CLASSIFICATION MODEL FOR IPB STUDENT'S GRADE OF DATA MINING COURSE BASED ON THEIR ACTIVITIES IN LEARNING MANAGEMENT SYSTEM

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ABSTRACT: *Learning process evaluation in higher education institutions is performed by measuring student's academic performance in completing a course. Prediction of course's grade can be done as an early warning for student's academic performance. Prediction results provide reference to evaluate the education process. There are several aspects of course evaluation, one of which is student activities on online learning management system (LMS). This study aims to build a classification model of final score of data mining course based on student's activities in LMS using the C50 decision tree algorithm. The data used are log files of LMS activities for data mining course which is offered for Bachelor students on Computer Science, Bogor Agricultural University. This study results the classification model with the accuracy of 85.71%.*

Keywords: *data mining, decision tree, learning management system*

INTRODUCTION

Data Mining (Course ID: KOM332) is one of major courses that is offered to Bachelor program of Computer Science, Bogor Agricultural University (IPB). The learning outcome of Data Mining Course is that after completing this course, students will be able to apply data processing steps and basic techniques in data mining to the real-world dataset. In order to achieve the learning outcome, this course covers several topics including introduction to data mining (topic 1), data and data exploration (topic 2), data preprocessing (topic 3), cluster analysis (topic 4), outlier detection (topic 5), classification using the decision tree algorithm (topic 6), other methods in classification (topic 7), association analysis (topic 8), other methods in association analysis (topic 9), data warehouse and OLAP (Online Analytical Processing) (topic 10), introduction to spatio-temporal data mining (topic 11), introduction to sequential pattern mining (topic 12), introduction to text and web mining (topic 13) and

applications of data mining techniques (topic 14). In order to support face-to-face learning activities in class room and computer laboratory, Data Mining course in IPB uses e-learning system which is provided in the Bogor Agricultural University Learning Management System (IPB-LMS), <https://lms.ipb.ac.id/>. IPB-LMS uses an open-source learning management system Moodle. Moodle is a learning platform written in PHP which is designed for educators, administrators and learners in managing course contents and learning activities. In addition to web-based version, IPB-LMS is also available in mobile application named Moodle Mobile that can be accessed by users using IPB access account. Based on the log activities of IPB-LMS for Data Mining course, this study calculates the number of page views since 8 November 2010 as presented in Figure 1. Data Mining course in IPB is offered in even semester in each academic year starting from February to August. High log activities are found this period as shown in Figure 2.

Figure 1. Number of views on IPB-LMS for Data Mining Course since 8 November 2010

Figure 2. Number of views of IPB-LMS for Data Mining Course in the period of 2014-2015

Currently students' performance in completing Data Mining course is measured by evaluating the grade of middle and final exams, practical works, and final project report. However, students' activities in IPB-LMS are not considered in students' performance evaluation in order to achieve the learning outcome of Data Mining course. Therefore, this study aims to analyze students' achievement in Data Mining course by involving their activities in IPB-LMS. Log files of students' activities in the academic year 2015/2016 are collected from IPB-LMS. The decision tree-based classification model is developed on the datasets containing log activities and data mining grade.

LITERATURE REVIEW

Data mining has wide applications in many sectors including higher education. Educational data mining is a growing discipline, that is implemented to discover interesting and useful information and knowledge from the data related to educational context. Basic techniques in data mining including clustering, association rule mining and classification have been applied in several studies to obtain data clusters, association rules and classification models from students-related datasets. Harwati et al (2015: 173 – 177) used the K-mean clustering algorithm to group students based on their demographic (gender, origin, GPA, grade of certain courses), and average of course attending. The result of this study is four student clusters namely: smart students (45.74), standard student (33.33%), and 20.92% belongs to low performance students. Buldu and Üçgün (2010: 5251–5259) applied the Apriori algorithm in association rules on data of students of Istanbul Eyup I.M.K.B. Vocational Commerce High School in order to obtain relation between the courses that the students failed. This study revealed that the students who are unsuccessful in numeral courses become unsuccessful again in numeral courses of one year after (Buldu and Üçgün, 2010: 5251–5259). Based on association rules discovered, the relation between performance of students in taking courses physics and chemistry, math, space science and astronomy, as well as basic electronics are analyzed in this study. Association rule mining approach was also applied by the study of Abdullah et al (2011: 107 – 111) to discover highly positive association rules on the dataset of students' enrolment dataset of computer science program at University Malaysia Terengganu (UMT). The results from association rules state that some students in UMT (intake 2008/2009) who have been offered in computer science program but not within their field interests (Abdullah et al, 2011: 107 – 111).

