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Forecasting of Occupied Rooms in the Hotel Using Linear Support Vector Machine

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Abstract: The hotel business is one of the important sectors in the tourism industry because it has a multiplier effect in social life and economics. Nowadays, the room reservation in hotels is more flexible so that the guests can extend or cancel their stay easily due to the development of technology. Based on the report on the number of room reservations, everyday, there are differences in the number of occupied rooms, so it is required that a forecasting in daily data be made. Forecasting is very important for the hotel management because it is affecting all hotel operations such as staff manning, amenities preparation, breakfast preparation, linen preparation to provide customer satisfaction. Customer satisfaction is a critical component of profitability [1]. The number of occupied rooms depends on in-house guests, same day reservation, extension of stay, early departure, today's cancellation, and walk-in. In this research, the classification method applied is the linear Support Vector Machine (SVM). The linear SVM uses the best hyperplane as a separator between two classes. In this method, we divide the dataset of guest reservation into training data and testing data in various proportions. Then the set of support vectors can be determined by the sequential programming method and we can test them in testing data. Based on simulation with various proportions of training data and testing data, the linear SVM can classify occupied rooms based on guest reservation with a good accuracy, error rate, recall, specificity, and precision.

Keywords: *classification; Support Vector Machine; pattern recognition; data mining*

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1 Introduction

Travelling is the activity which is often done by people when they also are looking for a hotel for a temporary stay. The hotel business is one of the important sectors in the tourism industry because it has a multiplier effect in social life and economics. Based on online hotel reservation sites, the purpose of booking a hotel is for a holiday, business, romance, or medical cure.

Nowadays, the room reservation in a hotel is more flexible so that the guests can extend or cancel their stay due to the development of technology. Based on the report on the number of room reservations, everyday, there are differences in the number of occupied rooms so that it is required that a forecasting in daily data be made. Forecasting is very important for the hotel management because it is affecting all hotel operations such as staff manning, amenities preparation, breakfast preparation, linen preparation to provide customer satisfaction. Moreover, customer satisfaction is also affecting the hotel performance, it is one of the measurements of the success of the hotel management in managing the hotel with all resources that they have [2]. The number of occupied rooms depends on in-house guests, same day reservation, extension of stay, early departure, today's cancellation, and walk-in. Using these variables, we can calculate the number of occupied rooms in a hotel. Based on the number of occupied rooms per day, they will be divided into two classes, i.e., the class where the number of occupied rooms is higher than its average and the other, where the number of occupied rooms is lower than its average.

In this research, there is a method for classifying the occupied rooms in a hotel, called the Support Vector Machine (SVM). The SVM uses the best hyperplane as a separator between two classes on input space [3]. This method has many applications in the classification of objects [4] or diagnosing the disease [5]. In this method, we divide the dataset of guest reservation into training data and testing data in various proportions. For training data, an optimization model of SVM is formed for determining the support vectors. After the set of support vectors can be determined by the sequential programming method [6], [7], we can test them in testing data.

In the previous researches, some clustering methods have been used, namely, clustering by the Kohonen Network in clustering airports [8] and clustering by the K-Means and Fuzzy Clustering Means in agriculture production [9]. Besides clustering, there are forecasting methods. The applications of a Neural Network have been used in forecasting by Backpropagation (BP) for forecasting of weather [10], estimation of AUV [11], [12], [13], estimation of the Vibrating Rod [14], estimation of disease spread [15], [16], forecasting of air temperature [17] and the Adaptive Neuro Fuzzy Inference System (ANFIS) in forecasting of humidity [18] or forecasting of sunlight intensity [19]. The forecasting methods are also applied by the Kalman Filter in stock price estimation [20], forefinger motion estimation [21], mobile robot estimation [22] and estimation of closed hotels and restaurants [23], [24], [25].

Based on simulation with various proportions of training data and testing data, the linear SVM can classify occupied rooms based on guest reservation with a good accuracy, error rate, recall, specificity, and precision.

2 Support Vector Machine (SVM)

Support Vector Machine (SVM) was introduced by Vapnik in 1992. SVM uses the best hyperplane as a separator between two classes on input space. The hyperplane can be determined by measuring the margin and optimizing the maximum point. The margin is the distance between the hyperplane and the closest pattern from each class. The closest pattern to the hyperplane is called the support vector. The illustration of SVM can be seen in Figure 1, with the red circle patterns being the class -1, blue square patterns being the class $+1$ and the hyperplane between them [3].

