

## Evaluation of university accreditation prediction system

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**Abstract.** Higher education accreditation body (Badan Akreditasi Nasional Perguruan Tinggi/ BAN-PT in Indonesian) is an Indonesian body with the main task to assess the quality of Indonesian university. The assessment result is called accreditation, which has 5 years of validation time. In order to monitor the quality, University has an internal mechanism which is called an internal quality assurance system (Sistem Penjaminan Mutu Internal/ SPMI in Indonesian). Usually, SPMI assesses the quality periodically, one or two times each year. This process needs much effort, i.e. time, manpower, and financial cost. Sometimes, internal auditor of the university does not have sufficient knowledge, as much as BAN-PT assessor. This condition causes a lack of assessment accuracy, then causes the quality of SPMI itself. On the other hand, University has abundant of condition data, saved in higher education database (HEDB). This paper proposes to exploit the availability of data in this case. Therefore university able to monitor the quality by machine learning process periodically without much effort as manual SPMI process. Furthermore, this paper evaluates two machine learning methods, i.e. naive Bayes and K-Nearest Neighbor (K-NN). This proposal exploits several data: student, academic, admission, and alumna. K-NN and naive Bayes work in registrant and capacity ratio, student registration ratio, average student Grade Point Average (GPA) in late five years, and on-time graduation scale. The experiment results show the average accuracy of naive Bayes and KNN are 70% and 95.2% respectively.

### 1. Introduction

In Indonesia, university quality benchmark is called accreditation, which is evaluated by BAN-PT. The accreditation assessment is done in every 5 years. Accreditation is one of important parameter to classify the quality of university, especially private universities [1]. University has an internal mechanism which is called as SPMI. This process needs much effort, i.e. time, manpower, and financial cost. The time effort such as filling in the accreditation form manually. The form involves much data, therefore it needs many employees to handle it. Moreover it involves person (assessor) to assess the form. The availability of assessor between one university and the other is different. The other cases are no assessor available in a university with appropriate capability toward specific study program. Because different types of study program are assessed in a different way. Doing the SPMI process need so much cost in the term of stationery and assessor fee.

On the other hand, University has abundant of condition data, saved in HEDB database. HEDB is a data storage system managed by the center of data and information (Pusat Data dan Informasi/ Pusdatin in Indonesian), the ministry of technology research and higher education (Kementerian Riset Teknologi



dan Pendidikan Tinggi/ Kemenristekdikti in Indonesian). The data is accurate because the academic data reporting process is done regularly, conducted twice a year or each semester. Data update can be done as well in every academic cycle, such as short semester. University able to use the data to monitor the accreditation quality periodically by machine learning process. So the university can evaluate and aware of the accreditation value without much effort as manual SPMI.

From this description, this research aims to exploit HEDB data for management information and improvement. This research transforms the data into a data warehouse. The appropriate data warehouse scheme is described in our previous publication [2]. The other publication [3] describes several ideas to use the warehoused data with several computer science and statistical approaches. This paper discusses further in data utilization by management with a classification technique for study program accreditation. The methods evaluated in here are KNN and naive Bayes, because some previous research on knowledge discovery data in field education, the best accuracy is naïve bayes and KNN [4-6]. That algorithm are work based on student, academic, admission and alumna data.

Several kinds of research have been done with data mining methods in academic and university data [7-9]. This paper discusses to exploit academic data in HEDB, which have not been discussed by the other researchers. Furthermore, this paper evaluates classification value of accreditation study program in university using data mining methods base on HEDB by comparing the performance of naive Bayes and K-NN classifier. Comparison is done to get the best accuracy for deployment purpose in real situation.

