6 REFERENCES

[1] Ghauth *et al.*, “Measuring learner’s performance in e-learning recommender systems.,” *Australasian Journal of Educational Technology*, vol. 26, no. 6, 2010.

[2] Jie Lu, “A Personalized e-Learning Material Recommender System,” Faculty of IT. University of Technology, Sydney, Proc. of the Int. Conf. on Information Technology for Application, 2004.

[3] Eitel J.M. Lauría and Joshua Baron, “Mining Sakai to Measure Student Performance: Opportunities and Challenges in Academic Analytics,” *School of Computer Science and Mathematics Marist College*, 2011.

[4] Ghauth, Khairil Imran, and Nor Aniza Abdullah. "The Effect of Incorporating Good Learners' Ratings in e-Learning Content-based Recommender System." *Educational Technology & Society* 14.2 (2011): 248-257. Faculty of Computer Science and Information Technology, University of Malaya, Malaysia

[5] Chellatamilan T and Suresh R. M, “An e-learning recommendation system using association rule mining technique,” *European Journal of Scientific Research*, Dept of Computer Science and Eng Arunai Engineering College, Tiruvannamalai, India, vol. 64, no. 2, pp. 330–339, 2011.

[6] Kimberly Arnold, “Signals: Applying Academic Analytics,” [Online]. Available: http://www.educause.edu/ero/article/signals-applying-academic-analytics/. [Accessed: 13-Nov-2012].

[7] Riccardo Mazza and Christian MILANI, “Exploring usage analysis in learning systems: Gaining insights from visualizations,” presented at the AIED Workshops (AIED’05), Faculty of Communication Sciences, University of Lugano,Switzerland, 2005.

[8] Sten Govaerts *et al.*, “The student activity meter for awareness and self-reflection,” in *CHI ’12 Extended Abstracts on Human Factors in Computing Systems*, ACM, New York, NY, USA, 2012, pp. 869–884.

[9] Ghauth *et al.*, "Building an E-learning Recommender System Using Vector Space Model and Good Learners Average Rating," presented at the Advanced Learning Technologies, 2009. ICALT 2009. Ninth IEEE International Conference, Riga, 2009, pp. 194 – 196.

[10] Paul S. Steif and Anna Dollár, "Study of usage patterns and learning gains in a web-based interactive static course," *Journal of Engineering Education*, vol. 98, no. 4, pp. 321 – 333, Oct. 2009.

[11] Khribi *et al.*, "Automatic Recommendations for E-Learning Personalization Based on Web Usage Mining Techniques and Information Retrieval," in *Advanced Learning Technologies, 2008. ICALT '08*, Santander, Cantabria, 2008, pp. 241 – 245.

[12] T. Tang and G. McCalla, "Smart recommendation for an evolving e-Learning system: Architecture and experiment," *Association for the Advancement of Computing in Education (AACE),* Chesapeake, VA, vol. 4, no. 1, 2005.

[13] Ivon Arroyo *et al.*, "Inferring Unobservable Learning Variables from Students' Help Seeking Behavior," in Intelligent Tutoring Systems, vol. 3220, *7th International Conference*, ITS 2004, Maceió, Alagoas, Brazil: Springer Berlin Heidelberg, 2004, pp. 782–784.

[14] David Monk, "Using Data Mining for e-Learning Decision Making," *E-learning Services, University of Glamorgan*, vol. 3, no. 1, pp. 41–54, 2005.

[15] Zaiane O.R., "Building a Recommender Agent for e-Learning Systems," in Computers in Education, *2002*, vol. 1, pp. 55 – 59.

[16] Zaiane O.R., "Web Usage Mining for a BetterWeb-Based Learning Environment," Department of Computing Science University of Alberta, Edmonton, Alberta, Canada., 2001.

[17] Myra Spiliopoulou, Lukas C. Faulstich, and Karsten Winkler, "A Data Miner analyzing the Navigational Behaviour of Web Users," in *the Workshop on Machine Learning in User Modelling of the ACAI99*, Faculty of Computer Science, Otto-von-Guericke-Universität Magdeburg, Greece, 1999.

