Predicting Network Availability Using User Context

Upendra Rathnayake †,*
†School of Electrical Engineering & Telecom's
The University of New South Wales
Sydney, NSW 2052, Australia
Upendra.Rathnayake@nicta.com.au

Max Ott *
*NICTA
Bay 15, Australian Technology Park
Eveleigh, NSW 1430, Australia
Max.Ott@nicta.com.au

ABSTRACT

Most mobile devices nowadays can simultaneously connect to different access networks with different characteristics at different times. Most solutions proposed for such an environment are reactive in nature. For example, when networks are encountered, the device performs a vertical handover to the network that offers the highest bandwidth. But the cost of handover may not be justified if that network is only available for a short time. Knowledge of future network availability and its capabilities would help to proactively handle the handover process more intelligently. Network availability prediction is often addressed as user path predictions with network coverage maps. In contrast, we model it as a more robust context prediction problem that can use any of the available context variables like GSM cell ID, WLAN AP, whether the power cable plugged, number of people around etc.

Specifically, we propose a Semi-Markovian context prediction model to predict WLAN availability. As collecting and processing context consumes power, we propose a method to rank each context variable according to their contributions to prediction accuracy. We also employ the same method for optimizing model parameters. Real user data collected in our experiments show that when WLAN status is static, prediction errors are nearly zero and even in changing environments, error is less than 26% on average and the obtained context variable ranking is realistic.

Keywords

Network Availability Prediction, Context Prediction, Semi Markov Model

1. INTRODUCTION

There are number of access possibilities for a wireless user nowadays, starting from low bit rate 2G GSM and GPRS networks to high bit rate 3G networks as well as wireless LANs with many tens of Mbps. The coverage area of each network type also varies, typically bit rate limited networks covering larger areas and high bandwidth networks covering small patches (Hot Spots).

Today's mobile devices are increasingly containing multiple radios which allow them to connect simultaneously to different access networks. Due to change of the environment of the mobile, it encounters different networks with different capabilities. Some networks may appear all the time whereas some (e.g. WLAN) do so only for shorter periods. When networks appear and disappear, the general criterion is to perform vertical handovers from high to low bandwidth networks if loosing the high bandwidth connectivity or low to high if encountering such good networks. But the availability of high bandwidth networks may be too short such that after or within the handover, the coverage just fades away. In other cases where the hand over is from a high to a low bandwidth network upon week signal strength, when the process is nearly done the high bandwidth network may reappear. In many of these cases, the vertical handover decision can be greatly aided by the knowledge of future availability of networks. And not just for handovers; if it is unlikely that a specific network will be encountered in the near future, power can be saved by simply switching off the respective interface [1].

Let us take a simple scenario of a daily commuter traveling on a train where his Smart Phone encounters WLAN APs only near stations and 3G otherwise. Also let us assume that he is having a VoIP call while the email client is accessing the server periodically to download new emails. Presence of WLAN lasts only for short periods when the train doesn't stop at stations and handovers for VoIP should be avoided in such cases although WLAN appears suddenly. On the contrary, the email client just periodically accesses the server and such accesses can be synchronized with WLAN presence at stopping stations (and probably at non stopping ones as well, with data transfer resuming facilities) as the application can wait without noticeable performance degradation to the user.

Although there are number of proposals in terms of domain specific mobility models coupled with network maps and domain unspecific mobility models, modeling in terms of context without any domain knowledge to predict availability with respect to time has not received considerable attention. This paper primarily addresses that problem and our contributions are as follows.

- We model availability prediction as a robust, context sensor agnostic prediction problem which uses any available context information like GSM cell IDs, Wi-Fi AP presence, whether LAN is connected, whether

∗ NICTA is funded through the Australian Government's Backing Australia's Ability initiative, in part through the Australian Research Council.

MobiQuitous 2008, July 21-25, 2008, Dublin, Ireland.

Digital Object Identifier: 10.4108/ICST.MOBIQUITOUS2008.3563
http://dx.doi.org/10.4108/ICST.MOBIQUITOUS2008.3563

power cable plugged, number of Bluetooth devices around etc.