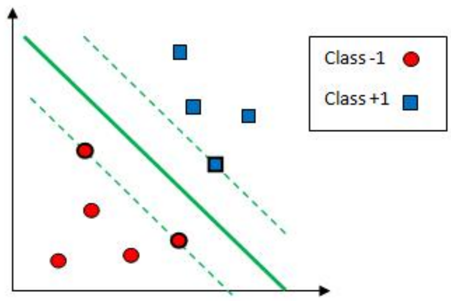

Figure 1: Support Vector Machine (SVM) Model.

Let $x_1, x_2, \ldots, x_n$ be the number of data and $y_1, y_2, \ldots, y_n \in -1, 1$ be the classes of $x_1, x_2, \ldots, x_n$, respectively. The optimization model of SVM is the maximizing margin m with $m = \frac{2}{\|w\|}$ subject to $y_i \left(w^T x_i + b\right) \geq 1, i = 1, 2, \ldots n$, so that the optimization model becomes

$$\min \frac{1}{2}\|w\|^2 \tag{1}$$

subject to

$$y_i \left(w^T x_i + b\right) \geq 1, \quad i = 1, 2, \ldots n. \tag{2}$$

In the constrained optimization above, we need to construct the Lagrange equation in equation (3) for optimizing the value of w, α, b,

$$L = \frac{1}{2} w^T w + \sum_{i=1}^{n} \alpha_i \left(1 - y_i \left(w^T x_i + b\right)\right). \tag{3}$$

For optimizing the value of w, α, b, the first differential of the Lagrange equation will be used,

$$\begin{aligned} \frac{\partial L}{\partial w} &= w - \sum_{i=1}^{n} \alpha_i y_i x_i = 0, \\ w &= \sum_{i=1}^{n} \alpha_i y_i x_i, \end{aligned} \tag{4}$$

$$\frac{\partial L}{\partial b} = -\sum_{i=1}^{n} \alpha_i y_i = 0. \tag{5}$$

Substitute $w = \alpha_i y_i x_i$ and $-\sum_{i=1}^{n} \alpha_i y_i = 0$ into the Lagrange equation

$$\begin{aligned} L &= \frac{1}{2}(\alpha_i y_i x_i)^T (\alpha_i y_i x_i) + \sum_{i=1}^{n} \alpha_i \left(1 - y_i \left(w^T x_i + b\right)\right), \\ L &= -\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j x_i^T x_j + \sum_{i=1}^{n} \alpha_i \qquad (6) \end{aligned}$$

so that the optimization model becomes

$$\begin{aligned} W(\alpha) &= \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j x_i^T x_j \\ subject\, to \sum_{i=1}^{n} \alpha_i y_i &= 0,\ \alpha_i \geq 0,\ i = 1, 2, \ldots, n. \qquad (7) \end{aligned}$$

In equation (7), an optimal $\alpha_i \geq 0, i = 1, 2, \ldots, n$, can be found by the sequential programming method [6],[7].

Generally, two classes on input space cannot be separated perfectly as in Figure 2 and the constraint in equation (2) is not satisfied.

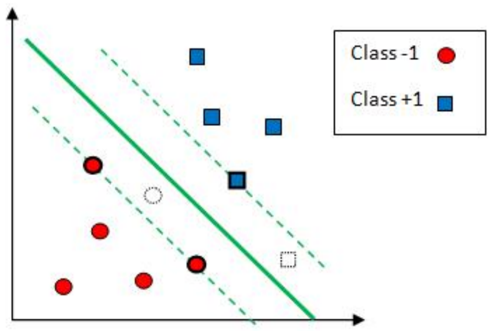

Figure 2: Soft Margin Method.

For solving this problem, the soft margin method will be applied using the slack variables $\varepsilon_i \geq 0, i = 1, 2, \ldots, n$,

$$\min \frac{1}{2}\|w\|^2 + C\sum_{i}^{n} \varepsilon_i \qquad (8)$$

subject to

$$y_i \left(w^T x_i + b\right) \geq 1 - \varepsilon_i,\ \varepsilon_i \geq 0,\ i = 1, 2, \ldots, n. \qquad (9)$$

With a similar process in equation (3) - (6), the optimization model becomes

$$\begin{aligned} W(\alpha) &= \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j x_i^T x_j \\ subject\, to \sum_{i=1}^{n} \alpha_i y_i &= 0,\ C \geq \alpha_i \geq 0, i = 1, 2, \ldots, n. \qquad (10) \end{aligned}$$

For testing data with the new data z, we use a discriminant function in equation (11):

$$f(z) = \sum_{i \in V}^{n} \alpha_i y_i \left(x_i^T z \right) + b, \tag{11}$$

where V is the set of support vectors.

