# Generating Licensure Examination Performance Models Using PART and JRip Classifiers: A Data Mining Application in Education

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Abstract—This study focused on the generation of the licensure examination performance models implementing PART and JRip classifiers. Specifically, it identified the attributes that are significant to the response attribute; it generated prediction models using the PART and JRip classifiers of WEKA; and it determined how likely is a reviewee to pass the LET. The respondents were obtained from the Education graduates of Isabela State University Cabagan campus who took a LET review and eventually took the September 2013 LET. The results obtained indicate the significance of the mock board exam, general weighted average of the reviewees in GenEd and MajorCore in predicting LET performance. The reviewee is predicted to fail the LET if he will obtain a mock board rating lower than 34% of the total points. It is further predicted that if the general weighted average in all the general education subjects is fair, or the general weighted average in all the general education subjects is fairly good and has a kinesthetic learning style, then the reviewee will fail the LET.

Index Terms—JRip, LET, PART, performance prediction.

### I. INTRODUCTION

Higher education institutions are presently giving much attention to licensure examination performance of their graduates. Thorough review of examination content is given to reviewees, review materials are carefully prepared and the best reviewers are selected. They gauge the reviewees' readiness to take the licensure exam by giving a mock board exam after the series of reviews. However, majority of the institutions conducting the review focus less on the result of the mock board exam. There were no feedback and support given to the reviewees after taking the said exam.

We previously conducted a research in response to the need of resolving this shortcoming. We identified significant predictors, derived prediction models using different classification techniques, and selected the best model based from their classification accuracy. This is to enable prediction of licensure examination performance of reviewees and eventually give review assistance on those who are most likely to fail. However, we recommended in the research that

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similar studies should be undertaken with the inclusion of other predictors and that thorough testing should be done using real institutional data.

Anticipating the foregoing situation, we decided to embark on a similar study with the inclusion of other predictors but keeping the Licensure Examination for Teachers' (LET) Performance as the response variable. The predictors to this study include the reviewees' (1) General Weighted Average (GWA) in General Education subjects, Professional Education subjects and Major or Core subjects, (2) review and participation, (3) learning style, and (4) mock board exam result. The PART and JRip algorithms were selected as they performed best in terms of classification accuracy and True Negative (TN) as well as False Negative (FN) ratings respectively in the previous study. Rule-based classifiers such as JRip and PART make use of the collection of if-then statements to present the rules derived which ensures that every record is covered by at most one rule. These algorithms will help determine the likelihood of a reviewee to pass the licensure exam by generating set of rules.

This study specifically sought to answer the following questions:

- 1) Which among the predictors are significant to the LET performance of the students?
- 2) What are the LET prediction models that can be derived from the predictors?
- 3) How likely is a reviewee to pass the LET based from the predictors?

# II. RELATED WORKS

There have been several attempts to discover models in predicting the performance in licensure examination but most studies recommend for an extensive study covering other independent variables and other approaches.

For instance, Arce, S. E. and Belen, J. L. undertook a study that revealed the relationship of In-House review to LET performance using descriptive – correlational method [1]. They found out that pre-board and LET results are significantly correlated. They recommended that similar research must be undertaken to include content courses and field of specialization of BEEd and BSEd respectively.

Roehrig, S. M. also made a study regarding the prediction of licensing examination scores in Physical Therapy graduates. American College Testing (ACT) scores, prerequisite and nonprerequisite grade point averages (GPAs), and interview and recommendation scores were used to predict licensing examination scores [2]. Hierarchical

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multiple regression analyses using the SPSS-X "regression" program were used in the analysis of data. The author said that the procedures used in the study could be applied by other institutions using their own data but can be modified to include other variables.

Ong, M. B. *et al.* determined the predictors of licensure examination performance of nursing graduates in their study using inferential techniques. The variables used were College Entrance Examination performance on IQ test, nursing aptitude test, the composite score of science, math and English tests, college grade point average and pre-board examination performance [3]. They concluded that students' academic performance in their baccalaureate program and their performance in the pre-board examination are important variables in establishing the success and failure of students' licensure examination performance.

Hafalla, V. and Calub, E. attempted to profile board passers and non-passers of the Electronics Engineering licensure examination and develop a discriminant function model using derived factor constructs from the pre-determined variables. Orthogonal rotation resulted in three factor constructs, namely, 1. Student's Academic Demographics, 2. Student's Exam Demographics, and 3. Interval Between Graduation and Exam. The authors suggested the inclusion of a "much broader set of predictor variables" in the re-estimation of discriminant function [4].

