Pick-up method + machine learning: a proved efficient approach to forecast hotel demand

Improving hotel demand forecasting accuracy by integrating machine learning with pick-up methods

Abstract

Keywords: forecasting, hotel revenue management, machine learning, advance booking, pick-up

1. **Introduction**

Hotel revenue consists of price and demand, and demand forecast is essential for successful revenue management since it has high uncertainties and has direct impact on issues such as inventory management, pricing strategies, and marketing plans. Different from industries such as retail where most of the bookings happen instantly when the clients arrive, the hotel industry usually sell the room ahead of the customer arriving, and thus generates valuable advance bookings information.

Advance booking method, an approach conducting forecast based on current realized bookings and historical booking patterns, is widely used in both academic and the industry. On top of the existed bookings so far, the advance booking predicts what will happen from today and the target future by estimating the incremental bookings. In practice, this method takes an average of the incremental bookings in history, or average the incremental ratios in percentage, then add on or multiple to the Reservations on Hand (ROH) today. This method is also called “pick-up” method since it estimates the number of incremental bookings “picked up” from today’s reservation.

Pick-up methods are initially used in airline revenue management (L’heureux, 1986), and this concept has been rapidly applied in the hotels due to the highly similarities between the two industries. Generally, there are four types of pick-up models: additive & multiplicative pick-ups, and traditional & advanced pick-ups (Zakhary, Gayar, & Atiya, 2008). From the perspective of the relationship between ROH and final arrivals, Additive Pick-up models conduct prediction by adding an estimated incremental booking to current ROH, while Multiplicative pick-up models multiplied an average ratio on current ROH. On the other hand, pick-up models can also be categorized according to data completion. Traditional pick-up methods only use completed booking curves and ignored records where an arrival day is still beyond “today”. In comparison, advanced pick-up methods use both complete and incomplete booking information. Many researchers have tested the performances of pick-up models in different settings (Weatherford & Kimes, 2003), or combined pick-up models with other methodologies such as quadratic regression (Tse & Poon, 2015), exponential smoothing (Chen & Kachani, 2007), Poisson process (Lee, 2018), etc. However, most of these researches still rely on statistical assumptions to describe the relations between ROH and final arrivals. Given the uncertain demand change with various external factors’ impact, the industry urges for more practice-adapting methods to improve the accuracy.

In recent years, machine learning method has been picking up attentions among both the industry and academia. Machine learning is a statistical method (**add more definition about machine learning**) and it has the benefit of (flexible, catching patterns, etc. )

Even though machine learning has been extensively applied in different areas (business failing prediction, stock price, exchange rate, etc.), it has not been given full attention in the hotel industry. As GlobalData (2017) mentioned, hotel has not been one of the industries considered to be at the forefront of technological innovation. Some researchers have attempted using machine learning in online review analysis (Ma et al, 2018), hotel success indicators (Phillips et al. 2015), and hotel online booking simulation (Corazza 2014), while no existed studies have used machine learning approaches in demand forecasting and revenue management.

However, machine learning approaches are specifically suitable for hotel demand forecasting because of three reasons: firstly, the amount of transaction data in the hotel industry has been surging in the recent decade, which provides a foundation for machine learning models. Secondly, machine learning is able to capture the complex and non-parametric relations between existed bookings and the final sales (Zhang, 2019). Hotel sales is impacted by multiple internal and external factors, and there has not been a clear relationship to capture those patterns. By simulating the arbitrary function from the data itself, machine learning approaches have the potential to better capture the complex relations. Last but not least, machine learning models are capable of dealing with high dimensional data (in the hotel industry’s case, the long days before arrivals). Given the current paucity of using machine learning in hotel demand forecasting, this study is able to provide insights on the prediction abilities of machine learning in the hotel setting, and make the first step to introduce this powerful approach in hotel revenue management.

1. **Methodology**
   1. pick-up models

Pick-up models estimate the increments of reservations over a time window then aggregate increments on top of the current reservations. Generally speaking, there are two types of pick-up models: additive pick-up and multiplicative pick-up. Additive pick-up models regard the final arrivals independent of the current ROH and calculate final arrivals by adding pick-ups to the current ROH (1.1). Instead, multiplicative pick-up models regard the ROH as a certain ratio of the final arrivals (1.2):

where is the forecasting target with the accumulated ROH on the arrival day (on DBA = 0). stands for the date with the newest reservation (usually “today” when the forecast is made). are the historical reservations observed on for day *t* where .

Linear regression wasn’t traditionally regarded as a pick-up model in hotel forecasting, however, the logic of linear regression is technically the combination of additive and multiplicative pick-up. By estimating both coefficients and intercept, linear regression model considers both additive (intercept) and multiplicative (coefficients) parts when describing the pattern relations:

(2)

All ­of the pick-up models can only accommodate the latest ROHs due to the restrictions of the statistical model. For instance, if include all previous ROHs in the regression model, it is highly likely to trigger multicollinearity during the model constructing.

