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顧客行動分析を活用した売上予測

Improve Sales Forecasting with Customer Behavior Analysis

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In this paper, we explore the utility of customer behavior analysis of un-structured video data for improving sales forecasting, which is an important task for supply chain management in retail store. Our work is motivated by the observation that *the needs and interest of customers will influence the sales performance and customers' needs and interest can be reflected in some degree by monitoring and analyzing the customers' behavior in a store.* To the best of our knowledge, this is the first work that introduces the customer behavior analysis of monitoring video data to sales forecasting task. In order to validate our observation, we conducted a series of experiments in a physical retail store and demonstrated that integrating video-based customer behavior analysis into a conventional sale forecasting model results in a performance improvement.

1. Introduction

Sales Forecasting is an important task for supply chain management, business planning, and customer relationship management in retail industries [Mentzer 98]. In particular, retail stores provide short shelf-life food products and inaccurate forecast tends to cause stock-outs and food waste [Mena 2014]. Therefore the accurate prediction is required for reliable planning and optimization.

A number of studies on sales forecasting have been conducted in the past decades. Recently machine learning based forecasting methods have achieved high accuracy compared with traditional statistical time series methods, such as moving average model [Alon 01, Penpece 14]. To improve the performance, demand influence factors have been explored[Pechenizkiy 16, Chen 10]. Generally, weather conditions, holidays, and public events are considered due to their impact on demand and public availability[Pechenizkiy 16].

On the other hand, behavior intelligence and insight play an important role in data understanding and business problem solving [Zhou 17, Liu 15]. Customer behavior contains valuable information for marketing analysis. Therefore, it is attractive to considering exploiting customer behavior analysis in sales forecasting. The idea of combining customer behavior analysis with sales prediction been previously reported in online sales forecasting, which consider visitor's behavior tracked in their online EC-site [Currie 10, Lohse 00, Yuan 14]. However, little research has been conducted in this direction for offline cases. Customer behavior inside a physical store, which represents a shopping process until purchasing or non-purchasing but not explicitly included in the point-of-sales (POS) data or other external data, is often neglected.

In this paper, we present an approach to improve the performance of sales forecasting by incorporating the customer behavior analysis into a conventional sales forecasting model. Specifically, we develop video-based customer behavior analysis system for monitoring and analyzing customer's shopping behavior, then extract the information about how the customers interact with the stores and products, and finally design a framework to incorporate the customer behavior analysis into a sales forecasting model. To demonstrate the effectiveness of our approach, we conduct a series of experiments in a physical convenience store. We show that our approach yields improvements for all the test collections and achieves better results than the conventional sale forecasting method.

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2. Proposed Method

In this section, we introduce our approach for incorporating customer behavior analysis into a conventional approach for sales forecasting. We first describe an overview of our video-based customer behavior analysis system, which can monitor the customer's shopping behavior inside a store. Second, we discuss how we can extract useful features from unconstructed data such as customer behavior. We adapt and extend the idea of famous technique called "conversion analysis", which is a strategy to transform a website visitor to an actual buying customer in online marketing. Finally, we explain the way to integrate new customer behavior features to the baseline model effectively. Figure 1 shows an overview of our approach for incorporating customer behavior analysis into a conventional model.

2.1 Customer Behavior Analysis

We developed video-based customer behavior analysis system for capturing and analyzing customer's shopping behavior in real stores. Our system is composed of multiple IP cameras and PCs with image processing modules installed. Specifically, surveillance cameras, which is utilized for monitoring, marketing, or security in a physical

