Application of Big Data Technology in Support of Food Manufacturers' Commodity Demand Forecasting

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Abstract

Forecasting commodity demand for food manufacturers is very difficult to achieve because it is easily affected by variable factors such as the weather and the success or otherwise of advertising campaigns. The ambiguity of demand forecasting results in burdensome supply and demand adjustments and causes an increase in the logistics and production costs, stock-out, excessive stock and/or disposal losses. NEC applies one of its big data technologies, the heterogeneous mixture learning technology, to perform commodity demand forecasting and to automate and optimize the supply chain management systematization. In addition, NEC also applies machine learning to the simulation of sales measures in order to maximize their effects and to increase the sales volume.

Keywords

food industry, big data, machine learning, heterogeneous mixture learning, demand forecasting, simulation

1. Introduction

Maturation of the Japanese domestic market and diversification of consumer preferences are forcing the food industry to expand its business to multiple commodities such as new products, products with limited-time offers, in addition to the regular products. Forecasting the shipment trends of these commodities significantly affects the production plan, material procurement and physical distribution and in some cases may cause an increase in costs or commodity disposal losses.

Meanwhile commodity demand forecasting is greatly dependent on the weather, events and sales promotion activities, as well as on competitor trends. This has long been regarded as a hard-to-systematize domain and reliability has depended on the experience and intuition of skillful supply and demand adjustment staff.

More recently, instances of applying big data technology such as machine learning to commodity demand forecasting have been increasing. In this paper, we will introduce a commodity demand forecasting solution by applying the heterogeneous mixture learning that is one of NEC's machine learning technologies.

2. Commodity Demand Forecasting

2.1 Issues of Food Commodity Demand Forecasting

Generally speaking, the value chain of the food industry consists of; (1) procurement from raw material manufacturers and provision to the production sites of food manufacturers; (2) production at food manufacturers; (3) shipment/delivery from food manufacturer to retailers via wholesalers; (4) sales from retailers to consumers.

The retailers and wholesalers place orders by considering the sales trends and inventories at the stores (4). The food manufacturer receives these orders and settles the order receptions usually on a daily basis. Although this procedure varies depending on the type of goods (3).

In contrast and in order to reduce the costs, the procurement of raw materials (1) and production planning at the production site (2) are performed via a long- or mid-term cycle (of six months or more). Therefore, burdensome supply and demand adjustments are needed to fill the gap between demand forecasting and the actual forecasting. If this gap cannot be filled, the business will be seriously impacted by stock-out, excessive stock, disposal losses due to returned commodities or out of

Fig. 1 Value chain and demand forecast of the food industry.

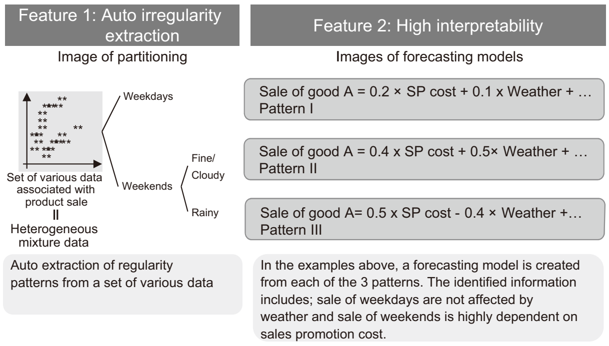

Fig. 2 Features of the heterogeneous mixture learning technology.

date materials stock (**Fig. 1**).

One of issues of the food industry is the demand fluctuation, and what make it more difficult is the wide variety of fluctuation factors and the large fluctuation amplitudes. These factors include meteorological conditions such as weather and temperature, the calendrical or seasonal conditions such as the day of the week, special dates and time zones. The shop conditions such as the location, trading zone and population configuration as well as the planogram (products layout on shelves), POP, bargain sales, campaigns, TV commercials and local events must also be considered.

In addition, the large number of commercial distribution processes makes it difficult to identify the channel inventory. The food manufacturers use not only the shipment data but they have always tried to acquire the warehouse out data via wholesalers and the POS data of the retailers. They have attempted demand forecasting by means of the moving-average or the exponential smoothing methods. However, as these methods were unable to deal with the high amplitude of the demand fluctuations, they have been seeking solutions that rather featured supply-and-demand adjustments, such as the ECR (Efficient Consumer Response) or QR (Quick Response). They have also tried to introduce SCM (Supply Chain Management) based on the TOC (Theory of Constraints), but difficulties with the setting and the maintenance/management have sometimes made it impossible to use the demand forecasting function. The difficulties of demand forecasting are further affected by the recent increase in the number commodity items and the shortening of product cycles.