* 1. Machine Learning Embedded Pick Up Models

Machine learning methods **(insert a general description)**. In this research, we combined six mainstream machine learning models with the concept of advance booking information to forecast hotel demand.

* + 1. Neural Network

Neural Network is generally regarded as a multistep regression.It usually takes two steps: firstly, it extracts linear combinations of the inputs as derived features using activation function , and secondly, models the target as a linear function of the derived features (Friedman, Hastie, & Tibshirani, 2001):

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In practice, it is usually necessary to scale the inputs before establishing the neural network model. Standardization all of the inputs ensures the model treats all inputs equally regardless of its numeric values. Besides, it is also critical to choose the appropriate number of hidden layers and the number of units in each layer. Without a standard rule of selecting the optimal number of hidden units and layers, the industry usually set the size of the hidden layers around 2/3 of the size of the input layer, also noting that the number of hidden units should not exceed the size of either input layer or output layer.

* + 1. Nearest Neighbors

Nearest Neighbors models make forecast by finding the most similar training data points of the target and then take the average of those “nearest neighbors” as the predicted value. K-nearest neighbor is the most common model in Nearest Neighbors family. It calculates the distances between all training samples and the target, then make the forecast by taking the average of the K nearest neighbors. On top of simply taking arithmetic average, the weighted K-NN model assigned larger weights to closer neighbors with shorter distance.

Using Nearest Neighbor methods, the model is trying to find the most similar ROH and DOW with the day of interest. Assuming only taking the newest ROH into consideration, the Euclidean distance between the day of interest and all other booking with the same DBA:

Taking the most straightforward instance, the Euclidean distance as the example:

It is critical to select the number of selected neighbors, the value of K, to make rational prediction. In practice, resampling method with the K-fold cross-validation is usually used to select the optimal K.

* + 1. Tree

Tree-based models conduct forecast by partitioning the features into a group of binary splits, then fit a simple model in each split. Decision tree, the most straightforward model among tree models, recursively finds the optimal split for features, then make forecast using the average value of the feature space the target falls into. The optimal split is defined by reducing the most chaos, usually calculated by the minimized RSS within each feature space. This recursive process continues until some thresholds (decreased RSS, the number of observations within each tree, etc.) are met.

(insert formula 3.13)

Random forest is an advanced tree model which uses bootstrap method to reduce the variance of decision trees. The bootstrap method subsets predictors randomly then generates trees using given predictors.

* + 1. Support Vector Regression

Support Vector Regression splits feature space using flexible boundaries. In addition to decision tree’s binary rectangle boxes, SVR draws non-parametric hyperplanes to divide features into various spaces. The optimal hyperplane is selected using the maximal margin rule, which find the boundary farthest from the surrounding training samples.

(Insert formula 3.15)

(Insert a table to list the pro & cons for each model)

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | Pro | Cons |
| NN |  | Non-parametric  No restrictions on input variables  Can handle high dimensional settings | Hard to interpret the coefficients and hidden layer  Subjective to choose parameters (requires statistical expertise) |
| Nearest Neighbor | KNN  Weighted KNN |  |  |
| Tree | Decision tree | Intuitive, easy to interpret  Can handle qualitative predictors without creating dummy variables | Low accuracy  Non-robust due to its binary splitting |
| Random forest | Robust | Hard to decipher |
| Support Vector Regression |  | Very flexible to capture the non-parametric patterns | Hard to decipher  High computational cost |

1. **Empirical Study** 
   1. Data description

An empirical study to demonstrate the performances of the proposed models were undertaken in collaboration with a hotel property.

This research uses one-year long booking records of a hotel, with the arrival dates from December 27, 2017 to December 31, 2018, of a hotel property. For each, this dataset records the booking date (the day the client makes this reservation) and the arrival date (the day the client checks in). Hence, for each arrival date, the ROH can be calculated accumulatively from the earliest booking date of each day. For instance, if the hotel is predicting the number of final rooms sold on February 14, 2021, while “today” is January 1, 2021, the realized booking (ROH) can be calculated by adding up all of the reservations for February 14, 2021 happened before January 1. In this way, a new variable, the ROHs is calculated as the main independent variable.

Another derivative variable, days before arrival (DBA), is used to describe the time window between the booking day and the arrival day. This study examines 12 different horizons: 1, 2, 3, 4, 5, 6, 7, 14, 21, 30, 60, 90, and beyond. The cutoffs are made in this way since in the hotel industry, the dynamic pricing plan is usually set following those horizons. It is noticeable that during early periods when the booking day is far away from the stay date, the reservations accumulate very slow. Therefore, a wider horizon in earlier periods allows information to accumulate, while when the stay dates are approaching closer, the booking window is broken into smaller horizons for a closer attention.

The whole dataset has booking record of 370 consecutive days with ROHs on 12 DBAs and the DOW of the arrival date. The dataset is randomly hold out as 80% in the training set, 20% in the test set. For all the models, this study uses the nearest ROH and DOW as the independent variables on different arrival date and DBA, to make predictions. The dependent variable here is the final accumulated reservations on the arrival day, in other words, the accumulative ROHs when DBA=0.