- We present a method to rank all context variables according to their contributions to predictions so that the unimportant variables can be removed to save power and processing without much (or at least known) effect on the quality of the predictions.
- We show from real user data collected in our experiments that the prediction errors are nearly zero when availability is static and even in dynamic situations (transit times) the difference between actual and predicted probabilities go up only to 26% on average. Further, the ranking of context variables are justified by prediction results and the same method is found to be useful in optimizing model parameters.

Also the QoS of the same network may change at different times depending on several factors like how many people accessing. Although we limit our work only to predicting presence of networks in this paper, the same methods would readily be extended for predicting not only presence, but quality parameters like available bandwidth etc. as well.

We present related work in section 2 and in section 3, we discuss modeling contextual information for predictions and propose a Semi-Markovian approach. Section 4 presents experimental and evaluation details with results followed by the conclusion and future work in section 5.

2. RELATED WORK

Predicting in mobile communications research is not new. But our approach is different in the sense that it uses any available context information to predict network availability with respect to time in a heterogeneous environment without using any domain specific knowledge and gradually learns important variables so as to remove irrelevant ones saving processing and power. In [1] for power saving aspects, they tried with recording the GSM cell ID and whether a WLAN was available for every 5 minutes. The ratio of number of times it was available over number of times recorded in a particular cell gives how probable to encounter a WLAN network in that GSM cell. But it lacks in that it does not give any indication of how probable the user would be under WLAN coverage within a finite duration of time ahead. Similar approaches with domain independent mobility models can be found in literature as surveyed in [10]. In [5] they evaluated such location predictors with extensive Wi-Fi data collected in a campus environment and found simple low order Markov predictors working as well or better than the more complex compression-based predictors, and better than high-order Markov predictors. But such proposals are mostly in a single network environment and do not give any indication of availability in a time frame ahead.

The network availability prediction can be treated as an embedded task in user mobility predictions as in [2], where mobility prediction is used for resource scheduling purposes with availability of (Bluetooth) connectivity being a known priory. Like wise, a lot of domain specific user path prediction approaches like [4], [12], [13], [14] can be coupled with network coverage maps or more sophisticated QoS maps as in [6] to find availability of networks in future. But these models are designed with assumptions like constant user speed, fixed cell size and shape etc which may not necessarily be the case in reality.

[11] contrasts between two approaches for high level context prediction, as a high level context formation first and then prediction, to a low level context prediction and forming high level context from predicted low level ones. Their context prediction approach based on local alignment methods is said to incorporate a constant learning mechanism and be able to predict an arbitrary number of future contexts. A context prediction architecture is proposed in [3] for knowing user activities in future, as a stepwise process of feature extraction, classification, labeling and prediction. The latter has been accomplished with a Markov predictor and states they seem to be generally suited well. [9] Discusses various usages of context predictions and further suggests an architectural solution for prediction. All these context prediction endeavors concentrate on higher level contexts like user activities, situations etc, and are different from our approach where we use it for network availability prediction that is something we can sense in future time and can be used to revalidate the predictors.

3. MODELING

Availability of a particular kind of network type (e.g. WLAN) primarily depends on where the user will be and what the networks covering that location are. The exact user location is hardly observable (e.g. GPS is generally not available indoors where the users spend most of their time – in office, home, traveling etc). But by using factors like GSM cell ID, LAC, WLAN AP name and their signal strengths, probably coupled with GPS, we can get a better hint about where he is. Even if we observe the location as above, it is not sufficient to predict what networks he will have as the future availability depends on the behavior of the user as well. For example, due to bad weather the user may decide to go home early, or he is having a lengthy call and staying in the office for some more time. This means that there is other information like his acceleration, the applications running in the mobile, temperature etc which may hint about the behavior of the user [7], [8] and may be beneficial in predictions. So we can think of this entire situation as a multivariate probability distribution with lots of complex interdependencies among them. The picture below shows this graphically.

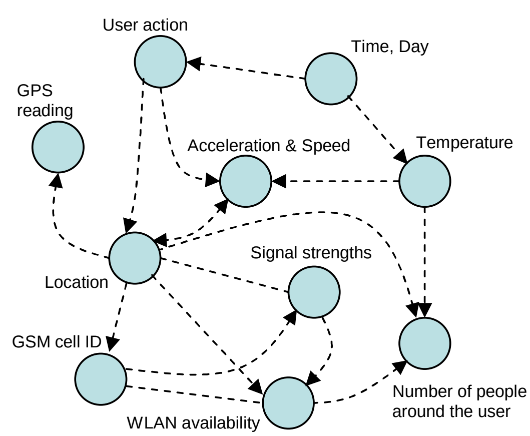

Figure 1. : Interdependencies between variables.

