Restaurant Sales and Customer Demand Forecasting: Literature Survey and Categorization of Methods

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Abstract. Demand forecasting is one of the important inputs for a successful restaurant yield and revenue management system. Sales forecasting is crucial for an independent restaurant and for restaurant chains as well. In the paper a comprehensive literature review and classification of restaurant sales and consumer demand techniques are presented. A range of methodologies and models for forecasting are given in the literature. These techniques are categorized here into seven categories, also included hybrid models. The methodology for different kind of analytical methods is briefly described, the advantages and drawbacks are discussed, and relevant set of papers is selected. Conclusions and comments are also made on future research directions.

Keywords: Restaurant sales forecasting · Guest count prediction · Forecasting survey · Revenue management · Yield management

1 Introduction

Demand forecasting is one of the important inputs for a successful restaurant yield revenue management system. Sales forecasting is crucial for an independent restaurant and for restaurant chains as well.

The sales transaction data collected by restaurant chains may be analyzed at both *the store level* and *the corporate level*. At the level of single store, exploring the large amounts of transaction data allows each restaurant to improve its operations management (e.g., labor scheduling) and product management (e.g., inventory replenishment, product preparation scheduling), and in consequence reducing restaurant operating costs and increasing quality of serving food. Whereas at the corporate level, extraction of relevant information across the restaurants can greatly facilitate corporate strategic planning. Management can assess the impact of promotional activities on sales and brand recognition,

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assessment of business trends, conduct price elasticity analysis and measure brand loyalty [17].

There do not exist any review of forecasting methods for the restaurant industry. The aim of this paper is to survey and classify restaurant sales forecasting techniques published over the last 20 years.

Historically, forecasting of restaurant sales has been judgemental based. This technique is still often used by the majority of the restaurant industry. Judgemental techniques consist of an intuitive forecast based on the manager's experience. But restaurant sales forecasting is a complex task, because it is influenced by a large number of factors, which can be classiffied as: time, weather conditions, economic factors, random cases etc. This makes judgemental techniques inaccurate. A wide variety of models, varying in the complexity form has been proposed for the improvement of restaurant forecasting accuracy.

The rest of this paper is organized as follows. Section 2 contains basic information on yield management for restaurants. Based on literature review we specified seven categories of restaurant forecasting techniques: multiple regression; Poisson regression; exponential smoothing and Holt-Winters model; AR, MA and Box-Jenkins models; neural networks; Bayesian network; and hybrid methods. They are arranged in roughly chronological order and discussed in Sect. 3. Section 3 is divided into nine subsections, one subsection for each category of restaurant forecasting techniques, the eighth subsection describes application of Association Rule Mining for the restaurant industry and ninth subsection is a summary of all described methods. Every subsection provides a brief verbal and mathematical description of each technique and gives a literature review of a representative selection of publications in the given category. Section 4 presents the discussion of advantages and disadvantages of each of methods. Section 5 includes summarizing of our research and some remarks.

2 Revenue Management

Revenue management (RM) is the application of information systems and pricing strategies to allocate the right capacity to the right customer at the right place at the right time [6]. The determination of "right" entails achieving both the most revenue possible for the restaurant and also delivering the greatest value or utility to the customer [8].

In practice, revenue management means determining prices according to forecasted demand so that price-sensitive customers who are willing to purchase at off-peak times can do it at lower prices, while customers who want to buy at peak times (price-insensitive customers) will be able to do it [9].

A pioneer in Revenue Management was airline industry [19]. Other examples of industries in which RM is implemented nowadays are hotel industry, car-rental industry, tour operators, restaurants and many others.

One critical element in a strategy for Restaurant Revenue Management is to predict future demand. Restaurant managers have always struggled with the question of how many guests will show up this day. Customer demand varies by the time of year, month, week, day and by the day part. Restaurant demand may be higher on weekends (especially on Fridays and Saturdays), during holidays, summer months, or at particular periods as lunch or dinner time. Restaurant operators want to be able to forecast time-related demand so that they can make effective pricing and table-allocation decisions [8].

Sales forecasting is the answer to the question how high will be sale under certain circumstances. The circumstances includes the nature of sellers, buyers, and the market (e.g., competitors). Thus, important factors are historical sales data, promotions, economic variables, location type or demographics of location. All variables that are useful in predicting demand are listed in Table 1. A multicriteria decision-making method used to rank alternative restaurant locations was presented in [30]. In [25] important attributes for restaurants customers were presented, what can help in determination and prediction customers' intentions to return.

