The role of contextual information in demand forecasting

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Abstract: The paper deals with clarifying the role of contextual information in demand forecasting. Both judgmental and statistical forecasting methods are often needed to provide accurate forecasts. However, in practice it is often difficult to tell when judgmental intervention is needed and when it is not. This paper presents a case example about judgmental forecasting, in which the forecaster has different pieces of information available for the basis of a forecast. The paper provides some guidelines on how to evaluate the value of contextual information with probability calculations. The calculations show that in some situations, it is impossible to improve forecast accuracy, even though the contextual information is seemingly valuable. With probability calculations, it is possible to give more objective and specific rules on when contextual information is useful in forecasting and when it is not. This can help in selecting proper forecasting methods, and setting more realistic accuracy targets.

Keywords: demand forecasting; contextual information; judgmental forecasting; judgmental adjustment; probability calculations; forecast accuracy

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1 Introduction

Demand forecasting is one of the fundamental managerial tasks, and there is a vast amount of literature about the issue. Yet, the environment where demand forecasting is applied has changed since the early days of forecasting literature. One of the trends is the increased volatility of demand patterns in many industrial contexts (Bartezzaghi et al., 1999; Miragliotta and Staudacher, 2004; Kalchschmidt et al., 2006; Mohebbi, 2010). Other trend is the increased use of information technology, and the enhanced ability to share information between trading partners.

Forecasting literature has responded to these changes. When the demand is irregular, and statistical methods provide unreliable forecasts, one option is to extend the information base of forecasting by looking directly at future requirements. In general, information about future demand can be referred as “contextual information”. Several studies show that judgmental forecasting methods are popular in business contexts (e.g. Klassen and Flores, 2001; Mentzer and Moon, 2005; McCarthy et al., 2006). The role of human judgment in demand forecasting has started to gain academic acceptance since the 1980s (Webby and O'Connor, 1996; Lawrence et al., 2006).

There are different approaches for linking future contextual information into forecasts. E.g. demand may be estimated based on the actual orders that have already been received for future delivery (e.g. Bartezzaghi et al., 1999), or future demand may be based on the early information that a customer generates during his purchasing process before he places his actual order (Bartezzaghi and Verganti, 1995). Today it is common that suppliers receive advance demand information from their customers (e.g. Forslund and Jonsson, 2007), but there is variation in how reliable and timely the information is. In practice the forecasters may need to use their judgment in evaluating which pieces of information are of use in creating the demand forecast.

The experiences about the ability of contextual information in improving forecasts are mixed. It can be expected that the success of judgemental forecasting depends on the quality of contextual information available, and on how it is integrated into the forecast. This raises a practical question: *How to evaluate when contextual information is of use in forecasting and when it is not?*

Being able to evaluate the value of contextual information will help in creating a more objective picture about the predictability of demand in the company as a whole. There are a few reasons why the value of contextual information in forecasting should be understood well. First, when selecting between judgmental and quantitative forecasting methods, it should be evaluated whether there are sufficient prerequisites for using judgmental methods. Using judgmental methods is generally more time-taking than using statistical methods, so it is an issue of resource efficiency. Secondly, it is possible to evaluate when a piece of information is able to improve forecast accuracy and when not. This is vital both in training the forecasters and in setting realistic targets for forecast accuracy.

In the following section, we review the literature that deals with contextual information in forecasting. After that, we present a case example of a company where judgmental forecasting is applied, but the contribution of contextual information is controversial. In the consequent sections we present an approach for assessing demand predictability so that also contextual information is taken into account. Finally, we make some concluding remarks.

2 Literature review

It has been noted that the main focus of forecasting research has been on the development of quantitative methods (McCarthy et al., 2006; Fildes and Goodwin, 2007). The methods vary from simple to complex, the basic idea being that demand history is projected into the future using a mathematical formula. In simple methods, such as the naïve method, the moving average and simple exponential smoothing the formula is very simple and permanent, whereas more sophisticated methods attempt to recognize patterns in demand history more precisely and to adjust the formula accordingly. Advanced methods have been designed to predict the future based on demand history even if the mathematical equation is unknown (e.g. Ardalani-Farsa and Zolfaghari, 2011). Even though many sophisticated methods have been developed, survey studies imply that simple methods are more popular in practice (e.g Mentzer and Kahn, 1995; Klassen and Flores, 2001; McCarthy et al., 2006) and it has also been shown many times that in practice simple methods do as well as sophisticated ones, e.g. the Auto-Regressive Integrated Moving Average (ARIMA) models (Makridakis and Hibon, 2000). The applicability of quantitative models in real life is limited, since in many cases the demand is very variable or intermittent by nature or demand history does not exist. When quantitative models are unable to produce sufficiently reliable forecasts, one option is to extend the information base of forecasting by looking directly at future requirements. Information about future events can be generally called ”contextual information”.

