An Efficient MODEL for Detecting LEARNING STYLE Preferences in a Personalized E-Learning Management System

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Abstract—**Improving the learning quality in e-learning environments has received considerable attention from researchers. One of the methods to improve the understanding of the students in a learning process is adapting the content to their learning styles. Adaptive Educational Systems can support different learning characteristics by building a model of the student's learning behaviour and subsequently adapting the learning environment to match different needs. In this work, a 'Personalized E-Learning Management System (PELMS)', is developed. As the student interacts with the learning environment, our predictive engine based on Naïve Bayes classifier multinomial model, and our efficient detective model (AO-EDM) predict the student's preferred learning style and adaptively customize the learning environment. The two models will be used in two different learning environments. Chi-square test is used to analyze our data. An ASP.NET 2.0 web technology model is used to build PELMS.**

Index Terms— **Learning style, Naïve Bayes, AO-efficient detective model, Chi-Square.**

I. INTRODUCTION

Advanced information technologies are increasingly used in higher education to facilitate learning and teaching, but inadequacies exist in current systems, materials, and pedagogy. The application of similar learning strategies to all students in a class can be ineffective. For example, programming introduction modules are often delivered using a text-based teaching method. However students have their individual preferences of how they can learn programming, and how to make learning programming less difficult is an issue in Computer Science education (Jenkins, 2002). Students often treat a course as a series of mechanical exercises rather than as systemic concepts, and a specific framework to support the change process is often lacking (Nunes and McPherson, 2002).

People learn in different ways. It is important to be aware of the differences between learners. This is especially relevant during the current expansion of tertiary education to a greater proportion of the population. New delivery systems are required; such systems should be individualized and able to provide different students with appropriate material, making the learning process more efficient and effective. Understanding a student's particular learning style and how to best meet the needs of that learning style is essential to performing better. (Clay and Orwig, 1996) defined learning style as a unique collection of individual skills and preferences that affects how a person perceives, gathers and processes information. Learning style affects how a person acts in a group, learns, participates in activities, relates to others, solves problems and works. Basically, a person's learning style is the method that best allows him/her to gather and use knowledge in a specific manner. Once you have identified your particular learning style you will be able to identify ways in which you can adapt the learning process and your studies to maximize your education.

We follow the traditional classification of learning into classical and non-classical, where Classical learning comprises traditional learning method and nomadic learning. While non classical learning is e-learning, distance education and mobile learning. The focus shall be on non-classical learning with particular emphasis on e-learning

Adaptive Educational Systems can support different learning characteristics by building a model of the student's learning behaviour and subsequently adapting the learning environment to match different needs. However major challenges exist, as it is not clear how a student's model of learning style can be accurately built. In this work, a 'Personalized E-Learning Management System (PELMS)', is designed to address these challenges by using Naïve Bayes Classifier multinomial model in addition to a newly formulated efficient detective model (EDM) to dynamically build a student model and determine learning style. It dynamically discerns skills in the user's behavior by observing the navigation profile, time spent on each page, and choices made regarding content.

This paper is structured as follows: the next section discusses the related work cited in literature. Section 3 describes the research methodology which includes the inputs and output in the proposed AO-EDM model. Brief introductory description of Naïve Bayes classifier and how they are applied to learning style classification is given in section 4.

In section 5 we establish a general model with its mathematical formulations and in the following section we present the model's application specifically in the Dunn and Dunn VARK Learning Style Model. In section 7 the result analysis of our research is presented and the references are presented in the last section.

II. RELATED WORK

The literature in this regard is vast. TANGOW (Paredes and Rodriguez, 2004) – is based on two dimensions of Felder and Silverman Learning Style Model (FSLSM): sensing/intuitive and sequential/global. Learners are asked to fill in the Inventory Learning Style (ILS) questionnaire when they log into the system for the first time and the student model is initialized correspondingly. Subsequently the student actions are monitored by the system and if they are contrary to the behavior expected for that learning preference, then the model is updated. The student observed behavior is restricted to four patterns, each corresponding to one of the four possible FSLSM preferences. Heritage Alive Learning System (Cha, Kim, Park, Yoon, Jung, and Leel, 2006) – is based on Felder-Silverman learning style model. Learning preferences are diagnosed implicitly, by analyzing the behavior patterns on the interface of the learning system using Decision Tree and Hidden Markov Model approaches. EDUCE (Kelly and Tangney, 2006) - is based not on a learning style model but on Gardner's theory of multiple intelligences (MI), using 4 types: logical/mathematical, verbal/linguistic, visual/spatial, musical/rhythmic (Gardner, 1993). The student diagnosis is done both dynamically (by analyzing the student's interaction with MI differentiated material and using a naïve Bayes classification algorithm) and statically (by applying a Shearer's MI inventory (Shearer, 1996)).

