Jurnal Mantik Penusa

Volume 3, No.1, Juni 2019

e-ISSN 2580-9741
p-ISSN2088-3943

360 DEGREES AND K-NEAREST NEIGHBOUR METHODS FOR LECTURER PERFORMANCE APPRAISAL SYSTEMS

Novita Br Ginting, Yuggo Afrianto*

Department of Informatic,
Faculty of Engineer, Ibn Khaldun University, 16162, Bogor, Indonesia

E-mail: yuggo@uika-bogor.ac.id

Abstract

The lecturer performance appraisal system functions to measure and evaluate the performance of the lecturers in a certain period of time. The purpose of this study is to apply the 360-degree and machine learning algorithm using the K-NN (k-nearest neighbour) method to model the lecturer performance appraisal system to be more objective and accountable. DP3 is List of Appraisal of Employee Work Implementation. DP3 data is used as knowledge datasets to be used as training data and test data for the classification process and prediction of lecturer performance values. The results obtained show the 360-degree method and K-NN is able to predict with 90% accuracy right on knowledge datasets that have not been normalized and K = 5 values. Hence, this model can then be used to become a lecturer performance appraisal system application.

Keywords: *360 degree method; k-nearest neighbor; lecturer performance appraisal; machine learning*

Abstrak

Sistem penilaian kinerja dosen berfungsi untuk mengukur dan mengevaluasi kinerja dari para dosen dalam periode waktu tertentu. Tujuan penelitian ini merapkan algoritma machine learning menggunakan metode K-NN (k-nearest neighbor) dan 360 derajat untuk memodelkan sistem penilaian kinerja dosen agar menjadi lebih obyektif dan akuntabel. Data DP3 (Daftar Penilaian Pelaksanaan Pekerjaan Pegawai) digunakan sebagai data set pengetahuan untuk dijadikan data latih dan data uji untuk proses klasifikasi dan prediksi nilai kinerja Dosen. Hasil yang didapat menunjukkan metode 360 derajat dan K-NN mampu memprediksi dengan akurasi 90% tepat. Hal ini karena menggunakan dataset pengetahuan yang belum dilakukan normalisasi dan nilai K = 5. Tentu saja model ini selanjutnya dapat digunakan untuk menjadi aplikasi sistem penilaian kinerja dosen. Selanjutnya model ini dapat digunakan untuk mendukung aplikasi penilaian kinerja tenaga pendidik.

Kata Kunci: K-NN; Machine Learning Metode 360 Derajat;

1. Introduction

The quality of education needs to be maintained in a college. That can be done by conducting lecturer performance evaluation activities regularly every semester to control individuals towards a better direction by Terttiaavini [1]. According to Law No. 14 of 2005. Lecturers are professional and scientific educators with the main task of transforming, developing and disseminating science, technology and art through education, research and community service [2].

Performance Appraisal is a continuous process for measuring employee's performance level against the predetermined goal or task of organisation [3]. It is had been carried out at the end of each semester, using many assessment instruments in the form of quantitative data obtained directly from the tri dharma lecturer support and qualitative data obtained from questionnaires given to each student, supervisor, staff, and colleagues. A manual assessment method makes it difficult and unaccountable to conclude how the performance of the lecturer. Given the importance of performance evaluation, it is essential that organisations take action for more effectiveness of it. Periodical evaluation in a system and its components can increase its effectiveness [4].

Machine learning algorithm is a subject that focuses on data analysis using various statistical tools and learning processes to get more knowledge from data [5]. The core of machine learning is to create models that reflect data patterns [6]. K - nearest neighbor technique is a machine learning algorithm that is considered as simple to implement. NEKD is lecturer performance evaluation value. The historical of NEKD value and test data are mapped into a set of vectors. Each vector represents N dimension for each NEKD features. Then, a similarity metric such as Euclidean distance is computed to take a decisions [7]. The 360-degree method assessment process is widely used by many organizations as feedback from each individual who is directly

e-ISSN 2580-9741
p-ISSN2088-3943

involved with employees. This process is to get the views and performance of the employee, by describing the weaknesses and strengths of an employee [8], so that this method can to combine with K-NN for assess employee performance to be more objective.

