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Cluster-based hierarchical demand forecasting for perishable goods

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ABSTRACT

Demand forecasting is of particular importance for retailers in the context of supply chains of perishable goods and fresh food. Such goods are daily produced and delivered as they need to be provided as fresh as possible and quickly deteriorate. Demand underestimation and overestimation negatively affect the revenues of the retailer. Stock-outs have an undesired impact on consumers while unsold items need to be discarded at the end of the day. We propose a DSS that supports day-to-operations by providing hierarchical forecasts at different organizational levels based on most recent point-of-sales data. It identifies article clusters that are used to extend the hierarchy based on intra-day sales pattern. We apply multivariate ARIMA models to forecast the daily demand to support operational decisions. We evaluate the approach with point-of-sales data of an industrialized bakery chain and show that it is possible to increase the availability while limiting the loss at the same time. The cluster analysis reveals that substitutable items have similar intra-day sales pattern which makes it reasonable to forecast the demand at an aggregated level. The accuracy of top-down forecasts is comparable to direct forecasts which allows reducing the computational costs.

1. Introduction

Retailers offering perishable fast-moving consumer goods face the challenge to provide the right quantity of an article in their store. Perishable goods are typically delivered several times per week (Van Donselaar, van Woensel, Broekmeulen, & Fransoo, 2006) and can only be sold for at most a few days as the freshness of such products decreases rapidly. Hence, items that are not sold by the end of the day are waste and lead to loss. On the other hand, running out-of-stock (OOS) leads to revenue loss as the customers cannot buy the item they are looking for. A retailer can increase its revenue by increasing the availability of the articles while limiting the waste. A common problem of retailers related to the ordering of fresh food is that the order quantities are often determined by store managers based on their experience (Van Donselaar et al., 2006; Van Donselaar, Gaur, Van Woensel, Broekmeulen, & Fransoo, 2010). Recent developments in the area of large scale data analysis provide new opportunities for optimizing sales planning of perishable goods by providing demand-driven short-term forecasts.

The benefits of expert systems in the context of supply chain management depend on the age of the dependent fact data as its value decreases between the occurrence of the respective business event and the executed action (Hackathorn, 2004; Watson, 2009). Traditional business intelligence (BI) (Chaudhuri, Dayal, & Narasayya, 2011) systems are too slow at gathering data that is relevant for short-term or day-to-day decisions (Hahn & Packowski, 2015; Sahay & Ranjan, 2008). However, this is necessary in the context of sales planning for perishable goods which are daily produced and delivered. Traditional BI systems access the data warehouse rather than the operational databases which are optimized for online transaction processing (OLTP) and contain the most recent data. This separation was necessary as the requirements of online analytic processing (OLAP) (e.g. filtering, aggregation, drill-down, pivoting) are different from OLTP. Hence, an ETL (extract transform load) process is necessary for replicating the data into the data warehouse that is accessible by BI systems. In the last decade, the developments of database technology led to column-based in-memory databases that are capable of efficiently handling OLTP as well as OLAP queries (Plattner, 2009; Sikka et al., 2012). A column-based data organization enables efficient data compression and fits the requirements of OLAP queries as they often depend only on a limited number of columns. Maintaining the data in-memory allows using data structures that are not suitable for disk based databases and reduces the latency which makes real-time analytics possible. Due to these advantages, in-memory based databases become more popular in supply chain management. The

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largest class of benefits of real-time BI are related to enhanced operational decisions (Sahay & Ranjan, 2008).

Demand forecasting for perishable goods is an application scenario that can be enhanced with a data-driven decision support system (DSS) (Power, 2008). In particular, a DSS that supports the retailer at different organizational level during the planning process by providing demand forecasts is required (Holsapple & Sena, 2005; Holsapple & Whinston, 1996) in order to standardize and optimize the process. It needs to access a satisfying amount of historical as well most recent point-of-sale (POS) data from the operational database in order to apply techniques and methods like pattern recognition, statistical analysis, regression analysis or predictive modeling. Thereby, POS data needs be aggregated in real-time to the required organizational level. Hence, all prediction models are able to access the same operational data that contains near real-time information of the sales. Those requirements are met by state-of-art technology.

In this paper, we present the core of a DSS that predicts the demand for articles and article groups at different organizational levels. Such a DSS belongs to the first phase of the evolution of Business Intelligence and Analytics (BI&A 1.0) (Chen, Chiang, & Storey, 2012). Our work is motivated by the requirements of an industrialized bakery with respect to demand forecasting. The bakery runs a large number of stores that are daily delivered with baked goods which are produced in a centralized production facility. In this scenario, the total demand for each article as well as the demand at every store needs to be forecast on a daily basis. Based on the forecasts, production and distribution of goods takes place. In the following, we summarize the characteristics and challenges of the domain and justify why it is important to provide demand forecasts to support day-to-day operations.