## 2. Literature review

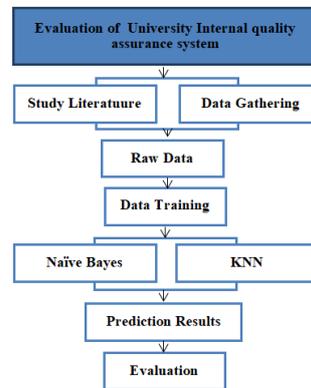
The accreditation is assessed regularly every 5 years with fluctuating values [10]. Accreditation is carried out by an independent institution who have been appointed by the government, namely BAN-PT [10]. The university itself can conduct internal evaluation by SPMI, sometime the value of accreditation by SPMI misses far from the results assessed by BAN-PT. there are 2 types of accreditation: Institutional accreditation and study program accreditation. Institutional accreditation shows the quality of educational programs and quality of alumna in the university. Study program accreditation shows the quality of educational programs and quality of alumna in the scope study program of university.

CRISP-DM is a systematic process to implement a data mining project. This research uses the CRISP-DM technique which consists of 6 steps [11]: business understanding, data understanding, data preparation, modeling, evaluation, and deployment. Data mining about academic data has been worked by many researchers for understanding, classification or prediction. For example, the researchers in [9] using K-NN and multivariate adaptive regression spline (MARS) for classification value of accreditation in public elementary school. The purpose of that research is comparing two classification algorithm. The evaluation metric of the two classification methods are statistic press's Q, APER, specificity, and sensitivity. The evaluation results show that using MARS method is better than K-NN method. Some researchers [8], work to improve relative accreditation methods based on data mining for higher education. The purpose of that research is applying IT in the accreditation system, therefore the process is run faster and more efficient. Some researches work to control the quality of education and accreditation by predicting period of student's study [7].

## 3. Method

This section explains the method to classify accreditation value of study program. Figure 1 explains the steps of data classification for accreditation prediction value. Data is obtained from HEDB through a web service application into one of the data warehouse scheme [2]. The data is processed from HEDB to obtain a dataset with attributes: registrant and capacity ratio, student registrant and pass test ratio, average of student GPA in late five years, and value of accreditation. The data is split into 2 types: independent and dependent variable. Independent variables of the attributes are registrant and capacity ratio, student registrant and pass test ratio, average of student GPA in late five years. The dependent variable is value of accreditation history, which is collected from university quality assurance unit. The

data is split into 2 parts: training data and testing data. Further detail of this paper research methods is described in the following subchapters.



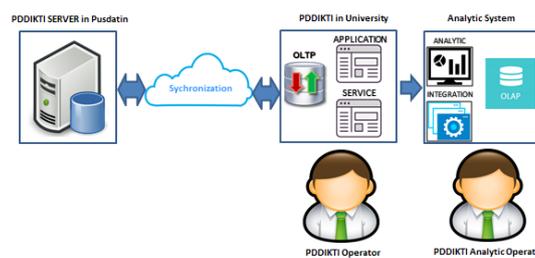
**Figure 1.** Method to classifying the value of accreditation.

*3.1. Business understanding*

The purpose of HEDB’s data mining is to find data patterns. This data mining is carried out to find data patterns of study program accreditation, so the higher education management able to conduct early detection of study programs quality based on existing transaction data. The expectation is with this monitoring and evaluation, the poor condition will be detected and improvement can be delivered, therefore the results of accreditation will be better.

*3.2. Data understanding*

Figure 2 shows the process of data collection and analytics from HEDB [2]. The dataset is obtained from HEDB at XYZ University in all undergraduate study programs. The dataset is collected from 2007-2018 academic calendar year. The data is obtained through the HEDB feeder web service application. This web service is installed in university. The data is transformed into data warehouse by integration service, especially developed with Python code. The data warehouse is implemented with MySQL database management system.



**Figure 2.** System architecture.

*3.3. Data preparation*

Selection and processing the data is needed for modeling with several machine learning algorithms. Therefore, the algorithms can be evaluated in order to obtain maximum accuracy result in accordance with the desired target. The data to be processed from HEDB are student, academic, admission and alumna data. Table 1 shows the data examples.