Many authors use the concept of “contextual knowledge” or “contextual information”, but the definition of it is not very precise. According to Webby and O’Connor (1996), contextual information is: ”*information, other than the time series and general experience, which helps the explanation, interpretation and anticipation of time series behavior”*. According to Sanders & Ritzman (2004) “*Contextual knowledge is information gained through experience on the job with the specific time series and products being forecasted.*”

Several terms are used in the literature that are similar to “contextual information”, e.g. “causal knowledge”, which pertains to an understanding of the cause-effect relationships involved (Webby and O'Connor, 1996), product knowledge (Edmundson et al., 1988) and extra-model knowledge (Pankratz, 1989). According to Mintzberg (1975), much of the information processed by managers is of an informal, verbal, qualitative or “soft” in nature. Experience of similar forecasting cases can be also seen as contextual information. Using such information, that is, analogies, in forecasting has been studied e.g. by (Hoch and Schkade, 1996; Green and Armstrong, 2007; Lee et al., 2007)

Fildes and Goodwin (2007) mention information about “special events, such as new sales-promotion campaigns, international conflicts or strikes” as examples about contextual information. Sanders and Ritzman (2004) mention ”rumors of competitor launching a promotion, a planned consolidation between competitors, or a sudden shift in consumer preferences due to changes in technology” and “causal information, such as relationship between snow shovels and snow fall, or temperature and ice cream sales.” Lawrence (2000) has mentioned “new marketing initiatives, promotion plans, actions of competitors, industry developments” as examples of contextual information that is actually discussed in forecasting meetings of manufacturing companies. Also customers own forecasts can be considered as contextual information. According to a survey reported by Forslund & Jonsson (2007), 87% of suppliers received forecast information from their customers. However, in many cases the customer forecasts suffered from quality problems.

2.1 Methods for using contextual information in forecasting

Different approaches exist for integrating contextual information in forecasting. One approach is to produce the forecast intuitively without any structured method. Other option is to integrate statistical forecasts with judgmental forecasts. Goodwin (2000) has named two different integration methods as *combining and correcting.* Combining means that the forecast is obtained by calculating a simple or weighted average of independent judgmental and statistical forecasts. Correcting methods involve the use of regression to forecast errors in judgmental forecasts. Each judgmental forecast is then corrected by removing its expected error (Goodwin, 2000). There is also one common method, called *judgmental adjustment* (Sanders and Ritzman, 2001), which means that statistical forecast is adjusted according to contextual information. Yet another method is *judgment as input to model building*, which means that judgment is used to select variables, specifying model structure, and to set parameters (Sanders and Ritzman, 2004).

2.2 Former studies about the contribution of contextual information in forecasting

The impact of judgment on demand forecasting has been studied both with laboratory research and some field studies. This section reviews the studies that compare the performance of judgmental forecasts with statistical forecasts.

Some studies report that forecast accuracy can be improved by combining statistical forecast and judgmental forecasts. Edmundson et al. (1988) tested the value of contextual knowledge in a business setting. Judgmental forecasts were generated and tested based on three knowledge levels of knowledge (technical knowledge, forecasting experience and product knowledge). Of the knowledge levels tested, specific product familiarity was the factor found most significant in improving forecast accuracy. In a case study by Sanders and Ritzman (1995), real business data was collected from a national public warehouse. In this study the main finding was that combining statistically derived forecasts with those of experienced practitioners improved forecast accuracy (over other combinations), especially when demand patterns were volatile. Franses (2011) found out in a case study that simple average of model and expert forecasts yielded the highest forecast accuracy. The behavior of judgmental forecasters was approximated by a judgmental bootstrapping equation, and the replicable part of expert forecast made the 50%-50% rule work.