The constant b can be determined using the average of the sum of support vector discriminant,

$$b = \frac{1}{N_v} \sum_{i \in V} \left(y_v - \sum_{i \in V} \alpha_i y_i x_i^T x_v \right) \;\; with \;\; y_v \in -1, 1. \tag{12}$$

If $f(z) \geq 0$, then the new data z is classified as the class $+1$ and if $f(z) < 0$, then the new data z is classified as the class -1.

3 Non Linear Support Vector Machine

When the SVM is applied to a nonlinear dataset, we need to define a feature mapping function $x \to \phi(x)$ to the higher dimensional feature space as in Figure 3. The feature mapping function is called the kernel function. The kernel function uses the inner product in the feature space.

$$K(x_i, x_j) \to \phi(x_i)^T \phi(x_j). \tag{13}$$

Kernel functions which are often used are as in Table 1.

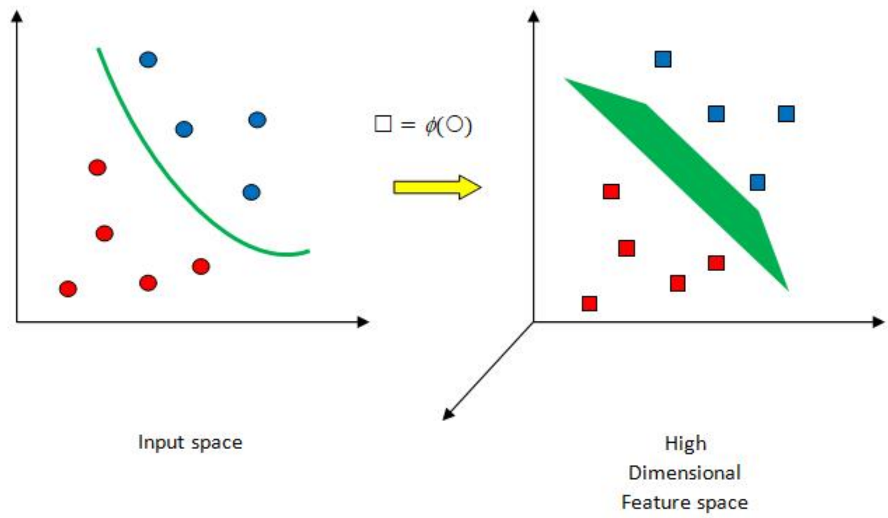

Figure 3: Transforming Data from the Input Space to the High Dimensional Feature Space.

Kernel Function	Type
$K(x_i, x_j) = \left(x_i^T x_j + 1\right)^d$	Polynomial Function
$K(x_i, x_j) = \exp\left(\frac{-\|x_i - x_j\|^2}{2\sigma^2}\right)$	Radial Basis Function
$K(x_i, x_j) = \tanh(\kappa x_i^T x_j + \theta)$	Sigmoid Function

Table 1: Kernel Functions.

There are some modifications due to the kernel function so that equation (10) becomes

$$\begin{aligned} W(\alpha) &= \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i, x_j) \\ subject\,to \sum_{i=1}^{n} \alpha_i y_i &= 0, C \geq \alpha_i \geq 0, i = 1, 2, \ldots, n. \end{aligned} \tag{14}$$

For testing data with the new data z, we use a discriminant function in equation (15),

$$f(z) = \sum_{i \in V}^{n} \alpha_i y_i K(x_i, z) + b \tag{15}$$

with V being the set of support vectors.

The constant b can be determined using the average of the sum of support vector discriminant,

$$b = \frac{1}{N_v} \sum_{i \in V} \left(y_v - \sum_{i \in V} \alpha_i y_i K(x_i, x_v) \right) \, with\, y_v \in -1, 1. \tag{16}$$

If $f(z) \geq 0$, then the new data z is classified as the class $+1$, and if $f(z) < 0$, then the new data z is classified as the class -1.

4 Methodology

In classifying occupied rooms in a hotel, there are reports on the number of room reservations by guests during 60 days, where the attributes which will be used as the inputs are: in-house guests, same day reservation, extention of stay, early departure, today's cancellation, and walk-in. The explanations of the attributes are:

1. In-house guest (x_1):
   The guest who is staying for today.

2. Same day reservation (x_2):
   The guest who makes a booking today for the check-in today as well.

3. Extention of stay (x_3):
   The guest who extends the stay from the check-out time.

4. Early departure (x_4):
   The guest who cuts the stay from the check-out time.

5. Today's cancellation (x_5):
   The guest who made a reservation on the previous days for today and makes a cancellation.