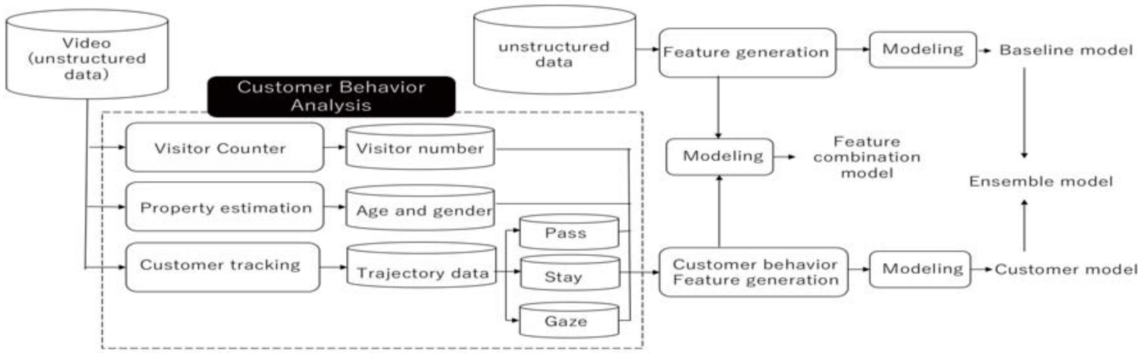

Fig. 1: Overview of the proposed approach

store, was installed. We developed several retail-oriented intelligent video analysis modules for analyzing customer's behavior inside a store. Visitor counter module receives frame images from a surveillance camera just above the store entrance and counts the number of people who visit or leave the store. Property estimation module estimate the age and gender of visitors. Customer tracking module processes multiple cameras mounted on the ceiling inside the store and this module conduct several image recognitions sub-modules, such as people detection and head orientation estimation.

We collect and analyze trajectory data of customers with the above system. In sales forecasting task, we mainly analyze the following customer behavior in a physical store:

- Visit the store
- Pass the shelf
- Stay in front of the shelf
- Gaze the shelf
- Purchase the shelf

We assume that such shopping behavior is strongly related to customer's demand, reveals the interest of customer to the product and reflected the way in which customers interact with the store and products.

2.2 Customer Behavior Feature Generation

In online marketing, conversion analysis is a well-known technique to investigate the overall business performance of an e-commerce site. Conversion analysis is conducted by measuring conversion rate, which is defined as the percentage of visitors to a web-site who complete a desired action (ex. transaction) out of total number of visitors.

In the case of physical store, if a customer has no interest to the product, he or she will neither look at the shelf nor turn to the shelf. As an initial interest level, he or she will stay in front of the shelf. If the customer has more interest, his or her gaze will fall upon the product. If the customer has further interest, he or she will gaze the shelf for a long time. If the customer has further interest, he or she probably stretches arm and touches the product. Therefore, we calculate the number of people who act these behaviors from trajectory data acquired by the customer behavior analysis system. Consequently, we extract customer behavior features, the daily number of visitors to the store at each age group and gender, people who pass by the shelf, stay in front of the shelf over 5/10 seconds, gaze the shelf over 1 second. Visitors' age is categorized into 6 groups, under 19, 20 29, 30 39, 40 49, 50 59, 60 or over.

As the daily customer behavior data of the target prediction day is impossible to obtain previously, we predict the customer behavior values in objective day using simple moving average (SMA) method. We adopted moving average of same days of week in past 4 weeks because daily sales are strongly related to the day of week. Predicted value is different but close to the actual value except the singular day such as holiday, and capture recent trends of customer behavior. Table 1 shows generated customer behavior features.

2.3 Feature Integration

To integrate the customer behavior features into the baseline model, the following two integration strategies are adopted:

- **Feature combination**

This is a simple concatenation of separate features and requires only single model. There is a possibility that high dimensional features cause overfitting or complexity of interpretation.

- **Ensemble learning**

Ensemble learning is an algorithm to acquire more accurate outcome by combining the predictions of multiple models. Ensemble modeling is most effective when large variance of outcomes or large difference among input data type. We here adopt the simplest way of ensemble averaging described as follows:

$$f_i(X) = \frac{1}{M}\sum_{i=1}^{M}\hat{f}_i(X)$$

Here, $\hat{f}_i(X)$ is the output of model i among all the multiple models and M is the number of models.

Feature Type	Feature	Description
Visitor features	$N_{visitor}$, $visitor \in g$	SMA of number of visitor each age and gender group.
Activity features	N_{pass}	SMA of number of people who pass by the shelf.
	$N_{stay_{five}}$	SMA of number of people who stay in front of the shelf over 5 seconds.
	$N_{stay_{ten}}$	SMA of number of people who stay in front of the shelf over 10 seconds.
	N_{gaze}	SMA of number of people who gaze the shelf over 1 seconds.