In this research, the machine learning algorithm approach is used to model the lecturer performance appraisal system, so that the machine can predict the lecturers' performance directly using the 360-degree method and K-NN. The working stages of the lecturer performance appraisal system model using machine learning include data collection, data preparation, knowledge dataset processes, classification and prediction processes. The computational procedure in this study uses the Python programming language because it is flexible and opensource.

2. Research Method

The research stages are the framework in providing an overview and ease of conducting research. In general, there are several stages, namely: data collection, data preparation, knowledge datasets process, classification and prediction processes. The steps in this study are presented in Figure1.

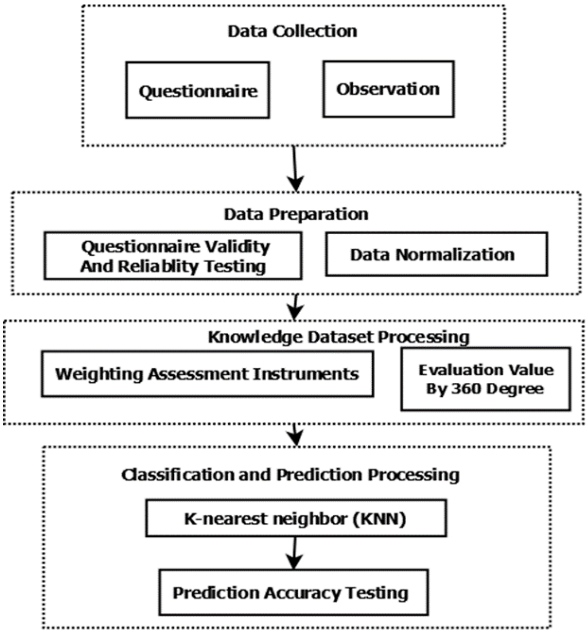

Figure 1. The research framework

a. Data Collection

This research uses data on documents of lecturers' performance appraisal forms, DP3 is List of Assessment of Employee Work Implementation in which there are several elements assessed. The data obtained are DP3 data from 2016/2017 and 2017/2018 Academic Year. This data is used as knowledge data for simulation of the lecturer performance evaluation system. The questionnaire is used to collect primary data by asking questions to stakeholders who interact directly with the lecturers to be assessed, to get the value of each element of a qualitative assessment instrument. The measurement scale used is Scale Linkert.

b. Data Preparation

Data preparation builds datasets to get attribute/ class/label tables from how many elements of the assessment are quantitative and qualitative. 360-degree method calculations are used to assess elements that are qualitative through questionnaires. The questionnaire was previously tested in 2 ways, namely:

1) Questionnaire Validity Testing.

Validity testing is used to measure whether a questionnaire is valid or not. A questionnaire is said to be valid if the question in the questionnaire is able to answer something that will be measured by the questionnaire [9]. Product moment correlation calculations are used to test validity using Equ. (1).

$$r_{xy} = \frac{N\Sigma xy - (\Sigma x)(\Sigma y)}{\sqrt{N\Sigma x^2 - (\Sigma x)^2 (N\Sigma y^2 - (\Sigma y)^2)}} \quad (1)$$

Where r_xy is a correlation between variables x and y, Σxy number of multiplications between variables x and y, Σx^2 the sum of squares of x, Σy^2 the sum of squares of y, (Σx)^2 the number of x values is then squared, (Σy)^2 the amount of y is then squared.

2) Questionnaire Reliability Testing.

