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USER PROFILING AND PREFERENCE MODELLING IN 4G TERMINALS

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Abstract
This paper discusses the problem of user preference modelling in the context of next generation terminals operating in heterogeneous environments. It includes an approach to the definition, mathematical formulation and solution of this problem. Indicative results of the proposed solution method are presented in the framework of a real-life scenario, which simulates a day in the life of an ordinary user.

I. INTRODUCTION

The next generation of mobile systems is expected to comprise heterogeneous networks consisting of diverse radio segments and hosting multimode terminals, capable of alternatively operating in the diverse radio segments available in the infrastructure. The different radio segments or access technologies (e.g. WLANs, cellular and broadcast networks) will thus constitute cooperating components of a composite radio infrastructure and will be interconnected by a backbone (e.g. an IP-based fixed network) and jointly operated in an optimized fashion [1][2]. This trend, often referred to as 'systems beyond 3G' or '4G', continues to attract notable research attention [3][4].

A central issue related to the above is the design of suitable management frameworks, both for the terminal and for the network, which will allow for seamless service provision. Another important aspect is the fact that the user will need to control the usage of the available networks, especially when this usage comes with a price. This involves a potentially complex decision-making process, which may be with support both from the user devices and the networks, thus giving rise to the cardinal issue of optimally distributing intelligence between the network and the mobile terminal in order to support seamless service provisioning [5][6].

Another challenge emerging communication systems are faced with involves the ability to trace and exploit a broad collection of data that characterize the so-called usage context. By context, we refer to any information related to user tasks and experience that being available to the system for further processing can assist it in fulfilling its goals [7][8]. User mobility creates situations where the user's context is highly dynamic and changes frequently. This implies that 4G middleware platforms must also provide a way for services and terminal settings to adapt appropriately to this ever-changing environment [9][10].

Hence, the goal in developing suitable middleware platforms for 4G systems proves to be twofold: not only does it lie in the seamless integration and the joint utilization of all available technologies, but also in the exploitation of a variety of contextual data for the development of personalized services. Accordingly, in the context of effectively managing wireless terminal operation in composite radio environments, two problems are identified: *Intelligent Access Selection* (IAS), which involves the computation of optimal allocations of services to access networks and to quality levels, given network availability and user preferences, and *Modelling an Adaptation to User Preferences* (MAUP), which involves, firstly, the processing and the 'decoding' of contextual information for the purpose of determining the usage context, and, secondly, the automatic determination of the user's preferences, according to the usage context and the set of services under consideration. We argue that appropriate functionality for handling the IAS and the MAUP problems must be incorporated in a middleware platform at the mobile terminal.

In [11] a terminal management architecture for handling both problems is discussed, and the formal definition and a possible solution to the IAS problem are given. In this paper we address the MAUP problem. This work can be the basis for further research in the area of preference modelling and dynamic user profiling.

This paper is structured as follows: Section II provides the high-level and formal description of the MAUP problem, Section III discusses a possible solution approach and Section IV discusses implementation issues and indicative results of the proposed solution. Finally, Section V concludes the paper.

II. PROBLEM DESCRIPTION

In the following subsections the MAUP problem is defined in a high-level and in a formal manner.

A. High-level description

We argue that next generation terminal management platforms should incorporate a system responsible for providing appropriate prioritization of the parameters that may influence the (terminal-controlled) access network selection process. This prioritization is equivalent to the specification of values for the weights of parameters 'quality', preferred 'network operator', preferred 'technology type' and 'cost', namely w_q, w_o, w_t and w_c, respectively. These values represent the measure by which each of the abovementioned parameters is weighted in the access network selection algorithm that is adopted by the terminal. For example, if the user chooses to specify that, at a given moment, 'quality' is for him the most important factor in access network selection, 'technology type' comes second, 'cost' comes third and last comes 'network operator', then it will hold that $w_q > w_t > w_c > w_o$.

In this paper, we propose an approach to the MAUP problem based on a system that models user preferences and the causal relationships between them using Bayesian networks – directed acyclic graphs with network structures that encode conditional independence assertions about a set of variables

[12][13]. This function presupposes the development of appropriate mechanisms through which: (a) the usage context will be inferred, given contextual information (user location, time and date, user's communicating counterpart) and (b) the user preferences will be inferred, given usage context and service requests. These functions are depicted in Figure 1.

