Dynamic Price Prediction for Revenue Management System in Hospitality Sector

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Abstract: Dynamic pricing prediction is widely adopted in many different sectors. In receptive structures, the price of services (e.g. room price) is usually set dynamically by the Revenue Manager (RM) which continuously monitors the Key Performance Indicators (KPIs) recorded over time, together with market conditions and other external factors. The prices of services are dynamically adjusted by the RM to maximize the revenue of the receptive structure. This manual adjustment of prices performed by the RM is costly and time-consuming. In this work we study the problem of automatic dynamic pricing. To this aim, we collect and exploit a dataset related to real receptive structures. The dataset is annotated by revenue management experts and takes into account static, dynamic and engineered features. We benchmark different machine learning models to automatically predict the price that a RM would dynamically set for an entry level room forecasting the price in the next 90 days. The compared approaches have been tested and evaluated on three different hotels and could be easily adapted to other room types. To the best of our knowledge, the problem addressed in this paper is understudied and the results obtained in our study can help further research in the field.

1 INTRODUCTION

Nowadays the use of dynamic pricing is widely exploited by different sectors, such as wireless operators (Elreedy et al., 2019), sales of tickets for sporting events (Sahin and Erol, 2017; Sahin, 2019), houses pricing (Ragapriya et al., 2023) and advertising spaces on digital billboards (Lak et al., 2015).

Dynamic pricing in hospitality sector regards a revenue management pricing strategy in which prices are upgraded overtime to maximize the revenue of a receptive structure. It therefore concerns the adoption of "flexible" rates that allow hoteliers to adapt sales prices to seize earning opportunities arising from changes in the market conditions. The use of dynamic price, and consequently of systems for automatic it, would therefore enable hoteliers to increase their turnover compared to the application of static rates. The positive effect of dynamic pricing on revenue has been confirmed by the results obtained in Alshakhsheer et al. (2017) and Abrate et al. (2019).

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In literature, attention has been paid to the factors which determine the dynamic change of prices. Some studies have analyzed what these factors are, both independently of the reference field (Deksnyte and Lydeka, 2012) and specifically for the hospitality sector (El-Nemr et al., 2019; Zhang et al., 2017). To correctly set a price rate, multiple variables must be taken into account. Among them, are to be considered the demand, internal factors such as Key Performance Indicators (KPIs), and external factors such as the price at which competitors sell. The season, events of different types (cultural, sports, etc.) and public holidays in the period of pricing are also to be considered.

In this context, Machine Learning techniques could give the possibility of taking into consideration the increasingly large amount of data collected by the receptive structures to support dynamic pricing process. Despite Machine Learning and traditional Data Analysis techniques have been used for many years, the hospitality sector has proven to be slow in its adoption. Indeed, considering the work of Pande (2020), it seems that the use of Machine Learning in the hospitality sector is very recent. The authors on Mariani and Wirtz (2023) have observed a noticeable

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increase in research works published in the context of hospitality and tourism sectors related the topic of analytics. Furthermore, from the study conducted by Goli and Haghighinasab (2022), it seems clear that there is a gap in the literature due to a lack of studies related to dynamic pricing in the B2B sector and to the absence of studies of this topic in Italy.

In this paper, we study the problem of dynamic pricing exploiting Machine Learning techniques. To this aim, we propose a dataset annotated by revenue management experts which takes into account static, dynamic and engineered features. We benchmark different machine learning models to automatically predict the price that a RM would dynamically set for an entry level room forecasting the price in the next 90 days. The approaches have been tested on three hotels and could be easily adapted to other room types.

To the best of our knowledge, the problem addressed in this paper is understudied and the results obtained in our study can help further research in the field. Thus, the main contributions of this work can be summarized as follows:

- we describe a method to collect a dataset for the specific purpose of predicting dynamic pricing for receptive structures;
- we benchmark different Machine Learning models to address the problem of automatic dynamic pricing to be incorporated into a Revenue Management System (RMS).

The paper is organized as follows. State-of-the-art works are discussed in Section 2. Section 3 discusses the dataset, the machine learning methods and the evaluation measures used for the proposed benchmark. Section 4 reports experimental settings and results. Section 5 concludes the paper and provides hints for future works.

2 RELATED WORKS

Three main line of research can be distinguished for addressing the problem of dynamic pricing. The main differences among the works depend 1) on the considered target variable, 2) on the exploitation of the price-elasticity coefficient in the process of determining the dynamic price and 3) on the specific market in which dynamic prices are applied. It seems there is not yet a standard procedure in the literature for dynamic pricing in the hospitality sector.

