A Novel Approach of Intermittent Demand Prediction in Industrial Domain

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Abstract. Intermittent demand, one of the categories of unusual demand, such as demand of spare parts of industry equipment management, seasonal and short life cycle products, is characterized by infrequent demand arrivals and variable demand sizes, which is difficult to predict. To solve this problem, a novel approach was proposed in this paper to predict intermittent demand. It provided mechanism to forecast demand arrival time with demand values at the same time when demand occurs. It firstly applied Decision Tree to predict a 0-1 binary values of demand arrival time. Meanwhile Neural Network was built to predict demand values. Then the time points of these two results were matched. The demand values for those moments when predicted demand that did not occur were replaced by zero. Finally we applied this approach to predict sparse demand of products, the results showed that the predicting accuracy was superior to traditional Back-propagation Neural Network through comparison.

Keywords: Intermittent Demand, Decision Tree, Neural Network.

1. Introduction
In the demand prediction of industrial domain, unusual demand is a special but often occurring. Unusual demand is characterized by infrequent demand arrivals and variable demand sizes, which is difficult to forecast [1]. The demands of spare parts of equipment in the production or industry equipment management, seasonal items or short life cycle products in the supply chain can be classified as intermittent demands. Therefore, companies tend to analyze their spare parts demand and try to estimate their future consumption [2]. Accurate demand prediction of spare parts demand is crucial to optimize spare parts management. As well as in supply chain management, demand prediction is the key issue to make the balance between supply and demand using effective dynamic operations, which would keep the sustainable stability operation of the supply chain, to improve its competitiveness.

Unusual demands generally have two typical characteristics. One is that the demand changes drastically and is extremely unstable; the other is that the time interval of demand is long and uncertain. And these two features often exist at the same time [3]. On one hand, such features lead to a limited sample size of the data used, which makes the traditional statistical theory-based requirement description method [2] difficult to be used in practice, so that the complexity of the problem is further raised. On the other hand, since such demand is stochastic and a big proportion of the demand data are zero for several periods of time, many existing studies have also attempted to propose some machine learning
methods to solve those problems. Regarding the study of unusual demand forecasting, the earliest method of prediction is Croston method [4]. But this method can only predict the average demand of each period. Thomas [5] used bootstrap method to predict the unusual demand but the assumption of this method was difficult to guarantee the autocorrelation of the demand time series and can only be used if the demand distribution was obtained in advance.

In the past, the methods of predicting the unusual demand were more focus on demand values, and less on demand arrival time. In our research, a novel approach was proposed to forecast the unusual demand. The methodology provided mechanism to forecast demand arrival time with demand values at the same time when demand occurs. The method was combined with Decision Tree and Neural Network. The demand arrival time was transformed into a 0-1 binary sequence, which, 0 was no demand arriving, and 1 indicated there existed demand. A binary Decision Tree classification was applied to predict the demand arrival time. The Neural Network was used to predict the demand values. Then the time points of these two results were matched. The demand values for those moments when predicted demand did not occur were replaces with zero. The method in this paper attempts to solve the shortcomings of the traditional methods, and combines the selected typical prediction problems to apply the application of the proposed new technology. The predicting accuracy was indicated improving through comparison.

The paper is organized as follows: The first section is dedicated to the introduction of related works of the unusual demand prediction. The second section made a detailed explanation of the categories of unusual demand and each characteristics. Then the third one presented the proposed method. Numerical analysis results and conclusions were illustrated in the fourth section.

2. Categories and characteristics of unusual demand

Many researchers have conducted studies on unusual demand and given definitions for unusual demand types as Slow Moving Demand [6], Intermittent Demand [7], Irregular/erratic Demand [8], and Lumpy Demand [9]. Syntetos proposed a simple and practical mathematical way to classify those unusual demands by means of demand values, standard variations, frequent changes, etc. [9] The method is illustrated in Figure 1.

![Figure 1. Syntetos method of classification of demand [1]](image)

In Figure 1, suppose ADI is the average demand interval, and CV is the coefficient of variation between non-zero demand values, which can represent the degree change of demand:

\[
CV(x) = \frac{\sigma}{\mu}
\]

(1)

Where \(\mu\) is the mean and \(\sigma\) is the standard deviation. With the increasing of ADI, the demand intervals tend to be obvious; and with the increasing of \(CV(x)\), the demand values tend to be unstable. If ADI > 1.32, the demand has the characteristics of intermittent behaviour. If the CV \((x) > 0.49\), the demand has significant instability. Features of unusual demand data include irregular/erratic demand, lumpy demand and intermittent demand, of which later two types are more typical [1].

At present, the research on the method of predicting unusual demand mainly focus on the intermittent demand. The common methods were mentioned before. Most of the methods focus on the prediction of
demand values. However, due to the particularity of the characteristics of intermittent demand data, only predicting demand values cannot obtain good accuracy for practical application. Therefore, we propose a novel approach that combines the prediction of demand arrival time and demand values to effectively improve the accuracy of traditional methods.