2.2 Advent of Heterogeneous Mixture Learning Technology

With regard to the demand forecasting that has long been an important issue of the food industry, some have started to adopt the approach of machine learning, which is one of the big data related technologies. Among them, the heterogeneous mixture learning technology proposed by NEC is regarded as being very effective in demand forecasting for the food industry because of the following features (**Fig. 2**).

(1) Feature 1: Auto regularity extraction

Machine learning is applied to the wide range of factors causing demand fluctuations by considering them as heterogeneous mixture data (of a large variety of data). It extracts regularities automatically and creates forecasting models according to the number of patterns. In the forecasting, an optimum forecasting model is selected automatically to calculate the optimum forecasting values.

Considering the super-wide range of commodity items, human labor has limitations in its ability to develop optimum forecasting model patterns by making judgments every time. The creation of forecasting models at realistic cost and period is possible only when it is performed automatically by the heterogeneous mixture learning technology.

Since the forecasting model deteriorates as time passes, the forecasting models should be reviewed periodically to maintain forecasting accuracy. Automation enables a significant reduction in the man-hours required for performing the reviews.

(2) Feature 2: High interpretability

Each forecasting model is expressed as the product of the fluctuation factors and the constants obtained automatically by the heterogeneous mixture learning.

The sizes of the constants indicate the level of the effect of each fluctuation factor (weather, temperature, etc.). This makes it possible to read information such as for example "which forecasting model is applicable on a shiny weekday" or "sales of commodity B increase at a temperature above 26°C". This information is also helpful for identifying issues, such as the fluctuation factors, when incorrect data is used during the fine tuning of forecasting models.

The two features described above enable the systematization of demand forecasting, which is a routine operation of the food manufacturers, by applying the heterogeneous mixture learning technology.

2.3 Commodity Demand Forecasting Solution

This section describes our commodity demand forecasting solution based on heterogeneous mixture learning by following the forecasting flow.

Roughly speaking, the flow is advanced in two processes of "learning" and "forecasting." In the learning process (**Fig. 3**), previous data is input to the heterogeneous mixture learning engine to create forecasting models by means of machine learning. In the forecasting process (**Fig. 4**), the latest and future data (calendar, etc.) are input to the forecasting models to calculate the forecasting results. Each process is detailed in the following:

(1) Preparation of learning data

The data to be subjected to machine learning should first be prepared. To perform highly accurate forecasting periodically, the data should be accurate enough and steadily available at optimum timings. Examples of such data include the following:

- Basic data: Shipment data, calendar information
- External data: Warehouse-out data, POS data, meteorological data
- Additional data: Advertising information, special sale information, event information

To acquire the external and additional data at a steady rate, it is required to clear several issues such as agreement with customers and the preparation of an in-house system.

The data should be cleansed before being input to the heterogeneous mixture learning engine. Cleansing consists of decisions on how to prepare POS data using different formats depending on each retailer chain, how to handle illegal data and abnormal values, and how to group customers and products based on their names.

(2) Learning and creating forecasting models

The prepared learning data is input to the heterogeneous mixture learning engine in order to create the forecasting models. When creating the forecasting models of "Sale of goods A," for example, the data of fluctuation related factors, which is the cleansed past data, should be input. This procedure causes the forecasting models partitioned according to applicable patterns (daytime on weekdays, other than rainy weather on weekends, rainy weekends, etc.) to be created automatically for the same number of patterns.

For each forecasting model so created, verification data is input to check the gap between the predicted and achieved values. If the gap is large, the process returns to step (1) "Preparation of learning data" and, while referencing the forecasting model, reviews the data. Steps (1) and (2) are repeated until a satisfactory forecasting result is obtained and the forecasting model is established.

The learning system is provided by NEC via the cloud environment.

(3) Preparation of forecasting data

The forecasting data is created by adding the future data to the learning data prepared in (1) and (2) above. The future data mainly consists of the calendar information but can also include effective external as well as additional data.

