A PART-Based Algorithm for Prediction of Daily Demand Orders

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Summary
The daily demand forecasts of orders in logistics businesses are critical in scheduling and planning supply chain activities in order to satisfy customer demand in a timely fashion, improve effectiveness and reduce expenses. Although some machine learning methods have been employed to predict daily demand orders of goods for the supply chain in logistics businesses, there are important concerns over the selection of the most suitable predictive technique. This paper examines the implementation of PART -based strategy to predict daily product requests in a brief period. A true database of a Brazilian logistics business gathered over 60 days evaluates the methodology. The PART classifier uses 10-fold cross-validation to forecast daily demand for orders within 6 days 10 times on this gathered dataset. The results demonstrate that the classifier suggested can predict a day-to-day order requirement with elevated precision compared to the state-of - the-art baseline classifiers.
Key words:
Daily demand of orders, Forecasting, Supply chain, Machine learning, PART classifier.

1. Introduction

Daily demand forecasting for orders is an important part of the supply chain management process in logistics businesses. In order to satisfy the requirements of consumers in a timely manner, improve effectiveness and cut expenses from manufacturing point to consumption it performs a significant role in the planning and schedule of supply chain activities. The forecast exercise of the consumption of products by logistics businesses constitutes a critical supply chain bottleneck process. It is used for monitoring, coordinating and managing resources needed for reliable, prompt and efficient movement of products [1]. The supply chain management subsequently monitors the motion of products to meet client requirements. In spite of the high productivity achieved by logistics companies, the prediction is made by the daily demand of products and services [1].
A strong and precise model for predicting daily orders demand is needed to enhance the business strategy that reacts to change in demand [2]. Effective market hypotheses [3] are recognized as the use of forecast techniques to devise future trends in finances and businesses. At the cutting-edge level, there are few methods to predict orders, pricing and expenses of historical information products.
Li et al. [4] indicated that there are certain external conditions to the sensitivity of product prices. These internal circumstances include regular quotations for rates in two international currencies (JPY, euro) for goods and services such as natural gas, crude oil, gold, cotton and maize. In experiments of the work, between 01/01/2000 and 11/11/2014, 2666 of the trading figures from US inventories are collected. The dataset includes the opened, closed, maximum, lowest and inventory volumes per day. The characteristics are obtained from the above internal factors and historical inventory information. The experiment findings show a high rate of logistic regression (LR) of 55.65%.
As a teaching dataset, Dai and Zhang [5] used an amount of 1471 daily stock recorded cases between 1/9/2008 and 11/8/2013.For the practice of the forecast model, several machine learning techniques are used. The techniques employed are LR, quadratic discriminant analysis (QDA) and support vector machine (SVM) classifiers. Methods used are the LR. They are used to forecast long-term and short-term rates respectively for the following day and the next night. The next day's forecast findings ranged between 44.52 and 58.2 percent. Nonetheless, the long-term forecast technique accomplished better outcomes, in particular when the period was 44. The SVM achieved the highest precision result of this work with 79.3%.
A hybrid model suggested by Devi et al. [6] is combining cuckoo search with Gaussian SVM kernel. As a technique to initiate the SVM parameters, the Cuckoo search algorithm is used. The trading agent forecast model with the neural network ensemble has been suggested by Giacomel et al. [7]. The model predicts whether an inventory will drop or increase. Two datasets were used to evaluate this model: the Brazilian and North American stocks. Boonpeng and Jeatrakul [8] used the Sell, Hold or Buy Data prediction model of a One-against-One (OAO) and One-against-All (OAA) neural network. Also comparable to the standard neural network is the performance of this model. Historical information from the Thailand inventory exchange (SET) for seven years between 03/01/2007 and 29/08/2014 are gathered and used for training purposes. The precision findings of OAA-NN were superior to traditional techniques of NN and OAO-NN, with a 72.5% precision.

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A research was implemented by Ferreira et al. [9] to predict the delay requirements of orders using artificial neural network (ANN). However, ANN faces the issues of over-fitting and local minima, as well as having many parameters to optimize.

Recently, Alsanad [10] proposed a method for predicting daily demand orders using random forest (RF). He used a 10-folds cross-validation technique to evaluate the experimental results. The author's method has achieved 88.333% of accuracy compared to the state-of-the art methods.