3. Approach to Predict Intermittent Demand

According to different application scenarios, the granularity of demand prediction can be divided into different grades. Generally, demand prediction has three dimensions [10]: (1) time, (2) spatial, and (3) product. In time dimension, demand can be divided into different time scales that hour, day, week, month, year, etc. In spatial dimension, demands come from different spatial levels that sales branch, area, distribution center, different levels of warehouses, factories, etc. And in product dimension, demand can be divided according to different product properties that product model, type, brand, series, item, etc. In this way, through the integration of the three dimensions, the predicting results can reach an intersection of time scale, spatial level, and product. For example, predicting hourly demands of each product model from each sales branch means the smallest granularity in the case of above classification.

For sparse data, the generalization capabilities of general machine learning methods such as Neural Network, Support Vector Machine, etc., become poor and are not suitable for direct prediction of sparse demand. Usually, when demand value at a certain point is 0 but predicting value is non-zero, then the predicting error is 100%. And vice versa, when demand value is non-zero but predicting value is zero then the predicting error also reaches to 100%. It is difficult for real application to use the results. In order to improve the predicting accuracy, we not only predicted demand values, but also took prediction of demand arrival time into consideration.

3.1. Prediction of Demand Arrival Time

In order to predict demand arrival time, actual demand values $X$ were converted into a 0-1 demand occurrence time series $F$, where $X = (x_1, x_2, \cdots, x_n)$ and $F = (f_1, f_2, \cdots, f_n)$. In 0-1 time series, 0 means no demand occurs and 1 means there exist non-zero demand values. Therefore, the prediction of demand arrival time becomes a 0-1 binary problem. The data are sparse for demand, however the data samples instead have a stable 0-1 distribution after transferring data into 0-1 time series.

Decision Tree is one of the most popular machine learning algorithms used all along. A Decision Tree is a tree where each node represents a feature (attribute), each link (branch) represents a decision (rule) and each leaf represents an outcome (categorical or continuous value). It has a good performance to solve a binary classification problem so that we choose it to predict the demand arrival time.

3.2. Prediction of Demand Values

Machine learning methods, such as Neural Network (NN), Support Vector Machine (SVM), Logistic Regression (LR), etc., are widely used in demand prediction [11]. In this case, we choose a feed-forward Neural Network to predict the demand values. While NN is a computational system based on an approximate model of the human brain, simple units called neurons are connected and form the network. It is a data-driven self-adaptive method where there are few a priori assumptions about the models for problems under study. It is capable of learning the complicated nonlinear relationships among the data and performs well. Multi-layer Perceptron (MLP) is widely used in demand prediction among NN models. These MLP networks often employ standard backpropagation (BP) algorithm and outperform the traditional statistical methods.

3.3. Combination of Demand Arrival Time and Demand Values

After finishing predicting demand arrival time and demand values, we matched the time points of these two results. The demand values for those moments when predicted demand did not occur were replaced with zero. And the remaining values is accordingly obtained as the predictive values. Figure 2 illustrated the detailed process flow of the proposed approach.
4. Experimental Methodology

The experimental data used in our research were obtained from a cosmetic and pharmaceutical industry and totally pre-processed by data masking. The data contained the shipping amounts of cosmetics and medicines from two warehouses during 2014/9 to 2017/7. We need to predict the daily shipping amount of each medicines and cosmetics in each warehouse in the next five days.

Though the observation of the data, we found that not every item has a daily shipping amount record. Data are characterized by intermittent demand. See Table 1.

**Table 1.** Statistics results of experimental data

| Year   | 2014 | 2015 | 2016 | 2017 | 2014 | 2015 | 2016 | 2017 |
|--------|------|------|------|------|------|------|------|------|
| Warehouse #1 |      |      |      |      |      |      |      |      |
| Number of items which have shipping amount records | 943  | 1001 | 1038 | 1066 | 1380 | 2066 | 2766 | 3048 |
| Ratio (%) | 88.46 | 93.9 | 97.4 | 100  | 45.28 | 67.78 | 90.74 | 100  |
| Number of items which have no shipping amount records | 123  | 65   | 28   | 0    | 1668 | 982  | 282  | 0    |

Since the demand values and demand arrival time were highly related with each other, we considered same methods to extract the corresponding features. For each item $i$, firstly we transferred the demand values $X_i = (x_{i1}, x_{i2}, \ldots, x_{in})$ into a 0-1 demand occurrence time series $F_i = (f_{i1}, f_{i2}, \ldots, f_{in})$, where $n$ is the number of days, $i$ is the item index, and

$$f = \begin{cases} 0, & x = 0 \\ 1, & x \neq 0 \end{cases} \quad (2)$$

After data pre-processing, we extracted features from demand values $X_i$ and demand arrival time $F_i$. The features of demand values and demand arrival time for each item $i$ were illustrated as

$$features(X_i) = \{x(t-1), x(t-2), \ldots, x(t-5), \bar{x}(t-14), \bar{x}(t-30), w(t), m(t), y(t), h(t)\}$$

$$features(F_i) = \{f(t-1), f(t-2), \ldots, f(t-5), \bar{f}(t-14), \bar{f}(t-30), w(t), m(t), y(t), h(t)\} \quad (3)$$

Where, $i$ is the item index, $t$ is day index, $x$ is the shipping amount, $f$ is the demand arrival time, $\bar{x}$ is the average shipping amount, $w$ is the week of the day, $m$ is the month of the day, $y$ is the year of the day, and $h$ is 0/1 value indicates whether there are holidays in day $t$.