[18] Félix Castro *et al.*, "Applying Data Mining Techniques to e-Learning Problems," in *Evolution of Teaching and Learning Paradigms in Intelligent Environment*, vol. 62, Springer Berlin Heidelberg, 2007, pp. 183–221.

[19] Feng-jung Liu and Bai-jiun Shih, “E-Learning Activity-Based Material Recommendation System,” vol. 4, no. 4, pp. 200–207, 2007.

[20] Cristóbal Romero, “Data Mining Algorithms to Classify Students,” in *1st Int. Conf. on Educational Data Mining (EDM’08),* p. 187191, 2008. 49 Data Mining 2009, Computer Science Department, Córdoba University, Spain, 2009.

[21] Jason Hunter, “JDOM and XML Parsing, Part 1,” *Oracle*, Oct-2002, [Online]. Available: http://www.jdom.org/docs/oracle/jdom-part1.pdf. [Accessed: 21-June-2013].

[22] Jianqing Zhang *et al.*, “Outsourcing Security Analysis with Anonymized Logs,” presented at the Securecomm and Workshops, 2006, Dept. of Comput. Sci., Univ. of Illinois at Urbana-Champaign, Urbana, IL, 2006, pp. 1 – 9.

[23] Sunita Beniwal and Jitender Arora, “Classification and Feature Selection Techniques in Data Mining,” *International Journal of Engineering Research & Technology (IJERT)*, vol. 1, no. 6, Aug. 2012.

[24] Mathew D. Pistilli and Kimbrly E. Arnold, “Mining real time academic data to enhance student success,” *American College Personal Association and Wiley Peroidocal, Inc*, 2010.

[25] Peter Brusilovsky *et al.*, “Personalisation in e-learning environments at individual and group level,” presented at the 11th International Conference on User Modeling, Corfu, Greece, 2007.

[26] Luis Talavera and Elena Gaudioso, “Mining Student Data To Characterize Similar Behavior Groups In Unstructured Collaboration Spaces,” Dept. Inteligencia Artificial, E.T.S.I. Inform´atica, UNED, Juan del Rosal 16, 28040 Madrid, Spain.

[27] Nikos Manouselis *et al.*, “Simulated Analysis of MAUT Collaborative Filtering for Learning Object Recommendation,” presented at the *Proceedings of the 1st Workshop on Social Information Retrieval for Technology-Enhanced Learning & Exchange.*

[28] “A Tutorial on Clustering Algorithms.” [Online]. Available: http://home.deib.polimi.it/matteucc/Clustering/tutorial_html/. [Accessed: 21-Sep-2013].

[29] “Introduction to Data Mining.” [Online]. Available: http://www-users.cs.umn.edu/~kumar/dmbook/index.php. [Accessed: 21-Sep-2013].

[30] Oded Maimon, “Data Mining and Knowledge Discovery Handbook,” in *Data Mining and Knowledge Discovery Handbook*, Department of Industrial Engineering Tel-Aviv University Ramat-Aviv, Tel-Aviv 69978, Israel.: Springer Science + Business Media, Inc, 2005, pp. 131–142.

[31] Galit Shmueli *et al.*, *Data Mining for Business Intelligence*. John Wiley & Sons, Inc, Hoboken, New Jersey.

[32] Rhonda Delmater and Monte Hancock Jr., Data Mining Explained: A Manager’s Guide to Customer-Centric Business Intelligence. Butterworth-Heinemann.

[33] Rapid Miner Studio [Online]. Available: http://rapidminer.com/. [Accessed: 02-July-2013].

[34] Zhiwen Yu *et al.*, “Ontology-Based Semantic Recommendation for Context-Aware E-Learning,” Academic Center for Computing and Media Studies, Kyoto University, Japan, 2007.

[35] Paul De Bra, “Personalized Links Recommendation Based on Data Mining in Adaptive Educational Hypermedia Systems,” Eindhoven University of Technology (TU/e), Eindhoven, The Netherlands, 2007.

[36] Ahmad Baylari and Gh.A. Montazer, “Design a personalized e-learning system based on item response theory and artificial neural network approach,” IT Engineering Department, School of Engineering, Tarbiat Modares University, Tehran, Iran.