In this article, we suggest an efficient forecast model for predicting orders on a daily basis using PART-based strategy. This model can learn from historical information and face issues that are over-fitting and under-fitting.

The following sections of this paper are as follows: Section 2 describes the algorithm of PART classifier. Section 3 introduces the suggested methodology. The experimental findings and analysis are presented in Section 4. Finally, the conclusion and future work are shown in section 5.

2. PART Classifier

The PART classifier is a separate and conquer rule model. The algorithm of this classifier produces a set of rules, called decision lists, which are prearranged set of rules. The new data that will be come are compared with each rule in the decision list, and finally, they are assigned to the class that achieves the first matching rule. The PART classifier constructs a partial decision tree for each iteration and puts the best leaf into a specific rule [11, 12]. In other words, the basic idea behind PART classifier is to construct a partial decision tree rather than fully built ones. The partial decision tree is a regular decision tree, in which its branches contain undefined sub-trees. In order to produce such partial tree, the building and pruning operations are integrated to discover a steady sub-tree that is normally simplified and no further. When this sub-tree is discovered, tree-building stops, returning a read off single rule [11].

The tree-building procedure of PART is illustrated in Figure 1. In this Figure, tree-building procedure splits recursively the examples into a partial tree. For the first step, it divides these examples after choosing a test case into subsets. This procedure will be continued recursively until the subset is expanded into a leaf, and then it will be continued further by the backtracking strategy. Recently, the PART classifier is used in many applications [13, 14].

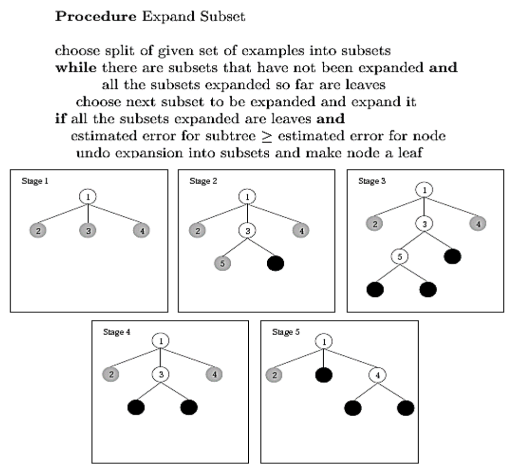

Fig. 1 Tree-building procedure with example of PART Classifier [11].

This study explores the application of the PART classifier to forecast daily orders in logistics companies.

3. Proposed Methodology

The methodology proposed is designed to build a robust model of prediction that achieves a high degree of accuracy when forecasting orders on a daily basis. It consists of three main steps as shown in Figure 2.

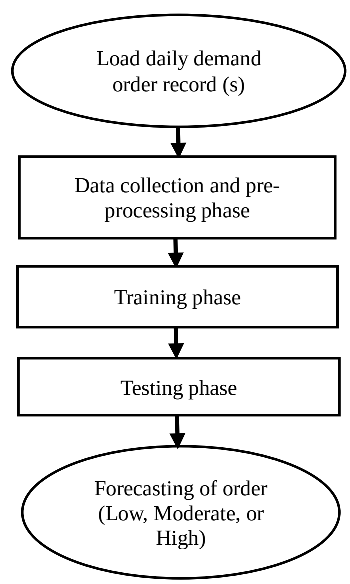

Fig. 2 Proposed methodology for orders forecasting.

The proposed methodology is explained in the following subsections.

3.1 Data Collection and Pre-processing Phase

We use the daily demand forecasting data set gathered in [9] in this phase of our suggested methodology. Features used are the week of the month in this dataset (first week, second, third, fourth or fifth week), ‘Day of the week (Monday to Friday)’, ‘Non-urgent order’, ‘Urgent order’, ‘Order type A’, ‘Order type B’, ‘Order type C’, ‘Fiscal sector orders’, ‘Orders from the traffic controller sector’, ‘Banking orders (1)’, ‘Banking orders (2)’, ‘Banking orders (3)’, and ‘Target (Total orders)’. We classify the ‘Target (Total orders’) according to the total number of orders into three classes. The class High represents the total number of orders that is more than 400 orders. The class Moderate represents the total number of orders that is less than 400 and more than 250. The class Low represents the total number of orders that is less than 250 orders. Figure 3 illustrates the distribution of the dataset obtained.

