Forecasting Provincial Government Expenditures in Indonesia Using Artificial Neural Network

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Abstract

The purpose of this research is to analyze using artificial neural network techniques in predicting the realization of provincial government spending in Indonesia according to the type of expenditure with Back-Propagation. This research needs to be done because it can be seen from the side of realization of provincial government spending in Indonesia that there can be a surplus and a deficit. Therefore, it is necessary to make predictions as an effort to address this. The data comes from the publication by the Central Statistical Agency of the provincial government of financial statistics (BPS). Financial provincial government data was collected through local government financial surveys from provincial government agencies in Indonesia. The analysis process uses the help of Rapidminer software and is validated with K-

Fold values from 2 to 10. The data is divided into training data and testing data. Training data is data from 2016-2018 and testing data is data from 2017-2019. Several architectural models were tested namely '3-2-1; 3-5-1; 3-10-1; 3-5-10-1 'to obtain an accurate prediction by considering the value of Root Mean Square Error (RMSE). The results of the back-propagation analysis state that the 3-5-1 model is the best model with an RMSE value of 0.027 at k-fold = 9 for training data and an RMSE value of 0.035 for testing data. These results confirm that the back-propagation algorithm can be implemented in this case.

Keywords

Prediction, Back-propagation, RMSE, Realization of Government Expenditure, Indonesia.

Introduction

Currently, public sector accounting trends, especially in Indonesia, are rapidly increasing as regional financial management is entering a new era [1]. Regional financial managers control the destiny of a region very greatly as a region may become a strong and powerful region and grow or become powerless depending on how its finances are handled [2], [3]. Regional spending usually exceeds or falls short in each region of Indonesia. According to financial reporting from the provincial government through the central statistical agency, there was a surplus in 2016-2018. IDR 275.57 billion, IDR 323.49 trillion and IDR 335.49 trillion, respectively (Figure 1), while IDR 264.1 trillion, IDR 307.04 trillion, and IDR 326.43 trillion, respectively) were generated in regional expenditure (Table 1). In 2019 the budget shortfall is expected to amount to an IDR 365.95 trillion of revenue (Figure 1), while IDR 382.63 trillion in regional expenditure (Table 1). This can be resolved by the use of a funding factor to meet the deficit. The achievement of public expenditure is detailed in Table 1.

Table 1 Actual expenditure of provincial government throughout indonesia by kind of expenditure (Billion Rupiah), 2016-2019

No	Type of Shopping	2016	2017	2018	2019 *)
A	**INDIRECT SHOPPING**	**157 922**	**186 536**	**198 763**	**219 129**
1	Employee Spending	41 421	72 477	80 187	89 194
2	Flower Shopping	56	69	77	188
3	Subsidized Spending	948	1 489	2 875	5 049
4	Grant Shopping	53 832	46 838	51 941	50 349
5	Social Assistance Shopping	3 405	4 130	4 964	5 345
6	Profit Sharing Shopping	35 734	40 014	40 947	46 230
7	Shopping for Financial Aid	22 466	21 324	17 650	21 628
8	Unexpected Shopping	62	195	120	1 144
B	**SHOP DIRECT**	**106 177**	**120 593**	**127 667**	**163 497**
1	Employee Spending	7 367	8 365	5845	10 009
2	Shopping for goods and services	54 033	64 809	70 299	89 484
3	Capital Expenditures	44 777	47 329	51 522	64 003
TOTAL NUMBER		**264 099**	**307 039**	**326 430**	**382 626**

