User Modeling in the Context of Cognitive Service Delivery: Application to Learning Management Systems

Y. Kritikou, P. Demestichas, *University of Piraeus – Department of Digital Systems, Greece*
kritikou@unipi.gr

E. Adamopoulou, K. Demestichas, *National and Technical University of Athens - Department of Electrical and Computer Engineering, Greece*

***Abstract*—A contemporary trend in the field of telecommunications is the development of a constantly increasing number of services available to users through computer networks. These services are being used in order to facilitate users' everyday life and save them time and effort. The following paper discusses on the service delivery and the way it can be adapted to each user's specific needs, in the context of cognitive networks and service provisioning. An example of such a service is being examined, namely a Learning Management System and specifically User Model entity, which is responsible for storing user's preferences. In support of this vision, a paradigm of Bayesian Networks' application is presented, aiming at predicting user's preferences in a Learning Management System, by managing a specific set of parameters that affect it and providing the information to configure the learning content to be delivered, accordingly. For the confirmation of this Model's validity a set of indicative results are also presented at the end of this paper.**

***Index Terms*—E-learning, Learning Management System, Service Provisioning, User model**

I. Introduction

THE last years have witnessed an explosion of activity around science and particularly in telecommunications. Today, someone is able to make a phone call, download his e-mails, make a videoconference or simply take some notes by using a single device. This means that users' have, and are encouraged to, become more demanding, requiring more complex services. On the other hand, service delivery cannot be the same for every user, since their expectations and preferences on the service features are most likely to differ between them. This means that it is necessary to reinforce the service delivery with a certain cognitive mechanism, able to collect, manage and effectively provide information to users. Thus, networks need not only to be able to provide users with advanced services, but also manage the information users' provide them, in order to evolve the service, so as to meet their needs.

In this context, this paper presents cognitive networks and service provisioning, developed to process users' needs and adapt the service to be delivered to them accordingly. More specifically, in Section II a brief description of network operation takes place, while in Section III cognitive networks and service provisioning are discussed. In Section IV management functionality is presented in order to support service delivery in a Learning Management System and more particularly, management functionality focused on User Model, for predicting users' needs. Finally, in support of this vision, we elaborate on the Bayesian Network Model (Section V), applied to predict users' preferences by observing the values of a certain set of parameters, as well as some indicative results concerning the application of this model. Summary, conclusions and future work are closing this paper in Section VI.

II. Network operation

As previously mentioned, today there are plenty of services offered with the aim to satisfy users' particular needs, along with a lot of different ways to achieve this service usage. For example, through a device a user may be informed of the flights' schedule to New York, the weather of the next days or the way to reach the house of a friend of his, in case he is lost. He only has to use a program to find a particular service and then require more specific information by sending it to his Service Provider. For this communication to be achieved the existence of a Network Infrastructure is essential, responsible for facilitating the communication between the user and the server, providing him the services he requests, as graphically

Manuscript received October 19, 2006. This work was partially supported by University of Piraeus, Department of Digital Systems and National Technical University of Athens, Department of Electrical and Computer Engineering.

Yiouli Kritikou and Panagiotis Demestichas are with the University of Piraeus, Department of Technology Education and Digital Systems, Karaoli and Dimitriou 80 Str, Piraeus 18534 (Telephone number: +30 210 414 2749, +30 6944 518 685, e-mail address: kritikou@unipi.gr)

Evgenia Adamopoulou and Konstantinos Demestichas are with the National Technical University of Athens, Department of Electrical and Computer Engineering, Iroon Polytexneiou 9 Str. Zografou, Athens, 15780

depicted in Fig. 1.

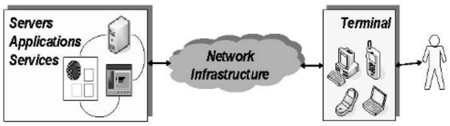

Fig. 1. Communication established between user and server

The communication between the terminal and the server would be impossible without the Network Infrastructure, for obvious reasons. The Network Infrastructure receives information from both the user and the server and ensures that this information will be distributed accordingly. Users usually request for a specific service or application. In this way, a simple form of communication between user and server takes place, in order to satisfy the users' requests. Of course, the things are not so easy and simple in the actual service or applications' requests, since current requirements for services are complicated and demanding.

The next section discusses on networks' infrastructure enhancement with cognitive features, in order to be able to manage effectively the knowledge it acquires on user's preferences and the context he is in and finally deliver to him the appropriate service.