Some authors have studied what kinds of judgmental adjustment improve the forecast accuracy. Syntetos et al. (2009) evaluated the performance on judgmental adjustments in intermittent demand forecasts. Finding was that negative adjustments were more effective than positive adjustments and large adjustments lead to forecasts that are particularly accurate. These findings are in similar with e.g. Diamantopoulos and Matthews (1989) who noticed that larger adjustments were more effective in improving accuracy.

However, some studies report that judgmental forecasts are not more accurate than forecasts produced with simple time series methods. Lawrence et al. (2000) studied the accuracy, bias and efficiency of judgmental forecasts in thirteen large Australian manufacturing organizations. The study showed that company forecasts were not uniformly more accurate than simple, un-seasonally adjusted, naïve forecast. Most of the source of error was due to both inefficiency (a serial correlation in the errors) and bias in the forecasts. These two factors seemed to mask any contribution of contextual information to accuracy. Based on a large survey Sanders and Manrodt (2003) point out that in general, judgmental focused companies have greater forecast error rates than statistical focused companies, though the difference might be explained by exogenous variables.

In general, it is said judges will outperform models when they have contextual information to help them comprehend discontinuities in the series. Human judgment is most effective if "broken leg cues" are available (Webby and O'Connor, 1996). A broken-leg cue refers to an unusual and important piece of information whose presence would dramatically alter the judgment compared to a model of that judgment (Kleinmuntz, 1990). According to Sanders & Ritzman (1995) contextual knowledge that helps practitioners deal with time series which have a significant amount of explainable variation. Lim and O'Connor (1996) found out in their study that adjustment of forecasts using causal information improved forecast accuracy when causal information was highly reliable. To summarize, contextual information in forecasting is most beneficial if it is highly reliable information about dramatic demand changes, but it is not defined how reliable is highly reliable and how big is dramatic.

2.3 Managerial problems related to judgmental forecasting

In a judgmental forecasting process the forecaster typically needs to take into account more than one source of information. Some studies have focused on the issue on how the forecasters handle the combination process.

One finding is that people in general *have difficulties in taking many cues into account*. According to Wright and Goodwin (1998) the forecasters tend to ignore cues, especially if there are several available. Judgmental forecasters carry out voluntary integration of statistical methods and judgmental forecasts inefficiently (Goodwin, 2000). Lim and O'Connor (1996) found out in their laboratory study that people often selected less reliable information when there were many types of information available to a forecaster. Goodwin and Fildes (1999) present an experimental study in which people were allowed to adjust their own forecasts in the light of statistical forecasts provided to them in a case where the series were subject to sporadic events (e.g. promotions). Although the availability of a statistical forecast improved judgment under some conditions, the use the judgmental forecasters made was far from optimal. The authors suggest that the reason for discounting the statistical forecasts might have been the amount of competing information that the forecaster has to handle.

Goodwin and Fildes (1999) suggest that the challenge is to design methods and support systems which will help the forecaster to make the most appropriate and effective use of their judgments, while encouraging them to delegate to the statistical model those aspects of the task where the exercise of judgment would be harmful. One type of support system is presented in the work of O'Connor et al. (2005) The authors presented a study in which the forecasters made forecasts by giving weights to three components from which the final forecast consisted of. Feedback for the forecaster improved the forecast accuracy, when he/she was allowed to compare the actual and optimal weights given for different components.

Other finding is that *people seem to count on their own or experts judgment more than on statistical methods.* E.g. Lim and O'Connor (1995) present an experimental study in which people were allowed to adjust their own forecasts in the light of statistical forecasts provided to them. The main conclusion was that there was a strong tendency to place too much faith on one's own forecast rather than that of the statistical forecast. Simple mechanical averaging would have been much preferable. Arkes (2001) suggests that overconfidence in judgmental forecasts is a typical finding in empirical studies. Önkal et al. (2009) presented a case study in which students forecasted stock prices in a laboratory setting, and they were given different advice. The conclusion was that participants took grater account of the advice when they thought it had been provided by a human expert rather than a statistical method.

Third finding is that *people are not fully rational when it comes to dealing with probabilities*. E.g. Costello (2009) studied the conjunction fallacies in judgmental weather forecasting. A conjunction fallacy occurs when people judge a conjunction B-and-A as more probable than a constituent B, contrary to probability theory's 'conjunction rule' that a conjunction cannot be more probable than either constituent. This fallacy that has been demonstrated in many studies was demonstrated also in estimating the probability of everyday events (weather conditions). Yaniv and Foster (1997) present that there are social norms that have impact on judgmental forecasts. Judges are expected to provide judgments that are not only accurate but also informative. This leads judges to provide too narrow confidence intervals for their estimates. In other words: the judge presents his/her forecast as more reliable than it really is.