The system presented in (Stathacopoulou, Grigoriadou, Samarakou, and Mitropoulos, 2007) - is based on Biggs' surface vs. deep student approach to learning and studying (Biggs, 1987). The student diagnosis is done by means of a neural network implementation for a fuzzy logic-based model. The system learns from a teacher's diagnostic knowledge, which can be available either in the form of rules or examples. The neuro-fuzzy approach successfully manages the inherent uncertainty of the diagnostic process, dealing with both structured and non-structured teachers' knowledge. AHA! (Stash, 2007) – uses the notion of "instructional meta-strategies" (inference or monitoring strategies), which are applied in order to infer the learner's preferences during his/her interaction with the system. A meta-strategy can track student's learning preferences by observing her/his behavior in the system: repetitive patterns such as accessing particular types of information – e.g. textual vs. visual form or navigation patterns such as breadth-first versus depth-first order of browsing through the course. These meta strategies are defined by the authors, who can therefore choose the learning styles that are to be used as well as the adaptation strategy. However, there is a limitation in the types of strategies that can be defined and consequently in the set of learning preferences that can be used, so these strategies cannot completely replace existing psychological questionnaires.

The system presented in (Garcia, Amandi, Schiaffino, and Campo, 2007) – is based on three dimensions of the FSLSM (active/reflective, sensing/intuitive and sequential/global). The behavior of students in an educational system (called SAVER) is observed and the recorded patterns of behavior are analyzed using Bayesian Networks. The system presented in (Graf, 2007) – is based on the FSLSM. The actions of the students interacting with Moodle learning management system (Moodle, 2008) are recorded and then analyzed using a Bayesian Network approach as well as a rule-based approach. Since the accuracy of the diagnosis was better in the latter case, the rule-based approach was implemented into a dedicated tool called DeLeS, which can be used to identify the learning style of the students in any Learning Management System (LMS).

The system presented in (Sangineto, Capuano, Gaeta, and Micarelli, 2008) - is based on Felder-Silverman learning style model, and uses fuzzy values to estimate the preference of the student towards one of the four categories (Sensing-Intuitive, Visual-Verbal, Active-Reflective, Sequential- Global). Initially, the system offers to the learner the possibility to use the Soloman and Felder's psychological test or to directly set the values of the category types, choosing an estimated value for each category (using a slider-based interface). Also, for those people who do not want or are not able to estimate their own learning style, the system sets the initial values of all the category types to 0.5, which means that the student is initially evaluated as indifferent with respect to any learning style preference. Next the learning style is automatically updated by the system taking into account the results obtained by the students at the multiple-choice tests presented at the end of each learning phase.

III. RESEARCH METHODOLOGY

We propose an efficient detective model that compares favourably with the Naïve Bayes classifier multinomial model technique. In the later, the machine learning task is to observe some of the user actions and use it to determine the learning style of the student. After which the most appropriate content for the user is presented to him/her on the next page. The input into the machine-learning algorithm or classifier takes the form of instances where we define an instance to be an independent example of the class to be learnt and is characterized by a predetermined set of attributes. An attribute measures the different aspects of an instance and will have different possible values. The output from the classifier is the predicted class of the instance.

In our proposal the Inputs are assigned time for learning, the hit rate (i.e. the no of visits to each resource type), time rate of learning spent on each resource type visited, hearing range (minimum), access mode (sequential or random), average test score for both pre and post test and total number of learning activities. It uses this information to determine the Output which is the learning style of the student.

IV. DATA FOR PARAMETER ESTIMATION NAÏVE BAYES (NB) CLASSIFIER

The data for parameter estimation for NB classifier is as shown in table I below. LSID is the Learning Style id and c is the learning style class.