Some works address the problem of estimating the Average Daily Rate (ADR) as the target variable. Studies in this context have tried to forecast ADR at the city level. In Shehhi and Karathanasopoulos (2018) is presented a method which exploits conventional time-series and machine learning models to forecast ADR. Luxury and upscale hotels of eight cities of the Middle East and North Africa have been considered in the study. The results show the usefulness of machine learning models for forecasting prices. Al Shehhi and Karathanasopoulos (2020) have employed data from five cities in the Persian Gulf for the ADR prediction. Also in this case luxury and upscale hotels have been considered to implement a price forecasting using both traditional statistical models and artificial intelligence models. Zhang et al. (2019) have focused on ADR prediction at the hotel level, proposing a dynamic pricing system which considers three main steps: a base price is set considering competitor prices, the future occupancy is predicted with a sequence learning model which combines DeepFM and the seq2seq model, and finally a DNN is employed to predict the ADR for each hotel and date.

A second group of works considers as fundamental the estimation of the coefficient of the price-elasticity of demand in the process that leads to the set of the dynamic price. Zhu et al. (2022) have proposed a model which predicts the price elasticity coefficient, both at the hotel and room type level, taking into account competitors, temporal and hotel-specific factors. Once the coefficient is obtained, it is used to estimate the occupancy for each eligible price via a specific demand function. The optimal price will be then the one that maximizes the expected revenue. Shintani and Umeno (2022) have presented a method that enables simulating the magnitude of changes in demand as a result of a change in price. Specifically, they have used a time-rescaling regression to forecast the demand and have introduced a parametric learning model that allows the price elasticity of demand coefficient to be estimated from historical data. Once a new price rate has been chosen, this is used together with the previously obtained coefficient to update the booking curve and to compute the new demanded quantity. Bayoumi et al. (2013) proposed to study the dynamic pricing process based on four price multipliers. The optimal parameters for the multipliers have been computed via the Covariance Matrix Adaptation Evolutionary Strategy (CMA-ES) using simulated data as input together with the Monte Carlo method. To determine how the influence of their method on the reference price set by the RM will affect the demand, the authors have inserted a module that computes a demand index, which is also used to appropriately moderate the new simulations. The simulation and optimization loop is repeated until the multipliers parameters that maximize the revenue are found. Vives et al. (2019) have proposed a data transformation system and the application of a demand model based on log-linear regression to estimate the price-elasticity coefficient for each predefined season and booking period. This approach has also been considered in Vives and Jacob (2020). The authors have adapted the online transient demand function to two mathematical models (one deterministic and one stochastic) to estimate prices and quantities that maximize the revenue along distinct booking horizons and seasons using Lagrange multipliers. In Vives and Jacob (2021) the aforementioned method using the deterministic model has been applied to several hotels of Spain. Bandalouski et al. (2021) have proposed to disaggregate the demand into categories and forecast it using time-series methods. The result of this step is used to estimate the two coefficients of the defined demand function. They then obtain the optimal price rates optimizing a concave quadratic objective function with linear constraints. Once the optimal prices are obtained, they can also be used to estimate the optimal quantity to sell via the demand function. Shadiqurrachman et al. (2019) have proposed a pricing policy system in which multiple linear regressions are used. Each linear regression aims to capture the relationship between the average price existing in one part of the planning horizon and the average price related to the other parts. The target variable of these multiple regressors is the quantity sold in the considered part of the planning horizon. The estimated coefficients are given as input to an integer nonlinear programming method to find the optimal pricing policy for the entire planning period. Once the optimal prices have been found, these are used as input of the demand model to compute the quantity of rooms that would be sold by adopting the estimated prices. The components employed for the dynamic pricing model of the latter work have been first presented by Shakya et al. (2012), who however used neural networks for the demand model and an evolutionary algorithm to find the pricing policy that maximizes the revenue along the planning horizon.

A third group of studies considers the problem of setting prices of Airbnb listings. Rather then estimating room prices, in this case the goal is the price estimation for the proposed accommodation, such as an entire house, a cabin, a boat and much more. Although this problem is not a market perfectly comparable to the one which consider the dynamic price estimation of hotel rooms, it is important to mention the studies in this context. Indeed, Ye et al. (2018) have introduced five evaluation metrics which have been widely adopted to evaluate the goodness of the dynamic prices predicted by machine learning models (Zhang et al., 2019; Zhu et al., 2022). In addition to the introduction of these metrics, the authors have proposed a pricing system composed of three steps. First, the booking probability for each listing is predicted per night performing a binary classification with Gradient Boosting. Secondly, this probability is used as input, together with other features, to predict the price for each listing-night through a regression model. As last step, a customised logic is applied to generate the final price to be used. Kalehbasti et al. (2019) used features of the rentals, owner characteristics and reviews with various machine learning models to predict the prices of Airbnb listings in Amsterdam. Peng et al. (2020) have made use of numerical, geospatial and textual data for Principal Component Analysis. The first six principal components have been employed as predictors together with XGBoost model. This last machine learning method has been also used by Liu (2021).