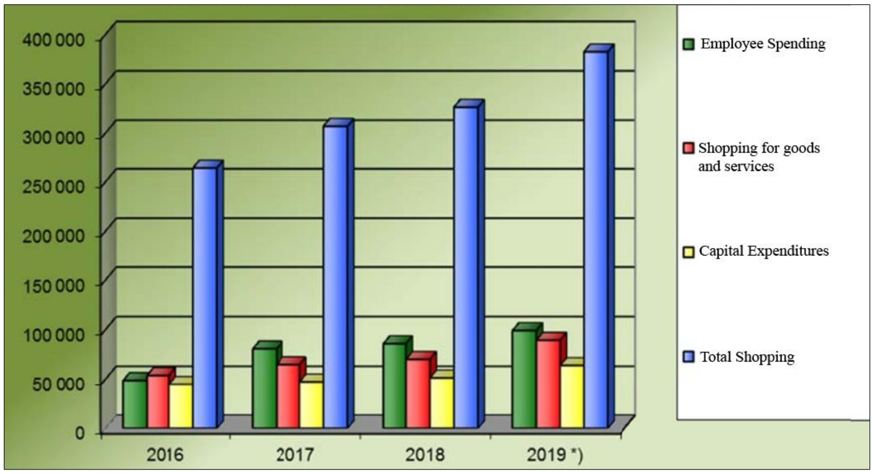

Figure 1 Graph of provincial government expenditure by type of largest expenditure (billion Rupiah)

The general expenditure structure says that the expenditure portion is controlled by expenditure on goods and services. In 2016-2018, these expenses amounted to 54.03 trillion rupiah, 64.81 trillion rupiah, and 70.30 trillion rupiah respectively or a rise of 19.94 percent in 2017 and 8.47 percent in 2018. In 2019, expenditure for goods and services was budgeted at 89.48 trillion rupiah or an increase of 27.29 percent compared to 2018. The next primary aspect of expenditure is personal expenses, a mixture of direct and indirect workers. In 2016, this expenditure was estimated at 48.79 trillion rupiah and in 2017 it was 80.84 trillion rupiah or experienced an increase of 65.70 percent from 2016. In 2018, however, staff expenditure was attributable to 86.03 trillion rupiah or a rise of 6.42 percent compared to 2017. And in 2019, staff expenditure is budgeted to rise by 15.31 percent or as much as 99.20 trillion rupiah.

Based on these reasons, a technique that can make predictions is required to anticipate this [4]. There are several artificial intelligence tools that can make predictions. Among them are artificial neural networks [5], [6]. Neural network is a classification algorithm that mimics the working theory of human neural networks. This algorithm maps the input data in the input layer to the target in the output layer through neurons in the hidden layer [7]. One of the neural network approaches is back-propagation. This approach has the potential to deduce information even though it has no certainty, can generalize and derive from patterns and can render a pattern of knowledge beyond learning boundaries [8]. Several previous studies, including [9] in predicting the availability of sugarcane stocks, have been conducted in backpropagation. A background method for the estimated production of sugarcane based on historical data from 2017 to 2019 is provided in this paper. The results show that 97% of production is predictable, and MAPE results 3%, thus the Back-Propagation method results have a decent prediction modeling capability.

Further investigation [10] into understanding the sexual characteristics of older drivers accidents in the UK was conducted. This article proposes to use the Generalized Delta Rule (GDR) learning algorithm to model factours, both male and female, which influence road accidents. The results of investigations into the back propagation method showed that the purpose of the journey was the main factor in accidents for older drivers in both sexes. Based on these benefits the back-propagation method is expected to be used to predict the execution of provincial expenditure in Indonesia by type of spending.

Methodology

This research uses quantitative approaches, including data collection and widespread explanation for particular population phenomena. The forecast algorithm for spending in Indonesia by provincial government is back-propagation which is one of the ANN algorithms that is often used for forecasting.

1. Data Collection

The data comes from the publication by the Central Statistical Agency of the provincial government of financial statistics (BPS). Financial provincial government data was collected through local government financial surveys from provincial government agencies in Indonesia. The details provided herein include the execution of the revenue and expenditure budget of the Provincial Government for 2016-2018. This publication also includes details on the Regional revenue and expenditure budget for 2019, along with data on the achievement of the APBD.

2. Research Stages

Research measures to forecast the achievement by form of expenditure of the provincial government in Indonesia include:

a) Collect the data set for use in the study.
b) Pre-treatment. The following equation normalizes knowledge.

$$x' = \frac{0,8\,(x-a)}{b-a} + 0,1 \qquad (1)$$

Description of formula: x': is the product of normalization, x: is normalized knowledge, a: is the lowest values, and b: is the highest values of normalization. The data are then divided into two fields, namely training and testing.

c) Evaluate the network architecture concept to be used for training and research.

d) Evaluate the architectural pattern used, then select the best architectural pattern.
e) Make forecasts using the best architectural model available.
f) Record a forecast.