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We can think that the behaviors of all the variables are dependent on each other; although we cannot observe exactly what they are (their interaction may be according to the directions of arrows for example). This forms a Markov Random Field. So the system of all the variables (not all shown here) evolves with time and we can observe some of these variables. What we want to know is the availability of a network type, say WLAN at a future time (i.e. to know the value of a particular random variable in future).

Imagine the system is sampled for every "m" seconds. Let us assign a random variable for each factor at each sampling time point as below (only 4 factors considered for demonstration).

Time (in units of m sec)	*1*	*2*	*3*	…	*t*
WLAN Availability	x_1	x_2	x_3	…	x_t
GSM Cell ID	a_1	a_2	a_3	…	a_t
GPS	b_1	b_2	b_3	…	b_t
Acceleration	c_1	c_2	c_3	…	c_t

Here t is the current time. What we want to know is WLAN availability at time $t+1$. Let us represent that variable with x_{t+1}. The best estimate we can get for the probability of x_{t+1} is $P(x_{t+1} \mid XABC)$ where X represents all variables x_i, A for a_i and so on and $i \in (1,2...t)$.

Our effort is to get this best estimate accurately with less computational complexity. In general, we know people have regularities in day to day activities, for example the daily commute of an office worker. He comes from home to the office and goes back in the evening (regular places and times). He may even browse a particular news web site on the way back (regular activities). He takes the same train everyday (regular paths). We can think of the above system pertaining to the described user transferring from one set of realizations of variables to another set and repeating this transfer daily (over some time period). If we have a trace of the system for few weeks, these patterns can be learnt and would be able to predict future values of each variable.

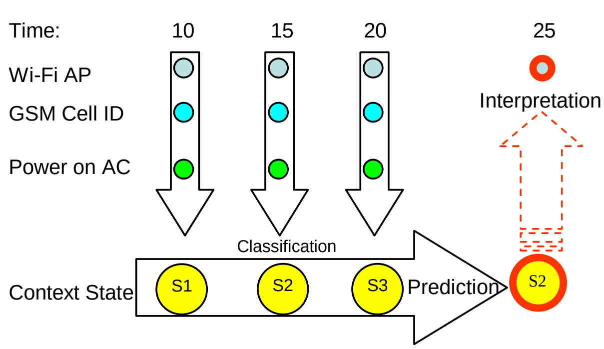

Figure 2. : Context prediction approach.

We can right away think that numerical methods like auto regressive moving average can be used here, but lots of variables being symbols; it puts forward the question as to how to meaningfully convert them to numbers. Alternately as in [3], we can follow a context state prediction approach with an additional interpretation step as in figure 2.

The idea is to classify all the variables at a time and derive a "context state" for each sampling time point. Then the history of the system would show how states transferred over the time and such patterns can be learnt as transition probabilities from state to state. Then, the required value has to be interpreted from the predicted state.

Markov Modeling (of order n) is a good candidate for state predictions. If we had identified the number of context states, we would have learnt the transition matrix which gives how probable it is to transfer from one state to another in the next sampling point. One major disadvantage of the Markov model is its inherent geometric state stay time distribution. If the probability of transferring from one state to itself is p, the probability that the state would last for u sampling intervals is p^{u-1} which may not necessarily be the actual distribution. Further, our sampling period (30 seconds) is very short compared to stay times of some states (for example, at night, the same state would last for hours as the surrounding situation is rather static). In such cases, the order of the model has to be increased so that it takes many more past states to capture "real" state transfers, as otherwise the transition probabilities would be overwhelmed by transfers from one state to itself. But with the order of the model, computational complexity increases exponentially. That means in order n Markov model having states with k realizations, the computations are in the order of k^n.