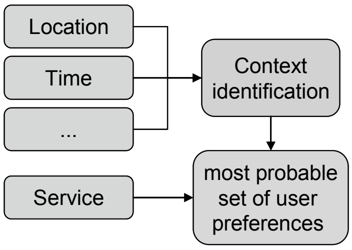

Figure 1. Profile handling at the mobile terminal

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 [14][15]. We propose the construction of a two-level Bayesian meta-network (based on an approach presented in [14]) (Figure 2), where the division of the MAUP problem in – initially – two separate stages is apparent: first, inference of usage context and, second, inference of user profile parameters. This structure assumes that probability distributions associated with nodes on the predictive level depend on probability distributions associated with nodes on the contextual level.

The Bayesian network of the second level (contextual level – Figure 2) consists of four nodes: one for the user's location, one for the time of day, one for the session's communicating counterpart, and one for the usage context. Each node represents a random variable. The values of random variables 'location' (L), 'time' (T) and 'communicating counterpart' (CP), the knowledge of the respective conditional probability distributions and the application of basic Bayesian inference rules lead to the determination of the most probable value for the random variable 'context' (C).

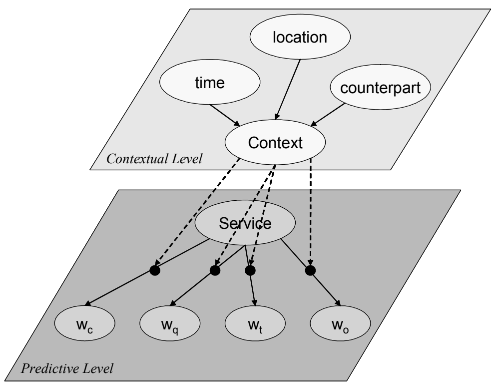

Figure 2. A Bayesian meta-network for modelling user preferences

The Bayesian network of the first level (predictive level – Figure 2) consists of five nodes: one for service (S) and four more, one for each of the coefficients w_q, w_o, w_t and w_c. The value of variable C, defined on the contextual level, influences the way in which the values of w_q, w_o, w_t, w_c depend on the value of variable S. Knowledge of the respective conditional probability distributions and the application of basic Bayesian inference rules leads to the determination of the most probable values of w_i.

The values of w_q, w_o, w_t and w_c that are computed following reasoning on the first level of the Bayesian meta-network, are used in turn for deciding on the optimal allocation of services to access points and to quality levels. The decision that is reached based on this input may or may not satisfy the user's needs, given the fact that his preferences were automatically defined, without his interference. Therefore, the ultimate goal is the training of the proposed network, in order to render it capable of accurately and independently predicting the user's preferences. This implies the development of an appropriate algorithm for the adjustment of the probability distributions used to determine the values of w_q, w_o, w_t and w_c.

This process involves the use of an appropriate training set, provided to the system by the user and comprising examples of his priorities in some situations. Our goal, therefore, is to extract knowledge about user preferences in *any* context, given his preferences in *some instances of* context, where he accepts or rejects some configurations of the w_i quadruplet, for given combinations of service and type of context. An underlying assumption we make, throughout our discussion of the MAUP problem, is the fact that the user's behaviour and preferences are not randomly decided upon, but rather comply with some implicit logic, which we are trying to approximate.

B. Formal description

1) Stage 1: inference of usage context

The goal is the computation of the conditional probability

$$P(C_i \mid T_j, L_k, CP_l),\ \forall i, j, k, l \in \square$$

and the determination of C_i (a state of random variable 'context') that corresponds to its maximum value. If we assume that variable T has n_{time} mutually exclusive and discrete states, variable L has $n_{loc.}$ and variable CP has $n_{c/p}$ discrete states, then a 4-dimensional table is required, where for every context state C_i the value of the aforementioned conditional probability will be given for every one of the $n_{time} \cdot n_{loc.} \cdot n_{c/p}$ possible combinations of the other variables.

2) Stage 2: inference of profile parameters

The goal is the computation of the joint conditional probability

$$P(w_q, w_c, w_t, w_o \mid S)$$

given S and C, and the determination of the values for w_q, w_o, w_t, w_c that correspond to its maximum value.