Results and Discussion

1. Normalizing Data

The results of the analysis in Table 1 must be converted by formula at the next stage (1). This is due to the Sigmoid activation function, where the range is 0-1. The data is divided into two parts, namely the data on training and testing. Training data are data on the implementation of provincial government spending for 2016-2018. Where are the input data (2016 and 2017) and the target data? (2018). While training data are data on the implementation of provincial government spending for 2017-2019. Where are the input data (2017 and 2018) and the target data (2019). The results of the conversion can be seen in the following table.

Table 2 Data Training

No	Type of Shopping	2016	2017	2018
1	Employee Spending	0.5130	0.8230	0.9000
2	Flower Shopping	0.1000	0.1001	0.1002
3	Subsidized Spending	0.1089	0.1143	0.1281
4	Grant Shopping	0.6369	0.5671	0.6180
5	Social Assistance Shopping	0.1334	0.1407	0.1490
6	Profit Sharing Shopping	0.4562	0.4989	0.5082
7	Shopping for Financial Aid	0.3237	0.3123	0.2757
8	Unexpected Shopping	0.1001	0.1014	0.1006
9	Employee Spending	0.1730	0.1830	0.1578
10	Shopping for goods and services	0.6389	0.7465	0.8013
11	Capital Expenditures	0.5465	0.5720	0.6138

Table 3 Data Testing

No	Type of Shopping	2017	2018	2019*)
1	Employee Spending	0.7478	0.8168	0.8974
2	Flower Shopping	0.1000	0.1001	0.1011
3	Subsidized Spending	0.1127	0.1251	0.1446
4	Grant Shopping	0.5184	0.5641	0.5499
5	Social Assistance Shopping	0.1363	0.1438	0.1472
6	Profit Sharing Shopping	0.4574	0.4657	0.5130
7	Shopping for Financial Aid	0.2902	0.2573	0.2929
8	Unexpected Shopping	0.1011	0.1005	0.1096
9	Employee Spending	0.1742	0.1517	0.1889
10	Shopping for goods and services	0.6792	0.7284	0.9000
11	Capital Expenditures	0.5228	0.5604	0.6720

Source: processed data

In this case, the RapidMiner software helps to determine the perfect architectural model for data analysis. The analysis was evaluated using four models: 3-2-1, 3-5-1, 3-10-1 and 3-5-10-1. The way to determine the best Backpropagation architecture is to look at the Root Mean Square Error (RMSE) value. The parameters used are the tansig and logsig activation functions and the training function at the maximum limit of 200 epochs and Lr 0.01. The following is the design of architectural models using the RapidMiner software.