Based on the systematic review in the current literatures on the data mining techniques that have been used to predict students' performance, Shahiri et al (2015: 414 – 422) found that the classification method is frequently used in educational data mining area. The classification techniques that are highly applied by the researchers for predicting students' performance are Neural Network and Decision Tree. Kaur et al (2015: 500 – 508) identified the slow learners among

students using a predictive data mining model by applying classification algorithms on the high school real world dataset. The classification algorithms used are Multilayer Perception, Naïve Bayes, SMO, J48 and REPTree using the Open source data mining tool WEKA. This study shows that among all classification algorithms, Multi Layer Perception performs best with 75% accuracy and F-measure of 82%. The study by Ratnaningsih and Sitanggang (2016: 87-97) compared three classification methods: Naïve Bayes, Bagging, and C4.5 with the evaluation criteria stratified cross-validation, confusion matrix, ROC curve, recall, precision, and F-measure. The three classification algorithms were applied on the dataset of non-active students in Indonesia Open University (IOU) for the period of 2004 to 2012. The results show that the Bagging method provided a higher accuracy than Naïve Bayes and C4.5. The accuracy of Bagging classification is 82.99%, while the Naïve Bayes and C4.5 are 80.04% and 82.74% respectively.

In addition to datasets of academic students' performance, basic and advance data mining techniques have been used in several studies to discover new patterns on online learning datasets in order to improve the benefits of using online learning management system. Romero et al (2008: 368–384) developed a Moodle data mining tool that can be used by users to apply the main data mining techniques used, such as statistics, visualization, classification, clustering and association rule mining of Moodle data. The tool is integrated with the Moodle environment and provides a user-friendly interface to perform data preprocessing and mining tasks automatically on Moodle data. Romero et al (2009: 828–840) built a web mining tool integrated into the AHA! System to facilitate instructors to perform web mining process in e-learning and Web-based adaptive educational systems. The AHA! System is an open source general-purpose adaptive hypermedia system, which is available from the Eindhoven University of Technology. Macfadyen and Dawson (2010: 588–599) analyzed Learning Management System (LMS) tracking data by applying regression and logistic modelling. This study identified 15 variables demonstrating a significant simple correlation with student final grade (Macfadyen and Dawson, 2010: 588–599). The best-fit predictive model using regression modelling shows that key variables such as total number of discussion messages posted, total number of mail messages sent, and total number of assessments completed influence the student final grade (Macfadyen and Dawson, 2010: 588–599). Moreover, Romero and Castro (2011: 77–88) developed a data mining tool that uses association rule mining and collaborative filtering that can be used by instructors to get recommendations in e-learning courses improvement. The real interactions between the students and the e-learning course can be analyzed using this tool. The results are important as decisions to improve the e-learning course. Al-Twijri and Noaman (2015: 836 – 844) proposed a data mining model, named the Data Mining Admission Model (DMAM), to facilitate the proper vision of selecting the best enrolment method in Saudi universities. The DMAM consists of five subsystems Database Management System, Model Management System, and Knowledge Base which run on the real datasets. The strategic levels of higher

institutions in Saudi universities can use the model to make decisions and regulation on students' admission.

METHOD

The data used in this research are log files of IPB-LMS activities for data mining course which is offered for Bachelor students on Computer Science, Bogor Agricultural University. Attributes selection in log files refers to the research conducted by Romero et al (2008: 368–384) that can be seen in Table 1.

Table 1. The attributes in log files of IPB-LMS

Attribute	Code	Descriptions
n_assignment	V1	Number of assignments done by students
n_view_assignment	V2	Number of views of data mining assignment
n_course_view	V3	Number of course view
n_course_module_view	V4	Number of course module view
Score	V5	Final score

The submission assignment page shows submission status such as grading status, due date, time remaining, last modified, file submission and submission comment that can be seen in Figure 3.