Table 1. Variables that can be used as predictors

No	External variable	Range or an example of the variable
1	Time	Month, week, day of the week, hour
2	Weather	Temperature, rainfall level, snowfall level, hour of sunshine
3	Holidays	Public holidays, school holidays
4	Promotions	Promotion/regular price
5	Events	Hockey games, other
6	Historical data	Historical demand data, trend
7	Macroeconomic Indicators (useful for monthly or annual prediction)	CPI, unemployment rate, population
8	Competitive issues	Competitive promotions
9	Web	Social media comments, social media stars
10	Location type	Street/shopping mall
11	Demographics of location (useful for prediction by time of a day)	The average age of customers

3 Literature Review

3.1 Multiple Regression

Multiple regression is a simple, yet powerful technique used for predicting the unknown value of a dependent variable X_t from the known value of two or more explanatory variables (predictors) $V_1, ..., V_k$. The equation for multiple regression is:

$$X_t = \alpha_0 + \alpha_1 V_{1t} + ... + \alpha_k V_{kt} + \varepsilon_t,$$

where ε_t is the error. Coefficients $\alpha_1, ..., \alpha_k$ can be estimated using least squares to minimize sum of errors [7].

For example, multiple regression models can be used in econometrics, where regression equation(s) model a casual relationship between the dependent variable (e.g., restaurant sales) and external variables such as disposable income, the consumer price index, unemployment rate, etc. One of the advantages of econometric models created for predicting restaurant sales is that the researchers can logically formulate a cause and effect relationship between the exogenous variables and future sales/demand. Econometric models have however some drawbacks. Geurts and Kelly [10] noticed that the future values of the independent variables themselves have to be predicted, what can cause data in an econometric model to be inaccurate and the model to be weak in its ability to forecast. Also the relationship found between the dependent and independent variables may be pretended or their causal relationship can change over time, causing the need for constant update, or complete redesign model.

An example of using multiple regression is presented in [13]. The purpose of this study was to identify the most appropriate method of forecasting meal counts for an institutional food service facility. The forecasting methods included naive models, moving averages, exponential smoothing methods, Holt's and Winter's methods, and linear and multiple regressions. The result of this study showed that multiple regression was the most accurate forecasting method.

Also in [14] multiple regression model was used to demonstrate its potential for predicting future sales in the restaurant industry and its subsegments. Authors considered in this study the macroeconomic predictors such as percentile change in the CPI, in food away from home, in population, and in unemployment. They collected data from 1970 to 2011 from a variety of sources, including the NRA, the USDA, the Bureau of Labor Statistics, and the US Census Bureau. The model, trained and tested on aggregated data from the past 41 years, appears to have reasonable utility in terms of forecasting accuracy.

In [15] authors used several regressions and Box-Jenkins models to forecast weekly sales at a small campus restaurant. The result of testing indicates that a multiple regression model with two predictors, a dummy variable and sales lagged one week, was the best forecasting model considered.

Regression model was also used in a specific situation described in [5], where the restaurant was open and close during different times of the week or year.

3.2 Poisson Regression

Restaurant guest count is an example of variable, that takes on discrete values. When the dependent variable consists of count data, there can be used Poisson regression. This method is one from a family of techniques known as the generalized linear model (GLM). The foundation for Poisson regression is the Poisson distribution error structure and the natural logarithm link function:

$$ln(X) = \alpha_0 + \alpha_1 V_1 + ... + \alpha_k V_k,$$

where X is the predicted guest count, $V_1, ..., V_k$ are the specific values on the predictors, ln refers to the natural logarithm, α_0 is the intercept, and α_i is the regression coefficient for the predictor V_i.

The method is used e.g. in [2,32]. In [28] authors noticed that Poisson Regression can be used to predict the number of customers being served at a restaurant during a certain time period.

3.3 Box-Jenkins Models (ARIMA)

Time series models are different from Multiple and Poisson Regression models in that they do not contain cause-effect relationship. They use mathematical equation(s) to find time patterns in series of historical data. These equations are then used to project into the future the historical time patterns in the data. The autoregressive model specifies that the output variable depends linearly on its own previous values. The autoregressive model of order p $AR(p)$ for time series X_t is defined as:

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t$$

where $\varphi_1, \ldots, \varphi_p$ are the parameters of the model, c is a constant, and ε_t is white noise. ε_t are generally assumed to be independent identically distributed random variables (i.i.d.) sampled from a normal distribution with zero mean [8].

Other common approach in time series analysis is a moving-average model. The notation $MA(q)$ indicates the moving average model of order q:

$$X_t = \mu + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q}$$

where μ is the mean of the series, the $\theta_1, \cdots, \theta_q$ are the parameters of the model and the $\varepsilon_t, \cdots, \varepsilon_{t-q}$ are white noise error terms [8].