Reliability testing is measuring a questionnaire for indicators from variables or constructs. A questionnaire is said to be reliable if someone's answer to the statement is consistent or stable over time [9]. Cronbach alpha calculations are used for reliability testing using Equ. (2).

$$r_{11} = \frac{(n)}{(n-1)}\left(1 - \frac{\Sigma\sigma_t^2}{\sigma_t^2}\right)(2)$$

Where r_11 is calculated reliability, n is the number of item questions that are tested, Σ σ_t^2 the total variance score of each item, σ_t^2 total variance.

c. Knowledge Dataset Processing

1) Weighting Assessment Instruments.

Each instrument attribute assessed by each lecturer will be given a percentage weight that refers to Table 1.

2) Evaluation Value.

The evaluation value is the value resulting from the sum of all instrument elements obtained from quantitative and qualitative data. Qualitative data is calculated using a 360-degree method. Calculation of evaluation values using Equ. (3).

$$\boldsymbol{NE} = \sum_{\boldsymbol{n=1}}^{\boldsymbol{n}} (\textbf{Assessment Instruments} * \textbf{weight}) \quad (3)$$

Where NE is the evaluation value from the number of calculations of the assessment instrument multiplied by the weight.

The results of the calculation of the evaluation value based on the weight of each instrument of assessment of the lecturer produce a collection of knowledge datasets. Furthermore, this knowledge dataset is used to predict the value of the new lecturer evaluation.

d. Classification and Prediction Processing

1) K-NN Calculation Method.

KNN is used to classify classes by looking for groups of k objects in training data that are the closest (similar) distance to objects in new data or testing data [10]. The calculation of the distance between two objects x and y uses the Euclidean formula with Equ. (4).

$$\boldsymbol{d_{xy}} = \sqrt{\sum_{\boldsymbol{i=1}}^{\boldsymbol{n}} (\boldsymbol{x_i} - \boldsymbol{y_i})^2}(4)$$

Where d_xy is the Euclid distance of the x data object and j data object, n is the number of data used, x_i is the data object x to i, and y_i is data object y to i.

2) Prediction Accuracy Testing.

This accuracy test uses Confusion matrix. A tool used to evaluate classification models to estimate objects that are right or wrong. A matrix of predictions will be compared with the original class of input or in other words, contain information on actual values and predictions in the classification by j han in [11]. Accuracy calculation on matrix confusion uses Equ. (5).

$$\boldsymbol{acc} = \frac{\boldsymbol{Number\ of\ True\ Values}}{\boldsymbol{Overall\ Data}}\ \boldsymbol{x\ 100}\% \quad (5)$$

Testing the prediction accuracy value to determine the best value of the K value parameter, the unnormalized and normalized knowledge dataset. Data normalization is done to change the data so that it is on a certain scale, to do this by the scaling method. Scaling is taken using the range (0-1) [12]. Calculation of scaling using the formula min-max uses Equ. (6).

$$\grave{N} = \frac{N - Nmin}{Nmax - Nmin} * (BA - BB) + BB \quad (6)$$

Where Ǹ is the normalized value, N is the initial value, Nmin is the smallest value of the amount of data, Nmax is the largest value of the amount of data, BA is the upper limit, and BB is the lower limit.

3. Results and Analysis

a. Data Collection

The data was collected by observing in the form of DP3 filling document data in 2016 and 2017. DP3 has several attributes assessed, where each attribute is given an assessment weight and grouped into 2 types of data, namely quantitative and qualitative data. The attributes of the DP3 Lecturer assessment data group can be seen in Table 1.