Cognitive and non-cognitive records of the education graduates were the concentration of Soriano, H. A. S. in her study. She aimed to determine the best predictors to LET performance. She found out that General Education grade point average, college entrance test score, course, and sex best predicted the LET performance of the respondents. She recommended however that "a follow-up study be conducted involving other variables such as class schedule, review attended, Field Study ratings, school environment, and teacher factor" [5].

On the other hand, the subsequent literature justifies the capabilities of data mining techniques in the prediction of students' performance which were considered helpful in the establishment of the framework of this study.

Fire, M. and his co-authors utilized regression and machine learning techniques using the R-project software and Weka respectively to predict the success of student in a course using social network data. They found out that "students' final grades are closely related to those of his friends' grades" [6]. They were able to prove using multiple linear regressions that a students' final grade is related to that of their friends.

Sembiring, S. *et al.* applied kernel method of data mining in their study to "analyze relationships between the student's behavior and their success and to develop the model of student performance predictors" [7]. Based from their study, they stated that data mining is useful particularly on the prediction of student's final performance.

Mellalieu, P. J., also stated in his study that predicting accurately the students' final course performance is feasible through data mining investigation using WEKA Explorer [8]. He created a prototype Decision Support System which was implemented as an interlocked series of spreadsheets known as ReXS.

Another relevant study was undertaken by Baradwaj,

Brijesh Kumar and Pal, Saurabh. They used decision tree method to predict the students' performance at the end of a semester [9]. Attendance, Class test, Seminar and Assignment marks were used as variables.

#### III. WORK DONE/ CONTRIBUTIONS

# A. Framework of the Study

The framework of the study was based on the Knowledge Discovery Process (KDP) illustrated by Jiawei Han and Micheline Kamber in their book Data Mining: Concepts and Techniques, Second Edition. The KDP was modified to suit the objectives of the study. The modified version is presented on Fig. 1 following the process from cleaning and integration, selection and transformation, data mining, and interpretation and evaluation to gain knowledge.

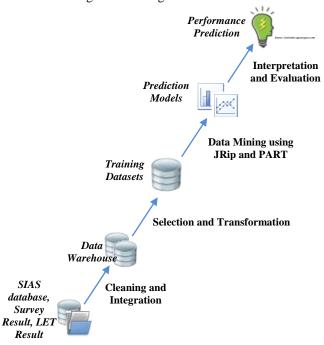


Fig. 1. Framework of the study.

## B. Methodology

The respondents of this study were the March 2013 Education graduates of ISU Cabagan campus who participated in the LET review and took the September 2013 LET. The academic records of these graduates were taken from the Students Information and Accounting System (SIAS) of ISU Cabagan campus while the data for review and participation and learning style were taken from the survey result. The LET performance was taken from the official website of the Philippine Regulatory Commission.

These data that were stored in different tables were cleaned by removing duplicate records. Records that contain empty values were likewise deleted. We integrated the different tables into one data warehouse, the data of which were transformed to create meaningful groups within the attributes to match that of the objectives of the study. The predictor and response attributes derived were shown in Table I.

We adapted the adjectival rating used by ISU as categories for GenEd, ProfEd and MajorCore. On the other hand, we personally selected the categories of the MBResult. Their corresponding range is given in Table II.

TABLE I: ATTRIBUTES AND THEIR VALUES

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Attribute	Description	Values		
GenEd	This is the general weighted	E, VS, S, FS, G, FG, F,		
(Predictor)	average of the reviewee in his	BF, P		
	general education subjects			
	taken from his academic			
	records.			
ProfEd	This is the general weighted	E, VS, S, FS, G, FG, F,		
(Predictor)	average of the reviewee in his	BF, P		
	professional education			
	subjects taken from his			
M-:C	academic records.	E VC C EC C EC E		
MajorCore (Predictor)	This is the general weighted average of the reviewee in his	E, VS, S, FS, G, FG, F, BF, P		
(Predictor)	major subjects (for BSEd) or	рг, г		
	core courses (for BEEd) taken			
	from his academic records.			
SelfReview	This tells if the reviewee	Y, N		
Belliteview	conducted self review.	1,11		
PeerStudy	This tells if the reviewee	Y, N		
recipitaty	participated in a peer review.	-,		
AskQuest	This tells if the reviewee asks	Y, N		
	questions during the review	-,		
	sessions.			
TDNotes	This tells if the reviewee takes	Y, N		
	down notes during the review			
	sessions.			
GiveIdeas	This tells if the reviewee	Y, N		
	shares ideas during the review			
	sessions.			
Visual	This indicates the rank of the	F, S, T		
	reviewee's visual learning			
A 11.	style.	T 0 T		
Auditory	This indicates the rank of the	F, S, T		
	reviewee's auditory learning			
Kinesthetic	style. This indicates the rank of the	гет		
Killestiletic	reviewee's kinesthetic	F, S, T		
	learning style.			
MBResult	This tells the score in the	VG, G, F		
MDResuit	Mock Board Exam.	, 0, 0, 1		
LETPerf	This is the LET performance	Passed, Failed		
(Response)	of the reviewee which makes	i asseu, l'aneu		
(Response)	use of 2 classes.			
	use of L classes.			