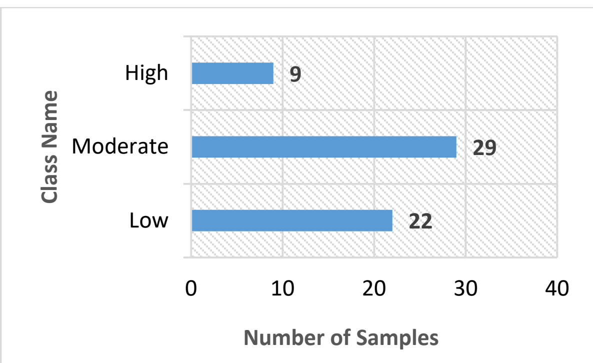

Fig. 3 Order samples distribution in dataset.

3.2 Training Phase

We use here 10-fold cross validation mode to train the PART classifier on the obtained dataset. The dataset can be split into 10 folds with 10 times cross validation, and the PART classifier is trained 10 times 9 out of 10 folds. In the testing phase, the remaining one-fold is used. This phase has resulted in 10 PART models trained.

3.3 Testing Phase

During the test phase, we train the PART classifier on the nine folds every time we take 10 times; we test it on the other fold. The result is averaged ten times using a weighted average method to obtain the result of the trained PART classification.

4. Experimental Results and Discussion

We used a WEKA tool, which is referred to Waikato Environment for Knowledge Analysis [15] for implementing the methodology of the study. It is a popular framework of machine learning in the field of data mining. In addition, we evaluated the results using three evaluation metrics. These evaluation metrics are the recall, precision, and the accuracy.

$$\text{Recall} = TP / (TP+FN) \quad (1)$$

$$\text{Precision} = TP / (TP+FP) \quad (2)$$

$$\text{Accuracy} = (TP + TN) / (TP+FP+TN+FN) \quad (3)$$

Where TN and FN are true and false negative rates. TP and FP are true and false positive rates.

The experimental results are computed based on the evaluation metrics of the 10-folds testing sets. These results are for six popular classifiers in the machine learning and state-of-the-art works, as well as the proposed classifier. The six classifiers used in the experiment are artificial neural network (multilayer perceptron (MPL) proposed in [9], random forest used in [10], bagging of decision trees (BDTs), linear support vector machine (LSVM), nearest neighbors (KNN), and decision tree (J48). In Figures 4-6 and Table 1, we demonstrate the results of recall, precision, and accuracy for our used classifier model in comparison with the state-of-the-art classifiers.

Table 1: Results of PART classifier compared to the six state-of-the-art classifiers.

Classifier Model	**Accuracy (%)**	**Weighted Avg. of Precision**	**Weighted Avg. of Recall**
ANN [9]	85	0.851	0.850
RF [10]	88.333	0.894	0.883
BDTs	81.667	0.822	0.817
LSVM	81.667	0.819	0.817
KNN	73.333	0.739	0.733
DT	86.667	0.868	0.867
Proposed PART	**90**	**0.900**	**0.900**

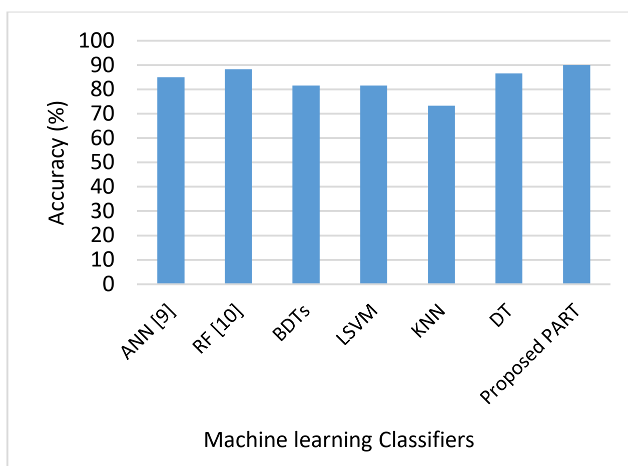

Fig. 4 Accuracy of PART classifier compared to other machine learning classifiers.

