Chapter I – Demand Sensing

Demand Sensing and Demand Shaping

Demand forecasting is imperative in supply chain management as it lays the foundation for inventory management and production planning. Generally demand forecasting is made on a long term basis as it aid strategic and tactical decisions. Hence, traditional demand forecasting models smoothens out fluctuations to arrive at an estimate. The fluctuations of demand in short time periods are not captured by these models. Demand Sensing is used for identifying these changes and improves the forecasting accuracy. Demand Shaping Models utilizes the corrected forecast and arrives at operational decisions for the supply chain.

Demand Sensing is dynamic demand management decision support system. In recent time, organizations have access to huge amounts of data collected from various channels. Demand Sensing is a specialized monitoring process which identifies changes in near-real or real-time demand based on demand signals. Demand signals are generated from structured data and unstructured data collected from various channels of the supply chain such as

- Market Segment Data (web, social media and email)
- Collaborative customer data (Demand anomalies)
- Marketing and sales data (promotions, productive life-cycle management and competitive analysis)
- Macroeconomic indicators applicable to specific industry

Although, demand sensing provides insights on fluctuations, demand sensing and demand shaping should be executed hand in hand to attain optimal supply chain profitability. Demand shaping is the process that supplies real-time and future demand and supply balancing. It is a dynamic and cross-functional process that focuses on reducing costs.

Implementation of Demand Sensing

Descriptive Analytics:

The statistics of the given data is summarized to get insights on the data at a high level. This maybe distribution of different attributes and correlation between each other. Data summarization and visualization are descriptive Analytics methods in the system which enables supply chain visibility and better understanding of data.

Predictive Analytics:

Demand sensing involves anomaly detection and sales estimation. Models to detect major deviation from sales are to be implemented to monitor the deviation from demand levels. Predictive Models should be built to estimate the near-real and real-time demand.

It is interesting to note that especially in retail industry different products compete and complement each other. The demand of one product is hence influenced by the other. These dependencies should be taken into consideration while sensing demand. Clustering is done to identify and group products that compete or complement each other.

Figure 1 shows the knowledge discovery involved in Demand Sensing. From the preprocessed data the following models can be implemented to sense demand.

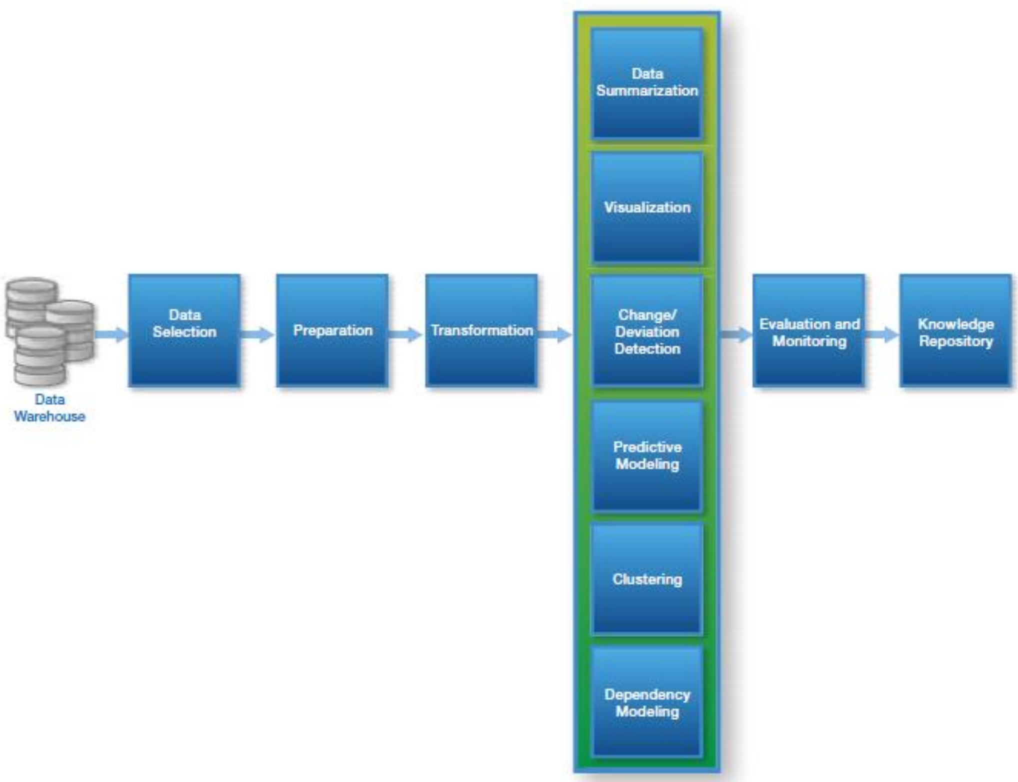

Figure 1: Demand sensing knowledge discovery process

Demand Sensing Models

Commercial tools to sense demand are developed by SAS and C-B4. Content Based 4casting has developed a robust model to sense demand. It is widely used in industries. The white paper by C-B4 on their forecasting model is added in the reference section [2]. C-B4 demand sensing model incorporates all the features discussed in the previous section.

On the other hand, not much of demand sensing model are reported from the research community. Dr. Charles W. Chase Jr. has discussed a case study on demand sensing in his textbook Demand-Driven Forecasting: A Structured Approach to Forecasting. He used a Multi-Tiered Causal Analysis (MTCA) model to for demand sensing in a CPG company. He used multi-layer linear regression to estimate demand and factory shipments for each product. [3]

The first layer estimates the value of customer demand using a linear regression model which has retail price, sales promotion, advertising, in-store merchandising, store distributions, coupons, product rebates, competitive activities and seasonality.

The first layer is

$$\mathbf{CD} = \beta_0\text{Constant} + \beta_1\text{Price} + \beta_2\text{Advertising} + \beta_3\text{Sales Promotion} + \beta_4\text{ACV Feature} + \beta_5\text{FSI} + \beta_6\text{Store Distribution} + \beta_7\text{Seasonality} + \beta_8\text{ Competitive Price} + \ldots \beta_{11}\text{ Competitive Variables},$$

Where, CD is Consumer demand.

The value of CD estimated y the first layer is fed to the second layer with a lag of one time period to estimated factory shipments. The predictors include consumer demand, trade promotions, gross dealer price, factory dealer rebates, cash discounts, co-op advertising and seasonality.

Second layer is

$$\mathbf{FS} = \beta_0\text{Constant} + \beta_1\text{CD (forward lag 1 period)} + \beta_2\text{ Gross Dealer Price} + \beta_3\text{Factory Rebates} + \beta_4\text{Cash Discounts} + \beta_5\text{Co-op Advertising} + \beta_6\text{Trade Promotions} + \beta_7\text{Seasonality}.$$

Where, FS is factory Shipments.

The given model was implemented on a dataset of 26 week and MAPE of the forecasting model was 9.2%

References

Demand Sensing

1. Unlocking the promise of demand sensing and shaping using big data analytics, A white paper by SAS enterprise
2. Demand sensing via C-B4 pattern analysis and SAS Forecast server, SAS global forum 2011
3. Intermittent demand forecasting and multi-tiered causal analysis, Charles Chase