**Table 1.** Dataset from HEDB.

| No | Admissions ratio | Registrants ratio | Average of GPA | Value of accreditation |
|----|------------------|-------------------|----------------|------------------------|
| 1  | 45,04            | 100               | 2,73           | A                      |
| 2  | 71,1             | 100               | 3,60           | B                      |
| 3  | 48,2             | 100               | 2,96           | B                      |
| 4  | 71,33            | 100               | 2,75           | A                      |
| .. | ..               | ..                | ..             | ..                     |
| .. | ..               | ..                | ..             | ..                     |
| 80 | 81,4             | 100               | 2,81           | A                      |

### 3.4. Modeling

The dataset modelled by k-NN and naïve bayes classifier, KNN uses neighbor classification as the predicted value of the new instance. K value of KNN means the closest k-data from the test data. Distance parameter commonly used is the euclidean distance. Euclidean distance between two points [12].

$$d(x_1, x_2) = \sum_{i=1}^n (x_{1i} - x_{2i})^2 \quad (1)$$

Determining value of K can effect value of accuracy. Naïve bayes classifier to predict the future of opportunities based on experience that has accrued. That formula is [12]:

$$P(X|H) = \frac{P(X|H)P(H)}{P(X)} \quad (2)$$

This paper uses Python with SciKit Learn library to perform the algorithm. The evaluation strategy uses stratified k-fold cross-validation with 3 and 5 for k value.

### 3.5. Evaluation

Evaluation is done by the confusion matrix. This evaluation produces accuracy, precision, and recall values [13,14]. The accuracy is a percentage of the number of the records that are classified correctly by the algorithm and the data is true [12]. The precision is amount of positive categorized data categorized correctly / total data classified correctly. The recall is amount of data classified positively / total testing data classified positively. The data will be modeled in two algorithms: K-NN and naive Bayes. This paper evaluates the best algorithm for this case based on the results of the accuracy metric.

### 3.6. Deployment

Creating prototypes from the results of modeling that produces the best accuracy values using python which retrieves data automatically from the database.

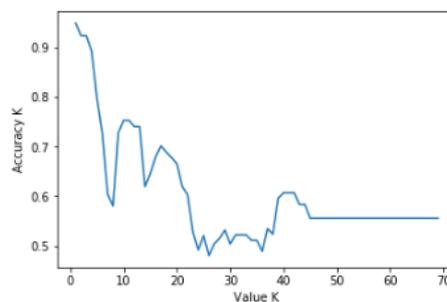
## 4. Result and discussion

In this experiment, training data is used to produce a model where testing data is used to test the model. Table 2 shows naive Bayes classifier results of accuracy, precision, and recall from several experiments evaluated by k-fold with value of k equals to 3 and 5. The results show the best average accuracy is in k=5 experiment with accuracy 70%.

**Table 2.** Accuracy, precision, and recall with naive Bayes.

| k-fold  | Accuracy (%) | Precision (%) |      |     | Recall (%) |      |      |
|---------|--------------|---------------|------|-----|------------|------|------|
|         |              | A             | B    | C   | A          | B    | C    |
| 3       | 70           | 22            | 100  | 67  | 36         | 79   | 80   |
|         | 70           | 30            | 93   | 100 | 56         | 76   | 86   |
|         | 62           | 11            | 87   | 100 | 20         | 72   | 67   |
| Average | 67.4         | 21            | 93.3 | 89  | 37.3       | 75.6 | 77.6 |
| 5       | 75           | 20            | 100  | 100 | 33         | 82   | 100  |
|         | 69           | 33            | 100  | 0   | 50         | 78   | 0    |
|         | 75           | 20            | 100  | 100 | 33         | 82   | 100  |
|         | 56           | 14            | 88   | 100 | 35         | 67   | 67   |
|         | 75           | 40            | 89   | 100 | 57         | 80   | 80   |
| Average | 70           | 25.4          | 95.4 | 80  | 41.6       | 77.8 | 69.4 |

Figure 3 shows the results of tuning parameter with value of k between 1 and 70. Based on the graph in the figure, the best accuracy of K-NN where k is 1

**Figure 3.** Tuning parameter of K-NN with k value between 1 and 70.**Table 3.** Accuracy, precision, and recall with K-NN value of k=1.