6. Walk-in (x_6):
   The guest who comes to the reception for today's check-in without a reservation.

These six attributes will be used to compute the number of occupied rooms by the formula:

Occupied rooms = In-house guests + Same day reservation + Extention of stays - Early departure - Today's cancellation + Walk-in

According to the number of occupied rooms on each day, they will be divided into two classes:

1. Class $+1$: the number of occupied rooms is higher than the average during 60 days.

2. Class -1 : the number of occupied rooms is lower than the average during 60 days.

In the classification, the data used are the accuracy, error rate, recall, specificity, and precision specified by the following formulae [2]:

$$accuracy = \frac{TP+TN}{P+N} \times 100\%, \tag{17}$$

$$errorrate = \frac{FP+FN}{P+N} \times 100\%, \tag{18}$$

$$recall = \frac{TP}{P} \times 100\%, \tag{19}$$

$$specificity = \frac{TN}{N} \times 100\%, \tag{20}$$

$$precision = \frac{TP}{TP+FP} \times 100\% \tag{21}$$

with the explanations:
TP : the number of positive tuples that are correctly labeled as positive by the classifier;
TN : the number of negative tuples that are correctly labeled as negative by the classifier;
FP : the number of negative tuples that are incorrectly labeled as positive by the classifier;
FN : the number of positive tuples that are incorrectly labeled as negative by the classifier;
P : the number of positive tuples in target data;
N : the number of negative tuple in target data;

Before using SVM, data partition into training data and testing data is made in various proportions.

5 Simulation Results

In classifying occupied rooms in a hotel, there are reports on the number of room reservations by guests during 60 days, where the attributes which will be used as inputs are: in-house guests, same day reservation, extention of stay, early departure, today's cancellation, and walk-in. Then, they will be classified into the class $+1$ (the number of occupied rooms is higher than the average during 60 days) and the class -1 (the number of occupied rooms is lower than the average during 60 days).

Before applying the classification process, five simulations of SVM will be applied with various proportions of training data and testing data.

- Classification model I : 50 % of training data and 50 % of testing data.
- Classification model II : 67 % of training data and 33 % of testing data.
- Classification model III : 75 % of training data and 25 % of testing data.
- Classification model IV : 80 % of training data and 20 % of testing data.
- Classification model V : 83 % of training data and 17 % of testing data.

After training data and testing data are determined, support vectors can be found by the sequential programming method aided by CPLEX software.

In the classification model I, the proportions of training data and testing data used are 50 % of training data and 50 % of testing data, with training data being the data which are not multiplied by $2\,(1, 3, 5, \ldots, 59)$ and testing data being the data which are multiplied by $2\,(2, 4, 6, \ldots, 60)$.

For training data, the best kernel function used is the polynomial kernel with degree $d = 1$ (linear model) so that based on objective equation (14) with its constrains, the support vectors obtained are

$$\begin{bmatrix} \alpha_5 = 0.013193 & \alpha_9 = 0.18556 & \alpha_{16} = 0.30668 \\ \alpha_{18} = 0.077692 & \alpha_{24} = 0.014615 & \alpha_{29} = 0.04201 \end{bmatrix} \alpha_i \approx 0,\ otherwise.$$

The objective function in equation (14) is 0.32. Using the support vectors obtained, we can find the best hyperplane for the training data. Then we use the best hyperplane for the new testing data, with the performance as follows.

	Training data	Testing data
Accuracy	100%	96.67%
Error rate	0%	3.33%
Recall	100%	94.7368%
Specificity	100%	100%
Precision	100%	100%

Table 2: Results of SVM Performance with 50 % of training data and 50 % of testing data.

In the classification model II, the proportions of training data and testing data used 67 % of training data and 33 % of testing data, with training data being the data which are not multiplied by $3\,(1, 2, 4, 5, \ldots, 59)$ and testing data being the data which are multiplied by $3\,(3, 6, 9, \ldots, 60)$.

For training data, the best kernel function used is the polynomial kernel with degree $d = 1$ (linear model) so that based on objective equation (14) with its constrains, the support vectors obtained are

$$\begin{bmatrix} \alpha_5 = 0.065524 & \alpha_6 = 0.0054547 & \alpha_{12} = 0.3411 \\ \alpha_{21} = 0.4495 & \alpha_{22} = 0.015323 & \alpha_{27} = 0.02614 \end{bmatrix} \alpha_i \approx 0,\ otherwise.$$

The objective function in equation (14) is 0.52. Using the support vectors obtained, we can find the best hyperplane for the training data. Then we use the best hyperplane for the new testing data, with the performance as follows.