We make the assumption that:

$P(w_t \mid w_o, S = S_i) = P(w_t \mid S = S_i)$,

$P(w_c \mid w_t, w_o, S = S_i) = P(w_c \mid S = S_i)$ and

$P(w_q \mid w_c, w_t, w_o, S = S_i) = P(w_q \mid S = S_i)$, that is, we assume that the probability of every one of the user's preferences obtaining a specific value is independent of his other preferences and depends solely on the service. Hence:

$$P(w_q, w_c, w_t, w_o \mid S = S_i) =$$
$$P(w_o \mid S = S_i) \cdot P(w_t \mid S = S_i) \cdot$$
$$P(w_c \mid S = S_i) \cdot P(w_q \mid S = S_i)$$

and the computation of $P(w_q, w_c, w_t, w_o \mid S)$ reduces to the computation of the product of partial conditional probabilities, which result from tables (Conditional Probability Tables – CPTs) of the following format (Table 1):

Table 1. CPT for variable w_i

	$S = S_1$	…	$S = S_n$
$w_i = a$	$P(w_i = a \mid S = S_1)$	…	$P(w_i = a \mid S = S_n)$
$w_i = b$	$P(w_i = b \mid S = S_1)$	…	$P(w_i = b \mid S = S_n)$
…	…	…	…

for $i = q, c, t, o$ and for every context state C_i.

3) Stage 3: learning and adaptation

The ultimate goal is the training of the proposed network and the proper adjustment of the values of the abovementioned CPTs. This may be done following the guidance of a training set, which the user has provided to the system.

In general, learning Bayesian networks (BNs) from data involves two aspects: learning network structure and learning network parameters. Here, we make a reasonable assumption about the structure of the Bayesian network that best describes our model, and seek efficient algorithms for learning the network's parameters (values of CPTs). The training of the Bayesian network may be achieved using a variety of different methods, such as linear regression [16][17], probabilistic neural networks [18][19] and probabilistic decision trees [20].

III. Problem solution

In this paper, we propose the construction of a probabilistic neural network that uses the training set as a reference for the appropriate adjustment of the values stored in the Bayesian network's CPTs. The probabilistic neural network (PNN) receives as input a new solution computed by the system: given $C = C_i$ and $S = S_j$ and for $w_q = a_1$, $w_o = a_2$, $w_t = a_3$, $w_c = a_4$ designated by the Bayesian network, it performs the following tasks:

- It assesses the similarity of the new instance ($C = C_i$, $S = S_j$, $w_q = a_1$, $w_o = a_2$, $w_t = a_3$, $w_c = a_4$) to the patterns stored in the training set (pattern layer neurons).
- It produces a probability vector, comprising classification probabilities to each class: $k_1 = '\mathit{accept}'$, $k_2 = '\mathit{reject}'$ (summation layer neurons).
- It selects the maximum of these probabilities, using the Bayes-optimal decision rule (output layer neuron).

The architecture of the employed PNN is drawn in Figure 3.

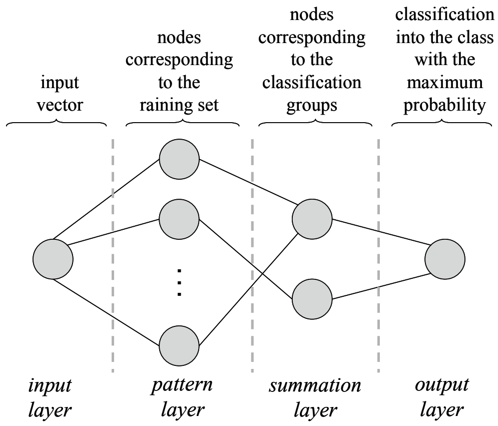

Figure 3. Probabilistic neural network architecture

The PNN's output is subsequently used for the reinforcement or the diminishment of the conditional probabilities $P(w_i \mid S)_C$ in the corresponding CPTs, in the case of classification of the system's decision into class k_1 or k_2 respectively. This correction of the $P(w_i \mid S)_C$ values is realized by applying Bayes' theorem, which allows the expression of the posterior probability of variable w_i given the newly performed classification, using prior probability $P(w_i \mid S)_C$ and the probability of performing this classification given the value of w_i (class-conditional probability):

$$P((w_i \mid S)_C \mid k_j) = \frac{P(k_j \mid (w_i \mid S)_C) \cdot P(w_i \mid S)_C}{P(k_j)}$$

where

$$P(k_j) = P(k_j \mid (w_i \mid S)_C) \cdot P(w_i \mid S)_C +$$
$$+P(k_j \mid \neg(w_i \mid S)_C) \cdot P(\neg(w_i \mid S)_C)$$

is a normalizing factor, which can be computed by requiring that $P((w_i \mid S)_C \mid k_j)$ and $P(\neg(w_i \mid S)_C \mid k_j)$ sum to unity.