Table. 1: Customer Behavior Features

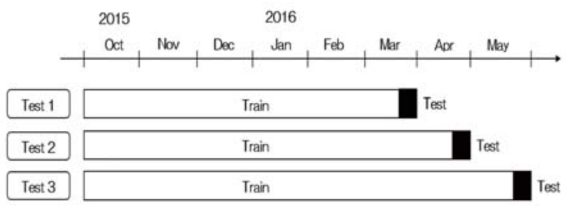

Fig. 2: Experimental data sets

3. Experiments

3.1 Experimental Setting

In this paper, we chose rice balls sale forecasting in a physical store as as our prediction targets. Specifically, we predict the daily sales number of rice ball in one week before the target day. In our study, we don't consider type difference of rice balls and the target value is total number of all types of rice balls. Our video-based customer behavior analysis system is installed in a physical store, which is composed with two surveillance cameras for visitor analysis, three omnidirectional cameras for acquisition of customer's trajectory inside the store, and two PCs with image processing modules installed.

The experiment is conducted from October 2015 to May 2016. In order to evaluate the generalization performance appropriately, we choose the last week of March, April, and May 2016 as validation period (Test1, Test2, and Test3). As we define forecasting day as one week before the target day, the training period covers from October 2015 to the day when one week before the target day as shown Figure 2.

3.2 Baseline Models

The baseline model is a conventional approach based on machine learning generally using the structured information, such as weather, calendar, and event information. We train our baseline model on Gradient Boosting Decision Tree (GBDT) proposed by Friedman [Friedman 01], which is demonstrated to be one of the most effective algorithms and is becoming a mainstream in forecasting competitions as well as Kaggle challenges. Baseline features are as follows:

- POS information: the same days of the week in past 4 weeks.
- Weather information: lowest/highest temperature, precipitation, humidity, wind speed, and categorized day-time/night weather (sunny, cloudy, rainy, snow).
- Calendar information: year, month, the day of week, seasons, quarters, public holiday, holiday, before/after holiday, between holidays, consecutive holidays, annual events, elapsed years/month/weeks/days, number of weeks in corresponding month.
- Promotion information: discount sales, special lottery, collaboration campaign, etc.

We use XGBoost[Chen 16] library for implementation of GBDT, which has become widely popular tool among various competitions. We tune the hyper parameters of XGBoost step by step for acquiring generalization ability as follows: (i) fix a relatively high learning rate (ex. η =0.1) and find the optimal number of trees under the fixed learning rate by cross-validation. (ii) tune tree-specific parameters such as the maximum number of depth, the minimum weight at child nodes, the ratio of subsamples, etc. (iii) tune regularization parameters which help to reduce model complexity. (iv) lower the learning rate (ex. η =0.01) and recalibrate the number of trees.

In addition to the conventional machine learning model, we built a moving average model with daily sales of same day of week in past 4 weeks for comparision. This is the widely-used simplest way for sales forecasting and our collaborative retail company also adopt this method for daily sales forecasting.

3.3 Experimental Results

We evaluated the effectiveness of our proposed method in a series of experiments. Specifically, we investigate the effect of incorporating customer behavior features, which is described in Section2.2, into baseline model.

We used Accuracy as evaluation metrics.

$$Accuracy = (100 - MAPE)\%$$

Here, Mean Absolute Percentage Error(MAPE) is defined as follows:

$$MAPE = \frac{100}{N} \sum_{i=1}^{N} \frac{f_i - y_i}{y_i}$$

Here, f_i is the predict value, y_i is the actual value and N is the predict data number.

Table 2 shows the final results for all experiments. From the evaluations, it is verified that the customer behavior information contributes to the improvement of prediction performance even though the customer related features are the values predicted by moving average over past 4 weeks.

Methods	Test1 (%)	Test2 (%)	Test3 (%)	Average (%)
Sales SMA model	87.18	91.28	83.55	87.34
Baseline model	88.78	92.68	87.31	89.59
+ (a) visitor features	**90.37**	93.78	84.46	89.54
+ (b) activity features	88.1	95.8	85.86	89.92
+ (a), (b)	87.44	**95.97**	86.07	89.83
Customer model	89.62	94.21	86.04	89.96
Ensemble model	89.2	93.71	**88.83**	**90.58**

Table. 2: The results of prediction models

It indicates that the latest trends of the customer behavior have impact on the sales of a product and the balance among the kinds of customer behavior should also be considered.

4. Conclusion

In this paper, we presented an approach to improve the performance of sales forecasting by incorporating customer shopping behavior analysis and investigated the impact of several strategies which can integrate the unstructured customer behavior features into a conventional structure data based model. The experimental results showed that customer behavior information provided improvements for all the test collections. Customer behavior analysis was demonstrated effective in sales prediction task.

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