer 2014 issue included the first part of a feature section on **Forecasting by Aggregation**. Two articles there examined “temporal aggregation” opportunities, which deal with the choices of time dimension (daily, weekly, monthly, etc.) for forecasting demands. Now we present Part Two on **Forecasting by Cross-Section Aggregation** within a product hierarchy. **Giulio Zotteri, Matteo Kalchschmidt**, and **Nicola Saccani** question the usual belief that the level of aggregation for forecasting is specified by the operational requirements of the company. Rather, they argue – quite convincingly – that the best level of aggregation for forecasting should be **chosen by the forecasters** in an attempt to balance the errors from forecasting with data at too granular a level with those at too aggregate a level.
Rob J. Hyndman and George Athanasopoulos extend the discussion by presenting a way for Optimally Reconciling Forecasts in a Hierarchy. Rarely will the sum of forecasts at a granular level equal the forecast at the group level; hence reconciliation is necessary. The authors argue that traditional reconciliation methods – bottom-up, top-down, and middle-out – fail to make the best use of available data. Their optimal reconciliation is based on a weighted average of forecasts made at all different levels of the hierarchy.

**Happy Anniversary**

We at Foresight are not in the habit of publicly patting ourselves on the back, but there are certain special occasions where acknowledging the journal on a job well done seems deserving – and this surely is one of them. Foresight’s decennial year of publication will be celebrated in 2015. From my perspective as the Editor of the journal from Day One, the production process for each issue – from receiving contributors’ articles in manuscript to the final layout sent off to the printer – at times felt interminable, and yet these ten years collectively seem to have gone by in a flash.

Foresight – we believe, we hope – is not merely a highly informative technical journal, but a stimulating, provocative, and often entertaining reading experience. It has virtually equal appeal to academicians, researchers, and front-line practitioners – a fact about which all of us here at Foresight are extremely proud. It would be impossible to list all of the individuals who, over the past decade, have made significant contributions to our success – whether they be editorial, marketing, or design/production personnel, members of the Practitioner Advisory Board, contributors and column editors, the IIF home office, and on and on – but I like to think you know who you are. My thanks to everyone who’s had a part in this venture, and may Foresight’s next ten years be as personally and professionally rewarding, for our staff and our readers, as the first.

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**UPCOMING in Foresight**

- The Role of S&OP in Demand-Supply Integration
- The Reliability of our Macroeconomic Data: Warts and All
- Understanding Seasonal Adjustments of Economic Data
- Financial Crises: Causes, Consequences, and Forecasting Models

*Aspens in the Colorado Autumn*
My previous Hot New Research column discussed the benefits of including information about uncertainty in forecasts ("Getting Real about Uncertainty," Foresight Issue 33, Spring 2014). Forecasts expressed as a single number (point forecasts) give no information about the forecast’s reliability, which is unhelpful when decisions have to be made about levels of safety stock or what cash reserves to hold for unexpected contingencies.

**REPRESENTING UNCERTAINTY**

One solution to this dilemma is to express the forecast as a probability distribution. For example, the distribution in Table 1 shows that sales of between 50 and 60 units are most likely. However, there is a 30% chance that they will be higher than this, and a 10% chance that they will be lower. It also shows that if you want to provide a customer service level of 95%, you should hold an inventory of 70 units.

The problem here is: how do we estimate the distribution?

As we saw in my last column, the latest algorithms embedded in some forecasting software products can produce quite accurate estimates, but often there is insufficient data available for the software to work efficiently. Newly launched products, for an example, have little or no sales history, or there may have been a fundamental change in market conditions so that the past sales data is not relevant. In these circumstances, we may have to rely on the judgment of managers to produce the estimates.

Table 1. Sales Forecasts Presented as a Probability Distribution

<table>
<thead>
<tr>
<th>Sales Forecast for Next Month (number of units)</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>30 to under 40</td>
<td>2%</td>
</tr>
<tr>
<td>40 to under 50</td>
<td>8%</td>
</tr>
<tr>
<td>50 to under 60</td>
<td>60%</td>
</tr>
<tr>
<td>60 to under 70</td>
<td>25%</td>
</tr>
<tr>
<td>70 to under 80</td>
<td>5%</td>
</tr>
<tr>
<td></td>
<td>100%</td>
</tr>
</tbody>
</table>

Yet there is plenty of evidence that people tend to underestimate the amount of uncertainty that they face. For example, when asked to produce a range in which they are 90% confident about the level of next month’s sales, most people came up with a range that was too narrow—a range, in fact, that had a much less than 90% chance of capturing the actual sales level.