We used four classes. These classes are based on Dunn and Dunn VARK Learning Style Model i.e. Visual, Auditory, Read/Write, and Kinesthetic (VARK). Each class has learning activity (for example, the objective of the course, overview, introduction, content, and summary). Resource type for example, the class visual can be accessed using animation, which is an example of our resource type and access mode (is either sequential or random). Note: Only visual class training set table is shown in this work. Auditory, read\write and kinesthetic is not included.

TABLE I: LEARNING ACTIVITY AS A FUNCTION OF RESOURCE TYPE

	LSID	**Set of instances**	**c = Visual**
Training Set	1	objective animation text-picture animation sequential	yes
	2	introduction animation animation audio sequential	yes
	3	summary animation text-picture sequential	yes
	4	overview text-picture animation audio sequential	no
	5	content audio text-picture animation random	no
Test set	6	overview text-picture animation animation audio sequential	?

TABLE II: RESOURCE TYPE AS A FUNCTION OF LEARNING ACTIVITY

	LSID	**Set of instances**	**c = Visual**
Training Set	1	animation objective overview intro content summary sequential	yes
	2	animation intro overview objective content summary random	yes
	3	animation intro overview content objective summary random	yes
	4	animation intro overview objective content summary random	no
	5	animation summary overview objective content intro seq uential	no
Test set	6	text-picture intro overview objective content summary random	?

From the training set, training the classifier is fairly quick and simple. It estimates the prior probabilities P(c), for a class c as

$$P(c) = \frac{N_c}{\mathrm{N}} \qquad 1.1$$

where N is that total number of instances and N_c is the number of instances that belong to class c. The classifier also estimates the conditional probabilities that a term x appears in class c:

$$P(x|c) = \frac{n_{x,c} + 1}{n_c + V} \qquad 1.2$$

where $n_{x,c}$ is the total number of times term x appears in all the instances that belong to class c, n_c is the number of terms in all the instances that belong to class c, and V is the equivalent sample size. In this consideration, we employ Laplace smoothing to eliminate zeros.

The probability of a term x being in class c is computed as

$$P(c\backslash x) \propto P(c) \prod_{1<x<nd} P(x|c) \qquad 1.3$$

where $P(x|c)$ is the conditional probability of term x

occurring in a term of class c. We interpret $P(x|c)$ as a measure of how much evidence x contributes that c is the correct class. $P(c)$ is the prior probability of a term occurring in class c. If a term's terms do not provide clear evidence for one class versus another, we choose the one that has a higher prior probability.

In learning style classification, our goal is to find the best class for the student. The best class in Naïve Bayes (NB) classification is the most likely or maximum a posteriori (*MAP*) class C_{map}:

$$C_{map} = \underset{c_j \in C}{argmax} P(c_j) \prod_{i \in P} P(x_i|c_j) \qquad 1.4$$

where P is the set of all positions in the test document that contain a term in the sample size, and x_i is the term that occurs at position i.

In our new proposed model, resource type and learning activity are differentiated with respect to time. The classifier observes some of the user actions such as the time spent on each resource type visited, the hit rate, access rate, average test score for both pre and post test and assigned time. It uses this information to determine the learning style of the student. Chi-square technique is used to analyze the data from the database, and object-oriented programming (OOP) is used to implement the programming constructs.

V. PROPOSED MODEL DESCRIPTION

In PELMS, the course Relational Database Management System (RDBMS) was used for illustration. The set of attributes used are:

Objective (O_a), which is the objective of the course, Test (T_a), that is the test taken by the students\users this includes both pre and post test. Content (C_a) that is the body of the course and Summary (S_a) which is the summary of the course RDBMS. All of these are referred to as Learning-activity.

Text (T_r), this means presenting the course RDBMS in form of text-based as seen in most E-learning sites. Audio (A_r), this means presenting the course RDBMS in form of audio. Animation (I_r) this means presenting the course RDBMS in animation form and Forum (F_r) this means presenting a forum environment to users. All of these are referred to as Resource-type.