TABLE II: NUMERICAL RANGE OF PREDICTORS' VALUES				
Value		Grade/ Numerical		
		Equivalent		
	For GenEd, ProfEd and	d MajorCore:		
E-	Excellent	100-98		
VS-	Very Satisfactory	97-95		
S-	Satisfactory	94-92		
FS-	Fairly Satisfactory	91-89		
G-	Good	88-86		
FG-	Fairly Good	85-83		
F-	Fair	82-80		
BF-	Below fair	79-77		
P-	Passed	76-75		
For MBResult:				
VG	Very Good	100-150		
G	Good	50-99		
F	Fair	0-49		

We used Weka in this study as the data mining tool since it is platform independent and portable. It offers a wide range of classification algorithms that can be easily applied to any dataset.

In order to evaluate the worth of the attributes, we computed the value of the chi-squared statistic with respect to the class. In this case, ChiSquaredAttributeEval of Weka was used.

For the generation of models, we used PART and JRip of Weka which are both classification algorithms.

# C. Simulation Results

Before applying PART and JRip classifiers to the dataset, attribute evaluation was first done in order to select attributes that are significant to the response variable which is the LET performance.

#### 1) Attribute evaluation

ChiSquaredAttributeEval of Weka was used to determine the importance of the predictors to the response attribute. The predictors were ranked according to their chi-square values as presented on Table III. MBResult attribute topped the rank in terms of chi-square values followed by GenEd, and MajorCore. The same result was established by Arce, S. E. and Belen, J. L. that pre-board result and LET result are significantly correlated [1]. It is interesting to note that GenEd and MajorCore were noted in our previous study to be the two most significant predictors to the same response attribute using a different dataset. SelfReview and TDNotes attributes have zero chi-square values which may suggest its exclusion in the dataset. However, all the predictors were still included in the dataset as they can be necessary to a specific instance. A similar case was experienced by Kovačić, Z. (2010) where in all available predictor variables in his dataset were included in the classification tree analysis in spite their insignificance detected during feature selection [10].

TABLE III: ATTRIBUTE EVALUATION

Attribute	Average	Merit
MBResult	24.833	+ - 2.284
GenEd	25.122	+ - 2.647
MajorCore	15.719	+ - 3.009
ProfEd	12.17	+ - 2.288
Visual	6.921	+ - 1.301
Auditory	3.963	+ - 1.053
Kinesthetic	3.373	+ - 0.912
AskQuest	2.387	+ - 0.697
PeerStudy	1.638	+ - 0. 854
GiveIdeas	0.759	+ - 0.575
SelfReview	0	+ - 0
TDNotes	0	+ - 0

# 2) PART prediction model

PART is a classifier that generates decision list. The prediction model generated using Weka by PART in a 10-fold cross validation and a confidence factor of 0.25 is presented in Fig. 2. It consists of four rules as interpreted below:

If the mock board exam result falls in the range of Good, then the reviewee is predicted to pass the LET.

If the general weighted average in all the general education subjects is fair, then the reviewee is predicted to fail the LET.

If the general weighted average in all the general

education subjects is fairly good and has a kinesthetic learning style, then the reviewee is predicted to fail the LET.

Otherwise, the reviewee is predicted to pass the LET.

MBResult = G: Passed (43.0/3.0)

GenEd = F: Failed (8.0)

GenEd = FG AND

Kinesthetic = T: Failed (4.0)

: Passed (8.0/2.0)

Number of Rules: 4
Fig. 2. PART decision list.

The model generated 82.54% correctly classified instances as shown in Table IV. There are only 11 incorrectly classified instances which indicate that the model is incorrect for 17.46% of the cases in the dataset.

TABLE IV: PART CONFUSION MATRIX

Actual Class	Predicted Class		
	Passed	Failed	Percent Correct
Passed	41	5	89.13%
Failed	6	11	64.71%
Overall Percentage	87.23%	68.75%	82.54%

# 3) JRip prediction model

JRip is an inference and rule-based learner, Repeated Incremental Pruning to Produce Error Reduction (RIPPER), which tries to come up with propositional rules that can be used to classify elements [11]. The prediction model generated using Weka by JRip in a 10-fold cross validation and a confidence factor of 0.25 is presented in Fig. 3. It consists of the following two rules:

If the mock board exam result falls in the range of Fair, then the reviewee is predicted to fail the LET.