1.1. Perishable fast moving consumer goods

Fast moving consumer goods (FMCG) comprise articles that are sold at a high frequency as they are mostly required to fulfill the daily needs (e.g. food, drinks, toiletries) (Kaiser, 2011). This group includes goods that have a short shelf life due to the high demand and/or because of the perishable character of the product which makes regular ordering necessary. Van Donselaar et al. (2006) classify items as perishable goods if they have a high rate of deterioration at ambient storage conditions (e.g. vegetables) or an obsolescence date that makes reordering impractical (e.g. newspapers). They report that perishable items have a 50% higher number of average sales per week and a 40% smaller median case pack size compared to non-perishable items. Thus, they conclude that the time between two orders is 2.5 times smaller for perishable goods which indicates that they are rather fast moving goods. Baked goods are classified as daily fresh items which are not only daily ordered but have also a high number of sales. The major cost factor for this type of articles are excessive stock levels that lead to marked down or thrown away items. For this product category, it is possible to rely on the customers' willingness to substitute and to keep the assortment limited (Van Woensel, Van Donselaar, Broekmeulen, & Fransoo, 2007). Studies indicate that the willingness to substitute is higher for perishable items (84%) than for other product categories (50% (Gruen, Corsten, & Bharadwaj, 2002)) which is caused by an immediacy effect, i.e., the item is needed on the day it is bought (Van Woensel et al., 2007). A high service level for all items leads to plenty of leftovers as the demand prediction is uncertain. Thus, it is beneficial to ensure the availability only for a subset of items of a category and to avoid waste of costly items.

1.2. Goods-in-stock: waste vs. out-of-stock/shelf

Inaccurate forecasts lead to overestimation or underestimation of the demand. The effects of overestimation can be quantified as the unsold items of perishable goods are waste and cannot be sold after the shelf life expires. From a financial point of view, the retailer loses the costs related to the production and delivery of the unsold items and has to pay waste collection fees or donate them to charity. For articles having a small profit margin, it is important to limit avoidable costs. On the other hand, demand underestimation leads to OOS which is much harder to quantify as the customer reaction is uncertain. Ehrenthal and Stölzle (2013) consider that an article is OOS if it cannot be bought by a customer at a given point in time. Studies suggest that the global average of OOS is 8.3% (Corsten & Gruen, 2003). OOS leads to an immediate revenue loss of 4% (Gruen et al., 2002) but also affects customer loyalty and jeopardizes future sales (Zinn & Liu, 2008). Hence, inaccurate demand forecasts have a negative financial impact. In the following, we summarize possible effects as well as causes of OOS.

The effects of OOS have been widely investigated (Campo, Gijsbrechts, & Nisol, 2000; Gruen & Corsten, 2007; Gruen et al., 2002; Helm, Hegenbart, & Endres, 2013). Campo et al. (2000) state that customers switch stores, substitute items, postpone the purchase or do not buy anything if the required item is not available. However, the actual response depends on factors like a pre-shopping agenda, urgency of the purchase, brand loyalty and store prices (Zinn & Liu, 2001). So, OOS leads to lost sales, dissatisfied shoppers and diminishes store loyalty. It also obstructs sales planning as the historic sales data is distorted and does not reflect the actual demand. This effects the forecast accuracy because of demand underestimation of items that were occasionally sold out in the past as well as to demand overestimation due to substitution effects. These effects are not limited to the directly affected article category. Ehrenthal and Stölzle (2013) report that OOS of fresh goods leads to the highest turnover loss compared to other categories. Hence, decreasing OOS is a possibility to reduce costs and to increase sales, especially for fresh items like baked goods.

The described effects of OOS underline that a retailer gains a competitive advantage by avoiding OOS. Thus, understanding the causes of OOS is required as it points to issues that need to be improved in order to achieve a better service level. Ehrenthal and Stölzle (2013) report that the causes for OOS in the retail industry are specific to retailer, store, category and item. However, many researcher identified inefficient store operations (Ehrenthal & Stölzle, 2013; Gruen & Corsten, 2007; Gruen et al., 2002) and not issues in the upstream supply chain (e.g. shortage) as primary cause for OOS (Aastrup & Kotzab, 2010). They also observed that the article availability decreases on the downstream towards the retail shelves. However, collaboration and communication between supplier and retailer provoke less problems regarding the article availability. Ehrenthal and Stölzle (2013) optimize the flow of goods by simplifying and structuring the tasks for the store personnel and bundling store deliveries and shelf replenishment. After these operational changes, OOS was mainly caused by erroneous orders instead of fulfillment and replenishment problems.

1.3. Addressing the bullwhip effect

The bullwhip effect is an issue in many supply chains (Lee, Padmanabhan, & Whang, 1997b). It describes the effect of increasing demand oscillation along the upstream supply chain and leads to excessive inventory levels and stock-outs. It is predominantly caused by long lead times, order batching/rationing, shortage gaming and price fluctuations (Lee, Padmanabhan, & Whang, 1997a). In order to resolve the bullwhip effect, the general concept of supply chain cooperation (e.g. collaborative planning forecasting and replenishment (CPFR)) is suggested (Danese, 2011; Hollmann, Scavarda, & Thomé, 2015; Kaipia, Korhonen, & Hartiala, 2006; Thomé, Hollmann, & Scavarda do Carmo, 2014). Thereby, it is typically tried to increase the responsiveness of the supply chain and to