The total number of learning activity $T_{LA} = (S_a + C_a + O_a + T_a)$. The total number of resource type $T_{RT} = (T_r + A_r + I_r + F_r)$

The dimensional equation for this dynamic system comprises of eight differential-equations

$$\frac{dT_r}{dt} = \beta_r \sum_{i=1}^{3} R_i - V_z \qquad 1.5$$

$$\frac{dA_r}{dt} = mT_r - W_z \qquad 1.6$$

$$\frac{dI_r}{dt} = acA_r \frac{C_a}{T_{LA}} - X_z \qquad 1.7$$

$$\frac{dF_r}{dt} = kI_r - Y_z \qquad 1.8$$

$$\frac{dO_a}{dt} = gC_a \qquad 1.9$$

$$\frac{dT_a}{dt} = \mu_v C_a \qquad 2.0$$

$$\frac{dS_a}{dt} = -abF_r \frac{S_a}{T_{LA}} \qquad 2.1$$

$$\frac{dC_a}{dt} = abF_r \frac{S_a}{T_{LA}} - U_z \qquad 2.2$$

From equation 1.5, $R_i = (A_r + I_r + F_r)$
and $V_z = -(mT_r + \mu_L T_r)$

Where text is differentiated with respect to time.

$(A_r, I_r, and\ F_r)$ are other resource type.

From equation 1.6,

$$W_z = -(acA_r \frac{C_a}{T_{LA}} + \mu_A A_r)$$

Again, audio is being differentiated with respect to

time. T_r is a resource type.
From equation 1.7,

$X_z = -(kI_r + \mu_A I_r)$

here, animation is being differentiated with respect

to time. A_r is a resource type involving no activity from learner.
From equation 1.8, $Y_z = \mu_A F_r$

Forum is being differentiated with respect to time. I_r is a resource type that involves some activity from the learner but

From equation 2.2, $u_z = -(\mu_v C_a + g C_a)$. In this consideration, content is differentiated with respect to time. The hit rate and assigned time is very important.

VI. MODEL ANALYSIS

To non-dimensionalize equations 1.5 to 2.2, we scaled time, *t*, with the quantity 1/*k* by setting $\delta = kt$, scaled all parameters to *k* (table 1) and scaled learning activity and resource type numbers by the initial total number of learning activity, T_{LA}. In the resulting dimensionless system (equations 2.3, 2.4, 2.5, and 2.6), the four learning style activities, s_a, c_a, o_a and t_a, indicate summary, content, objective and test respectively, where the total learning activity, t_{la}, is $0 \leq t_{la} = \sum_{i=1}^{4} \alpha_i \leq 1$. The four resource types, f_r, a_r, i_r and t_r represent forum, audio, animation and text, respectively. The total resource type, t_{rt}, is $0 \leq t_{rt} = \sum_{i=1}^{4} r_i$. Where $r_i = (t_r + a_r + i_r + f_r)$

We set the rescaled system as

$$\frac{do_a}{d\delta} = \omega c_a \qquad 2.3$$

$$\frac{dt_a}{d\delta} = \mu_v c_a \qquad 2.4$$

$$\frac{ds_a}{d\delta} = -\alpha_a f_r \frac{s_a}{t_{la}} \qquad 2.5$$

$$\frac{dc_a}{d\delta} = \alpha_a f_r \frac{s_a}{t_{la}} - u_z \qquad 2.6$$

$$\frac{dt_r}{d\delta} = \rho_r \sum_{i=1}^{3} r_i - v_z \qquad 2.7$$

$$\frac{da_r}{d\delta} = \varphi t_r - w_z \qquad 2.8$$

$$\frac{di_r}{d\delta} = \alpha_r a_r \frac{c_a}{t_{la}} - x_z \qquad 2.9$$

$$\frac{df_r}{d\delta} = i_r - y_z \qquad 3.0$$

TABLE III: AO-EDM PARAMETERS

symbol	Values	description	dimensionless
T_r	0.1	Text Content	
A_r	0.2	Audio	
I_r	0.3	Animation	
F_r	0.4	Forum	
O_a	0.01	Objective	
T_a	0.02	Test	
C_a	0.03	Content	
S_a	0.04	Summary	
T_{LA}	1.0	Total number of Learning Activities	
T_{rt}	0.1	Total number of Resource type	
a	count	hit rate (no of visit to each resource type)	
b	60 mins (3600 seconds)	assigned time	$\varphi = b/k$
c	20Hz	hearing range (minimum)	$\alpha_r = ac/k$
m	<u>Access mode either S/R</u> Total no of access type	probability of access	$\alpha_a = ab/k$
β_r:	<u>Time spent on LO and Test</u> Maximum time allowed for the LO and Test	rate of understanding	$\rho_r = \beta_r/k$

