PREDICTING RENTAL PRICE RANGES USING THE NAIVE BAYES METHOD FOR BMN OPTIMIZATION (CASE STUDY IN BUKITTINGGI CITY AND SURROUNDINGS)

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Abstract: *This study aims to develop a predictive model for determining the rental price range of State Property (BMN), including accommodations and ATM rooms, using the Naive Bayes algorithm to mitigate bias in rental optimization within the KPKNL Bukittinggi work area. By utilizing market transaction data for ATM room rentals and market offering data for accommodation rentals, the authors constructed a predictive model to estimate the rental price range of BMN. The model achieved accuracy rates of 61.85% for accommodation rentals and 70.15% for ATM room rentals. The originality of this study lies in addressing the potential bias risk in BMN rental assessments, which can lead to inefficient and suboptimal transactions. The findings reveal that of the 7 BMN accommodations analyzed, 4 were undervalued. Additionally, out of 24 BMN ATM room rentals, 3 were undervalued, and 3 were overvalued, indicating the model's potential to enhance the accuracy of rental value assessments.*

Keywords*: 4P marketing mix (product, price, promotional place) SWOT, Purchase Interest.*

PENDAHULUAN

Ownership of assets is highly influential and plays a significant role, both in the private and public sectors (Hanif et al., 2016). However, ownership must also be accompanied by effective management. In support of this, the vision of the DJKN as a government institution responsible for managing state assets states that the management of national wealth, including non-movable state-owned assets, needs to be optimized in order to achieve a productive Indonesian economy for the prosperity of the people. According to the Directorate General of State Wealth of the Ministry of Finance of the Republic of Indonesia (2021), the average non-tax revenue obtained from the utilization of state assets from 2016 to 2020 averaged between 300 and 500 billion Indonesian Rupiahs, reaching 1.57 trillion Rupiahs in 2018.

According to Siregar, D. D. (2004), to achieve asset optimization, several stages are needed in asset management, one of which is asset valuation. Presidential Regulation Number 27 of 2014 itself states that the valuation of state assets is carried out, among other things, to obtain a fair value for the purpose of optimization in the form of utilization and transfer. One of the principles of state asset management in Presidential Regulation Number 27 of 2014 is related to the certainty of value. This means that determining a fair value through asset valuation will affect the results of state asset optimization.

Valuation for the purpose of state asset optimization carries the risk of inefficiency. Inefficiency refers to a condition where there is a difference, either in an over or under condition, that harms one party (Lombantoruan, 2015). This condition is caused by a bias known as overvalued or undervalued. Furthermore, according to Riyanto (2020), the form of utilization of state assets for leasing purposes has a high frequency because the application procedures are easier and faster compared to other forms of state asset utilization such as Public Service Units (KSP), so inefficiency in lease transactions may also occur. Several empirical studies, such as those by Cho and Megbolugbe (1996), Horne and Rosenblatt (1996), and Calem et al. (2017), have found that approximately 90% to 95% of valuations result in values above market prices or are overvalued.

Pagourtzi et al. (2003) mentioned that to address the shortcomings of bias in traditional methods such as market data and income approaches, advanced methods like Artificial Neural Networks, ARIMA, or GIS analytics can be employed. Previous research has attempted to apply these methods to mitigate bias risks and provide confidence in the fairness of a property's value by using predictive modeling to obtain value ranges. As seen in studies by Park & Bae (2015), Baldominos et al. (2018), and Mohd et al. (2020), they examined predictive modeling for property price objects and assessed the accuracy of comparisons. With the advancement of technology, there are several new methods as tools to enhance property valuation quality, as demonstrated in the research by Nilawati and Martin (2020) that utilized data analytics methods, specifically the Naive Bayes method, to classify the discrete value of a property based on data patterns in a location. The results showed that classification modeling using this method could achieve accuracy of over 90%. Their research revealed that predictive modeling with data mining techniques can instill confidence in property valuations.