Semi-Markov gives the answer for above. It still models the process as a Markov process but state stay times can be decoupled and separately modeled. For example, a simple average of stay times would give the expected duration in that state. By this way, the order of the model can be maintained within manageable limits while capturing real state transfers and the underling process can be decoupled from the absolute sampling time and separately learnt. This is a very good interpretation for our system as the behavior of a user can be thought of as a sequence of activities (or states) and the start time of the sequence can vary (he may come from home in the morning at 7:00, 7:30 etc). On top of that, the stay times can also vary but still the sequence happens daily, to say, coming from home, then to the train station and taking a train, then to the office, back to the station in the evening and returning home. Semi-Markov's power is to capture this sequence irrespective of stay times of states and absolute start time of the sequence. The n^{th} order Semi-Markov (where a state cannot transfer to itself, but only to a different one) can be expressed mathematically as below.

$$P(S_{v+1} \mid S_v, S_{v-1}....) = P(S_{v+1} \mid S_v,....S_{v-(n-1)}) \qquad (1)$$

Here S_v is the current state. The next state S_{v+1} given all the previous states depends only on previous "n" states. We used this model in our analysis with n = 0 and n = 1.

Digital Object Identifier: 10.4108/ICST.MOBIQUITOUS2008.3563
http://dx.doi.org/10.4108/ICST.MOBIQUITOUS2008.3563

Coming back to our best estimate described in the beginning, it now becomes $P(x_{v+1} \mid XABC)$, and in the same way all X, A, B and C represents random variables in each state (not at each sampling point). Now let us take the case where we have the history of only X, B and C. In that situation we would get the best estimate as $P(x_{v+1} \mid XBC)$. According to Bays theorem, these two probabilities are related as follows.

$$P(x_{v+1} \mid XBC) = \frac{P(A \mid XBC)}{P(A \mid XBCx_{v+1})} * P(x_{v+1} \mid XABC) \quad \text{....(2)}$$

So the second estimate is deviated from the first estimate by a factor $P(A \mid XBC) / P(A \mid XBCx_{v+1})$. If the variables A are conditionally independent of x_{v+1} given X, B and C, both sides of the equation become the same. This tells us that, there is no harm to include all the variables to estimate x_{v+1}, but if we drop one which is conditionally dependant with x_{v+1}, the best estimate is changed by a factor governed by how A and x_{t+1} are dependant.

This result can be used to get a notion of the importance of context variables in predictions. We can remove one variable at a time and find out the probabilities $P(x_{v+1} \mid XBC)$, $P(x_{v+1} \mid XCA)$ etc. and check how different they are from the best estimation $P(x_{v+1} \mid XABC)$. In general, if the difference is more, the more the absent variable tells us about x_{v+1} and accordingly we can rank them based on their relevance.

4. EXPERIMENT, ANALYSIS & RESULTS

We instrumented four mobile phones to log following measurements for every 30 seconds.

- Time of the day (morning/evening)
- WLAN AP availability
- LAN availability
- Power on AC or not
- Number of Bluetooth devices around
- GSM Location Area (LAC)

All above variables are binary except the last where we took each encountered LAC as a separate realization. In analysis we used a moving average of 5 data points of Bluetooth and checked whether it is above (or below) some threshold. An example data vector looks like "0-0-0-0-1-LACa", which reads from left as "morning" - "WLAN not available" – "LAN not available" – "power not on AC" – "number of Bluetooth devices around is higher than the threshold" – "location area a".

We gave our mobile phones to four users to use as their personal phone for 3-4 weeks. For logging, we used in-house built software as well as two open source software applications called NiceTrack and RilTest (both for GSM), after doing some modifications to their code for logging purposes. We encountered some difficulties initially and some logs were partially usable. For example, HTC TyTn phone switches off the WLAN interface in sleep mode and Imate-Kjam switches off the WLAN interface when LAN is connected. The former was avoided by setting always active mode. The latter was corrected in log files using a script. Another problem with TyTn is it switches off the Bluetooth interface after 2-3 days of continuous running, although it shows "active" on the interface details. Some log files of the fourth user were unusable due to this reason. Due to inconsistencies of log files of the 3rd user, only evening parts were used for analysis.

In our evaluation, as encountered number of different states were less (below 200) and for easy interpretation from predicted states back to variables, each such combination of variables was assigned a unique state. First, we learnt order 1 and 2 state transition matrices for each user using their initial 2 weeks data. For order 1, the next state depends only on the previous state and for order 2, it is previous two states. These matrices were used with the next day log file of the corresponding user for evaluation. For the day after that, the log file of the day before was also used and absorbed to the matrices. So for the last day, the matrices contained information of all previous days' data.