3 METHODOLOGY

In this section we introduce the logic used to build the dataset used to perform the benchmark, together with details about the features collected. We give also a brief explanation of the Machine Learning models exploited for the analysis, as well as the evaluation measures used to assess the different approaches.

3.1 Dataset

The logic adopted for the construction of the dataset was to replicate the structure of the data on which a revenue manager daily looks at in order to decide whether to increase, decrease of leave unchanged the selling price for a specific Day Of Stay (DOS). It is a data structure that embeds the current situation of the accommodation facility on the DOS for which a prediction is requested, as well as the changes that have occurred for the same DOS over the n days preceding the date in which the prediction is made. The built dataset structure is illustrated in Figure 1.

Each record r of the dataset is a tuple $(e_d, s_d, x_{t-n,d}, y_{t,d})$ where the subscript d is related to the DOS objective of the price prediction, the subscript t is related to the date in which the prediction of the price is asked, whereas the subscript n is related to the number of days to subtract from the date in which the prediction of the price is asked. The description of the mentioned variables is reported in the next section.

e_d			s_d		$x_{t-n,d}$					$y_{t,d}$
$l_{t,d}$	WD	…	SR	…						
0	0	…	SR_0	…	$x_{0-n,0}$	…	$x_{0-2,0}$	$x_{0-1,0}$	$x_{0-0,0}$	$y_{0,0}$
1	0	…	SR_1	…	$x_{0-n,1}$	…	$x_{0-2,1}$	$x_{0-1,1}$	$x_{0-0,1}$	$y_{0,1}$
2	0	…	SR_2	…	$x_{0-n,2}$	…	$x_{0-2,2}$	$x_{0-1,2}$	$x_{0-0,2}$	$y_{0,2}$
…	…	…	…	…	…	…	…	…	…	…
90	0	…	SR_{90}	…	$x_{0-n,90}$	…	$x_{0-2,90}$	$x_{0-1,90}$	$x_{0-0,90}$	$y_{0,90}$
0	0	…	SR_1	…	$x_{1-n,1}$	…	$x_{1-2,1}$	$x_{1-1,1}$	$x_{1-0,1}$	$y_{1,1}$
…	…	…	…	…	…	…	…	…	…	…
89	0	…	SR_{90}	…	$x_{1-n,90}$	…	$x_{1-2,90}$	$x_{1-1,90}$	$x_{1-0,90}$	$y_{1,90}$
90	0	…	SR_{91}	…	$x_{1-n,91}$	…	$x_{1-2,91}$	$x_{1-1,91}$	$x_{1-0,91}$	$y_{1,91}$
…	…	…	…	…	…	…	…	…	…	…
0	1	…	SR_7	…	$x_{7-n,7}$	…	$x_{7-2,7}$	$x_{7-1,7}$	$x_{7-0,7}$	$y_{7,7}$
…	…	…	…	…	…	…	…	…	…	…
90	1	…	SR_{97}	…	$x_{7-n,97}$	…	$x_{7-2,97}$	$x_{7-1,97}$	$x_{7-0,97}$	$y_{7,97}$
…	…	…	…	…	…	…	…	…	…	…

Figure 1: Dataset structure.

3.1.1 Dynamic, Static and Engineered Features

The nature of the features used as input to train ML models can be distinguished into three main groups described in the following.

- **Static Features** (s_d): these features are linked to internal factors of the accommodation facility recorded for a DOS. They do not change over time. An example is the starting selling rate, which is set, for each DOS, at the beginning of the period that marks the new financial business season for a hotel.
- **Dynamic Features** ($x_{t-n,d}$): these features change over time and have been collected both as a variation from the last recorded value and as an aggregate. An example is given by the number of Room Nights (RNs) booked on a single day for a DOS and the number of RNs booked since the financial business season has started up to the considered day for a DOS.
- **Engineered Features** (e_d): these features are obtained through an engineering process, therefore resulting from a data transformation process, or built from scratch. Examples are provided by the LeadTime column ($l_{t,d}$), which computes the number of days between the date on which the prediction is asked and the DOS for which the prediction is requested, and from the Weekend-Day column (WD), which indicates if the DOS is a week-end day or not, and many others.

In addition to the aforementioned features, there is the target variable ($y_{t,d}$) which is the price dynamically set by the revenue manager of the receptive structure as the market conditions, together with the Key Performance Indicators (KPIs) and other factors change.