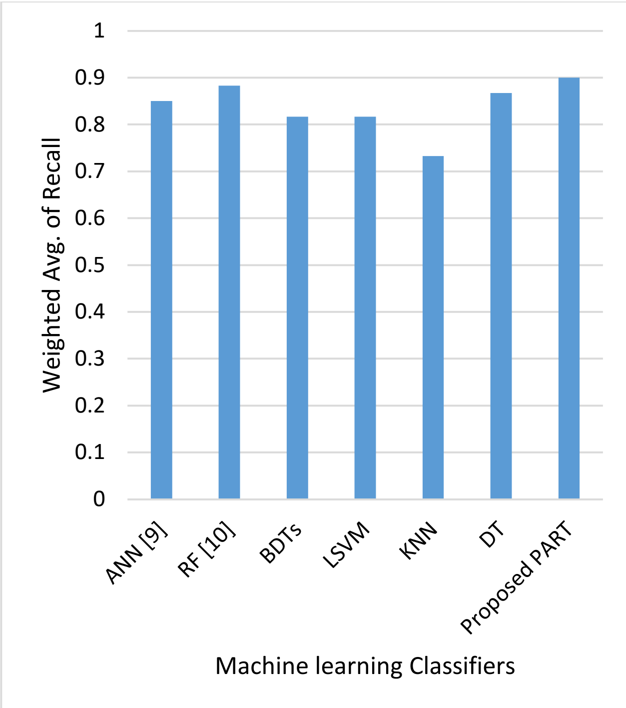

Fig. 5 The Average of weighted avg. recall of PART classifier compared to other machine learning classifiers.

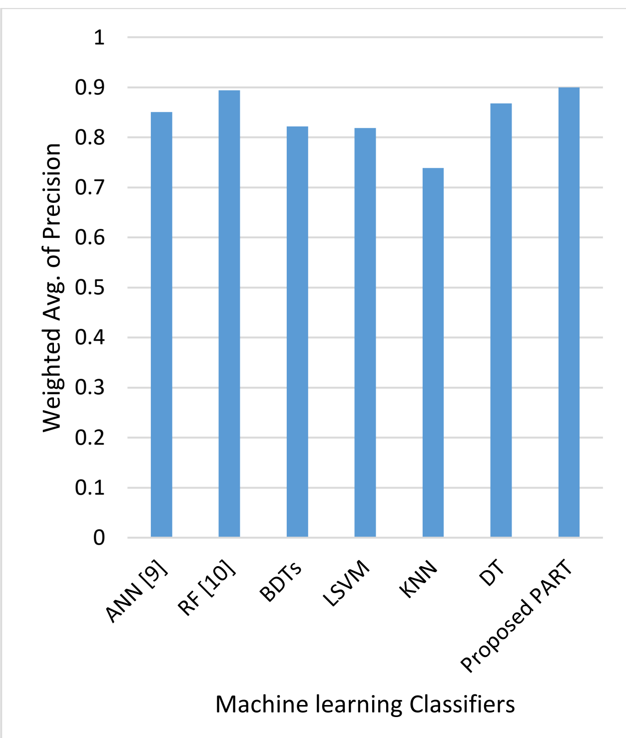

Fig. 6 The Average of weighted avg. precision of PART classifier compared to other machine learning classifiers.

As shown in Figures 4-6 and Table 1, the PART classifier can attain 90 % of accuracy, which is the best compared to all other machine learning classifiers. Moreover, it achieves the best results of recall and precision with 0.900 and 0.900, respectively. We can also see that the method proposed in [10] achieves the second highest accuracy result with 88.333% against the other state-of-the-art classifiers.

5. Conclusion and Future Work

This paper has proposed an effective methodology to use PART classifier for predicting the daily demand of orders in logistics companies. The PART classifier constructs a partial decision tree for each iteration and puts the best leaf into a specific rule. It normally achieves much better accuracy result than using a decision tree classifier as a lone. The 10-folds cross validation has been used for training and testing in order to evaluate the proposed classifier.
The experiments are implemented using WEKA tool. Precision, recall, and accuracy are employed as evaluation measurements to assess the output results of the classifier. Six baseline classifiers are adopted to compare the effectiveness of the PART classifier for predicting the daily demand of orders. The experimental results demonstrated the ability and robustness of PART classifier compared to the baseline classifiers in the state-of-the-art.
In the future work, a new machine learning classifier will be proposed to improve precision, recall, and accuracy of predicting the daily demand of orders in logistics companies.

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