AR and MA models were used to make a prediction for many different time series data. One of the example is presented in paper [12], which is the first research looking into the casino buffet restaurants. Authors examined in this study eight simple forecasting models. The results suggest that the most accurate model with the smallest MAPE and RMSPE was a double moving average.

Another tool created for understanding and predicting future values in time series data is model $ARMA(p, q)$, which is a combination of an autoregressive (AR) part with order p and a moving average (MA) part with order q. The general $ARMA$ model was described in the 1951 in the thesis of Peter Whittle [11]. Given a time series of data X_t, the $ARMA$ model is given by the formula:

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}.$$

where the terms in the equation have the same meaning as above.

An autoregressive integrated moving average $ARIMA$ model is a generalization of an autoregressive moving average $ARMA$ model. $ARIMA$ models

(Box-Jenkins models) are applied in some cases where data show evidence of non-stationarity (stationary process is a stochastic process whose joint probability distribution does not change over time and consequently parameters such as the mean and variance do not change over time).

The first step in developing $ARIMA(p, d, q)$ model is to determine if the time series is stationary and if there is any significant seasonality that needs to be modelled [18].

3.4 Exponential Smoothing and Holt-Winters Models

Exponential smoothing, proposed in the late 1950s, is another technique that can be applied to time series data to make forecasts. Whereas in the simple moving average the past observations are weighted equally, exponential smoothing uses exponentially decreasing weights over time. The more recent the observation the higher the associated weight. For the sequence of observations $\{x_t\}$ begins at time $t = 0$, the simplest form of exponential smoothing is given by the formula:

$$s_0 = x_0; \qquad s_t = \alpha x_t + (1 - \alpha)s_{t-1},\ t > 0$$

where α is the smoothing factor, and $0 < \alpha < 1$.

Triple exponential smoothing (suggested in 1960 by Holt's student, Peter Winters) takes into account seasonal changes and trends. Seasonality is a pattern in time-series data that repeats itself every L periods. There are two types of seasonality: "mutiplicative" and "additive" in nature. For time series data $\{x_t\}$, beginning at time $t = 0$ with a cycle of seasonal change of length L, triple exponential smoothing is given by the formulas:

$$F_{t+m} = (s_t + mb_t)c_{t-L+1+(m-1)modL}$$

$$s_0 = x_0; \qquad s_t = \alpha\frac{x_t}{c_{t-L}} + (1 - \alpha)(s_{t-1} + b_{t-1})$$

$$b_t = \beta(s_t - s_{t-1}) + (1 - \beta)b_{t-1}$$

$$c_t = \gamma\frac{x_t}{s_t} + (1 - \gamma)c_{t-L}$$

where F_{t+m} is an estimate of the value of x at time $t + m, (m > 0)$, α is the data smoothing factor, β is the trend smoothing factor and γ is the seasonal change smoothing factor, $0 < \alpha, \beta, \gamma < 1$, $\{s_t\}$ represents the smoothed value of the constant part (level) for time t, $\{b_t\}$ estimates of the linear trend for period t and $\{c_t\}$ represents the sequence of seasonal factors.

Exponential smoothing was one of the most common and simple methods for food and beverage sales forecasting (e.g., [23,24]). The results of the study [16] show that for the actual sales in the restaurant, located in a medium size university town, Box-Jenkins and exponential smoothing models performed as well or better than an econometric model. Since time series models are usually more economical in terms of time and skill levels of the users, the results of this study is important for forecasting in the restaurant industry.

Interesting case of big data mining project for one of the world's largest multi-brand fast-food restaurant chains with more than 30,000 stores worldwide is illustrated in [17]. Time series data mining is discussed at both the store level and corporate level. To analyze and forecast large number of data researchers used Box-Jenkins seasonal ARIMA models. Also an automatic outlier detection and adjustment procedure was used for both model estimation and prediction.

3.5 Artificial Neural Networks

All the forecasting methods we have discussed in previous subsections have the same strategy: make a functional assumption for the relationship between the observed data and various factors and then estimate the parameters of this function. In contrast, neural network methods, inspired by research on the human nervous system, use interactions in a network architecture to automatically estimate the underlying unknown function that best describes the demand process. ANNs are systems of connected "neurons", where the connections have numeric weights that can be tuned based on historical data, what makes that neural networks are adaptive to inputs and capable of learning.