* 1. Models

This research tests the performance of nine models as listed in Table X:

where f\_i represents pick-up methods and machine learning approaches respectively (formula 1.1). The model constructing is iterated on DBAs at 1, 2, 3, 4, 5, 6, 7, 14, 21, 30, 60, and 90 days ahead. Taking DBA=5 as the example, the training set only uses the DOW and the newest ROH as input, and the predicting results are tested only given the relevant DOW and ROH accordingly. In other words, there are 12 models built using each methods, and the performances are tested accordingly.

Table 2 presents the calculated pick ups for additive model, and table 3 displays the results for multiplicative pick ups. Generally speaking, the longer the DBA, the larger value / higher lever it will need to add on or multiple to. There are also visually significant difference among DOW on any given DBA.

A screenshot of a cell phone

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Table A shows the results of the regression models. The results are in line with our previously stated observation that the regression model combines both additive and multiplicative models: the longer the DBA, the higher the add-on value (as the intercept in regression), and the larger the weights to be multiplied on (as the coefficient in regression). As in the table, some of the DOWs are significant, and all of the nearest ROHs are significant (with p<0.001) in the model. When there are more days between today and the day the forecast is made, less information is given, therefore the standard deviations of the fitted coefficients are larger. Similarly, the explained variances of further models are smaller than those with closer DBA.

Machine learning models, on the other hand, have difficulties showing the specific coefficients or formula between the predictors and response. However, there are additional preprocessing and cleaning steps for each model. Besides, machine learning methods uses cross-validation or bootcamp methods to increase accuracy.

For neural network model, numeric variables are standardized as follows to remove the effect of different numeric values on network weights:

where is the standard deviation of all in the training set. Also

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For K-NN, the critical element -- the value of K was selected through cross-validation. The model firstly randomly selects 5 different values, then uses each of them to build a model. Beforehand, the training set was randomly split into 10 equal-size buckets. Nine of them were used to build models using , then the best performing model with was chosen to build the final model.

Same cross validation was applied on the weighted K-NN model as well. 10 randomly selected K values were tested to find the optimal On top of selecting K values, weighted K-NN also tests the kernel shapes. This research allows the models to test among the rectangular, triangular, epanechnikov, gaussian, rank, and optimal kernel shapes.

For random forest model, a 10-fold cross validation was also applied to select the optimal number of variables used when growing each tree. Whichever number of variables generating the least Root Mean Square Error (RMSE) is selected.

For Support Vector Regression, a list of kernel shapes are tested manually: linear, polynomial, radial and sigmoid. Through cross validation, the model further tested gamma values of 0.1, 0.5, 1, and 2 with the radial kernel each time and selected the optimal gamma value to build the model.

* 1. Results

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(add time unit)

Table X presents the errors and computing time of the pickup models and machine learning models. The ME and MPE are used to describe the biases of the models. Except for Multiplicative Pickup and Neural Network models, all of the models have positive average mean errors, which means they tend to overestimate the demand. All models have mean errors within the range of (-2, 2) and mean percentage error from +-10%. , which (why do we care about mean error?)

The MAE and MAPE columns show the accuracy of models. As seen from the table, Support Vector Regression results in the lowest MAE of 5.06 and the lowest MAPE of 0.126. Random Forest

Another critical element to consider here is the computing time. As shown in Table X, pick up models need very little time since they are simply algebraic calculations. In comparison, machine learning models tend to need longer time due to model complexity and cross validation. For instance, the time needed for constructing Random Forest is significantly higher since it needs repetitive iteration to prune the model. However, it is noticeable that the parameter selection process is flexible, thus the time consumed could be different. For instance, the Support Vector Regression model in this current research tested for kernel shape to narrow down the optimal shape first, then it tested five values. low gamma value, far reach, lower weight to the near-boundary vectors, more linear; vice versa.

An important question is whether machine learning based models are robust to hotel demand forecasting. We conduct a sensitivity analysis with a different randomly selected dataset. As in Table A shows, the results in either errors, variance or time consumed are mostly similar. The only difference is … Finally,

for KNN: the longer the forecasting window, the larger the chosen K value - makes sense, since less information is given. Similar to weighted K-NN, d

1. **Conclusion & Discussion**

On average, pick up models embedded with machine learning approaches were shown to have higher accuracy than classic pick up models.

What stands out in the results is Neural Network performed significantly poorer than other models. Since machine learning models are black boxes, it is challenging to decipher the exact reason why it wasn’t the suitable. One guess is that Neural Network’s performance is extremely volatile depending on the parameter selection. Different number of hidden layers and the number of hidden units shift the model completely. However, it requires solid statistical background to select the optimal parameters, or is extremely time consuming to select through cross validation.

Another guess is, Neural Network (guess why NN is inferior? bcz it’s “two linear” so not quite suitable for hotel? then why SVR and others are doing well?)

limitation: without feature selection

**Declaration of Conflicting Interests**

The author(s) declared no potential conflicts of interest with respect to the research, authorship, or publication of this article.

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**Appendix**

A close up of a piece of paper

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