3.2 Machine Learning Methods

We have performed a benchmark for dynamic price prediction considering five machine learning methods. Specifically, we have considered a Multiple Linear Regression (MLR), three models belonging to the ensemble method with Decision Trees and a Multilayer Perceptron (MLP).

- **Multiple Linear Regression** assumes that a linear relationship between the dependent variable and the independent variables exists. It is defined as

$$y_i = \beta_0 + \sum_{j=1}^{p} \beta_j X_{ij} + \varepsilon_i, \quad (1)$$

where the β terms are the coefficients to be estimated, X are the features related to the model variables and ε is the model's error term. The objective for the MLR is to learn the β terms exploiting training data in order to minimize the residual sum of squares between the actual targets and the ones predicted by the model.

- **Ensemble Method with Homogeneous Learners**. The Ensemble method is a learning technique that combines predictions from multiple weak learners with the aim of building a strong learner. The idea under this approach is that more accurate predictions are obtained combining different models than those made by one single model. Since we employed only decision trees as learners, the ensemble is called homogeneous. Using decision trees, a distinction must be made between bagging and boosting method depending on how the training of the models in the ensemble is performed (Figure 2).

  In our experiments we have used an ensemble model that is based on bagging, namely the Random Forest (RF), and two models based on boosting, i.e., the Gradient Boosting (GB) and the Light Gradient Boosting (LGB). In RF trees are built in parallel using bootstrap replicas, obtained by sampling with replacement. In regression problems, for a new data point, the model output is the average of the tree predictions for that point. In GB and LGB trees are instead built sequentially and additively. These algorithms owe their name to the use of the gradient descent procedure to minimize the loss function when trees are added. In particular, after the first model is fitted to the training data, the other trees are added one at a time in order to correct the errors made by the previous models. The prediction for a new data point is the sum of the results of each weak learner contained in the strong learner. What differentiates the two models is that in GB trees are grown level-wise, i.e. giving priority to the nodes closest to the root, while LGB uses a leaf-wise strategy, selecting from time to time the leaf that leads to the most significant reduction of the loss function (Figure 3). Furthermore, LGB employs two techniques that allows it to be faster than other boosting models, which are: Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB). The former aims to filter out data to find a split value, by selecting all records with large gradients and randomly sampling instances with small gradients. The latter is intended to reduce the complexity of the model in terms of variables and to speed up the training phase, by identifying the mutually exclusive variables, i.e. features which never take on zero value simultaneously, and grouping them into a single bundle.

- **Multi-layer Perceptron** is a feed-forward neural network, where the data is propagated in only one direction. It is composed by an input layer, one or more hidden layers and an output layer (Figure 4). Each neuron in the hidden layers transforms the values coming from the previous layer with a weighted linear summation, adds the bias term, and apply a non-linear activation function.

  The model is trained using the backpropagation, which at each iteration updates the weights of the network so as to minimize the loss function.

3.3 Evaluation Metrics

To compare the performances of the different models we have employed the three evaluation measures described below.

- **Mean Absolute Error (MAE):** it measures the average deviation between predictions and actual values. Consequently, the lower it is the better is the model. It is defined as

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{2}$$

  where $\hat{y}_i$ is the value predicted by the model, whereas y_i is the target value. Since it uses the absolute value, i.e. it does not consider the direction of the error, it is a measure that is not sensitive to extreme values. It is expressed in the same unit of measure of the target variable, and for this reason it is a very useful measure for evaluating the performance of various models on a single accommodation facility but not for comparing performances across hotels. In fact, similar low MAEs do not necessarily constitute good results in each case. The goodness of the MAE value must be evaluated considering the range of the distribution of the target variable, which clearly differs from hotel to hotel.

- **Mean Absolute Percentage Error (MAPE):** it measures the average percentage of error between predictions and actual values. It is defined as

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right|, \tag{3}$$

  Like MAE, it is not sensitive to outliers and the lower the better. It overcomes the highlighted disadvantage of MAE because, being expressed as a percentage, it allows comparison of performances among hotels.

- **Coefficient of Determination:** it is also called R^2, and it measures the goodness of fit of a regression model. It is defined as