Otherwise, the reviewee is predicted to pass the LET.

Number of Rules : 2

Fig. 3. JRip rules.

The overall percentage of correct classification of JRip is 80.95% as shown in Table V. There are only 12 incorrectly classified instances which indicate that the model is incorrect for only 19.05% of the cases in the dataset.

TABLE V: JRIP CONFUSION MATRIX

Actual Class	Predicted Class		
	Passed	Failed	Percent Correct
Passed	39	7	84.78%
Failed	5	12	70.59%
Overall Percentage	88.64%	63.16%	80.95%

#### IV. CONCLUSION

In light of the results obtained in attribute selection, we conclude that the result of the mock board exam along with general weighted average in the General Education and Major or Core subjects are considered significant to the response attribute which is the LET performance. In case of the prediction models obtained using PART and JRip classifiers, we conclude that a reviewee is predicted to fail the LET if the reviewee will obtain a mock board rating lower than 34% of the total points. It is further concluded that if the general weighted average (GWA) in all the general education subjects is fair, or the general weighted average in all the general education subjects is fairly good and has a kinesthetic learning style, then the reviewee is predicted to fail the LET. Other than these specified rules, the reviewee is predicted to pass the LET. These models can be of help to the reviewer as it identifies students who needed special review assistance and eventually increase the licensure exam passing rate.

#### V. FUTURE WORKS

This study simply shows that mining educational data is possible and hence useful in gaining knowledge, in this case, the prediction of licensure examination performance. Having tried this kind of endeavor, we are looking forward to integrate the model generated into a Decision Support System. Customized attribute selection for data mining using specific classification techniques can be a good feature which could be incorporated to the system.

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# REFERENCES

- S. Arce and J. Belen, "The pre-board examination part of the in-house reviews as predictor of LET results," MSEUF Research Studies, vol. 13, no. 1, Feb. 2011.
- [2] S. Roehrig. Prediction of licensing examination scores in physical therapy graduates. *PHYS THER*. [Online]. *1988*(68). pp. 694-698. Available: http://ptjournal.apta.org/content /68/5/694
- [3] M. Ong, D. Palompon, and L. Bañico. (January 2012). Predictors of nurses' licensure examination performance of graduates in Cebu normal university, Philippines. *Asian Journal of Health*. [Online]. 2(1). Available: http://dx.doi.org/10.7828/ajoh. v2i1. 122
- [4] V. Hafalla Jr. and E. Calub. (2011). Modeling the performance of electronics and communications engineering students in the licensure examination. *UB RJ*. [Online]. *35(1)*. Available: http://www.ubaguio.edu/rdc/?cat=23
- [5] H. A. Soriano. (2009). Factors associated with the performance of USM College of Education graduates in the 2007 licensure examination for teachers. USM R & D. [Online]. 17(2). pp. 151-159. Available:
  - http://www.usm.edu.ph/rd-journal/rd-july-to-december-2009/factors-associated-with-the-performance-of-usm-college-of-education-gradua tes-in-the-2007-licensure-examination-for-teachers
- [6] M. Fire, G. Katz, Y. Elovici, B. Shapira, and L. Rokach, *Active Media Technology*, Springer Berlin Heidelberg, 2012, pp. 584-595.
- [7] S. Sembiring, M. Zarlis, D. Hartama, S. Ramliana, and E. Wani, "Prediction of student academic performance by an application of data mining techniques," in *Proc. 2011 International Conference on Management and Artificial Intelligence*, 2011, vol. 6, pp. 110-114.
- 8] P. Mellalieu, "Predicting success, excellence, and retention from students' early course performance: progress results from a data

- mining-based decision support system in a first year tertiary education programme," in *Proc. International Conference of the International Council for Higher Education*, New Zealand, 2010.
- [9] B. Baradwaj and S. Pal, "Mining educational data to analyze students' performance," *International Journal of Advanced Computer Science* and Applications, vol. 2, no. 6, 2011.
- [10] Z. Kovačić, "Early prediction of student success: mining students enrolment data," in *Proc. Informing Science & IT Education Conference*, New Zealand, 2010.
- [11] A. Hindle, D. German, R. Holt and M. Godfrey. (August 2009). Automatic classification of large changes into maintenance categories. [Online]. Available:

http://swag.uwaterloo.ca/~ahindle/pubs/hindle09icpc.pdf



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