**SPIES**

In a recent blog, Uriel Haran and Don Moore (2014) of Ben-Gurion University present a simple method that aims to improve the accuracy of judgmental forecasts involving probability distributions. They call their method SPIES, for Subjective Probability Interval Estimates.
You begin by estimating the lowest possible value and the highest possible value for whatever you are forecasting. You then split this range into a set of sub-ranges or bins. For example, we may view our worst-and-best-possible sales levels for next month as being 100 and 200 units, respectively, and split this into the five bins shown in Table 2.

You then allocate points to each bin to reflect your estimate of the relative probability that it will include the actual sales. We might, say, allocate 40 points to the “most likely” bin (120 to <140 units), and then decide that the “next most likely” bin (140 to <160 units) has only half the chance of including the sales, so we consequently give it 20 points, and so on—as shown in Table 3. We then represent each number of points as a percentage of the total (in this case, 80) to get probability estimates that sum to 100%.

Haran and Moore have provided a quite handy tool on their blog page (http://blogs.hbr.org/2014/05/a-simple-tool-for-making-better-forecasts/) where you simply input the lower and upper values of the range and the bin size that you want (in our case, 20 units). Slider bars allow points to be assigned to the bins using a mouse, and a histogram is then produced to show the probability distribution that you have estimated. The tool also automatically determines a 90% prediction interval for your sales, based on your distribution. In our case, it tells us that there is a 90% likelihood that sales will be between 116 and 184 units. This can be adjusted if you want your prediction interval to have another coverage probability, such as 95%.

When they tested SPIES, the researchers found that people produced intervals that were wider—and hence a more realistic reflection of the level of uncertainty associated with a forecast (Haran and colleagues, 2010). For example, when people used the method to produce 90% prediction intervals for the high temperature in Pittsburgh one month ahead, 88.35% of their intervals included the true value, which is near-perfect calibration.

There are several reasons why SPIES appears to work so well. First, it breaks the estimation problem into a series of separate tasks, one for each bin, so you can focus on each range in turn rather than having to consider lots of possibilities at once. Second, people are apparently better at estimating the probability that sales will be within a particular range than they are in estimating a range that has, say, a 90% chance of including actual sales. Perhaps most important, the method forces people to consider all possible outcomes; these include the possibility of extreme values, which—although they may be rare—could have a major impact if they occur.

<table>
<thead>
<tr>
<th>Possible Sales Ranges (Bins)</th>
<th>Points</th>
<th>Probability (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>100 to under 120 units</td>
<td>5</td>
<td>6.25</td>
</tr>
<tr>
<td>120 to under 140 units</td>
<td>40</td>
<td>50.00</td>
</tr>
<tr>
<td>140 to under 160 units</td>
<td>20</td>
<td>25.00</td>
</tr>
<tr>
<td>160 to under 180 units</td>
<td>10</td>
<td>12.50</td>
</tr>
<tr>
<td>180 to under 200 units</td>
<td>5</td>
<td>6.25</td>
</tr>
<tr>
<td>Total</td>
<td>80</td>
<td>100.00</td>
</tr>
</tbody>
</table>

Table 2. Splitting the Range of Possible Sales

Table 3. Assigning Points to the Bins
SPIES is apparently designed to improve the estimation of prediction intervals, but there seems to be no reason why it could not be used to estimate complete probability distributions. After all, having made the effort to obtain such a distribution, why discard much of the data it contains and settle for a prediction interval that is much less informative?

**AVOIDING SURPRISES**

If you do use the method, be careful when you estimate the lower and upper limits of your range. In the study where SPIES worked so well, the researchers provided these end values; when they are not provided, there is the danger that your range will be too narrow. Having estimated your initial range, it is a good idea to double its width (e.g. turn 100-to-200 into 150-to-250). You can always assign zero points to the bins at either end of the range, but at least you will have been forced to ask yourself whether it is just possible that sales might occur at these extremes. Indeed, time spent trying to think of scenarios leading to extreme levels of sales may be time well spent. That way, you are more likely to avoid the occasional surprise that can be so costly.

**REFERENCES**


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Paul Goodwin is Emeritus Professor of Management Science, University of Bath. This is his 13th Hot New Research column for *Foresight*.

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*Foresight* congratulates Paul on his retirement from the University of Bath and thanks him for his many wonderful columns and articles in this journal.