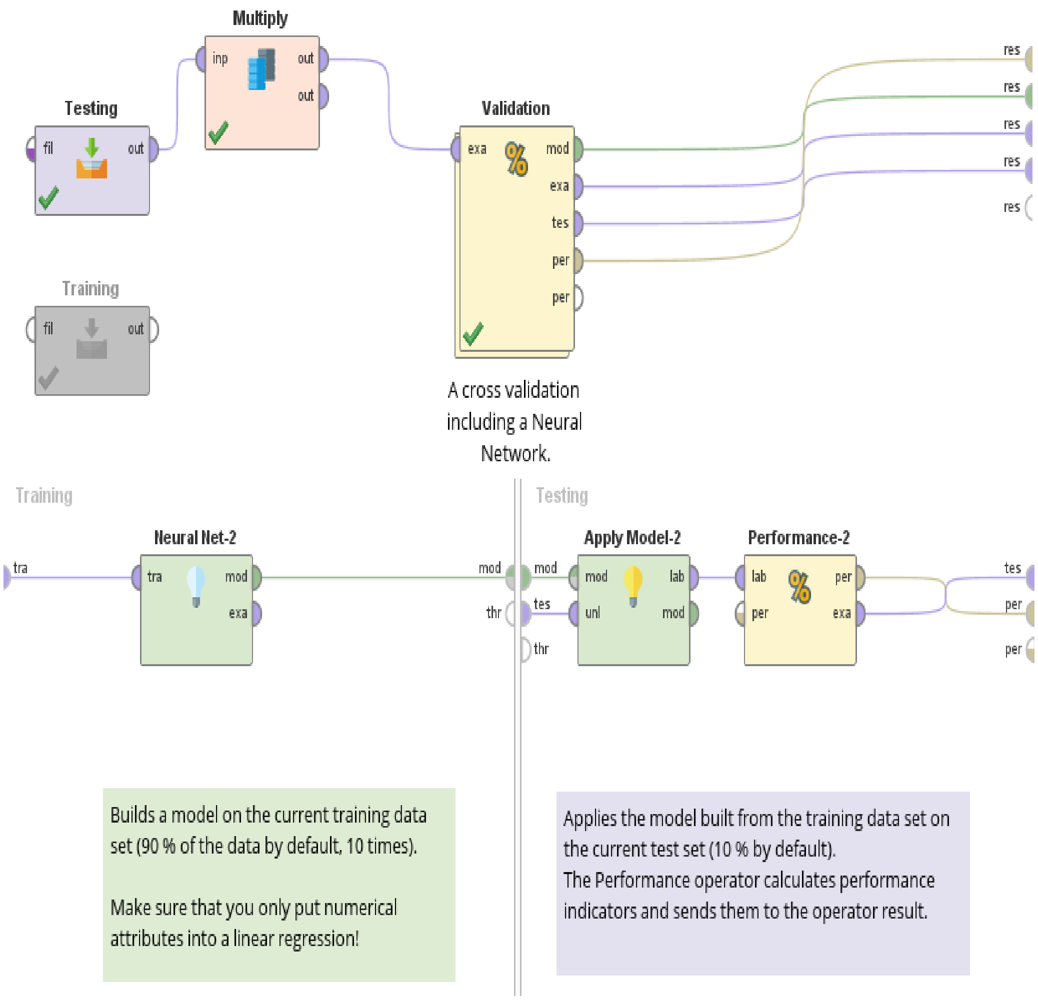

Figure 1 Neural Network Model with Rapid Miner software

Based on Figure 1, Data Sets can be processed using the back-propagation method. The following X-Validation display will validate the methods used, namely the back-propagation method with the Apply Model, which is useful for testing data and then linked to Performance to generate accuracy data in the form of a Root Mean Square Error (RMSE). The data set will be trained with k-fold values ranging from 2 to 10. The following are the results of the RMSE for each architectural model tested as shown in the following table:

Table 4 The results of the RMSE value for each k-fold in the back-propagation architectural model

3-2-1		3-5-1		3-10-1		3-5-10-1	
k-fold	**RMSE**	**k-fold**	**RMSE**	**k-fold**	**RMSE**	**k-fold**	**RMSE**
2	0.050	2	0.072	2	0.069	2	0.294
3	0.047	3	0.045	3	0.041	3	0.304
4	0.040	4	0.042	4	0.04	4	0.271
5	0.043	5	0.041	5	0.039	5	0.295
6	0.037	6	0.037	6	0.034	6	0.31
7	0.041	7	0.039	7	0.038	7	0.272
8	0.030	8	0.029	8	0.035	8	0.268
9	0.028	9	0.027	9	0.029	9	0.263
10	0.033	10	0.032	10	0.034	10	0.161