Figure 3. IPB-LMS page to upload data mining assignments

To view assignments in data mining courses, student can directly download the assignments in IPB-LMS. Figure 4 shows the IPB-LSM page to view data mining assignments.

Figure 4. IPB-LSM page to view assignments in data mining course.

In this study, there are several steps including data collection, preprocessing data, data partition into training and testing datasets, modelling using the C50 decision tree algorithm, model evaluation, and analysis of the classification model. Figure 5 shows the steps of this study.

Figure 5. Research steps

The data used in this study are log files of IPB-LMS activities for 144 students who enroll the data mining course in the academic year 2015/2016. As many 37.161 log files were collected from IPB-LMS for Data Mining course. Figure 6 shows the example of data in IPB-LMS log files.

Time	User full name	Affected user	Event context	Component	Event name	Description	Origin	IP address
18 Jul, 09:	MIFTAH FAQIH G64130082	-	Course: KOM332 Data Mining	System	Course viewed	The user viewed	web	172.17.71.172
18 Jul, 09:	ARFAN ANHARI G64130059	-	URL: PALO	URL	Course module view	The user viewed	web	172.17.71.163
23 Jul, 11:	BINTANG JP PUTRA G64144011	-	Course: KOM332 Data Mining	System	Course viewed	The user viewed	web	182.253.163.50
22 Jul, 14:	MUHAMMAD ALVIAN SUPRIADI G	-	Course: KOM332 Data Mining	System	Course viewed	The user viewed	web	203.123.61.235
28 Jul, 15:	Husnul Khotimah, S.Komp M.Kom	-	Course: KOM332 Data Mining	System	Course viewed	The user viewed	web	172.17.212.2
28 Jul, 15:	Imas Sukaesih Sitanggang Sitanggang	-	Course: KOM332 Data Mining	System	Course viewed	The user viewed	web	172.17.212.2
15 Jun, 15:	PANDU WARJAYA G64144049	-	Course: KOM332 Data Mining	System	Course viewed	The user viewed	web	182.253.163.51
15 Jun, 15:	JEANNETTE CLAUDYA WEYA PANT	-	File: Kuliah 12 - Text &am	File	Course module view	The user viewed	web	103.14.18.164

Figure 6. The example of data in IPB-LMS log files

Preprocessing data is done to improve data quality so that accuracy of model increases. The preprocessing tasks include data cleaning and attribute selection. The IPB-LMS activities were obtained from the attribute event name on the IPB - LMS log files. The attributes include course view, course module view, assignments view, assignments upload, and final score as decision class. The output of data preprocessing steps is a task relevant data for classification process using the decision tree algorithm.

The next step is calculating the number of each activity in the log file. Each activity is grouped into 4 groups including high (3), moderate (2), low (1) and no information (0). Table 2 shows the value range for each category of attributes.

Table 2. The value range of each attributes' category

Category	V1	V2	V3	V4
No information (0)	0	0	0	0
Low (1)	1 - 5	1-19	8-102	8 - 68
Moderate (2)	6 - 9	20-37	103 - 198	69 - 126
High (3)	10 - 14	38-56	199 - 293	127 - 185

The next step is labelling of class for each student's log file. The class labels are C1 for final grade A and AB and C2 for final grade B and BC. There are 63 data with the class label C1 and 81 with the class label C2. For classification task, the data are divided into a training dataset and a testing dataset using the k-cross fold validation with k=10. The training data are used to build decision tree model, while the testing data are used to test the decision tree model. The classification model was created using the C5.0 decision algorithm. This algorithm uses information gain in making decision trees. The classification model is created using the R programming language with the C50 package.