4.1 State Transition Probabilities

Our first attempt was to observe the probabilities of state transfers given by the matrix when such a transfer has happened. In other words, let us assume the states have transferred in following manner in evaluation log file.

Transfer	$S_1 \rightarrow$	$S_2 \rightarrow$	$S_3 \rightarrow$	S_4
WLAN Status	0	1	0	1

This says that state 1 (S_1) which is a WLAN unavailable state (WLAN status given directly under S_1 is "0") has transferred to WLAN available S_2 state (WLAN status "1"). Similarly state S_2 has transferred to S_3 and then to S_4.

At the second transfer from state 2 (S_2) to state 3 (S_3), we calculated from the matrices, the "state transfer probability" that the state 2 would transfer to state 3 (in order 1) or having transferred from state 1 to 2 initially, from state 2 to 3 (in order 2). Further, from state 2 to 3, WLAN status has changed from "availability" to "non-availability". So we found out the probability given by the matrices to transfer from state 2 to a state where WLAN would not be available (in order 1) or having transferred from state 1 to 2 initially, from state 2 to a WLAN not available state (in order 2), by integrating over all the WLAN non-available states after state 2 (this is "WLAN transfer probability"). These probabilities were found for all the state transfers in the evaluation log file and such "state" and "WLAN" transfer probabilities for a user for a particular evaluation day are shown below in figure 3.

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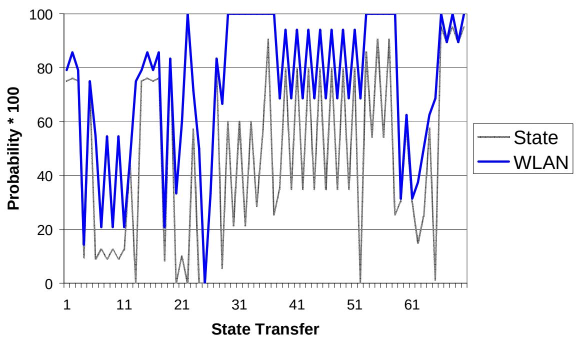

Figure 3. : Transfer probabilities.

All such probabilities for a particular user were averaged over all five evaluation days and the results of all users are as below.

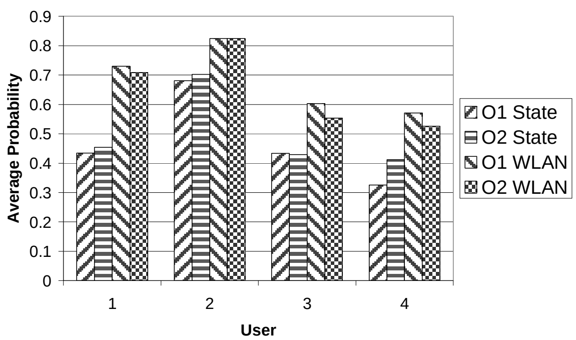

Figure 4. : Average transfer probabilities.

We can see that although predicting the next specific state is less accurate, predicting the WLAN availability in next state is around 66 % in both order 1 and 2 models on average, even over 80% for the 2nd user. Further, we don't see any noticeable gain by using order 2 in next state's WLAN availability predictions or next particular state predictions. Third and fourth users' prediction results are comparably low and can be accounted for less training data. For example, for the fourth user, the reduction is mainly caused by the first day's results where the matrices were not quite matured. They were around 15% for state predictions and around 35% for next state's WLAN status prediction. But towards the end of evaluation days, they gave better results.