IV. Implementation

The approach to the MAUP problem discussed in this paper has been implemented as a Java-based middleware platform. In the scenario presented here, we simulate a typical day in the life of an ordinary user X. This user commutes from his home to work, and uses a multimode 4G terminal which is capable of performing optimal access network selection, given network availability, service requirements and user preferences.

We consider two usage contexts (business and leisure) and three services (voice call, video streaming and web browsing). A high-level description of X's preferences is given in Table 2.

Table 2. User preferences (implicit)

General Preferences	***Leisure context*** cost > quality	***Business context*** quality > cost
Voice Call	–	–
Video Streaming	technology > operator	operator > technology
Web Browsing	technology > operator	operator > technology

The user has specified 'Oper#1' as his preferred operator and WLAN as his preferred technology for video streaming and voice call. The lowest available quality level for each of these services is level '1', while the highest one is level '5'. Finally, ' > ' denotes 'more important than'. On the basis of these preferences, the user provides the following 'accept' or 'reject' answers to several configurations of w_q, w_o, w_t, w_c, for each service and type of context (Table 3).

Table 3. User's answers to randomly selected questions

Context	Service	Accept				Reject			
		Q	*C*	*O*	*T*	*Q*	*C*	*O*	*T*
Leisure	*Voice call*	4	1	3	2	1	4	2	3
	Video str.	4	1	2	3	2	4	1	3
	Web brows.	4	2	3	1	1	3	4	2
Business	*Voice call*	1	4	2	3	4	1	2	3
	Video str.	2	4	1	3	3	1	4	2
	Web brows.	3	4	1	2	4	1	2	3

Thus, the user answers one pair of questions for each available service. The first question (configuration) of each pair is randomly generated, while the second one is appropriately selected so as to significantly differ from the first one. We also note that 'Q' stands for quality, 'C' for cost, 'O' for network operator and 'T' for technology, and that coefficients w_q, w_o, w_t and w_c are assigned values 0.8, 0.6, 0.4 and 0.2, according to their prioritization as first, second, third and fourth.

These answers constitute the training set, based on which the system is trained to accurately and independently predict the user's preferences. It should be noted that we assume X to be an average user, without any specific knowledge of the factors he is trying to prioritize. Thus, it is possible that X answers a question incorrectly (with respect to the underlying preferences initially considered), or gives contradictory answers. The system tries to smooth out these contradictions and determine what the user actually has in mind, and is still able to predict his preferences, even if he accepts or rejects both of the proposed configurations, or even if he provides answers for less than two questions per service and per context.

Table 4. Network coverage in scenario

	Available APs		Signal	Av. BW (Kbps)
	Tech.	Oper.		
at home	GSM	#2	5	44
	UMTS	#3	4	900
	WLAN	#3	3	2000
at work	GSM	#2	5	44
	UMTS	#1	5	800
	WLAN	#5	4	1000
	DVB	#4	4	2000

In the following, every step of the scenario, along with the corresponding allocations of services to networks and quality levels, are described in more detail. Moreover, in the third step of the scenario, the proposed solution to the MAUP problem is compared to a solution based on a simple rule-based system, which encodes user preferences in different contexts as rules. Table 4 illustrates network coverage in each scenario step. For every available access point, its access technology, network operator, signal strength and available bandwidth are indicated.

(a) Morning, at home

As user X prepares to leave for work, he initiates a web browsing service and visits a sport news web site.

Table 5. Allocation selected in phase 0

Service	Context	Prioritization				Allocation	
		Q	*C*	*O*	*T*	*Tech.*	*QoS*
Web browsing	Leisure	4	2	3	1	WLAN	1

At first, the usage context is determined. Based on current location (home), time (morning) and communicating counterpart (sports web page), context is defined as 'leisure'. Then, the system successfully predicts X's preferences for the specified context and service. 'Cost' is deemed more important than 'quality', and 'technology' more important than 'operator'. Thus, the WLAN access point is selected, in combination with the lowest quality level, as this is the most cost-effective solution. This decision is also reinforced by the fact that WLAN is the preferred technology type.