Additionally, in studies conducted by Lang and Nakamura (1993), Blackburn and Vermilyea (2007), and Ding (2014), it was found that asset valuation bias is reinforced in small areas, such as in the city of Bukittinggi and its surroundings. Despite its small size, Bukittinggi is known as one of the largest wholesale trade centers in Sumatra. According to Islahuddin & Irawanto (2020), among the 514 cities and regencies in Indonesia from 2014 to 2018, selected cities have the potential to excel in their trading sectors. Bukittinggi is one of them, with a 33% contribution to the Gross Regional Domestic Product (PDRB) in the trade sector. This contribution surpasses the percentages of Pekanbaru and Jambi cities in the Sumatra region. Additionally, Sanesta (2015) also stated that Bukittinggi ranks highly in surveys of travelers and tourists regarding their perception of "The Most Beautiful City" in Indonesia. This ranking rivals Yogyakarta and Denpasar as tourists' favorite cities. Tourism activities have a multiplier effect, one of which strengthens the trade sector. Therefore, this study is expected to provide insights to government appraisers to obtain reliable rental values for the optimization of state-owned assets' leasing.

METODOLOGI

A. Types and Sources of Data

a. Data Types

The type of data used in this study is secondary data. This data consists of a collection of data indirectly sourced from other parties, where these parties indirectly provide data that has been further processed and then presented to other parties (Sugiyono, 2010). The independent variables used in this study for modeling refer to Director General of State Assets Regulation Number Per-4/KN/2018 regarding Technical Guidelines for the Assessment of State-Owned Moveable Property Rentals, which include location, accessibility, room/building condition, and the availability of supporting facilities. In more detail, for state-owned movable property (BMN) objects in the form of ATM room rentals, additional independent variables are included, referring to ATM KPKNL survey data, such as the type of ATM machine. For state-owned movable property (BMN) objects in the form of lodging or accommodation rentals, data from the internet is used, and additional independent variables include room types. The dependent variable in this study is the rental price range class, which will be derived from annual rental price data for ATM objects and daily lodging rental price data in the market, categorized as conducted in previous research journals.

b. Data Source

Riyanto (2020) stated that data sources encompass everything that provides information related to the data. The data is derived from BMN rental assessment reports requested from KPKNL Bukittinggi to obtain a list of BMN that has been operated for rent, both in the form of ATMs and accommodations. Transaction data for ATM rentals in the market is obtained from KPKNL Bukittinggi. In addition, data collection was also carried out by the author through the internet and websites for accommodation rental offers in the vicinity of Bukittinggi City. The ATM rental transaction data used covers the period from 2016 to 2021, while the accommodation rental offer data covers the period of 2021.

B. Analysis Techniques and Research Models

According to Arikunto (2013), when researchers only want to describe sample or population data for conclusions that are not universally applicable or generalized, descriptive analysis is used. In this case, if the data used is the population of BMN in the form of land in the working area of KPKNL Bukittinggi, then the results of this study will describe market analysis related only to the population of BMN in the form of land/buildings that are rented in parts of West Sumatra, not in all of Indonesia.

The initial step performed according to the CRISP-DM stages is the data pre-processing stage, involving descriptive statistical analysis. Descriptive statistics are used to describe the scope of the collected data but not to draw conclusions from it (Sugiyono, 2010). Next is the conversion of data attribute types from numeric to categorical based on predefined categories. According to Hofmann & Klinkenberg (2016), this activity is referred to as discretize by binning operator. Discretization involves dividing the continuous values of numeric data into several groups. The operator for converting from numeric to nominal or categorical groups is the data discretization transformation. Numeric values will be grouped based on bins (groups) divided based on the minimum and maximum parameter values of the data. Each group will have different frequencies but the same range of values. Afterward, input the data set and save it in Rapidminer as a dataset.

The next step is to process the data using Rapidminer version 9.7 using the Naive Bayes algorithm. This step involves modeling the training data first and then conducting K-fold cross-validation evaluation. After obtaining the results, simulation and evaluation of the fair rental value performed by government assessors at KPKNL Bukittinggi are carried out. The simulation results will be compared with field practices to analyze whether there is an indication of bias in the fair rental value of BMN.

HASIL DAN PEMBAHASAN

A. Naive Bayes Modeling

a. Retrieve Data

Modeling using the Rapidminer application requires importing the .xls file format into the Rapidminer dataset format. The next step is to perform modeling. The operators needed at this stage are Cross Validation, the Naive Bayes algorithm, Apply Model, and Performance. Cross Validation, also known as X-Validation, is one of the techniques for estimating the accuracy of a model by evaluating the algorithm, in this case, the Naive Bayes algorithm, on repeated folds or subsets. For relatively small dataset sizes, not like Big Data, the use of cross-validation is relatively better (Hofmann & Klinkenberg, 2016).

b. Cross Validation

In this cross-validation operator, the Naive Bayes algorithm is executed along with performance testing and testing data operators. Cross-validation is set with the parameter "Number of Folds" set to 9 folds and automatic sampling type. These parameters are recommendations from the Rapidminer application. These parameters instruct the dataset to divide into 9 parts, with 8 parts used as training data, while 1 part is reserved for testing data. Testing will automatically sample the testing data (randomly). Through this validation, it is expected to obtain performance evaluation results for the model.