TABLE1
WEIGHTING ASSESSMENT AND DATA TYP ATTRIBUTES

Assessment Attribute	Data Type	Weighting
Presence	Quantitative	10%
Training	Quantitative	40%
Research	Quantitative	20%
Communitie Service	Quantitative	10%
Application of Tridharma College	Qualitative	5%
Commitment and Discipline	Qualitative	5%
Leadership and Teamwork	Qualitative	5%
Initiative, Motivation and Integrity	Qualitative	5%

Table 1 shows quantitative data assessed based on supporting components obtained directly by the lecturer, such as attendance attribute data, syllabus for educational attributes, journals for research attributes and PkM reports for community service attributes. Qualitative data was assessed based on questionnaires to receive feedback from various parties on a regular basis who interacted with lecturers and evaluated using the 360-degree method. There are 4 lecturer performance indicators that are qualitatively assessed from a DP3 format, namely (1. Implementation of Tri dharma, 2. Commitment and Discipline, 3. Leadership and cooperation, 4. Initiative, Motivation and Integrity), then these 4 indicators are each made questionnaire form for different respondents. There are 4 criteria of respondents used in this study, namely (1. Students, 2. Administrative Staff, 3. Bosses, 4. Colleagues). The mapping of respondents based on questionnaires from lecturer performance indicators and assessment criteria based on a DP3 format that have been determined by University Agencies can be shown in Table 2.

TABLE 2
RESPONDENTS ASSESSING LECTURER SUPPORTING COMPONENT

Questionaires Supporting Components	Respondents
Application of Tridharma College	College Student and Staff
Commitment and Discipline	Senior
Leadership and Teamwork	Colleague
Initiative, Motivation and Integrity	Senior

The NE calculation results using equation 3 produce different lecturer classification performances shown in table 3. Based on these calculations generate a collection of knowledge datasets. Furthermore, this knowledge dataset is used to predict new lecturer evaluation values.

TABLE 3
LECTURER PERFORMANCE CLASSIFICATION BASED ON THE VALUE OF VECTURER

Total NE	Performance Classification
91 – 100	Strongly agree
76 – 90	Agree
61 - 75	Neither agree nor disagree
46 – 60	Disagree
0 - 45	Strongly disagree

b. Data Set Preparation Results

1) Questionnaire Validity Test Results.

The calculation of the validity of the questionnaire was done using the Equation 1 for each questionnaire form of the respondents. This value is then compared with the r-table value that is sought, at a significant 5% (0,05) with a two-sided test and N (number of respondents). The question is declared valid or feasible when r-count greater than r-table. The value of DF (Degree of Freedom) of each respondent can be calculated by the Equ. (7).

$$DF = N - 2 \qquad (7)$$

Where DF is a free degree, the results are converted to T-Table values. N is the number of respondents. Data from the calculation of the validity test can be seen in Table 4.

TABLE 4
QUESTIONNAIRE VALIDITY TEST RESULTS

Number Of Question	Staff (N = 68)		Colleague (N=15)		Senior (N=16)		College Student (N= 82)		Results
	R - Count	R- Table	R- Count	R- Table	R - Count	R -Table	R –Count	R – Table	
1	0,893	≥ 0,2387	0,676	≥ 0,5140	0,694	≥ 0,4973	0,928	≥ 0,2172	Valid
2	0,908	≥ 0,2387	0,855	≥ 0,5140	0,875	≥ 0,4973	0,866	≥ 0,2172	Valid
3	0,888	≥ 0,2387	0,804	≥ 0,5140	0,829	≥ 0,4973	0,916	≥ 0,2172	Valid
4	0,903	≥ 0,2387	0,767	≥ 0,5140	0,812	≥ 0,4973	0,946	≥ 0,2172	Valid
5	0,924	≥ 0,2387	0,823	≥ 0,5140	0,89	≥ 0,4973	0,905	≥ 0,2172	Valid
6	0,742	≥ 0,2387	0,594	≥ 0,5140	0,72	≥ 0,4973	0,635	≥ 0,2172	Valid
7	0,878	≥ 0,2387	0,691	≥ 0,5140	0,666	≥ 0,4973	0,891	≥ 0,2172	Valid
8	-	-	-	-	0,674	≥ 0,4973	0,886	≥ 0,2172	Valid
9	-	-	-	-	-	-	0,85	≥ 0,2172	Valid
10	-	-	-	-	-	-	0,87	≥ 0,2172	Valid
11	-	-	-	-	-	-	0,797	≥ 0,2172	Valid

Based on Table 4, it can be seen that the validity test conducted on each respondent produces questions that are declared valid because r-count is always greater than r-table. It can be concluded that all questions made are considered feasible and can be used.