μ_V:	(pre + post test/2)	the average test score rate (pre and post test)	$\mu_v = \mu_V/k$
μ_A:		time rate of learning	$\mu_a = \mu_A/k$
μ_L:		time rate in accessing text learning content	$\mu_l = \mu_L/k$
k:	1	Transition rate	-
g:	1= sequential, 0= random	Access mode (sequential or random)	$\omega = g/k$

From equation 2.6, 2.7, 2.8, 2.9 and 3.0

$u_z = -(\mu_v c_a + \omega c_a)$

$r_i = (a_r + i_r + f_r), v_z = -(\varphi t_r + \mu_l t_r)$

$w_z = -(\alpha_r a_r \frac{c_a}{t_{la}} + \mu_a a_r)$

$x_z = -(i_r + \mu_a i_r)$

$y_z = \mu_a \mathbf{f}_r$

One learning activity can only be accessed one at a time. Thus learning- activity- equilibrium LAE is given as

$(S_a, C_a, O_a, T_a) = (1, 0, 0, 0)$ 3.1

$$\beta_r = \frac{\mu_A(m + \mu_L)}{m} \quad 3.2$$

$$T_a = \frac{\beta_r A_r}{(m + \mu_L)}, \quad t_a = \frac{\rho_r a_r}{(m + \mu_l)} \quad 3.3$$

(t_r, a_r, i_r, f_r)
$=(\rho_r a_r)/(\varphi + \mu_l), a_r, 0, 0)$ 3.4

Animation and forum is 0 because of their transition rate that is dimensionless. Also activity is also involved from the students.

Following the work of van den Driessche & Watmough (2002) in evaluating our learning style classifier L_s, we introduce vector notation to rewrite the equations in which content appeared in terms of the difference between *fr*, the rate of accessing the resource types in *r*, and *vr*, the rate of understanding by the students. Content C_a, Text $T_r$animationi_r Audio $A_r$and forum $f_r$is very important in determining our learning style. Considering content c_a which must be present for learning to take place, animation i_r and forum f_r that requires some activity from the students, we present a differential equation as shown below:

$$\frac{d}{d\tau}\begin{bmatrix} c_a \\ i_r \\ f_r \end{bmatrix} = f - v = \begin{bmatrix} \alpha_a f_r \frac{s_a}{t_{la}} \\ \alpha_r a_r \frac{c_a}{t_{la}} \\ 0 \end{bmatrix} - \begin{bmatrix} \mu_v c_a + \omega c_a \\ \mu_a i_r + i_r \\ -i_r + \mu_a f_r \end{bmatrix} \quad 3.5$$

The corresponding Jacobian matrices, F and V, describe the linearization of this reduced system about the LAE

$$F = \begin{bmatrix} 0 & 0 & \alpha_a \\ \alpha_r i_r & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \quad V = \begin{bmatrix} \mu_v + \omega & 0 & \alpha_a \\ 0 & \mu_a + 1 & 0 \\ 0 & -1 & \mu_a \end{bmatrix}$$

3.6

Our learning style classifier, L_s, is given as the dominant eigenvalue of FV^{-1} (Driessche &Watmough 2002):

$$L_s = \sqrt{\frac{\alpha_a}{\mu_a} \frac{\alpha_r a_r (\frac{1}{1+\mu_a})}{(\mu_v + \omega)}} \quad 3.7$$

$$L_s = \sqrt{\frac{ab}{\mu_A} \frac{ac \frac{A_r}{T_{LA}} (\frac{k}{k + \mu_A})}{(\mu_V + g)}} \quad 3.8$$