Total features were prepared as following formulas:

$$features(X) = \{features(X_1), features(X_2), \ldots, features(X_k)\}$$

$$features(F) = \{features(F_1), features(F_2), \ldots, features(F_k)\} \quad (4)$$

Where, $k$ is the total number of items. Then the features($X$) and features($F$) reached to the Neural Network and the Decision Tree models as inputs, respectively.

For each model, we obtained the predicted values of demand arrival time and demand values of each item as,
\[ P_F(t) = \{ p_{f1}(t), p_{f2}(t), \ldots, p_{fk}(t) \} \]
\[ P_X(t) = \{ p_{x1}(t), p_{x2}(t), \ldots, p_{xk}(t) \} \]  

(5)

Where, \( P_F \) is the predicted values of demand arrival time and \( P_X \) is the demand values of all items.

Finally, we matched the time points of \( P_F(t) \) and \( P_X(t) \) as,

\[ p_i(t) = \begin{cases} 
0, & p_{fi}(t) = 0 \\
p_x(t), & p_{fi}(t) = 1 
\end{cases} \]  

(6)

and got the final predicted values \( P \) in day \( t \):

\[ P(t) = \{ p_1(t), p_2(t), \ldots, p_k(t) \} \]  

(7)

The prediction accuracy were evaluated by Symmetric Mean Absolute Percentage Error (SMAPE),

\[ SMAPE = \frac{1}{N} \sum_{t=1}^{N} \frac{2|P_t-D_t|}{(|P_t|+|D_t|)} \]  

(8)

Where \( P_t \) is the forecast value, \( D_t \) is the actual value, \( N \) is the number of prediction in testing samples.

5. Results and Application

5.1. Results

Based on the experimental data and the process flow of the models aforementioned, we obtained the results of the precision indicated in Table 2 and Table 3.

Table 2. Comparison of precisions by using traditional neural network and Our Approach

|       | SMAPE (Traditional Neural Network) | Our approach |
|-------|-----------------------------------|--------------|
| Day 1 | 0.974                             | 0.737        |
| Day 2 | 1.023                             | 0.797        |
| Day 3 | 1.011                             | 0.792        |
| Day 4 | 1.103                             | 0.795        |
| Day 5 | 0.993                             | 0.797        |

Table 3. Precision of demand arrival time, demand values and final demands of each next 5-days

|       | Demand arrival time | Demand values | Final demands |
|-------|---------------------|---------------|---------------|
| Day 1 | 0.532               | 0.974         | 0.737         |
| Day 2 | 0.522               | 1.023         | 0.797         |
| Day 3 | 0.619               | 1.011         | 0.792         |
| Day 4 | 0.564               | 1.103         | 0.795         |
| Day 5 | 0.601               | 0.993         | 0.797         |

Table 2 showed the comparison of precisions by using traditional Neural Network and our approach, which is the difference between only predicting demand values and combing predicting demand arrival time and demand values. It indicated that by combing the demand arrival time and demand values, the precision improved instead of only predicting demand values.

Table 3 showed the precision of demand arrival time, demand values and final demands of each next five days. The Decision Tree had a good behaviour to classify the demand arrival time and the precision of final demands improved.

5.2. Application
Our approach was also applied to another use case to predict demands of a household appliances enterprise. Data were collected from three different types of products and weekly-demand prediction was made. Data were also characterized by intermittent demand after pre-processed. By using the proposed approach, the results reached to approximately same precision level as shown in Table 4.

Table 4. Demands Precision of Household Appliances Enterprise

|          | Type 1 | Type 2 | Type 3 |
|----------|--------|--------|--------|
| Week 1   | 0.934  | 1.348  | 1.19   |
| Week 2   | 0.908  | 1.323  | 1.07   |
| Week 3   | 0.827  | 1.137  | 0.99   |

6. Conclusions

In our research, a novel approach of intermittent demand prediction was proposed. The methodology provided mechanism to forecast the demand arrival time couple with the demand values when demand occurs. Compared with the results obtained by only predicting the demand values, it comes to a conclusion that our approach will get a more accurate predicting results. Meanwhile, we also applied the approach to different use cases, and the approach has been proven to be available. Therefore, it can be concluded that the generalization of this predicting method performs well.

In the future work, more data will be collected to improve our approach. Meanwhile with the change of new and old products, the demand arrival time will become sparse as the product changes, thus it will lead to the unbalance between demand arrival time data. We will improve the approach to solve the unbalance between demand arrival time data in order to raise the accuracy. In addition, the approach will also be used in other application cases such as demand prediction of the important spare parts for large machines in manufacturing.

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