(4) Execution of demand forecasting & reporting

The forecasting models created in (2) are preset in the forecasting system and the forecasting data prepared in (3) is input to calculate the forecasting results. The forecasting results are compiled into a report in an easy-to-use format. The report is output to the supply-and-demand adjustment consultations in the associated departments or as a file containing the initial values to be input to the supply-and-demand adjustment system. In order to make these procedures possible we will develop a reporting mechanism according to the needs of each customer.

(5) Feedback of forecasting results & review of forecasting models

In the initial period, the demand forecasting of (3) and (4) is performed using the forecasting models created in (1) and (2). However, the created forecasting models tend to deteriorate gradually due to changes in the market environment and the forecasting accuracy may drop accord-

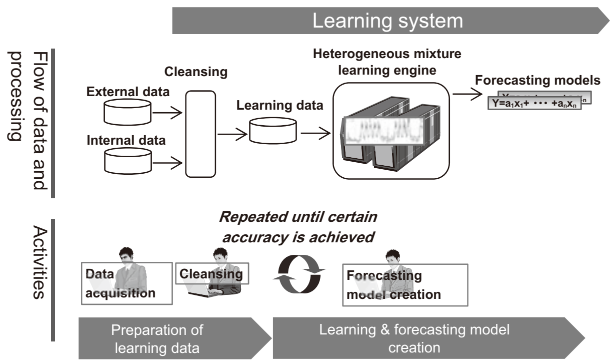

Fig. 3 Demand forecasting flow (Learning).

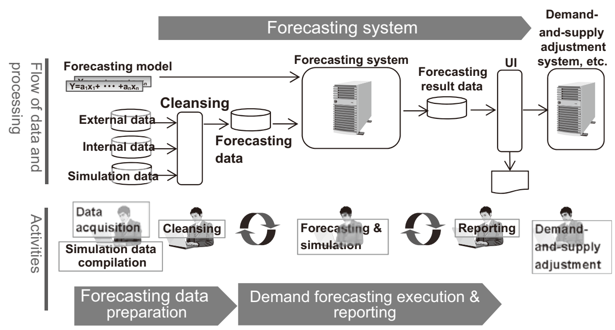

Fig. 4 Demand forecasting flow (Forecasting).

ingly, which makes it necessary to review the forecasting models periodically. At an optimum interval of generally three to six months, the forecasting models should be reviewed routinely by evaluating the difference between the forecast results and those actually achieved.

2.4 Expected Effects

Our proposed solution automates and systematizes demand forecasting based on the machine learning, so that it contributes to the production operation at a food manufacturer that handles multiple commodity items. When the system was evaluated for a food manufacturer, it was found that forecasting with a relatively high accuracy was achieved for 70% of the target commodities.

Effects to be expected from this solution include an improvement in the demand forecasting for the supply-and-demand adjustment operations and the possibility of optimizing demand forecasting by performing reviews at constant timings such as daily reviews. Also of importance are the results made possible by the above, such as the production/distribution cost reductions due to reduced stock-out and special vehicle arrangements as well as a reduction in disposal losses thanks to the optimized inventory.

Furthermore, the concept of demand forecasting that used to rely on the experience and intuition of skilled engineers will now be expressed in the form of forecasting models. The knowledge gained from ongoing forecasting jobs and its transfer to non-skilled engineers will also be possible.

3. Various Simulations

The commodity demand forecasting solution employs the heterogeneous mixture learning technology and forecasts the commodity demand based on the time axis. Simulating various cases, e.g. the sales when a certain amount of campaign budget is invested, are also available by entering different fluctuation factors such as sales campaign, bargain, etc. as the simulation values.

Food manufacturers are sometimes provided POS data by retailers and are expected to propose some ideas to improve the sales of retailers' shops. The data such as channel inventory, consumers purchasing results, etc. of the vending machine is occasionally stored at food manufacturers. In order to cope with such cases, the heterogeneous mixture learning technology provides the solution, and simulates the sales campaign results, planogram, column display, etc. Utilizing big data makes it possible to achieve a significant sales improvement.

4. Conclusion

Application of the heterogeneous mixture learning technology is enabling the systematization of demand forecasting that has long been an issue in the food industry. Systematization and accuracy improvement of demand forecasting can reduce the distribution costs and disposal losses.

When the forecasting is performed as a simulation, it is also possible to adopt proper measures for increasing sales.

At NEC, we will continue development of solutions for the food industry by utilizing big data and in order to contribute ultimately to a sustainable and efficient society.

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Vol.10 No.1

December, 2015

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