2.4 Research gap in judgmental forecasting

Based on former literature, some conclusions can be made. Judgmental methods are know to be time-taking, and managing their application is not simple. A study by Syntetos et al. (2009) imply that time does not mend these problems; judgmental forecasts do not seem to improve over time. This implies that more clear rules are needed on when judgmental intervention in forecasting is needed and when it is not needed. Also Lawrence et al. (Lawrence et al., 2006) end up into this same conclusion after reviewing 200 studies about judgmental forecasting. In addition, there are no clear rules on what kind of accuracy targets to set for the judgmental forecasts. E.g. Bunn and Taylor (2001) state that cross-company comparisons have not generally been relevant or feasible in the area of setting the goals of forecasting quality.

A relevant question is how the management can be supported in this kind of situation. After all, selecting the way the forecasts are made is an issue of resource efficiency. Categorizing products or customers can help in focusing the forecasting resources. Mentzer & Moon (2005) suggest that the forecasting efforts should be focused on the most important products/customers. Also some approaches are presented in which customers with similar demand patterns are clustered together (Caniato et al., 2005; Thomassey and Fiordaliso, 2006).

The quality of contextual information is an important prerequisite for judgmental forecasting, but former literature does not offer tools for assessing the quality of contextual information. In general, more case studies are needed to enhance the understanding what the method selection situations are really like. This paper presents one case example, and suggests an approach for assessing demand predictability so that also contextual information is taken into account.

3 Description of a case company

A case company provided a motivation for this study. In this section, it is described how forecasting is performed in the case company, and what kind of managerial problems occur. The case company is a large international process industry company that has several sales units and several production units. The forecasts are produced individually by salespeople in separate sales units, and collected together to be used in allocating production capacity in production units and between production units.

3.1 Contextual information in the case company

On mill level, forecasting is quite accurate, but between different markets there is great variation. Other empirical studies imply that this is typical to paper industry (Hamalainen and Tapaninen, 2011). The customer base is heterogeneous, and the customers operate in distinct businesses: contractual markets and spot markets. On the latter markets, each order is competed for, so the predictability is considerably lower than in the contractual markets. From different customers, different pieces of information about demand are available in advance. In contractual markets, contracts are made for four months or twelve months ahead. In practice, these contracts define only the maximum volume the customer may receive during the given time period. In addition to this, some customers place preliminary orders before they place their actual order. In the spot markets, customers make inquiries, that indicate customers buying intentions, but inquiries are not as reliable indicators as contracts. Customers are not the end users of the products, so their demand depends on their own customers. Salespeople are usually aware in what kind of end-products the material ends up. However, the demand profiles of the end products vary, some end-products having regular demand and some having irregular demand. In the case company, managers were in many cases able to explain major discontinuities in demand patterns, when they were shown exceptional demand profiles. Reasons for discontinuities were for example that customer substituted the product with another (cheaper) product, or sales were allocated into other sales unit.

Using a questionnaire, six managers of the case company were asked how they see the importance of preliminary orders, contracts, customers' predictions about their future demand and demand history as information sources in forecasting[1]. The managers are responsible for leading the work of forecasters, but they do not personally produce forecasts. The results showed that managers saw customer's predictions about future demand as important as demand history. Also contracts and preliminary orders were seen important by some managers, thus some disagreed. In this case company, contextual information obviously exists, but it is not clear what is its' role in forecasting.

3.2 Accuracy measurement in the case company

The sales people produce sales forecasts for each customer on a monthly basis. However, typical order frequency of a single customer is one order per month or less. As a result, the forecasts are often made at a higher frequency than the orders arrive. Orders do not always fall to same moths as the forecasted amounts, so therefore forecast accuracy for individual customers is typically low.

The forecast accuracy is measured on monthly level. The forecast accuracy is calculated by comparing actual sales with forecasts. The value of contextual information can be evaluated with comparing judgmental or judgmentally adjusted forecasts by forecasts made on the basis of demand history. Comparisons show that the accuracy of judgmental forecasts is not uniformly better than the accuracy of statistical forecasts. When forecasting the demand of individual customers, judgmental forecasts in some cases are more accurate than statistical forecasts, but when forecasts are aggregated from different customers, statistical forecasts provide closely same accuracy as judgmental forecasts.