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2} \tag{4}$$

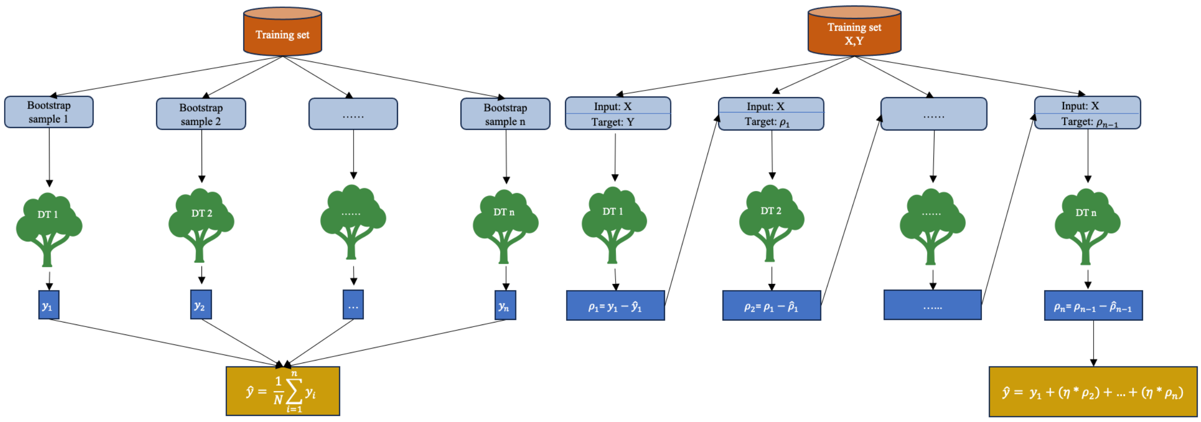


Figure 2: Bagging (left) vs Boosting (right) technique.

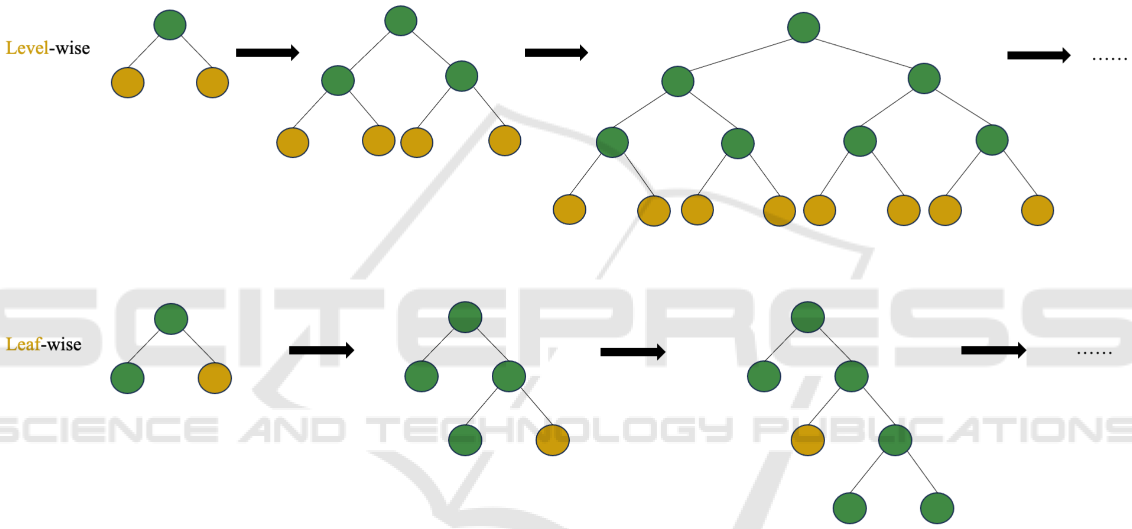


Figure 3: Leaf-wise vs level-wise tree growing method.

R^2 can take on values between 0 and 1. The higher, the better. In fact, the higher the value, the greater the variability in the dependent variable Y expressed by the independent variables X. This measure therefore also allows us to validate or deny the logic of the dataset we have built.

4 EXPERIMENTS

This section is dedicated to all aspects related to the implementation of what has been described so far. We begin from the presentation of the data collected and used for the experiments, and then we move on to the method used to find the optimal set of hyperparameters for each machine learning model. We proceed with the evaluation of the results achieved by the different methods and with the description of the matrix constructed to break down the error into time and price bands. The last part of this section reports some consideration regarding the results obtained and the consequent practical implications.

4.1 Data Collection, Pre-Processing and Training Details

With the methodology detailed in Section 3, data of three hotels have been extracted from the database of a Revenue Management System. Experiments have been performed for the entry level room of each accommodation facility, where for entry level it is intended the cheapest double room. The reason of this choice is twofold. First, revenue managers usually set the selling price for the entry level room and the prices for all the other rooms are derived from it through a set of rules. Second, to better evaluate results. In fact,