The C5.0 algorithm produces tree model and a rule-based model. A tree model has a flowchart-like tree structure. In the tree model, each internal node (non-leaf node) indicates the test on an attribute, each branch represents the results of the test, and each leaf node is a class label (Han et al, 2012). A rule-based model is a set of if-then conditions derived from a tree model. C5.0 has been designed to analyze substantial databases containing thousands to millions of records and tens to hundreds of numeric, time, date, or nominal fields (Rulequest Research, 2018). The C5.0 is implemented based on the decision tree algorithm (Han et al, 2012):

Algorithm: Generate_decision_tree

Input:

- a. Data partition, D , a set of training tuples and their associated class labels
- b. *attribute_list*, the set of candidate attributes
- c. *attribute_selection_method*, a procedure to determine the splitting criterion that best partitions the data tuples into individual classes. This criterion consists of a *splitting_attribute* and, either a *split-point* or *splitting_subset*

Output: a decision tree

Method:

1. create a node N
2. if tuples in D are all of the same class, C , then
3. return N as a leaf node labeled with the class C
4. if *attribute_list* is empty, then
5. return N as a leaf node labeled with the majority class in D
6. apply *attribute_selection_method* (D , *attribute_list*) to find the best *splitting_criterion*
7. label node N with *splitting_criterion*
8. if *splitting_attribute* is discrete-valued and multiway splits allowed then
9. *attribute_list* $\leftarrow$ *attribute_list* – *splitting_attribute*
10. for each outcome j of *splitting_criterion*
 - i. let D_j be the set of data tuples in D satisfying outcome j
 - ii. if D_j is empty then
attach a leaf labeled with majority class in D to node N
 - iii. else, attach the node returned by Generate_decision_tree (D_j , *attribute_list*) to node N
11. return N

The classification model was evaluated by calculating accuracy. The accuracy indicates success rate of the model on testing data which is calculated based on number of data that are correctly predicted or not by the model. In addition to accuracy, precision and recall are used to evaluate the classification model.

$$\text{Accuracy} = \frac{\text{number of correct classification}}{\text{total number of testing data}} \times 100\% \quad (1)$$

Precision dan recall are calculated based on the confusion matrix on Table 3.

Table 3. Confusion matrix

	Predicted: Yes	Predicted: No
Actual: Yes	TP	FN
Actual: No	FP	TN

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

RESULT AND DISCUSSION

The C5.0 algorithm was applied on the datasets to result tree and rule-based models. Model evaluation was done using 10-cross validation. Accuracy of the tree model at each fold is shown in Figure 7.

Figure 7. The accuracy of each fold

Based on Figure 7, the highest accuracy of tree model is obtained in the dataset at fold 5 that reach 85.71%. The tree has the attribute `course_module_view` (V4) as the root as shown in Figure 8. It means that this attribute has most influence the final score of data mining course. According to the tree on Figure 8, if $V4 \leq 1$ then as many 84 data are classified as the class C2 whereas if $V4 > 1$ then as many 46 data are classified as the class C1. These rules indicate that students who frequently access the course module have the better final grade than students who never access the module or access the module only once. Students in the class label C1 have final grade A and AB whereas students in the class label C2 have final grade B and BC for Data Mining course. Table 4 provides the precision and recall of the model.

Figure 8. The decision tree with the best accuracy, precision and recall .

Table 4. Precision and recall of the model

Class	Precision	Recall
C1	100%	66.67%
C2	80%	100%

According to Table 1, IPB-LMS log files for Data Mining course have four variables namely number of assignments done by students (*n_assignment*), number of views of data mining assignment (*n_view_assignment*), number of course view (*n_course_view*) and number of course module view (*n_course_module_view*). However, the tree model shows that only one variable that classify students into the class C1 with final grade A and AB or the class C2 with final grade B and BC. Students' activities in viewing and submitting the assignment do not influence the students' performance on completing Data Mining course. Therefore, in further work teachers should evaluate the assignment module in IPB-LMS for Data Mining course so that students' activities in finishing the assignment in IPB-LMS influence the final grade of the course. In addition, future work is expected to involve larger datasets that are obtained from log files for several academic years. So that trend of students' activities in IPB-LMS for Data Mining course can be evaluated.

CONCLUSION AND SUGGESTION

This study has successfully developed decision tree-based classification model for IPB students' grade in Data Mining Course by involving students' activities in IPB Learning Management System (IPB-LMS). The best classification model has the accuracy of 85.71%. The students' activities in IPB-LMS that provides high influence in Data Mining grade is *course module view*. Student's activity in accessing course modules in LMS represents how is student interesting in topics that discuss in the class room and computer laboratory. Course modules help students in understanding the material that will be examined in middle and final exams as well as final project evaluation. Therefore, student's activities in LMS represented by the parameter *course module view* will support student's achievement in Data Mining course in IPB.

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