3.3 Development actions in the case company

It is reasonable to focus the salespeople's efforts on tasks that have the most value in forecasting with adequate rules and tools. Therefore it is justified to categorize the items to be forecasted. When forecasts are made separately for product/customer categories that have different predictability of demand, it is easier to get a general view about the reliability of forecasts. However, before categorization, it should be clear when contextual information is of value in demand forecasting and when it is not. In the following sections, we present a model for

[1] The questionnaire is provided in the appendix

classification and some examples on how to use probability calculations in evaluating the value of contextual information.

4 A framework for classifying the predictability of demand

From technical point of view, simple statistical forecasting methods are easy to apply. However, if the demand is highly volatile and intermittent, it may be an option to make the forecasts based on other information than demand history. Using this kind of an approach is known to be more resource-consuming, so the managerial problem is how to focus judgmental forecasting efforts to such cases where the approach is applicable and needed the most. This requires classifying the items to be forecasted.

Figure 1 presents a conceptual model for classification. Depending on the forecasting task, the items to be forecasted can be products, product families or customers. In general, there are three options for making the forecasts: making them on the basis of demand history or contextual information, or combining the two basic options. From resource-efficiency point of view, the use of judgmental adjustment as a combination method is proposed. In cases where the relevance of contextual information is low and the demand is highly intermittent, the prerequisites for accurate forecasting are low, and the question is whether any effort should be put in forecasting. Most statistical forecasting methods are designed for continuous demand. In theory, also intermittent demand can be forecasted accurately if the demand interval is somewhat regular. In that case, the demand creation process can be modeled, focusing on forecasting not only order sizes but also order intervals (e.g. Syntetos and Boylan, 2001). In practice, if the demand interval is regular, there must be contextual information about the source of demand.

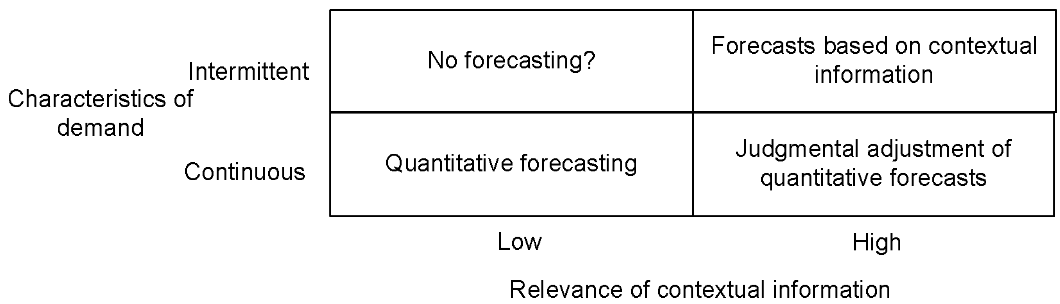

Figure 1: Classification of predictability of demand

When applying the classification model, a fundamental question is how to define the limits between regular and irregular demand, and between low and high relevance of contextual information. For distinguishing regular and irregular demand, some ready-made criteria are available. Average demand interval has been used as a classification criterion for intermittence (e.g. Heinecke et al., 2011). Even though some reference values have been suggested in former literature, their applicability needs to be considered separately in the context where the classification is to be performed.

For the other classification criterion (relevance of contextual information), it is more difficult to find an unambiguous, general indicator. In practice it needs to be defined case-specific, but some general guidelines are useful. It has been defined in former literature that contextual information is of use in forecasting if it helps in predicting major discontinuities in demand patterns. The question is whether the information about discontinuities is reliable enough, and the discontinuity is significant enough to improve forecast accuracy. In practice, pieces of contextual information are in different formats, and are often context-specific. Empirical observations have shown that in many cases discontinuities in demand patterns can be explained by an event that was known beforehand. Some discontinuities are repetitive by nature, so it is possible to analyze past discontinuities and thereby find out the types of contextual information that have been available, e.g. preliminary orders, promotions, changes in the customer base, etc.