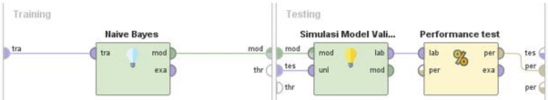

Figure 1. Naive Bayes Algorithm Modeling with X-Validation Operator (processed with Rapidminer).

The parameters of the Naive Bayes algorithm are configured by enabling Laplace correction. The purpose of activating this mode is to prevent the influence of high zero probabilities (Kotu & Deshpande, 2014). Furthermore, the Naive Bayes algorithm is also set to full kernel bandwidth estimation mode, with a fixed bandwidth of 0.01. The function of this kernel is to provide boundaries during algorithm execution to achieve an optimal model (Kotu & Deshpande, 2014).

c. Model Optimization

Based on the results of the initial performance testing of the previous accommodation price range prediction model, the modeling conditions were still not satisfactory. Therefore, to address this issue, model optimization is necessary. Tokuc (2021) suggests that to improve the performance of a Naive Bayes algorithm model, one way is to control variables with continuous or numeric data types. Managing numeric data involves a different process, where data is measured by mean and standard deviation.

Tokuc (2021) recommends binning and converting continuous data into discrete data. It is also not advisable to perform parameter hypertuning to avoid disrupting the already established model due to uncontrollable factors. As a step to optimize the accommodation price range prediction model, discretization is performed on several variables, as was done with the price variable. These variables are processed with binning by interval, dividing the minimum and maximum data range to obtain class intervals and dividing them into 2 classes. This binomial division is done to increase the model's focus, thereby improving the probabilities. In line with the previous explanation, Brownlee (2019) also suggests optimization by segmenting data to make the Naive Bayes probabilistic approach more focused, resulting in better model performance.

d. Apply Model

The next step is to perform model application and simulation. The operators required for this stage are Multiply, Apply Model, and Model Simulator. Multiply is one of the operators used to duplicate a result by adding output points, which appear as new branches. For both the accommodation and ATM room training datasets, this operator is used because it is needed as input for the Apply Model and Model Simulator operators. In addition to being used in the training dataset, the Multiply operator is also used in the output model from the X-Validation operator and the accommodation and ATM room BMN datasets. This operator does not require any parameters. All that is needed is to connect the output points to the inputs. In the output of the training dataset, it is connected to the input point of the X-Validation and Model Simulator operators. In the BMN dataset output, it is connected to the input points of the Apply Model and Model Simulator operators. For the last Multiply operator, it connects the output of X-Validation, which is the predicted price range model for BMN with the Naive Bayes algorithm, to the input points of Apply Model and Model Simulator.

According to Kotu & Deshpande (2014), the Apply Model operator is used to input data values from a dataset without label attributes that will be simulated into a model, and then produce a prediction example set in the form of a dataset with label attributes. This operator does not require parameter settings, and it is important to connect the input points accurately. The "mod" point must be connected to the X-Validation "mod" output, and the BMN data must also be connected to the "unl" point on the Apply Model operator. After that, the Model Simulator operator is connected in a similar way to the Apply Model, but it also needs to be connected between the input points from the training dataset to the "tra" point.

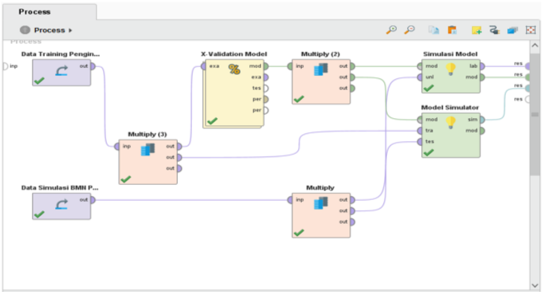

Figure 2. Display of the Modeling Process Design to Prediction Model Simulation in Rapidminer (processed with Rapidminer).

B. Performance Measurement of the Model

After running the modeling, in addition to the predictive model for the BMN rental price range, a confusion matrix table was obtained, indicating the model's performance along with its accuracy.