[37] Moodle [Online]. Available: https://moodle.org/. [Accessed: 03-June-2013].

APPENDIX A: PROGRAMS

```
public class ParseXMLUsingJDOM {

	public static void main(String[] args) throws SQLException, IOException {

		SAXBuilder builder = new SAXBuilder();

		String filePath = "I:\\MSc\\Tharsan \\backup-cs5404cns-2010s3-
20130518-1701";

		File xmlFile = new File(filePath +"\\moodle - orignal.xml");

		try {

			Document document = (Document)builder.build(xmlFile);

			Element rootNode = document.getRootElement();

			List infoElements = rootNode.getChildren("INFO");

			if(infoElements.size() > 0 ){

			for(int a = 0; a < infoElements.size(); a++){

			Element node  = (Element) infoElements.get(a);

			String name     = node.getChildText("NAME");

			String moodleVersion  = node.getChildText("MOODLE_VERSION");

			if(users != null){

			List userList = users.getChildren("USER");

			if(userList.size() > 0)   {

			for(int l = 0; l < userList.size(); l++){

			Element userElement  = (Element)userList.get(l);

			String userName = userElement.getChildText("USERNAME");
			String userFirstName= userElement.getChildText("FIRSTNAME");
			String userEmail = userElement.getChildText("EMAIL");
			String userTimeZone   = userElement.getChildText("TIMEZONE");
			String userCountry = userElement.getChildText("COUNTRY")
```


Figure -1 XML Parsing

```sql
USE Moodle

GO

DECLARE @CourseId INT

DECLARE @ResourceId VARCHAR(250)

DECLARE @TotalNumberOfResourceAccessInCourse INT

DECLARE @numberOfAccessOfSingleResource INT

DECLARE @percentageOfAccessOfSingleResource NUMERIC(16,2)

DECLARE @getMoodleResources CURSOR

SET @getMoodleResources = CURSOR FOR

SELECT [CourseId],[Id]

FROM [Moodle].[dbo].[ModResource]

OPEN @getMoodleResources

FETCH NEXT

FROM @getMoodleResources INTO @CourseId, @ResourceId

WHILE @@FETCH_STATUS = 0

SET @TotalNumberOfResourceAccessInCourse = (SELECT COUNT(*)

FROM (SELECT DISTINCT logUserId, logInfo
            FROM [Moodle].[dbo].[log]
            WHERE logModule = 'resource' AND logAction = 'view'  AND
CourseId = @CourseId) AS X )

SET @numberOfAccessOfSingleResource = (SELECT COUNT(*)
FROM ( SELECT DISTINCT logUserId, logInfo
             FROM [Moodle].[dbo].[log]
            WHERE logModule = 'resource' AND logAction = 'view'  AND
CourseId =  @CourseId AND logInfo = @ResourceId) AS Y)


SET @percentageOfAccessOfSingleResource   = @numberOfAccessOfSingleResource * 100
/ CAST(@TotalNumberOfResourceAccessInCourse AS DECIMAL(16,2))
```

Figure - 2 **Calculate the percentage of access by good students**

APPENDIX B: RESULTS

Table 1 Accuracy of student model with manual split with three class labels

Algorithms \ Used data set	Average ratio greater than 0.5	Outliers removed first time	The label boundary changed up	The label boundary changed down	Outliers removed second time
Decision Tree	54.90	55.56	53.33	53.33	53.57
Neural Networks	60.78	46.67	53.33	44.44	57.14
SVM	50.98	48.89	53.33	48.89	53.57
k-NN	33.33	40.00	48.89	42.22	46.43
Naive Basis	45.10	57.78	48.89	48.89	57.14
Rule Induction	45.10	42.22	53.33	35.56	53.57
Perceptron	45.10	17.78	51.11	40.00	50.00
Linear Regression	47.06	57.78	55.56	51.11	50.00
Polynomial Regression	31.97	42.22	24.44	33.33	42.86
Vector Linear Regression	19.61	24.44	24.44	24.44	21.43
Gaussian Process	39.22	46.67	53.33	48.89	50.00