In practice, evaluating the relevance of contextual information for all possible items would be very time-consuming. Therefore, instead of classifying all the items at once, it is important to find extreme cases in each category first. E.g. an item with highly irregular demand and with high amount of contextual information assumed is a pilot for testing the forecasting approach where the forecast are based purely on contextual information. Similarly, an item with regular demand and high amount of contextual information assumed is a pilot for testing judgmental adjustment. These items offer the best case scenarios that tell if the approach is applicable at all in the context in question. After that, the borderline cases between categories are searched for experimentally. This way, the limits between categories are defined iteratively. After all, the point of the classification is to help in deciding upon rules of thumb on when each basic approach is potentially applicable. This categorization can serve as a basis for a more detailed selection of methods.

Earlier literature shows that it is easy to overestimate the value of contextual information intuitively, so it is advisable to use an objective way to define when a piece of information is of use in forecasting and when not. In the following section, we present some examples of evaluation that is based on probability calculations.

5 Probability calculations to evaluate the relevance of contextual information

In practice, information about the customer's forthcoming orders may include contracts, unconfirmed orders, and/or information about the customer's future plans. These pieces of information differ from each other by their reliability and exactness. Timing and volume of demand are known accurately when the orders arrive, but before that there is some amount of uncertainty.

The main point in analyzing contextual information is to find out if such contextual information exists that is truly valuable in forecasting and available only for the salespeople. It is expected that the value of contextual information is easy to overestimate intuitively, but can in many cases be concluded to some extent with probability calculations. Contextual information is of value in forecasting only if the expected value of a forecast error decreases with using it. This can be illustrated with some examples.

The following examples present simplified situations in which the forecaster has partial information of a forthcoming exception in otherwise stable demand. It is analyzed if the piece of information is essential for planning and if the piece of information can be used in improving the demand forecast. In the following calculations the forecast error is measured as absolute values. The most common error measures, such as MAPE (Mean Absolute Percentage Error) use absolute values in calculating the error. Also in the case company, the error measurement is based on absolute values.

5.1 Example 1: A sporadic event with uncertain timing

A salesperson produces monthly forecasts for a single customer. The salesperson receives information that in the future there will be a large order, and the magnitude of this order is known accurately. However, the timing of this large order is not known exactly. It is assumed that excluding this large order, the demand is smooth. It is assumed that the probability of the large order is the same each month.

n: number of months in the period when the demand peak is possible
x: magnitude of the demand peak
X: forecast error

If the forecaster does not react to this contextual information, the cumulative expected value of the forecast error from the sum of months is x, (on a single period of time: x/n), since probability that the demand peak occurs in a specific month is 1/n.

If the forecaster adjusts the forecast according to this information, he/she can adjust the forecast with an adjustment parameter a (0 < a < x), so the expected value of the forecast error in one period is:

$$E(X) = \frac{1}{n}(x-a) + \frac{n-1}{n}a = \frac{x+na-2a}{n} \tag{1}$$

The adjustment succeeds in decreasing the expected value of forecast error if $na - 2a < 0$, which is true when n<2, which means that the timing of the demand peak should be known accurately before information about it is of value in the forecasting. This is an example of a situation where seemingly correct contextual information is unable to improve forecast accuracy.

5.2 Example 2: More than one sporadic event with uncertain timing: aggregate forecasting

This example is similar to the previous example, but now there is more than one customer that will place a large order with uncertain timing, and the forecaster produces an aggregate forecast for the customers.

c: number of customers
n: number of months of the period when large orders are possible
x: magnitude of one large order

If the forecaster does not react to this contextual information, the cumulated expected value of the forecast errors is xc, on one period of time xc/n.

If the forecaster does adjust the forecast with adjustment parameter a, (cx > a > 0), the expected value of the forecast error on one period is:

$$E(X) = \sum_{i=0}^{c} |a - ix| \left(\frac{1}{n}\right)^{i} \left(\frac{n-1}{n}\right)^{c-i} \binom{c}{i} \tag{2}$$

so the adjustment is of value when the expected value of forecast error with adjusted forecast is smaller than the expected value of forecast error with unadjusted forecast:

$$\sum_{i=0}^{c} \left| a - ix \right| \left(\frac{1}{n} \right)^{i} \left(\frac{n-1}{n} \right)^{c-i} \binom{c}{i} < \frac{cx}{n} \qquad (3)$$

For example, if c is 2 and n is 2, the formula (3) results as follows:

$$\left| a \right| \frac{1}{4} + \left| a - x \right| \frac{2}{4} + \left| a - 2x \right| \frac{1}{4} < \frac{cx}{n} \qquad (4)$$

In this case the expected value of forecast error minimizes with adjustment parameter a=x . If the forecast is not adjusted, the expected value of forecast error is x, and if the forecast is adjusted with the optimal adjustment parameter, the expected value of forecast error is x/2. In this case, the expected value of forecast can be decreased with adjusting the forecast.