For the optimized prediction model of accommodation rental price range, a confusion matrix table was obtained, showing the model's performance along with its accuracy. In the accommodation rental price range prediction model, an accuracy rate of 61.85% was achieved, which is an improvement of 3.58% from the previous accuracy of only 58.27%, with a micro-average also increasing to 61.90%, or an additional 3.28% from the previous modeling. The error tolerance also decreased from 17.72% to 15.40%. Furthermore, an RMSE (Root Mean Square Error) closer to 0 was obtained, specifically 0.546 +/- 0.121 with a micro-average of 0.558 +/- 0.000, compared to the previous RMSE value of 0.599 +/- 0.110 with a micro-average of 0.606 +/- 0.000. According to Ghozali (2011), an RMSE value close to 0 is considered good, as RMSE can range from 0 to infinity. In previous research conducted by Riyanah & Fatmawati (2021), Suryanto et al. (2019), Wijaya & Rizal (2017), and Rahayu et al. (2019), which also used the Naive Bayes algorithm, it was concluded that a model can be considered usable if its accuracy exceeds 60%. In those studies, the accuracy ranged from 60% to 70%.

accuracy: 61.85% +/- 15.40% (micro average: 61.90%)

	true Mahal	true Sedang	true Murah	class precision
pred. Mahal	11	9	1	52.38%
pred. Sedang	4	23	9	63.89%
pred. Murah	1	8	18	66.67%
class recall	68.75%	57.50%	64.29%	

Figure 3. Confusion Matrix Table for Predicting the Range of Accommodation Rental Prices (processed with Rapidminer).

In the predictive model for the ATM room rental price range, a confusion matrix table was also obtained, indicating the modeling performance along with its accuracy. In this prediction model, an accuracy rate of 70.15% was achieved, with a micro-average of 70.25% and an error tolerance of 10.70%. Additionally, an RMSE (Root Mean Square Error) of 0.526 +/- 0.096 with a micro-average of 0.532 +/- 0.000 was obtained. Based on the RMSE value, the predictive model for the ATM room rental price range is considered quite good, as per Ghozali (2011), a good RMSE value is one that approaches 0, and RMSE can range from 0 to infinity. Referring to previous research, such as the studies conducted by Borman & Wati (2020), Riyanah & Fatmawati (2021), Fatmawati (2016), and Rahayu et al. (2019) that used the Naive Bayes algorithm, it was concluded that the model is sufficiently good for use with an accuracy rate of over 70%.

accuracy: 70.15% +/- 10.70% (micro average: 70.25%)

	true Mahal	true Sedang	true Murah	class precision
pred. Mahal	2	2	1	40.00%
pred. Sedang	8	57	17	69.51%
pred. Murah	3	5	26	76.47%
class recall	15.38%	89.06%	59.09%	

Figure 4. Confusion Matrix Table for Predicting the Range of ATM Room Rental Prices (processed with Rapidminer).

C. Model Implementation

a. Prediction Results of Accommodation Rent Price Range

Based on the predictive model using the Naive Bayes algorithm developed in the previous section, predictions for the price range of accommodation rentals in the market in Bukittinggi City and its surrounding areas in 2021 were obtained. Out of the 7 BMN data that were assessed by the appraiser from KPKNL Bukittinggi in mid-2020, all of them were predicted by the model to fall into the "Medium" price category, ranging from Rp195,833.00 to Rp341,666.00 per night.

Table 1. Rental Prices of BMN Indicated as Undervalued.

No.	Kelas Kamar	Satuan Kerja	Nilai Sewa		Prediksi Model		Confidence		
			Rp/malam	Kelas Harga	Rentang Harga	Kelas Harga	Mahal	Sedang	Murah
1	Standar 1	KPPN Bukittinggi	183.000	Murah	195.833 - 341.666	Sedang	0,007646	0,732704	0,259650
2	Standar 2a		163.000	Murah	195.833 - 341.666	Sedang	0,101136	0,810142	0,088722
3	Standar 2b		127.000	Murah	195.833 - 341.666	Sedang	0,000041	0,590714	0,409245
4	Standar 2c		109.000	Murah	195.833 - 341.666	Sedang	0,000041	0,590714	0,409245