When $L_s < 4$ the student has less preference for the resource type accessed; when $L_s \geq 4$ the student has most preference to the resource type accessed. Following from equation 3.8 the first term under the square root represents the learning style L_s from resource type to learning activity as the probability of access (*ab*) multiplied by the time rate of learning ($1/\mu_A$:). The second term represents L_s from learning activity to resource type as the hearing range (*ac*) multiplied by the number of audio content per learning activity ($\frac{A_u}{T_{LA}}$) that was used in learning and the transition rate ($k/[k + \mu_A]$), multiplied by the average test score rate for both pre and post test and the access mode (sequential or random), ($1/([\mu_V + g])$. The square root represents the geometric mean L_s for a student using both learning activity and resource types combined. Looking at audio content and Setting $L_s = 1$ returns the equation below:

$$A_r = \frac{\mu_a(1+\mu_a)(\omega+\mu_v)}{\alpha_a \alpha_r} \quad 3.9$$

Using linear analysis, we then calculate the access rate such that for the LAE $(s_a, c_a, o_a, t_a, t_r, a_r, i_r, f_r) = (1, 0, 0, 0, (\rho_r a_r)/(\varphi + \mu_l), a_r, 0, 0)$, we defined small perturbations in each variable, (s_a, c_a, o_a, t_a, t_r, a_r, i_r, f_r). The corresponding Jacobian matrix, F (which reduces to five dimensions since s_a, o_a and t_a i.e. summary, objective and test, changes, describes the linearization with respect to content c_a and the four resource types (c_a, t_r, a_r, i_r, f_r):

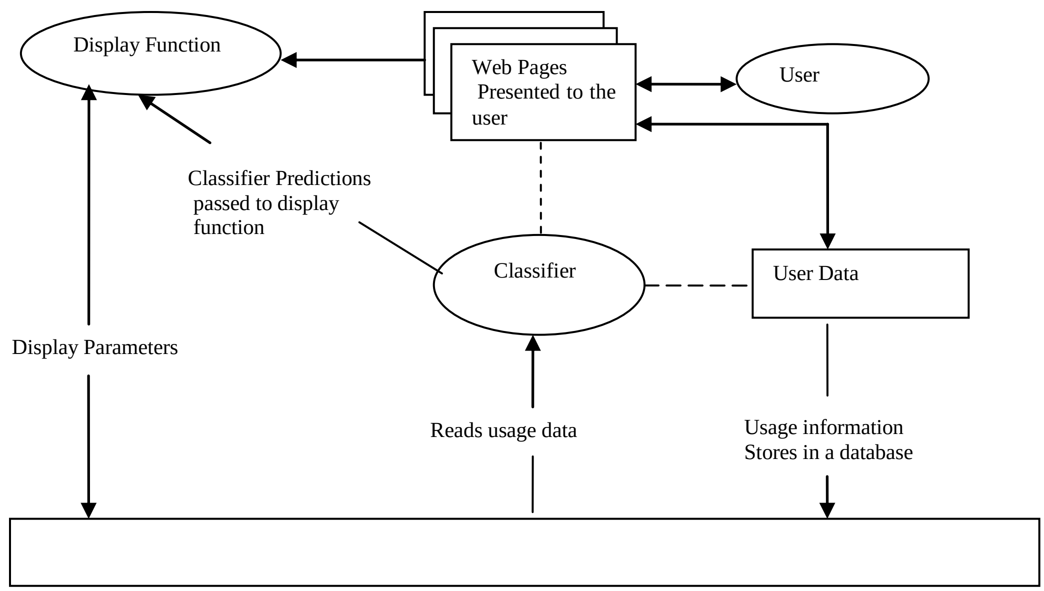
$$F = \begin{vmatrix} -\mu_v - \omega & 0 & 0 & 0 & \propto_a \\ 0 & -\varphi - \mu_l & \omega_r & \omega_r & \omega_r \\ -\alpha_r a_r & \varphi & -\mu_a & 0 & 0 \\ \alpha_r a_r & 0 & 0 & -\mu_a - 1 & 0 \\ 0 & 0 & 0 & 1 & -\mu_a \end{vmatrix} \qquad 3.10$$

This yields the characteristic polynomial in λ:

$$0 = \det(F - \lambda I) = \lambda\left(\lambda + \mu_a + \frac{\varphi\omega_r}{\mu_a}\right)(\lambda^3 + a_1\lambda^2 + a_2\lambda + a_3) \qquad 3.11$$

Where I is the 5 x5 identity matrix and $a_1 > 0$, $a_2 > 0$.