2) Questionnaire Reliability Test Results

Calculation of the questionnaire reliability test was carried out using Equation 2 for each questionnaire form of the respondents. This value is then compared, if the Alpha value is greater than the r-table then each question used is declared reliable or consistent, on the contrary, if the Alpha value is smaller than the r-table then each question that is used is declared not reliable or inconsistent. Calculation data can be seen in Table 5.

TABLE 5
RELIABILITY TEST RESULTS

Responden Questionaires	Alpha Cronbach	R-Table	Results
College Student	0,785	≥ 0,2172	Reliabel
Staff	0,804	≥ 0,2387	Reliabel
Senior	0,850	≥ 0,4973	Reliabel
Colleague	0,804	≥ 0,2387	Reliabel

Based on Table 5, it can be seen that the reliability test carried out on each questionnaire form of the respondents produces questions that are declared reliable because the Alpha value is greater than r-table. It can be concluded that all questions made are considered feasible and can be used.

c. Knowledge Dataset Processing Result

The results of the calculation of the NE value of the lecturer produce a knowledge data set. Furthermore, the dataset is used for the dataset of knowledge about the accuracy of K-NN calculations. Tests are carried out with two knowledge dataset models, namely: Datasets that have not been normalized as shown in Table 6 and which have been normalized using equation 6, shown in Table 7.

TABLE 6
DATASET BEFORE NORMALIZATION

NIK	N1	N2	N3	N4	N5	N6	N7	N8	Score	Classification
410100567	7,0	37,25	0	5,0	3,75	3,5	4,25	4,25	65,00	Neither agree nor disagree
410100206	7,7	38	20	7,0	4,65	4,65	4,0	4,0	90,00	Agree
410100250	6,0	38	18	0	4,0	3,75	4,0	3,75	77,50	Agree
410100295	10	38	15	10	4,0	4,0	4,0	4,0	89,00	Agree
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
410100321	7,5	35	20	10	4	4,25	4,5	4,5	89,75	Agree
410100454	10,0	35	20	10	3,5	3,5	3,5	3,5	89	Agree
410100405	8,2	33	20	10	4,25	4,25	4	4,25	87,95	Agree

TABLE 7
DATASET AFTER NORMALIZATION

NIK	N1	N2	N3	N4	N5	N6	N7	N8	Classification
410100567	0,70	0,93	0	0,50	0,75	0,70	0,85	0,85	Neither agree nor disagree
410100206	0,77	0,95	0,74	0,70	0,93	0,93	0,80	0,80	Agree
410100250	0,60	0,95	0,67	0,00	0,8	0,75	0,80	0,75	Agree
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
410100295	1,00	0,95	0,56	1,00	0,80	0,80	0,80	0,80	Agree

d. Prediction Accuracy Testing Result

Test results use a knowledge dataset that has not been normalized and normalized, with the total distribution of knowledge datasets being 2. That is test data and training data. The amount of distribution of test data and training data is made randomly by determining different percentages of the total knowledge dataset for each test. The first test uses 10% test data and 90% training data. The second test uses 20% test data and 80% training data. The third test uses 30% test data and 70% training data. The fourth test uses 40% test data and 60% training data. The fifth test uses 50% test data and 50% training data. From each training set data and test data the accuracy value is measured, both those that have not and those that have been normalized at K value 1,3,5,7,9,11,13,15,17,19,21,23,25,27, 29 using equation 5. The conclude the results by calculating the total average value for each K value in the knowledge dataset that has not been normalized and that has been normalized into a graph. The results of the test graph for the prediction of knowledge datasets and K values are shown in Figure 2.