III. Cognitive Network Infrastructures and Service Delivery

Current network infrastructures seem to become more and more complex, as the demand for more complex services increases. This means that networks are being developed with regard to supporting the delivery of services to users', e.g. e-services [10]. Yet, it is extremely difficult and time consuming for a user to learn how to use each e-service. Time and effort increase dramatically in case the user is not accustomed to using such services and equipment. In order to make networks appear simpler and thus more accessible and available for a bigger proportion of users, Cognitive Networks and Service Provision are proposed as a solution for this problem. Cognitive networks [9] aim at achieving external simplicity, while disguising the complexity of networks, optimizing overall network performance. Context – awareness is the ability to know the place the user is, what equipment he is using and the service he wants to access. Service provisioning has set its goals in predicting user's demand for e-services. This is achieved by acquiring telecommunications service from the submission of the requirement through the activation of service [10].

This creates the necessity for the development of Advanced Management Functionality, both on network's side and on application's side. In other words, it is essential to create cognitive mechanisms for managing network's decisions as far as its actions for the type of service to be delivered and the features incorporated in this service (technical features of the service) are concerned, as well as cognitive mechanisms for managing the decisions an application makes regarding the content to be delivered.

In support of this vision, the following section discusses on a part of Management Function applied to a Learning Management System and more specifically to the User Model.

IV. Learning Management System and Management Functionality for Cognitive Service Delivery

As mentioned in the previous section, e-services are developing at very high rates and are available through computer networks, which have become notably complex. Such e-services aim at replacing user's presence in a conventional environment, providing him the opportunity to complete certain tasks through a device, by simply accessing an application or platform. One such e-service is e-learning, which refers to computer-enhanced training [8].

As depicted in Fig. 2, an e-learning platform, or Learning Management System, comprises four main entities, each of which playing a separate, irreplaceable role for the platform's operation. More precisely, Domain Model stores the sections of each learning field and accordingly composes the learning material, as requested from the User Model and the application Server. The User Model keeps separate records for each user, regarding his interests, his preferences, his skills, the level of knowledge on the subject and his goals, according to the course he is about to "attend". Moreover, log files about the user's history, the learning path he follows each time he visits the platform and his general behavior during his navigation in the system, as well as data concerning the context, and more specifically the equipment/ device and the technology (wired or wireless connection) he usually uses to access the platform, are also elements stored in the User Model. Finally, the Learning Management System provides the user with a set of exercises and tests at the end of each lesson, along with evaluation and self evaluation tests at the end of each course, in order to verify and assess the acquired knowledge, which are managed by Exercises – Tests and Evaluation – Self Evaluation entities, respectively.

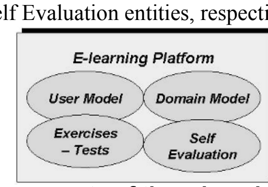

Fig. 2. Components of the e-learning platform

The User Model entity, being the one to store the user's general behavior and preferences information, affects to a great extent the information the system decides to provide him each time he inquires something. This means that, if well evaluated, the parameters kept in the User Model are able to configure the content to be delivered to him, adapted to each user's needs and expected outcomes. Another factor that should be taken into account is that the parameters mentioned previously change as the user enhances his knowledge, because of taking the offered courses of the platform.

Thus, considering these elements, we presume that in order to achieve correct content configuration and delivery, it is essential for the User Model to be enhanced with a certain point of cognition. This means that the User Model will have to be equipped with a mechanism able to collect information, plan, decide and finally act upon the collected information. Management Functionality has this role, aiming at aiding the Learning Management System make the correct decision on the content to be delivered to the user. This means that Management Functionality collects information on user's context and effectively decides on the content to be delivered to users.

Bayesian Networks provide a mechanism, which can support the probabilistic inference of user's preferences, by observing a certain set of parameters and thus provide the way to manage the information to be presented. This mechanism is thoroughly presented in the next section.

V. USER MODELING THROUGH LEARNING BAYESIAN NETWORKS

This section discusses on the prediction of user's preferences, using Bayesian Networks.

A. Bayesian Inference

In this section, we propose an approach to the problem of user preferences prediction based on a system that models user preferences and the causal relationships between them using Bayesian networks. Bayesian networks are directed acyclic graphs with network structures that encode conditional independence assertions about a set of variables [1]-[3].