The zero root of the fifth-order polynomial (equation (3.11) comes from (equation (3.3). Our resource type $(\rho_r a_r)/(\varphi + \mu_l), a_r, 0, 0)$ is neutrally stable to changes in a_r. For $a_3 > 0$, by the Routh–Hurwitz conditions, all roots of the cubic polynomial in equation (3.11) have negative real parts. A student has a no preference for a particular resource type when $a_3 = 0$ or, equivalently, when zero is the largest eigenvalue of F.



– – – – – – – – Represents the virtual links within the system

Fig. 1. SYSTEM ARCHITECTURE

VII. RESULT ANALYSIS

AO-EDM is a prediction engine that reads user actions, such as the time spent on each resource type visited, the hit rate, access mode, average test score for both pre and post test and assigned time. This is achieved when a student is interacting with PELMS. The Learning style L_s classifier will now classify the student according to the usage data , i.e. it will use this information to determine the learning style of the student. Naïve Bayes (NB) Classifier was also used to determine the learning style of students. The observed behaviour from the students serves as input into the algorithm which is in form of instances. The popular and well known NB Classifier compares favourably with our own formulation.

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REFERENCES

[1]. J. Biggs, Student Approaches to Learning and Studying, *Australian Council for Educational Research*, Hawthorn. (1987).

[2]. H. J. Cha, Y. S. Kim, S. H. Park, T. B. Yoon, Y. M. Jung, and J. H. Lee. Learning styles diagnosis based on user interface behaviors for the customization of learning interfaces in an intelligent tutoring system. *Proceedings. ITS* . Lecture Notes in Computer Science, (2006) Vol. 4053, Springer. pp. 513-524

[3]. J. Clay and C.J Orwig, Your learning style and language learning. *Lingual links library*, *Summer Institute of Linguistics ,Inc (SIL) International* version 3.5 (1999).

[4]. P. Garcia, A. Amandi, S. Schiaffino, and M. Campo, Evaluating Bayesian Networks' Precision for Detecting Students' Learning Styles. *Computers & Education*, 49(3) pp. 794-808. (2007).

[5]. H. Gardner, (1993). *Multiple Intelligences: The Theory in Practice*. Basic Books, New York.

[6]. S. Graf, *Adaptivity in Learning Management Systems Focussing on Learning Styles*. Unpublished doctoral dissertation, Vienna University of Technology, Austria. (2007).

[7]. T. Jenkins, The Difficulty of Learning to Program. *Proceedings of the 3rd Annual Conference of the LTSN Centre for Information and Computer Sciences*, vol. 4, pp. 53-58. (2002).

[8]. D. Kelly and B. Tangney, Adapting to intelligence profile in an adaptive educational system. *Interacting with Computers*, 18, pp. 385-409. (2006).

[9] Moodle (2008). Available at: http://moodle.org.

[10] M. B. Nunes and M. McPherson, Managing Change in Continuing Professional Distance Education through Action Research. *Proceedings of the 3rd Annual Conference of the LTSN Centre for Information and Computer Sciences*, vol. 4, pp. 20–25. (2002).

[11] P. Paredes and P. Rodriguez, A Mixed Approach to Modelling Learning Styles in Adaptive Educational Hypermedia. *Advanced Technology for Learning*, 1(4) pp. 210-215. (2004).

[12] E. Sangineto, N. Capuano, M. Gaeta and A. Micarelli, Adaptive course generation through learning styles representation. *Journal of Universal Access in the Information Society*, 7(1) pp.1-23. (2008).

[13] B. Shearer, *The MIDAS Handbook of Multiple Intelligences in the Classroom*, Greyden Press, Ohio. (1996).

[14] N. Stash, *Incorporating Cognitive/Learning Styles in a General-Purpose Adaptive Hypermedia System*. (2007). Unpublished doctoral dissertation, Eindhoven University of Technology, Netherlands.

[15] R. Stathacopoulou, M. Grigoriadou, M. Samarakou and D. Mitropoulos, "Monitoring students' actions and using teachers' expertise in implementing and evaluating the neural network-based fuzzy diagnostic model." *Expert Systems with Applications*, 32, pp. 955-975. (2007).