e-ISSN 2580-9741
p-ISSN2088-3943

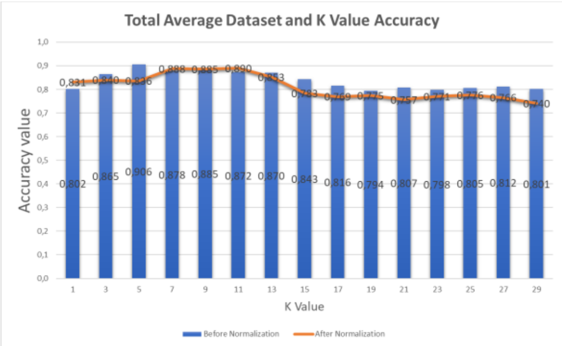

Figure 2. Total average dataset and K value accuracy

Figure 2 shows the conclusion of the total average accuracy of the dataset and the value of K where the highest overall accuracy is the knowledge dataset that has not been normalized with an accuracy of 90% at the value K = 5.

4. Conclusion

In this study, 360 degrees and k nearest neighbour methods can be applied to the Lecturer performance appraisal system. The questionnaire test phase states that each form of questionnaire question has been valid and reliable so that it is suitable to be used for value retrieval in the 360-degree method process. KNN method can be used to classify the performance of each lecturer, from the results of the prediction accuracy test, the number of training data is increasing and fewer test data have the best accuracy values. Overall a very good dataset to use is a dataset that has not been normalized and the determination of K = 5. The high accuracy is 90%, meaning that if a performance assessment is done with both methods, a more accountable assessment of the performance of a lecturer.

5. References

[1] Terttiaavini, Lecturer Performance Evaluation Information System with WEB-based 360 Degree Method, pp. 137–142, 2014.

[2] P. R. Indonesia, Undang-undang Republik Indonesia Nomor 14 Tahun 2005 tentang Guru dan Dosen. 2005, p. 54.

[3] A. S. Akade and H. K. Padmanabhan, A Study of Employee Performance Appraisal at Paper Manufacturing Industry, vol. 03, no. 10, pp. 142–151, 2016.

[4] S. B. Ali, A. Mahdi, and J. Malihe, The Effect of Employees Performance Appraisal Procedure on their Intrinsic Motivation, Int. J. Acad. Res. Bus. Soc. Sci., vol. 2, no. 12, pp. 166–167, 2012.

[5] A. I. Faruk A, Cahyono ES, Eliyati N, Prediction and Classification of Low Birth Weight Data Using Machine Learning Techniques, Indones. J. Sci. Technol., vol. 3, no. 1, pp. 18–28, 2017.

[6] J. Wira and G. Putra, Introduction to the Concept of Machine Learning, 2017.

[7] K. Alkhatib, H. Najadat, I. Hmeidi, and M. K. A. Shatnawi, Stock price prediction using K-nearest neighbor algorithm, Int. J. Business, Humanit. Technol., vol. 3, no. 3, pp. 32–44, 2013.

[8] S. P. Jagtap, 360 Degree Feedback Tool – Pros and Cons, vol. 5, no. 2, pp. 2–5, 2018.

[9] I. Ghozali, Application of Multivariate Analysis with the SPSS Program. Semarang: UNDIP, 2009.

[10] G. O. Mustakim, K-Nearest Neighbor Classification Algorithm As a Student Achievement Prediction System, J. Sains dan Teknol. Ind., vol. 13, no. 2, pp. 195–202, 2016.

[11] A. D. Poernomo, "Indonesian online travel agent sentiment analysis using machine learning methods," Indones. J Elec Eng Comp Sci, vol. 14, no. 1, pp. 117–122, 2019.

[12] Y. Afrianto, H. Sukoco, and S. Wahjuni, "Weighted Round Robin Load Balancer to Enhance Web Server Cluster in OpenFlow Networks," TELKOMNIKA (Telecommunication Comput. Electron. Control., vol. 16, no. 3, pp. 1402–1408, 2018