Bayesian networks have proven to be valuable tools for encoding, learning and reasoning about probabilistic relationships, and once they have "learned" the correct structure and parameters, they may support probabilistic inference of the user's preferences [4]-[7].

B. User Preferences Modeling

Without loss of generality, let us assume that a user's profile is characterized by two parameters: (a) the content's preferred *level* of difficulty, and (b) the suitable type of *interface*. These are the model's target parameters, i.e. the parameters whose most probable values we are trying to approximate, in order to deduce the most probable user profile. Possible discrete values for these two parameters are, respectively: (a) "Low", "Medium", "High", and (b) "Type 1" (i.e., simple and plain), "Type 2" (i.e., simple but attractive), "Type 3" (i.e., complex but plain), "Type 4" (i.e., both complex and attractive).

In order to offer personalized learning experience, we consider that each user has his unique profile, his own needs and capabilities. Thus, our final goal is the determination of the most probable values of the parameters *level* and *interface* for a specific user. Fig. 3 is a representation of the corresponding probabilistic model.

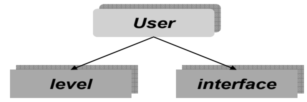

Fig. 3. Probabilistic model for the prediction of user preferences

In order to estimate the most probable values of these two variables, the determination of a set of estimation (predictive) parameters affecting these values is needed. For our case, we can consider two predictive parameters: (a) *time* needed to complete a lesson, and (b) the corresponding performance (i.e., *grade*). Possible discrete values for these two parameters are, respectively: (a) "Slow", "Medium", "Fast", and (b) "A", "B", "C".

The predictive parameters affect the target ones, in the way depicted in the model of Fig. 4.

As it is obvious, the value of the target parameter interface is determined only by the *time* needed to complete a learning unit, whereas the *level* is affected by both the *time* and the *grade* of the trainee.

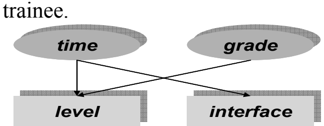

Fig. 4. Probabilistic model for learning and adaptation

For the remainder of this subsection we will use the notations depicted in Table I.

Table I. Parameters' Notation

Name	Symbol
Level	ℓ
Interface	i
Grade	G
Time	T
User	U

The goal is the computation of the maximum value of the joint conditional probability $P(\ell, i \mid U = U_j)$. In what follows we prove that the desired probability $P(\ell, i \mid U = U_j)$ is equivalent to the computation of the products of the conditional probabilities $P(\ell \mid U = U_j)$ and $P(i \mid U = U_j)$, i.e.:

$$P(\ell, i \mid U=U_j) = P(\ell \mid U=U_j) \cdot P(i \mid U=U_j) \quad (1)$$

Relation (1) means that the two predictive parameters, level and interface, can be decoupled. Two independent conditional probability tables (CPTs) can, consequently, be organized.

Table II shows a sample of the structure of a CPT for level.

Table II. Sample of the CPT for parameter *level*

Interface	U = U1	..	U = Un
i1 = "Type 1"	P(i=i1|U=U1)	..	P(i=i1|U=Un)
i2 = "Type 2"	P(i=i2|U=U1)	..	P(i=i2|U=Un)
i3 = "Type 3"	P(i=i3|U=U1)	..	P(i=i3|U=Un)
i4 = "Type 4"	P(i=i4|U=U1)	..	P(i=i4|U=Un)

The CPT for interface is similar.

The proof of relation (1) starts from the Bayesian chain rule formula, which suggests that:

$$P(\ell,i,U=U_j)=P(U=U_j)\cdot P(\ell|U=U_j)\cdot P(i|\ell,U=U_j) \quad (2)$$

Assuming that the value of interface is independent of the value of level, it can be deduced that:

$$P(\ell,i,U=U_j)=P(U=U_j)\cdot P(\ell|U=U_j)\cdot P(i|U=U_j) \quad (3)$$

According to the joint probability formula:

$$P(\ell,i,U=U_j)=P(U=U_j)\cdot P(i,\ell|U=U_j) \quad (4)$$

Hence, from (3) and (4), relation (1) is proved, thus the calculation of the desired conditional probability can be achieved by computing the product of two simple conditional probabilities.