(b) Noon, at work

While at work, X initiates a video streaming service, in order to have a video conference with his supervisor. After terminating this service, he makes a voice call to his wife, and also visits a music web site (web browsing).

Table 6. Allocations selected in phase (b)

Service	Context	Prioritization				Allocation	
		Q	*C*	*O*	*T*	*Tech.*	*QoS*
Video streaming	Business	2	4	1	3	DVB	5
Voice call	Leisure	4	1	3	2	WLAN	1
Web browsing	Leisure	4	2	3	1	WLAN	1

For video streaming, the DVB access point is selected, as it is able to provide the maximum quality level, due to its high available bandwidth. This access point is also characterized by a strong signal. On the other hand, voice call and web browsing are allocated to the WLAN access point and delivered at the minimum quality level, as their usage context use is defined as 'leisure'.

It should be noted at this point that the user's preferences where web browsing in leisure context is concerned, have already been determined in phase 0, and cached. The system's ability to cache already determined user preferences for a particular service and context further reduces the computational load.

(c) Evening, at home

When X returns home in the evening, he connects to the company's web site to download a financial report.

Table 7. Allocation selected in phase (c)

Service	Context	Prioritization				Allocation	
		Q	*C*	*O*	*T*	*Tech.*	*QoS*
Web browsing	Business	3	4	1	2	WLAN	5

Web browsing is allocated to the WLAN access point and to the maximum quality level, as its usage context is 'business'.

An interesting point involves the comparison of the proposed 'Bayesian' approach for determining user preferences with a simple rule-based system, which encodes user preferences in different contexts as rules. For this purpose, let us assume that the terminal's manufacturer has integrated the following rules into the terminal:

- When in 'leisure' context, let $w_c = 0.8$ and let all other factors be weighted equally, i.e. $w_q = w_o = w_t = 0.4$.
- When in 'business' context, let $w_q = 0.8$ and let all other factors be weighted equally, i.e. $w_c = w_o = w_t = 0.4$.

Simulating phase (b) of the scenario using the above-mentioned rules would result in the allocations given in Table 8. As can be observed, only the first allocation is the same compared to the 'Bayesian' approach. The other two are different, and apparently do not truly satisfy the user's preferences. Voice call is allocated to a GSM access point and to quality level 5, although a more cost-effective solution is appropriate. The same applies for the allocation of web browsing to a WLAN access point at quality level 3, as a lower quality level should have been chosen.

Table 8. Allocations of a rule-based system for phase (b)

Service	**Context**	**Allocation** *Tech.*	*QoS*
Video streaming	Business	DVB	5
Voice call	Leisure	GSM	5
Web browsing	Leisure	WLAN	3

In general, our approach to the MAUP problem is more 'sensitive' and effective than a simple rule-based solution, without entailing any severe computational load. Furthermore, the use of a rule-based system presents the following significant drawbacks:

- It is not as adaptable and extendible, and the user is not able to edit them according to his own needs and preferences. Even if the modification of these rules was permitted, it would be too complicated for an average user to successfully personalize this set of rules. On the other hand, the proposed 'Bayesian' system can easily be trained, requiring the user to just answer a few questions.
- A rule-based approach cannot entirely satisfy the needs of a non-average user. For example, a user should be able to define more than two different context types. What is more, a complex personal profile would require a very complicated set of rules. In contrast, all these requirements can be easily handled by the proposed system.
- A contradictory or false rule would result in allocations that do not correspond to the user's true preferences. In contrast, the proposed approach attempts to smooth out contradictory answers, in order to optimize the allocation decisions.

V. Conclusions and Future Work

This paper identified and elaborated on the problem of user profiling and preference modelling, in the domain of wireless terminal operation within 4G. This problem was defined, mathematically formulated and solved. Implementation issues were also discussed. Results were presented, in the context of a real-life scenario. These results were compared to an alternative approach to the MAUP problem, involving the use of a simple rule-based system that emulates a user's reasoning where his preferences are concerned.

Directions for extending our work can be the following: (a) the expansion of profile features taken into account, and (b) the development of an efficient algorithm for learning the structure of the Bayesian network used for modelling user preferences, when no initial assumption about variable independence is made.

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