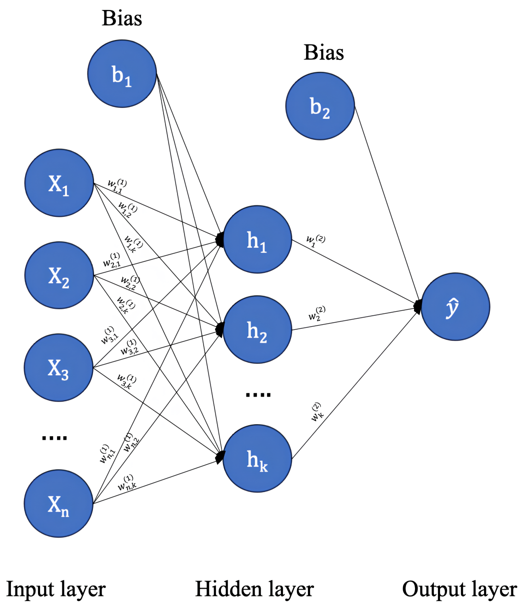


Figure 4: Multi-layer Perceptron structure for regression tasks.

hotels may have multiple room types with various prices depending on the room characteristics. Thus, a way to compare the performance of approaches is to assess it on “products” that are as similar as possible. The selected hotels are different in terms of geographical location, number of available rooms and revenue manager. Consequently, each hotel has its own dynamic price logic. Hotel_1 has 27 operative rooms (OPRs) of which 17 are entry level. Hotel_2 has 78 OPRs of which 14 are entry level. Hotel_3 has 107 OPRs of which only 10 are entry level. Moreover, Hotel_1 and Hotel_2 are located in Italy, while Hotel_3 is based in Switzerland. After being collected, data of each hotel have been pre-processed and divided into training, validation and test set. The set of data of each hotel contains a total of 59423 samples, covering the period from 1^{st} of January 2022 to 15^{th} of October 2023. Table 1 reports details related to the split for each set of data.

Table 1: Training, validation and test sets for each hotel.

SET	PERIOD	N° OF SAMPLE
Training	from 2022/01/01 to 2022/12/31	33215
Validation	from 2023/01/01 to 2023/05/31	13741
Test	from 2023/06/01 to 2023/10/15	12467
TOT. Samples		59423

Since each hotel has its own dynamic pricing strategy, the hyperparameters required by each Machine Learning model has been set on a per-hotel basis. For this purpose, we have picked out for every model the hyperparameters to be optimized (shown in Table 2) and, for each of these, we have defined a zone of interest, i.e., the possible values they can took on. We have subsequently carried out a grid search to find the best set of hyperparameters per model per hotel, where ”best” means that values that minimize or maximize our evaluation measures (i.e., MAE, MAPE and R^2) have been chosen. This step has been performed by looking at the results on the validation sets.

Table 2: Hyperparameters optimized with a grid search for the compared models.

MODEL	HYPERPARAMETERS OPTIMIZED
MLR	positive
RF	n_trees max_features max_depth
GB	n_trees max_features max_depth learning_rate
LGB	n_trees colsample_bytree max_depth num_leaves learning_rate
MLP	hidden_layer_size solver learning_rate

4.2 Results

Table 3 reports the performances of the different machine learning models on the test sets of the three hotels. For a better evaluation of the results, the predictions and actual values related to Hotel_3 have been converted from Swiss francs into euros considering the currency existing at the time of the experiments, i.e., 1.04 Swiss francs for 1 euro. Looking at the results, it can be observed that there is no model that clearly prevails over the others: Light Gradient Boosting (LGB) provides the best results for Hotel_1 while for the other two receptive structures it seems that Multiple Linear Regression (MLR) is better. Comparing the performances across hotels, the significantly better performance was obtained for Hotel_3, with a MAPE of 0.3771 and an R^2 of 0.9662.

Since we deal with a dynamic pricing strategy, it is important to discern the error and understand if there is a time horizon and/or a price range in which the model produces worse performances and detect for possible reasons. To this end, the test data sets have been divided into four time horizons (H_i) and

Table 3: Results on test sets for Hotel_1, Hotel_2 and Hotel_3.

Hotel_1				Hotel_2				Hotel_3			
MODEL	**MAE**	**MAPE**	**R^2**	**MODEL**	**MAE**	**MAPE**	**R^2**	**MODEL**	**MAE**	**MAPE**	**R^2**
MLR	3.1820	1.9087	0.9189	MLR	**3.4445**	**2.0197**	**0.9037**	MLR	**0.9380**	**0.3771**	**0.9662**
RF	2.5146	1.4629	0.9232	RF	6.7323	3.4384	0.8423	RF	1.8742	0.7391	0.9112
GB	1.9479	1.1307	0.9240	GB	5.9982	3.2247	0.8429	GB	1.7649	0.7051	0.9124
LGB	**1.8845**	**1.1000**	**0.9340**	LGB	5.9894	3.1863	0.8343	LGB	1.7659	0.6711	0.8676
MLP	2.7272	1.6201	0.9182	MLP	3.5753	2.1117	0.9080	MLP	1.0482	0.4136	0.9650