C. Learning and Adaptation

In the previous subsection, focus was given on the problem of user preferences modeling. In order to construct a complete approach, we need to investigate how to achieve the learning and adaptation of the proposed model. This is the part where the estimation (predictive) parameters are involved. By monitoring their values, we can utilize them, in order to properly adjust and correct the probabilities of the target parameters. In this way, the system receives feedback about the user's profile through tracking the values of the predictive parameters, and thus gains knowledge which can, thereafter, be exploited for the provision of automatic personalized learning experience.

Based on the model of Fig. 4, it holds that:

$$P(\ell,i,T=T_m,G=G_n)=P(T=T_m,G=G_n)\cdot$$
$$P(\ell|T=T_m,G=G_n)\cdot P(i|\ell,T=T_m,G=G_n) \quad (5)$$

By considering that the probable values of level are independent from the probable values of interface, (5) becomes:

$$P(\ell,i,T=T_m,G=G_n)=P(T=T_m,G=G_n)\cdot$$
$$P(\ell|T=T_m,G=G_n)\cdot P(i|T=T_m,G=G_n) \quad (6)$$

In addition, it holds that:

$$P(\ell,i,T=T_m,G=G_n)=$$
$$P(T=T_m,G=G_n)\cdot P(\ell,i|T=T_m,G=G_n) \quad (7)$$

Thereby, from (6) and (7), and by applying the independency of the values of interface from the values of grade:

$$P(\ell,i|T=T_m,G=G_n)=$$
$$P(\ell|T=T_m,G=G_n)\cdot P(i|T=T_m) \quad (8)$$

The computation of the conditional probabilities $P(\ell|T=T_m,G=G_n)$ and $P(i|T=T_m)$ will be conducted through the use of suitable conditional probability tables (CPTs), the values of which are predefined, and based on statistical data and the opinions of learning experts.

From the computation of the maximum conditional joint probability $P(\ell,i|T=T_m,G=G_n)$ (relation (8)), the most probable values of level and interface are inferred. Let us denote as (ℓ_u,i_v) the most probable values of the couple (level, interface). Consequently, the corresponding probabilities $P(\ell=\ell_u|U=U_j)$ and $P(i=i_v|U=U_j)$ should be reinforced appropriately, in order to accomplish the system's adaptation.

D. Results

In this scenario, we will examine the model's behavior in a random situation, using a more realistic example. We take as a fact that w_{hist} and $w_{instant}$ reflect the weights attributed to the historical estimation and the current instantaneous estimation, respectively. In this scenario the value of the ratio $w_{hist}/w_{instant}$ has been set equal to 1.

The causal relationships between the parameters under consideration in this scenario are as follows (Fig. 5):

- Content Difficulty dependencies: This parameter depends directly on the values of all evaluation parameters. The actual lesson duration, the test duration and the user's performance dictate the difficulty level of the content that should be provided in the next lesson to the user.
- Content Volume dependencies: The volume of the content that should be provided in the next lesson to the user is affected by the time needed to complete both the previous lesson and the corresponding test. The Content Volume's dependency on the performance can be considered negligible, since large content volume does not necessarily suggest great difficulty.
- Interactivity dependencies: It is assumed that the degree of the required interactivity is determined solely by the user's past performance. More specifically, if a user achieves low performance, it is quite probable that he needs further guidance, thus more interactivity, through the lesson.
- Lesson Interface dependencies: It is realistic to assume that the only indicator affecting the type of interface needed throughout a lesson is the amount of time that the user has spent in the previous lesson.

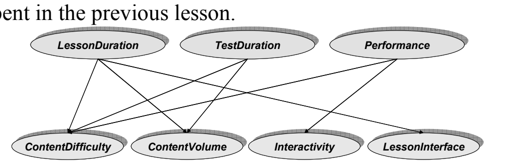

Fig. 5: Bayesian network employed by the Modeling and Evaluation Layer

The notations depicted in Table III will be used for estimating the desired probabilities.