	Training data	Testing data
Accuracy	100%	100%
Error rate	0%	0%
Recall	100%	100%
Specificity	100%	100%
Precision	100%	100%

Table 3: Results of SVM Performance with 67 % of training data and 33 % of testing data.

In the classification model III, the proportions of training data and testing data used are 75 % of training data and 25 % of testing data, with training data being the data which are not multiplied by $4\,(1, 2, 3, 5, \ldots, 59)$ and testing data being the data which are multiplied by $4\,(, 4, 8, \ldots, 60)$.

For training data, the best kernel function used is the polynomial kernel with degree $d = 1$ (linear model) so that based on objective equation (14) with its constrains, the support vectors obtained are

$$\begin{bmatrix} \alpha_7 = 0.013193 & \alpha_{13} = 0.18556 & \alpha_{24} = 0.30668 \\ \alpha_{27} = 0.077692 & \alpha_{36} = 0.014615 & \alpha_{43} = 0.04201 \end{bmatrix} \alpha_i \approx 0, \textit{ otherwise.}$$

The objective function in equation (14) is 0.32. From the support vectors obtained, we can find the best hyperplane for the training data. Then we use the best hyperplane for the new testing data, with the performance as follows.

	Training data	Testing data
Accuracy	100%	93.33%
Error rate	0%	6.67%
Recall	100%	90%
Specificity	100%	100%
Precision	100%	100%

Table 4: Results of SVM Performance with 75 % of training data and 25 % of testing data.

In the classification model IV, the proportions of training data and testing data used are 80 % of training data and 20 % of testing data, with training data being the data which are not multiplied by $5\,(1, 2, 3, 4, 6, \ldots, 59)$ and testing data being the data which are multiplied by $5\,(5, 10, 15, \ldots, 60)$.

For training data, the best kernel function used is the polynomial kernel with degree $d = 1$ (linear model) so that based on objective equation (14) with its constrains, the support vectors obtained are

$$\begin{bmatrix} \alpha_6 = 0.070096 & \alpha_7 = 0.0091087 & \alpha_{14} = 0.34108 \\ \alpha_{25} = 0.4266 & \alpha_{26} = 0.1492 & \alpha_{46} = 0.015526 \end{bmatrix} \alpha_i \approx 0, \textit{ otherwise.}$$

with the objective function in equation (14) being 0.506. From the support vectors obtained, we can find the best hyperplane for the training data. Then we use the best hyperplane for the new testing data, with the performance as follows.

	Training data	Testing data
Accuracy	100%	91.67%
Error rate	0%	8.33%
Recall	100%	87.5%
Specificity	100%	100%
Precision	100%	100%

Table 5: Results of SVM Performance with 80 % of training data and 20 % of testing data.

In the classification model V, the proportions of training data and testing data used are 83 % of training data and 17 % of testing data, with training data being the data which are not multiplied by 6 $(1, 2, 3, 4, 5, 7, \ldots, 59)$ and testing data being the data which are multiplied by 6 $(6, 12, 18, \ldots, 60)$.

For training data, the best kernel function used is polynomial kernel with degree $d = 1$ (linear model) so that based on objective equation (14) with its constrains, the support vectors obtained are

$$\begin{bmatrix} \alpha_6 = 0.065524 & \alpha_7 = 0.0054547 & \alpha_{15} = 0.3411 \\ \alpha_{26} = 0.4495 & \alpha_{27} = 0.15323 & \alpha_{34} = 0.02614 \end{bmatrix} \alpha_i \approx 0, \, otherwise.$$

with objective function in equation (14) is 0.52. From the support vectors obtained, we can find the best hyperplane for the training data. Then we use the best hyperplane for the new testing data, with the performance as follows.

	Training data	Testing data
Accuracy	100%	100%
Error rate	0%	0%
Recall	100%	100%
Specificity	100%	100%
Precision	100%	100%

Table 6: Results of SVM Performance with 83 % of training data and 17 % of testing data.

6 Conclusion

Forecasting is significantly important for the hotel operation. It can help the hotel management to prepare guest amenities and supplies, scheduling of the staff, and controlling energy. Shortly, accurate forecasting will help the hotel management to manage the hotel efficiently without sacrificing service quality. The linear SVM uses the best hyperplane as a separator between two classes. In this method, we divide the dataset of guest reservation into training data and testing data in various proportions. For training data, the optimization model of SVM is formed for determining the support vectors. After the set of support vectors can be determined by the sequential programming method, we can test them in testing data. Based on simulation with various proportions of training data and testing data, the linear SVM can classify the occupied rooms based on guest reservation with accuracy, error rate, recall, specificity, and precision. The developments of this research are classification techniques with big data using the machine learning process.

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