Table 2 RMSE of student model with manual split with three class labels

Algorithms \ Used data set	Average ratio greater than 0.5	Outliers removed first time	The label boundary changed up	The label boundary changed down	Outliers removed second time
Decision Tree	0.63	0.62	0.62	0.60	0.62
Neural Networks	0.58	0.70	0.63	0.71	0.61
SVM	0.60	0.62	1.08	0.62	0.60
k-NN	0.82	0.78	0.72	0.76	0.73
Naive Basis	0.61	0.59	0.63	0.62	0.62
Rule Induction	0.72	0.74	0.65	0.62	0.62
Perceptron	0.73	0.88	0.69	0.77	0.71
Linear Regression	0.65	0.55	0.86	0.65	0.64
Vector Linear Regression	0.90	0.87	0.87	0.87	0.89
Gaussian Process	0.78	0.73	0.70	0.71	0.71

T able 3 Accuracy of student model with manual split with four class labels

Algorithms \ Used data set	The label boundary changed down	The label boundary changed up	Outliers removed second time	Outliers removed third time
Decision Tree	33.33	40.00	42.86	36.84
Neural Networks	37.78	31.11	35.71	31.58
SVM	33.33	42.22	53.57	36.80
k-NN	33.33	37.78	39.29	42.11
Naive Basis	37.78	37.78	39.29	31.58
Rule Induction	33.33	33.33	46.43	47.37
Perceptron	15.56	40.00	39.29	36.84
Linear Regression	24.44	40.00	50.00	42.11
Polynomial Regression	33.33	33.33	28.57	26.32
Vector Linear Regression	24.44	24.44	21.43	15.79
Gaussian Process	40.00	44.44	39.29	47.37

Table 4 Accuracy of student model with manual split with five class labels

Algorithms \ Used data set	The label boundary changed down	The label boundary changed up	Outliers removed second time	Outliers removed third time
Decision Tree	33.33	20.00	28.57	26.32
Neural Networks	28.89	28.89	21.43	41.11
SVM	31.11	31.11	28.57	26.32
k-NN	28.89	26.67	25.00	26.32
Naive Basis	26.67	22.22	25.00	21.05
Rule Induction	17.78	26.67	25.00	31.58
Perceptron	11.11	17.98	14.29	21.05
Linear Regression	35.56	28.89	39.29	31.58
Polynomial Regression	31.11	20.00	14.29	21.05
Vector Linear Regression	24.44	24.44	21.43	15.79
Gaussian Process	35.56	33.00	25.00	31.58

Table 5 Accuracy of resource model with random split with three class labels

Used data set / Algorithms	% of access by good students at split borders 2.25 and 1.8	% of access by good students at split borders 2.5 and 1.8	% of access by good students at split borders 2.6 and 1.8	% of access by good students at split borders 2.25 and 1.9	% of access by good students at split borders 2.25 and 1.7
Decision Tree	88.60	86.60	82.47	87.63	88.60
Neural Networks	88.60	89.69	86.60	87.63	88.60
SVM	71.13	78.35	85.57	74.23	71.13
k-NN	60.82	60.82	63.92	59.79	60.82
Rule Induction	79.38	86.60	82.47	83.51	79.38
Naive Basis	78.35	77.32	82.47	78.35	78.35
Perceptron	43.30	37.11	49.48	37.11	43.30
Linear Regression	83.19	89.69	81.44	71.38	83.19

Table 6 Accuracy of resource model with random split with four class labels

Used data set / Algorithms	% of access by good students at split borders 2.25-1.8-1.[illegible]	% of access by good students at split borders 2.25-1.8-1.4	% of access by good students at split borders 2.25-1.8-1.4
Decision Tree	70.10	81.44	81.44
Neural Networks	75.26	87.63	85.57
SVM	74.23	64.95	62.89
k-NN	51.55	56.70	56.70
Rule Induction	78.35	79.38	77.32
Naive Basis	69.07	77.32	77.32
Perceptron	45.36	45.36	45.36
Linear Regression	72.16	64.95	63.92