With formula (3) it can be calculated whether the adjustment is of value in a specific situation where n, c, and x are known. The best possible a is the expected amount of total order volume, and when c grows, the forecast error of adjusted forecast compared with unadjusted forecast decreases. In real life, the order quantities vary, but this general rule holds true.

A practical example about a sporadic event with unclear timing is a special event (e.g. sports event) that affects the end demand, but the actual timing when it impacts the customer's orders is not known because of the customer's unknown production timetables, unknown ordering timetables and inventory policies.

5.3 Example 3: A demand level change with uncertain timing

A salesperson produces monthly forecasts for a single customer. The salesperson receives information that in the future there will be a change in demand level, and the magnitude of this change is known accurately. However, the timing is not known exactly. It is assumed that excluding this change, demand is smooth. It is assumed that the probability of the rise in level is the same in each month, and it is too late for the forecaster to react to the change when it has already occurred.

n: number of months of the time period when the change is possible
x: magnitude of the change

If the forecaster does not react to the contextual information, the cumulative expected value of forecast error on n months is

$$E(X) = \frac{xn}{2} \qquad (5)$$

If the forecaster reacts to the contextual information, it is possible to adjust the forecast in each month with an adjustment parameter a_i. If the change is anticipated like this, the cumulative expected value of the forecast error is

$$\frac{xn}{2} - \sum_{i=1}^{n} \frac{a_i i}{n} + \sum_{i=1}^{n} a_i \frac{n-i}{n} \qquad (6)$$

The adjustment is of value if:

$$\frac{xn}{2} - \sum_{i=1}^{n} \frac{a_i i}{n} + \sum_{i=1}^{n} a_i \tfrac{n-i}{n} < \frac{xn}{2} \quad \rightarrow \tag{7}$$

$$\sum_{i=1}^{n} a_i (n - 2i) < 0 \tag{8}$$

This shows that adjustment can always be of value, not depending on n. The decrease in the expected value of the forecast error depends on adjustment parameter a_i. When i > n/2, it is best to adjust the forecast with parameter a=x. When i < n/2, it is best not to adjust the forecast, so a=0. This shows that in a case of permanent demand level change with uncertain timing the forecast should always be adjusted, and it should be assumed that the level change happens at the middle of the time period when the change is possible. A practical example of this type of demand change is a situation where a customer increases its buying volume because of entering new markets, but it is not known exactly when.

5.4 Example 4: A demand level change with uncertain probability: aggregate forecasting

A salesperson produces an aggregate forecast for a group of customers. The salesperson receives information that the level of demand will rise in the future, but the rise is not certain. The value of this information depends on both the amount of uncertainty and the number of customers, as presented in this example. For the sake of simplicity it is assumed that all the customers have similar magnitude of demand.

c: number of customers
p: probability of demand level rise
x: magnitude of demand level rise

In a certain time period, the expected value of forecast error without adjustment is

$$E(X) = \sum_{i=1}^{c} p_i x \tag{9}$$

which is the expected value of level change. The forecast can be adjusted with adjustment parameter a. The expected value of the forecast error with adjustment is

$$E(X) = \sum_{i=0}^{c} |a - ix| (p_i)^i (1 - p_i)^{c-i} \binom{c}{i} \tag{10}$$

If there is only one customer, the expected value of forecast error is px, and adjustment is of value when the expected value of forecast error of the adjusted forecast is smaller than the expected value of the unadjusted forecast:

$$p(x - a) + (1 - p)a < px \tag{11}$$

This is possible only when p> 0.5

If there are two customers, the adjustment can be of value if

$$a(1-p)^2 + (x-a)(1-p)2p + (2x-a)p^2 < 2px \tag{12}$$

This is possible only when

$$2p - p^2 > 0.5 \tag{13}$$

In case of two customers, the adjustment can be of value when p > 0.3. The general message is that pieces of information that are unable to improve the forecast on the single-customer level due to a high amount of uncertainty can still be of value on the aggregate level, if similar events are expected for several customers. A practical example of an uncertain level-change is a situation where several customers are selecting a supplier for a time-period ahead.