Table III: Parameter Notations

Parameter	Notation
LessonDuration	LD
TestDuration	TD
Performance	R
ContentDifficulty	CD
ContentVolume	CV
Interactivity	I
LessonInterface	LI

Initially (step 0), as depicted in Fig. 6(b), all the possible values of each target parameter are considered equally probable (uniform distribution). Hence, a lesson with random content difficulty, content volume, interactivity and interface is generated and delivered at this step. At the end of this lesson, the model's monitoring mechanism reports the following evidence: Lesson Duration = Medium, Test Duration = High, Performance = C. This set of evidence serves as input for the formation of the next lesson, i.e. the lesson of step 1, as depicted in Fig. 6(a). At the beginning of step 1, the aforementioned evidence is utilized in order to produce a set of instantaneous probability estimations concerning the target parameters. This is carried out with the use of equation:

$$P(CD, CV, I, LI \mid LD, TD, R) = P(CD \mid LD, TD, R) \cdot P(CV \mid LD, TD) \cdot P(I \mid R) \cdot P(LI \mid LD),$$

making use of the Bayesian Model, as thoroughly described in Section V, after setting LD=Medium, TD=High and R=C. Subsequently, the instantaneous estimations of this step (step 1), in conjunction with the adapted probability estimations of the previous step (step 0), are utilized for the computation of the adapted probability estimations (Fig. 6(c)) of the current step (step 1). Based on the adapted probability estimations, we come to the conclusion that, at step 1, Low is the most probable value for Content Difficulty, Medium for Content Volume, High for Interactivity, and Rich for Lesson Interface. Thus, the lesson of step 1 should comply with these suggestions, in order to best fit the user's preferences. The same method is followed for inferring the most probable values of the target parameters throughout the rest of the steps.

Based on the results of Fig. 6(c), we construct the diagrams of Fig. 7. As may be observed from the curves of Fig. 7, the adapted estimations smooth out the sharp fluctuations of the instantaneous estimations, which is the desired behavior. Indeed, they tend to moderate the fast oscillations of the instantaneous estimations, by adapting to the evidence at a slower pace. This has the clear advantage of exploiting not only the most recent evidential data, but also knowledge about the past.

Step	Evidence		
	LessonDuration	TestDuration	Performance
0	-	-	-
1	Medium	High	C
2	Medium	Medium	B
3	Low	Low	A
4	Low	Low	A
5	VeryHigh	VeryHigh	D
6	Medium	Low	A

(a)

Step	Instantaneous Estimations												
	ContentDifficulty			ContentVolume			Interactivity			LessonInterface			
	Low	Medium	High	Low	Medium	High	Low	Medium	High	Simple	Normal	Rich	Advanced
0	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.25	0.25	0.25	0.25
1	0.5	0.3	0.2	0.35	0.5	0.15	0.2	0.3	0.5	0.1	0.3	0.35	0.25
2	0.3	0.3	0.4	0.15	0.45	0.4	0.5	0.3	0.2	0.1	0.3	0.35	0.25
3	0.1	0.2	0.7	0.1	0.2	0.7	0.6	0.3	0.1	0.1	0.25	0.3	0.35
4	0.1	0.2	0.7	0.1	0.2	0.7	0.6	0.3	0.1	0.1	0.25	0.3	0.35
5	0.7	0.25	0.05	0.75	0.2	0.05	0.1	0.2	0.7	0.45	0.35	0.15	0.05
6	0.2	0.2	0.6	0.15	0.25	0.6	0.6	0.3	0.1	0.1	0.3	0.35	0.25

(b)

Step	Adapted Estimations												
	ContentDifficulty			ContentVolume			Interactivity			LessonInterface			
	Low	Medium	High	Low	Medium	High	Low	Medium	High	Simple	Normal	Rich	Advanced
0	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.25	0.25	0.25	0.25
1	0.40	0.33	0.27	0.36	0.40	0.24	0.27	0.33	0.40	0.17	0.28	0.29	0.26
2	0.35	0.33	0.32	0.25	0.44	0.31	0.36	0.34	0.30	0.14	0.29	0.32	0.26
3	0.25	0.30	0.45	0.20	0.36	0.44	0.44	0.34	0.21	0.12	0.27	0.31	0.30
4	0.19	0.27	0.55	0.17	0.30	0.54	0.51	0.34	0.16	0.11	0.26	0.31	0.32
5	0.33	0.32	0.35	0.31	0.31	0.37	0.36	0.33	0.31	0.23	0.33	0.24	0.20
6	0.28	0.27	0.45	0.24	0.30	0.46	0.45	0.34	0.21	0.16	0.32	0.29	0.23

(c)

Fig. 6: Scenario 1: (a) Evidence; (b) Instantaneous Estimations; and (c) Adapted Estimations