In the predictions obtained for BMN rentals in the form of accommodation, it is known that there are 4 units that are indicated to be undervalued compared to the market rental prices. It is noted that all four of these units are BMN rented by KPPN Bukittinggi, specifically the standard class 1, standard 2a, standard 2b, and standard 2c room units.

b. Prediction Results for ATM Room Rental Price Range

Based on the predictive model using the Naive Bayes algorithm developed in the previous section, predictions for the price range of ATM room rentals within the Bukittinggi City work area and the period from 2017 to 2021 were also obtained. Out of the 24 BMN data that have been assessed by the appraiser from KPKNL Bukittinggi since 2017, it was found that 14 BMN rental values were predicted as "Cheap" and 10 BMN rental values were predicted as "Medium." Unlike the accommodation rental price range prediction model, the ATM room rental price range prediction model includes the year as an indicator for predicting the range of its market transaction values.

In the results of Table IV.2 obtained for BMN rentals in the form of ATM rooms, it is known that there are 3 units that are indicated to be undervalued and 3 other units that are indicated to be overvalued compared to the range of market rental prices for ATM rooms. Out of these 6 units, none of them are located within the city of Bukittinggi but are situated in satellite districts/cities such as two units in Agam Regency, two units in Tanah Datar Regency, one unit in Payakumbuh City, and one unit in Padang Panjang City. This is in line with previous research findings conducted by Lang and Nakamura (1993), Blackburn and Vermilyea (2007), as well as Ding (2014), where asset valuation bias is reinforced in smaller areas due to the difficulty in finding similar comparable data and the heterogeneity of property types.

Table 2. Indications of Undervalued/Overvalued Rental Prices for ATM Room BMN

No.	Satuan Kerja	Nilai Sewa		Prediksi Model		Confidence		
		Rp/Tahun	Kelas Harga	Rentang Harga (dalam ribuan Rp/Tahun)	Kelas Harga	Mahal	Sedang	Murah
1	Kantor Imigrasi Kelas II Agam	8.000.000	Murah	10.931 - 19.860	Sedang	0,000049	0,991279	0,008672
2	IAIN Bukittinggi	8.285.000	Murah	10.931 - 19.860	Sedang	-	0,776097	0,223903
3	ISI padang panjang	10.434.000	Murah	10.931 - 19.860	Sedang	-	0,557790	0,442210
4	Polres Payakumbuh	13.450.000	Sedang	2.000 - 10.930	Murah	-	-	1,000000
5	Pemkab Tanah Datar	17.520.000	Sedang	2.000 - 10.930	Murah	-	0,000099	0,999901
6	Pemkab Tanah Datar	18.067.000	Sedang	2.000 - 10.930	Murah	-	0,000068	0,999932

KESIMPULAN

Penelitian From the results of this research, the following conclusions can be drawn (1) through the models developed in this study, it is possible to predict the price range for accommodation and ATM room rentals in the operational area of KPKNL Bukittinggi, categorized as "Low," "Medium," and "High" prices. However, these models require support from pre-processed ATM transaction data and accommodation rental offer data in the operational area of KPKNL Bukittinggi, (2) the accuracy levels of the models in predicting the price ranges for ATM room and accommodation rentals in the operational area of KPKNL Bukittinggi are quite good. Based on accuracy measurements using the confusion matrix and RMSE (Root Mean Square Error), the predictive model for ATM room rental achieved an accuracy of 70.15% with a micro-average of 70.25%. The RMSE was 0.526 +/- 0.096, with a micro-average of 0.532 +/- 0.000. This indicates that the model can predict well, with 70.15% of predictions being accurate, a micro-average accuracy of 70.25%, and a low RMSE, suggesting that the variation in predicted values closely matches the variation in observed values. Similarly, for the predictive model of accommodation rental price ranges, an accuracy of 61.85% was achieved with a micro-average of 61.90%. The RMSE was 0.546 +/- 0.121, with a micro-average of 0.558 +/- 0.000. This implies that the model can predict reasonably well, with 61.85% of predictions being accurate, a micro-average accuracy of 61.90%, and a low RMSE indicating that the predicted values closely align with the observed values' variation, (3) the application of the Naive Bayes method can be utilized to predict the price ranges for accommodation and ATM room rentals in the operational area of KPKNL Bukittinggi. The method has generated predictions for field samples of government-owned properties (BMN) that are available for rent. These predictions indicate instances of both overvalued and undervalued rental prices. The Naive Bayes method can elucidate the factors influencing prediction decisions with a high level of confidence.

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