Article [20] compares artificial neural networks and traditional methods including Winters exponential smoothing, Box-Jenkins ARIMA model, and multivariate regression. The results indicate that on average ANNs are more successful compared to the more traditional statistical methods. Analysis of experiments shows that the neural network model is able to capture the trend and seasonal patterns, as well as the interactions between them. Despite many positive features of ANNs, constructing a good network for a given project is a quite difficult task. It consists of choosing an appropriate architecture (the number of hidden layers, the number of nodes in each layer, the connections between nodes), selecting the transfer functions of the middle and output nodes, designing a training algorithm, selecting initial weights, and defining the stopping rule.

Fuzzy neural network with initial weights generated by genetic algorithm can be found e.g., in [3]. In the study [22] authors combined an artificial neural network and a genetic algorithm to design and developed a sales forecasting model. They collected sales data from a small restaurant in Taipei City and used them as the output for the forecasted results while associated factors including seasonal impact, impact of holidays, number of local activities, number of sales promotions, advertising budget, and advertising volume were chosen as input data. Firstly, this approach applies the ANN to select the relevant parameters of the current sales condition as the input data. Then it uses a genetic algorithm to optimize the default weights and thresholds of the ANN. Researchers used empirical analysis to examine the effectiveness of the model. The results indicate that this is a scientifically practical and effective sales forecasting method that can achieve rapid and accurate prediction.

3.6 Bayesian Network Model

Paper [26] proposes a service demand forecasting method that uses a customer classification model to consider various customer behaviors. A decision support system based on this method was introduced in restaurant stores. Authors automatically generated categories of customers and items based on purchase patterns identified in data from 8 million purchases at a Japanese restaurant chain (48 stores, data from 5 years). They produced a Bayesian network model including the customer and item categories, conditions of purchases, and the properties and demographic information of customers. Based on that network structure, they could systematically identify useful knowledge and predict customers behavior. Details of this demand forecasting technique are given in [29].

3.7 Hybrid Models

In the literature there is also proposed a hybrid approach to sales forecasting for restaurants. It is often difficult in practice to determine whether one specific method is more effective in prediction then the other. Thus, it is difficult for

Table 2. Summary of sales/demand forecasting methods

Method	Description	Examples of papers
Multiple regression	Multiple Regression uses least squares to predict the unknown value of a dependent variable from the known value of two or more explanatory variables (predictors)	[5, 10, 12–15]
Poisson regression	Poisson regression uses the Poisson distribution error structure and the natural logarithm link function	[28]
Box-Jenkins model (AR, MA, ARIMA)	The autoregressive model specifies that the output variable depends linearly on its own previous values. The simple moving average weights the past observations equally	[15, 18]
Exponential smoothing and Holt-Winters models	Exponential smoothing uses exponentially decreasing weights over time	[13, 16, 17, 23, 24]
Artificial neural networks	ANNs use interactions in a network-processing architecture to automatically identify the underlying function that best describes the demand process	[3, 22]
Bayesian network model	Bayesian Network can represent the probabilistic relationships between the variables	[26, 29]
Hybrid model	Hybrid models combine 2 different models in one	[1, 21]
Association rules	Association Rules algorithms find frequent patterns in the data	[4, 27, 31]

researchers to choose the right technique for their unique situations. Usually, different models are tested and the one with the most accurate result is selected. However, the final chosen model is not always the best for the future use. The problem of model selection can be facilitated by combining methods [21].

Researchers use hybrid model in many different areas of forecasting. As an example of a hybrid system with excellent performance can be shown the application on daily product sales in a supermarket proposed in [1]. Authors combined ARIMA models and neural networks to a sequential hybrid forecasting system, where output from an ARIMA-type model is used as input for a neural network.

For restaurant industry a hybrid methodology that combines both ARIMA and ANN models is proposed in [21]. Experimental results with real data sets indicate that the combined model can be an effective way to improve forecasting accuracy achieved by each of the models used separately.

3.8 Association Rules (Market Basket Analysis)

In this subsection we want to mention an additional method which can help in restaurant forecasting. In [4] there is studied the problem of mining association rules which holds either in all or some of time intervals. As an example there are considered association rules in a given database of restaurant transactions.

In [27] authors applies a simplified version of market basket analysis (MBA) rules to explore menu items assortments, which are defined as the sets of most frequently ordered menu item pairs of an entre and side dishes. In some cases, MBA does not provide useful information if data-item is the name of goods. In [31] authors proposed a new MBA method which integrates words segmentation technology and association rule mining technology. Characteristics of items can be generated automatically before mining association rules by using word segmentation technology. This method has been applied to a restaurant equipped with electronic ordering system to give recommendations to customers, where the experiments were done. The experiment results show that the method is efficient and valid.