| k-fold  | Accuracy (%) | Precision (%) |     |     | Recall (%) |     |     |
|---------|--------------|---------------|-----|-----|------------|-----|-----|
|         |              | A             | B   | C   | A          | B   | C   |
| 3       | 100          | 100           | 100 | 100 | 100        | 100 | 100 |
|         | 89           | 91            | 85  | 100 | 87         | 88  | 100 |
|         | 96           | 88            | 100 | 100 | 93         | 97  | 100 |
| Average | 95           | 93            | 95  | 100 | 93.3       | 95  | 100 |
| 5       | 100          | 100           | 100 | 100 | 100        | 100 | 100 |
|         | 94           | 88            | 100 | 100 | 93         | 89  | 100 |
|         | 88           | 100           | 75  | 100 | 86         | 86  | 100 |
|         | 100          | 100           | 100 | -   | 100        | 100 | -   |
|         | 94           | 80            | 100 | 100 | 89         | 95  | 100 |
| Average | 95.2         | 93.6          | 95  | 100 | 93.6       | 94  | 100 |

**Table 4.** Accuracy, precision, and recall with K-NN value of k=2

| k-fold  | Accuracy (%) | Precision (%) |     |       | Recall (%) |      |     |
|---------|--------------|---------------|-----|-------|------------|------|-----|
|         |              | A             | B   | C     | A          | B    | C   |
| 3       | 100          | 100           | 100 | 100   | 100        | 100  | 100 |
|         | 89           | 91            | 85  | 100   | 87         | 88   | 100 |
|         | 92           | 100           | 88  | 100   | 89         | 94   | 100 |
| Average | 93.66        | 97            | 91  | 100   | 92         | 94   | 100 |
| 5       | 100          | 100           | 100 | 100   | 100        | 100  | 100 |
|         | 75           | 88            | 100 | 25    | 93         | 67   | 40  |
|         | 88           | 100           | 75  | 100   | 86         | 86   | 100 |
|         | 100          | 100           | 100 | -     | 100        | 100  | -   |
|         | 94           | 80            | 100 | 100   | 89         | 95   | 100 |
| Average | 91.4         | 93.6          | 95  | 81.25 | 93.6       | 89.6 | 85  |

**Table 5.** Accuracy, precision, and recall with K-NN value of k=3.

| k-fold  | Accuracy (%) | Precision (%) |     |       | Recall (%) |      |     |
|---------|--------------|---------------|-----|-------|------------|------|-----|
|         |              | A             | B   | C     | A          | B    | C   |
| 3       | 96           | 89            | 100 | 100   | 94         | 97   | 100 |
|         | 89           | 91            | 85  | 100   | 87         | 88   | 100 |
|         | 81           | 62            | 88  | 100   | 67         | 86   | 100 |
| Average | 88.66        | 80,6          | 91  | 100   | 82.6       | 90.3 | 100 |
| 5       | 100          | 100           | 100 | 100   | 100        | 100  | 100 |
|         | 75           | 88            | 100 | 25    | 93         | 67   | 40  |
|         | 88           | 100           | 75  | 100   | 86         | 86   | 100 |
|         | 100          | 100           | 100 | -     | 100        | 100  | -   |
|         | 81           | 40            | 100 | 100   | 57         | 87   | 100 |
| Average | 88.8         | 85.6          | 95  | 81.25 | 87.2       | 88   | 85  |

Table 3, 4, and 5 show the results of accuracy, precision and recall from several experiments evaluated by k-fold with the value of k equals to 3 and 5 respectively. The experiment results show that the best accuracy value is 95.2%, where K is 1. The number K=1 will make the classification result feel bad because it only takes into account the nearest neighbor or the closest characteristic record, but if the number of K is too much produce cryptic classifications [15].

## 5. Conclusion

This paper has exposed the possibility of HEDB data exploitation for university management purpose, especially accreditation monitoring and prediction system. This paper also evaluates the usage possibility of several data mining/ machine learning techniques in this issue, i.e. K-NN and naive Bayes classifier. The experiment results show the average accuracy of naive Bayes and KNN are 70% and 95.2% respectively. The results of this data mining method can be used to monitor the accreditation prediction value every semester because the data transactions in HEDB is refreshed in every semester as well. The data in HEDB database affects the results of accreditation prediction.

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