5.5 Discussion of the examples

Earlier empirical research has shown that reliable information about future events may improve forecast accuracy, and aggregate forecasts are in general more accurate than detailed forecasts. The examples presented in this paper show that the same conclusions can be made using relatively simple probability calculations. It can be said that there is always some amount of uncertainty in pieces of information that deal with future demand events: uncertainty of the event itself, uncertainty of timing, and uncertainty of volume. The examples presented in this paper were simplified so that only one type of uncertainty was dealt with in one example.

In real life, many types of uncertainty may occur at the same time, and modeling real situations in detail would make the calculations more complex. However, the information about future event uncertainty is, even at its best, a rough estimate, and therefore exact modeling is not relevant. Instead, this kind of calculations can be used for identifying roughly the situations where it is possible and where it is not possible to improve forecast by adjusting it on the basis of contextual information, and enhancing understanding on how great a decrease in forecast error it is realistic to expect.

The illustrative examples also point out that it is possible that there is contextual information available that can be valuable for planning, but the forecast accuracy cannot be improved with that information (Example 1), or the expected amount of error decrease is marginal. In this kind of cases it is understandable that judgmental methods are used despite the low forecast accuracy, since they may offer a better possibility to discuss future demand events. Thus, short term forecast accuracy measurement is not the best method to evaluate the performance of such a forecasting process. Instead, the focus should be on encouraging the personnel to acquire future demand information that is of use for planning (advance information about planned orders, great changes in demand patterns).

6 Conclusions

Former research about forecasting practice shows that so-called contextual information plays a crucial role in demand forecasting. Judgmental forecasting is commonly applied in industrial companies, and the performance of judgmental forecasts depends on the contextual information used. However, it is also noted that there are problems with managing judgmental forecasting approaches, and judgmental methods do not always provide more accurate forecasts than statistical methods. The definition of contextual information is not very precise, and there are no clear rules on when contextual information is useful in forecasting and when it is not.

The heterogeneity of the customer base brings extra challenge in managing demand forecasting. The type of contextual information that are available may vary by customer and by product, and therefore it is difficult to get a general view about the predictability of demand. Therefore, it would be reasonable to classify customers and products on the basis of available contextual information. However, there are no ready-made criteria on how to measure the quality of contextual information. Former studies imply that the value of contextual information in forecasting is easily misestimated intuitively. Therefore, an objective measurement tool for the value of contextual information could be useful.

In this paper, a probability-based approach for evaluating the value of contextual information was presented. With the approach, it is possible to demonstrate when incomplete demand information is useful in forecasting and when it is not. With the approach, it is possible to gain more objective suggestions about when a cue should be followed and when advance demand information is too imprecise to be used in forecasting. The approach may be most useful in a situation, where there is uncertainty on many levels; uncertainty about the probability of demand change, uncertainty about the magnitude of a change and uncertainty about the timing of the change. In addition, approach can be used in modeling situations where expected demand change involves many customers. The results of probability calculations show that contextual information that is unable to improve forecast accuracy on a detailed level, can be useful when making forecasts on more aggregate level.

The approach is not limited to the case company, but the case company served as a motivation for this study. The case example pointed out a need to evaluate the value of contextual information in a more systematic way. The potential benefit of the approach is that more realistic targets can be set for judgmental forecasting.

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APPENDIX

Using the scale below, please answer how well you agree with the following statements

5: Strongly agree
4: Agree
3: Neither agree nor disagree
2: Disagree
1: Strongly disagree

1. Accurate demand forecasts are indispensable for capacity planning
2. If the market situation is good, the role of demand forecasts is emphasized
3. Demand forecasts help to level the production capacity between production units
4. The main role of demand forecasting is to recognize the ability to supply
5. Forecasts become more reliable if there are more people involved in creating the forecasts
6. The liability distribution of the current forecasting process is suitable
7. Forecasts must be made for each customer separately
8. Monthly level is a suitable time scale for making forecasts
9. Preliminary orders are an important source of information in forecasting
10. Contracts are an important information source in forecasting
11. Customers' predictions about their future demand are an important information source in forecasting
12. Demand history is an important information source in demand forecasting
13. There are clear and adequate instructions for creating forecasts
14. The current forecast accuracy is acceptable
15. Forecast accuracy should be improved
16. The greater the forecast errors are, the more damage they cause to the company
17. The current forecast error measurement practice works well