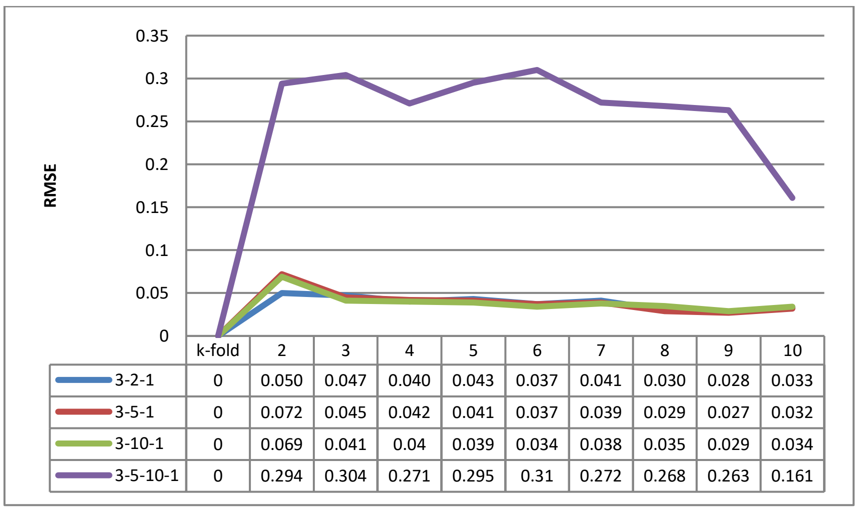

Figure 2 The RMSE value graph on the k-fold is different

In Table 4, the best architectural model is 3-5-1 with an average value (k-fold = 2 to 10) is 0.040 with the smallest RMSE value is 0.027 at k-fold = 9.

2. The Best Architectural Model

By testing 4 back-propagation architectural models on the predicted realization of provincial government spending in Indonesia, the best architectural model is 3-5-1. This model will then be tested to predict the realization of provincial government spending in Indonesia in 2019. The following are the complete results of the best architectural models (3-5-1) along with the complete prediction results as shown in the following figure:

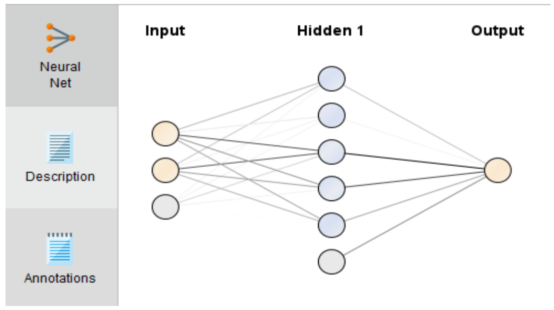

Figure 3 Full details of architectural models 3-5-1

Hidden 1
========
Node 1 (Sigmoid)

2017.0: -0.403
2018.0: -0.323
Bias: -0.059
Node 2 (Sigmoid)

2017.0: -0.116
2018.0: -0.068
Bias: -0.067
Node 3 (Sigmoid)

2017.0: -0.984
2018.0: -0.950
Bias: 0.242
Node 4 (Sigmoid)

2017.0: 0.609
2018.0: 0.563
Bias: -0.070
Node 5 (Sigmoid)

2017.0: -0.515
2018.0: -0.443
Bias: -0.004

Output
======
Regression (Linear)

Node 1: -0.341
Node 2: 0.053
Node 3: -1.451
Node 4: 1.094
Node 5: -0.516
Threshold: 0.671

Table 5 Prediction results with an architectural model 3-5-1

Type of Shopping	2019*)	Prediction (2019*))
Subsidized Spending	0.145	0.124
Social Assistance Shopping	0.147	0.147
Shopping for Financial Aid	0.293	0.260
Flower Shopping	0.101	0.114
Grant Shopping	0.550	0.661
Shopping for goods and services	0.900	0.808
Capital Expenditures	0.672	0.629
Employee Spending	0.189	0.166
Employee Spending	0.897	0.902
Profit Sharing Shopping	0.513	0.544
Unexpected Shopping	0.110	0.112

Figure 4 Graph prediction results with the best 3-5-1 architectural model with testing data

The prediction results shown in Table 5 can be done with the final RMSE value of 0.035.

Conclusion

From the results of research conducted using the back-propagation method the prediction of the realization of provincial government spending in Indonesia can be applied. By using four architectural models to test, the best architectural model is obtained 3-5-1 with an average RMSE value of 0.040. In the future, this research can be developed by making a model with a much smaller RMSE value by combining it with several methods such as the PSO method, genetic methods and others.

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