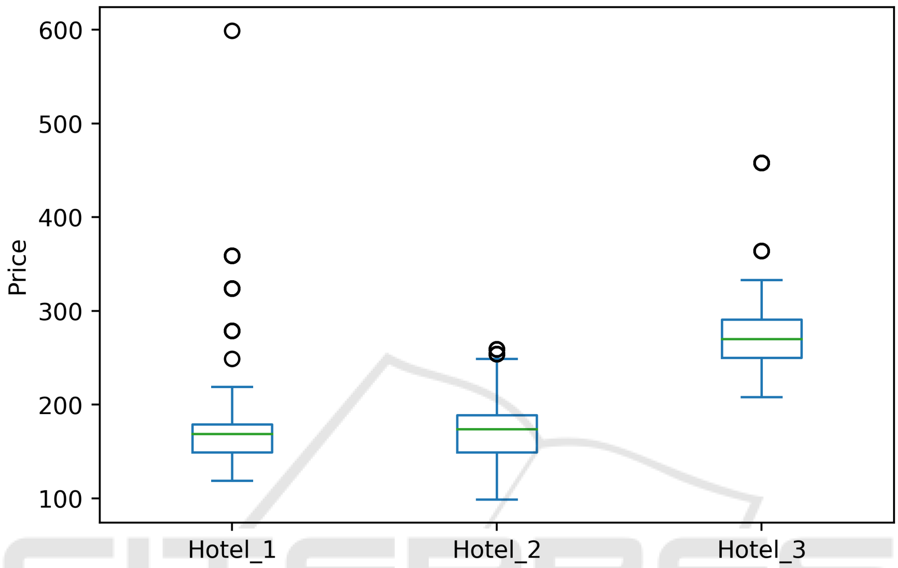


Figure 5: Boxplot of the test set price distribution per hotel.

Table 4: Statistical indexes computed on the test set for the target variable for Hotel_1 (a), Hotel_2 (b) and Hotel_3 (c).

STATISTICAL INDEX	VALUE
Max	599
75 p.	179
50 p.	169
25 p.	149
Min	119

(a)

STATISTICAL INDEX	VALUE
Max	259
75 p.	189
50 p.	174
25 p.	149
Min	99

(b)

STATISTICAL INDEX	VALUE
Max	458
75 p.	291
50 p.	270
25 p.	250
Min	208

(c)

four price bands (B_i). To identify the ideal splits for the prediction horizons we have consulted the domain experts and set the following periods:

H_1: predictions from 0 to 7 days ahead.

H_2: predictions from 8 to 15 days ahead.

H_3: predictions from 16 to 30 days ahead.

H_4: predictions from 31 to 90 days ahead.

Since the distribution of prices in the test sets differs even considerably among hotels (see boxplots in Figure 5), it would not have been possible to arbitrarily create four price ranges. For this reason, we decided to make use of the main statistical indices (shown in Table 4) together with a criterion applicable regardless of the distribution of the prices. We used the minimum value, the 25^{th}, the 50^{th} and the 75^{th} percentile and the maximum value of each distribution to split prices, obtaining the following bands:

B_1: prices between the minimum value and the 25^{th} percentile.

B_2: prices greater than the 25^{th} percentile and less than or equal to the 50^{th} percentile.

B_3: prices greater than the 50^{th} percentile and less than or equal to the 75^{th} percentile.

B_4: prices greater than the 75^{th} percentile and less than or equal to the maximum price.

By considering the time horizons and the price bands, we have computed matrices to highlight the MAPE for each horizon-price combination (Figure 6).