4 Discussion of Methods and Data Mining Algorithms

The summary of all approaches is presented in Table 2.

It is difficult for forecasters to choose the right technique for their unique situations. Typically, a number of different models are tried and the one with the most accurate result is selected. Below, in Table 3 there is a brief description of the advantages and disadvantages of methods of demand and sales prediction. In our opinion techniques that take into account external factors mentioned in Table 1 are the best. Not only the choice of method but also preparing the relevant data affects the high efficiency of the model.

Table 3. Advantages and disadvantages of sales/demand forecasting methods

Method	Input Data	Output	Advantages	Disadvantages
Multiple Regression	Exogenous variables such as disposable income, the consumer price index, unemployment rate, personal consumption expenditures, housing starts.	E.g., restaurant sales/ customer demand	+ the decision maker can logically formulate the model based on a cause and effect relationship between the causal variables and future sales	- Multiple regression analysis can fail in clarifying the relationships between the predictor variables and the response variable when the predictors are correlated with each other. - The relationship found between the dependent and independent variables may be spurious or can change over time, making it necessary to constantly update or totally redesign the model.
ARIMA (Box-Jenkins models)	Historical time series demand/ sales data.	Long-term or short term predictions of future demand/ sales.	+ Do not need any external data.	- The input series for ARIMA needs to be stationary, that is, it should have a constant mean, variance, and autocorrelation through time.
Exponental smoothing model, Holt-Winters models	Historical time series demand/ sales data.	Long-term or short term predictions of future demand/ sales.	+ Exponential smoothing generates reliable forecasts quickly, which is a great advantage for applications in industry. + Do not need any external data.	- Method is influenced by outliers (sales/demand that are unusually high or low).
Bayesian Network Model	Particular set of variables.	The probability of the variable, e.g. high sale.	+ All the parameters in Bayesian networks have an understandable interpretation.	
Neural Networks	E.g., associated factors including seasonal impact, impact of holidays, number of local activities, number of sales promotions, advertising budget, and advertising volume can be used as input data. All the training and test data used in this study are required to be pre-processed. The input and output data used for training and the input data used for testing have to be pre-processed so that the data were mapped between [1,-1].	Sales amount can be chosen as the output data for the forecasted results. An inverse transformation should be conducted on the results of the simulated forecast to restore the actual value of the forecasted sales condition.	+ Have high tolerance of noisy data. + Ability to classify patterns on which they have not been trained. + Can be used when there is little knowledge of the relationships between attributes and classes. + They are well-suited for continuous-valued inputs and outputs, unlike most decision tree algorithms. + Are parallel; parallelization techniques can be used to speed up the computation process. + Can model complex, possibly nonlinear relationships without any prior assumptions about the underlying datagenerating process + Overcome misspecification, biased outliers, assumption of linearity, and re-estimation.	- Neural networks involve long training times and are therefore more suitable for applications where this is feasible. - They require a number of parameters that are typically best determined empirically, such as the network topology or structure. Constructing a good network for a particular application is not a trivial task. It involves choosing an appropriate architecture (the number of hidden layers, the number of nodes in each layer, and the connections among nodes), selecting the transfer functions of the middle and output nodes, designing a training algorithm, choosing initial weights, and specifying the stopping rule. - Neural networks have been criticized for their poor interpretability.
Association Rule Mining (Market Basket Analysis)	Transactional database (TDB) or Relational database (RDB). Given a minimum support (min_{sup}) and a minimum confidence (min_{conf}).	All association rules that satisfy both min_{sup} and min_{conf} from a data set D.	+ Association rules that satisfy both min_{sup} and min_{conf} can help with discover factors which influence high/low demand.	

5 Conluding Remarks

Demand prediction plays a crucial role in planning operations for restaurant's management. Having a reliable estimation for a menu items future demand is the basis for other analysis. Various forecasting techniques have been developed, each one with its particular advantages and disadvantages compared to other approaches. The evolution of the respective forecasting methods over past 20 years has ben revealed in the paper. A review and categorization of consumer restaurant demand techniques is presented in the paper. Techniques from a range of methodologies and models given in the literature are classified here into seven categories: (1) multiple regression, (2) Poisson regression, (3) exponential smoothing and Holt-Winters model, (4) AR, MA and Box-Jenkins models, (5) neural networks, (6) Bayesian network, and (7) hybrid methods. The methodology for each category has been described and the advantages and disadvantages have been discussed. This paper conducts a comprehensive literature review and selects a set of papers on restaurant sales forecasting. It is almost universally agreed in the forecasting literature that no single method is best in every situation.

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