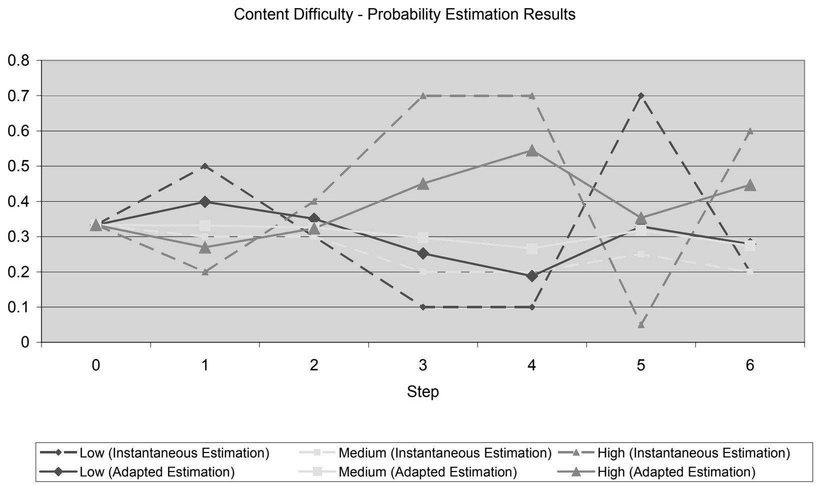

Fig. 7: Scenario 1: Estimation results for the *Content Difficulty*

As an indicative example of this behavior, let us observe the estimation results for the Content Difficulty parameter, at steps 4 and 5. At step 4, we may observe that the adapted estimation indicates High as the most probable value. However, at step 5, a radical change is detected at the evidential data. According to the instantaneous estimations, Low is by far the most probable value at step 5. However, the adapted estimation takes into account the historical knowledge, by moderating this oscillation, and suggests again High as the most probable value; this time, of course, the probability of value High has significantly been decreased. This gradual adaptation to the evidence allows the system to avoid temporary and impulsive oscillations.

VI. Summary, Conclusions and Future Work

As already noted, nowadays the demand for services through computer networks has increased remarkably, as e-services are gaining constantly ground in the field of telecommunications. Consequently, users are getting more demanding regarding the services offered to them. On the other hand, we will also have to take into account users that are not so accustomed to using computer devices and thus need simple and practical services to be delivered to them. For these reasons we have introduced cognitive networks, which aim at making the part that users interact with more comprehensible and easy, hiding from them network's complexity. Along with this, it is necessary for the service to be able to manage information provided by users and provide the system with the cognition of the way it will have to be configured so as to meet users' needs. For the validation of this vision we presented Bayesian Networks and the way they can manage and effectively predict the values of certain parameters of the User Model in a Learning Management System, in order to predict users' future preferences and thus develop the content. This was also certified by a simple but realistic scenario we presented in brief. Such prediction shall be done in every aspect of e-services, in order to achieve the management of a more advanced service delivery, which will most likely lead to a more massive e-services usage.

References

[1] J. Pearl, Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference, Morgan Kauffman, 1988.

[2] V. Terziyan, "A Bayesian Metanetwork", International Journal on Artificial Intelligence Tools, vol. 14, 2004.

[3] D. Heckerman, "A Tutorial on Learning with Bayesian Networks", Technical Report MSR-TR-95-06, Microsoft Research, March 1995.

[4] E. Homayounvala, S. A. Ghorashi, A. H. Aghvami, "A Bayesian approach to modelling user preferences for reconfiguration", in: E2R Workshop on Reconfigurable Mobile Systems and Networks Beyond 3G, Barcelona, Spain, September 2004.

[5] J. Cheng, R. Greiner, "Learning Bayesian belief network classifiers: algorithms and system", Proc. 14th Canadian Conference on Artificial Intelligence, pp. 141-151, 2001.

[6] E. Adamopoulou, K. Demestichas, A. Koutsorodi, and M. E. Theologou, "Access Selection and User Profiling in Reconfigurable Terminals", in Proc. of the 15th Wireless World Research Forum (WWRF), Paris, Dec. 2005.

[7] J. Cheng and R. Greiner, "Learning Bayesian belief network classifiers: algorithms and system", in roc. of the 14th Canadian Conference on Artificial Intelligence, pp. 141-151, 2001.

[8] http://en.wikipedia.org/wiki/E-learning

[9] D. Boscovic, Cognitive Networks, http://www.motorola.com/mot/doc/6/6005_MotDoc.pdf

[10] http://en.wikipedia.org/wiki/Main_Page