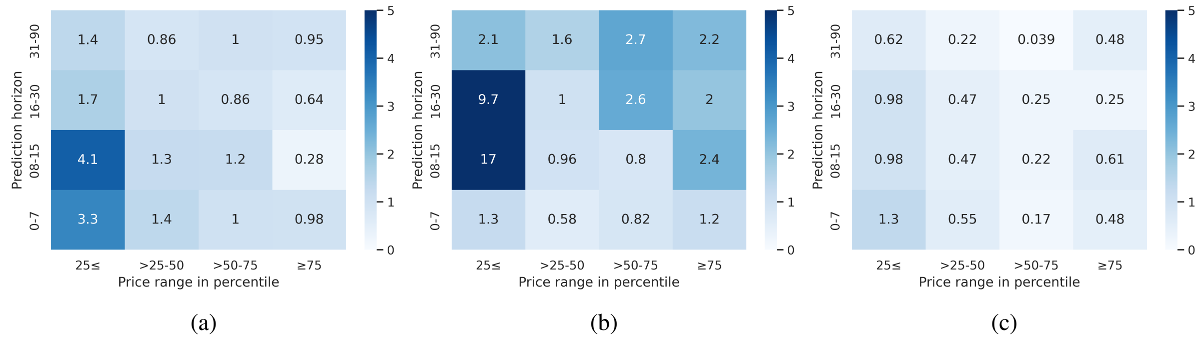
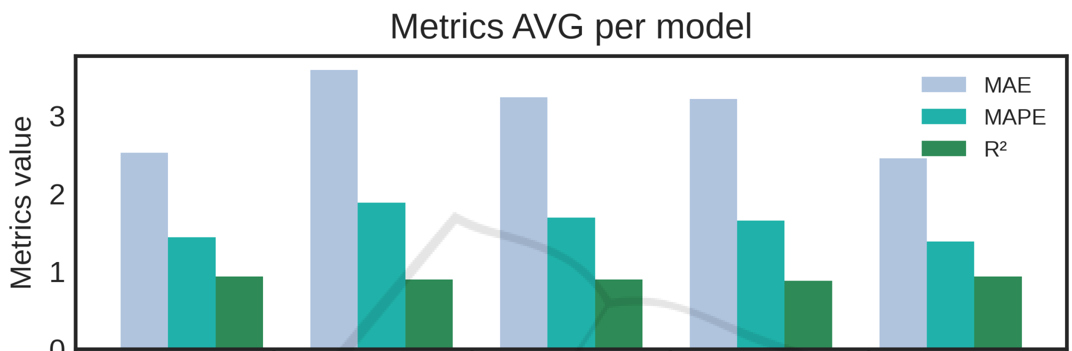


Figure 6: Matrices with MAPE over the fixed temporal horizons and price bands for Hotel_1 (a), Hotel_2 (b) and Hotel_3 (c).



	MLR	RF	GB	LGB	MLP
MAE	2.5215	3.587	3.237	3.2133	2.4502
MAPE	1.4352	1.8801	1.6868	1.6525	1.3818
R²	0.9296	0.8922	0.8931	0.8786	0.9304

Figure 7: Bar chart and table with the average of MAE, MAPE and R^2 computed on the performances of the three hotels per each model, MLR, RF, GB, LGB and MLP.

4.3 Discussion and Implications

Although the best performing models are LGB and MLR as shown in Table 3, the model that allows for an overall lower average error is the MLP, as shown in Figure 7. From a practical point of view, this implies that if an RMS wish to implement a single model for all the accommodation facilities, MLP is to be preferred among the ones compared in this study.

Another consideration concerns Hotel_2. As can be seen, looking at the results in Table 3 and Figure 6b, Hotel_2 is the receptive structure with the highest errors in terms of MAE and MAPE. It has also the lowest coefficient of determination. We hypothesized that this behavior could be linked to the fact that this property has changed its revenue manager starting from the 1^{st} of May of 2023. This means that the predictions have been obtained based on models trained on the pricing strategy of the previous domain expert and tested on the pricing strategy of the new domain expert. Despite this, the results are still satisfactory and, in these cases, we should simply give the model time to adapt and learn the new strategy. Our hypothesis could also be confirmed by the fact that while for the other two hotels the results on the test set are slightly better than those obtained on the validation set, for Hotel_2 there is instead a worsening of 1.0323 in MAE and 0.4218 in MAPE. It should be specified that although the validation set has been used to tune the hyperparameters, we are not surprised by the fact that we got small improvements on the test set. We supposed that these are linked to the period tested; in fact, the test set covers the summer season in which sales price changes are usually more frequent, and therefore the model may have learned better because it have had more relevant examples in the training set. Lastly, observing the average percentage error matrices in Figure 6 it can be noted that the highest errors are more concentrated in the B_1 price band and approximately in the H_1 and H_2 time horizons. One of the possible explanations could be that we are not taking into account some variables that are closely linked to bookings that take place between 0 and 15 days before the DOS, i.e., meteorological variables. In fact, when the price is lower than normal, weather conditions can be decisive in the choice to make a reservation or not.

5 CONCLUSIONS AND FUTURE WORKS

In this study we have performed a benchmark of different machine learning methods with the aim to build a support useful for a revenue manager working on dynamic prices. Having a well-established dynamic pricing strategy, the continuous monitoring and manual adjustment of prices performed by a revenue manager becomes costly and time-consuming. For this purpose we built a dataset containing static, dynamic and engineered variables and applied five machine learning models, MLR, RF, LGB, GB and MLP to predict the dynamic price that a revenue manager would set every day for the next 90 days for the entry level room of a receptive structure. The approaches have been tested on three different hotels. Since it emerged that the highest errors in terms of MAPE are concentrated more in the predictions between 0-15 days and in the lowest price range, in future works we will try to exploit additional variables that could influence the decision of the price in these cases.

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