Our main objective is to get an idea of how probable it is to have WLAN available in next few minutes (we did it for 5 minutes). That means, out of next 5 minutes, for how many minutes we will have WLAN available. Above results suggest us that when using state transition matrices for predictions, it is less accurate only taking the next most probable state but accuracy can be improved by taking all those states where WLAN is available (or not available, depending on the aggregated probability being above 0.5). If we consider the same example given previously, and imagine that we are at the state 2 now, so the current state in order 1 is S_2 and in order 2, it is S_2 having transferred from S_1 initially. For the stay time duration for a state, we simply averaged all encountered stay times of that state. We could get the stay time for the state 2 directly from the matrices. The prediction is such that the current state would last for that duration and the WLAN status is current state's WLAN status till the end of the duration. If the predicting time point is further ahead of this expected stay time duration, then as step 2, we found out the next probable states where WLAN is available (or not available depending on the probability). The duration for that step is taken as the weighted average of such next states' stay times, weighting factor being the number of transfers recorded from the current state to those particular states. For the third step, we took all the probable state transfers from states in step 2 and selected those next states having same WLAN status and above 0.5 aggregated transfer probability. Duration for the step 3 is taken similarly as described above, by averaging the selected states' stay times. Like wise, we ran this algorithm on the matrices until we came up at a step where predicting time point is within the duration of that step. The predicted WLAN availability status is the WLAN status of those states in that step. We did predictions for each 5 minutes blocks of the day. By dividing actual availability minutes and predicted minutes by 5, we got the actual and predicted probabilities. The results of order 1 and 2 for a particular evaluation date for a user is shown below (the mid of the graph where probability is constantly 1 is shrunk).

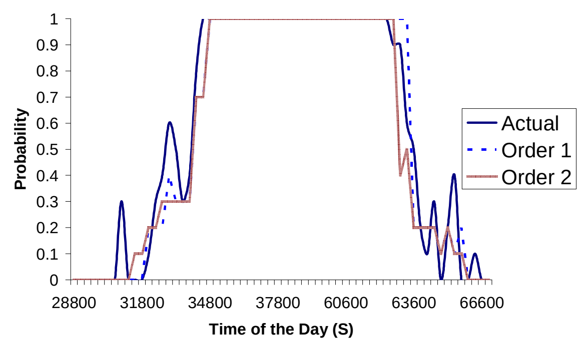

Figure 5. : WLAN availability probabilities.

In general, we could observe that when WLAN is available (or not available) continuously, predictions for those durations are nearly accurate. But we were rather interested in finding the differences between the predicted and actual probabilities in 5 minutes durations when they were fluctuating in transit times, to see the quality of predictions even in dynamic situations. Averages of such differences of four users are diagrammed below in figure 6.

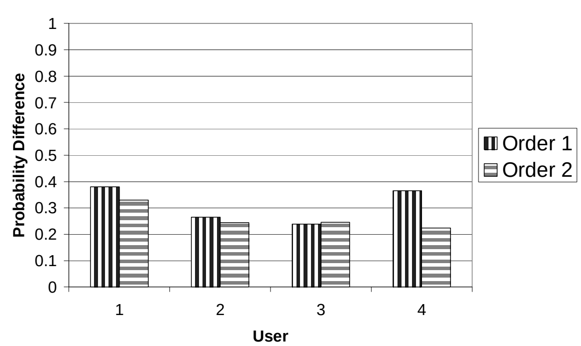

Figure 6. : Prediction probability difference.

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We can see that order 2 over performs (difference are less and 26% on average) than order 1 model in most of the users although we did not see any gain of using order 2 model than order 1 in next state's WLAN status predictions (figure 4).

4.2 Relevance of Context Variables

The next interesting question is finding how each context information variable contributes to the final prediction results. According to our conditional independence check method discussed in section 3 following equation (2), we here demonstrate it for the order 1 model where the next state depends only on the previous state. That means, the WLAN availability/non availability depends on the previous state only. We calculated the average difference between probability of next WLAN given all previous variables and the same given all previous variables except a particular one. That means, by assigning variable names as follows,

State	**WLAN**	**Time**	**Power**	**LAN**	**Blue.**	**GSM**
Current	x_v	a_v	b_v	c_v	d_v	e_v
Next	x_{v+1}					

we calculated the probability $P(x_{v+1} \mid x_v a_v b_v c_v d_v e_v)$ from the data. Then we calculated $P(x_{v+1} \mid a_v b_v c_v d_v e_v)$ (i.e. without previous WLAN) and found the average probability difference from above (with all variables) and similarly, removed one variable at a time and calculated average probability difference without that particular variable, for all the variables. The results are tabulated below.

Table 1. Context variable relevancies

User	Time	WLAN	Power	LAN	Blue.	GSM
1	0.040	0.114	0.028	0.007	0.092	0.151
2	0.034	0.147	0.076	0.000	0.045	0.149
3	-	0.117	0.027	0.000	0.087	0.105
4	0.076	0.127	0.082	0.001	0.056	0.144

For almost all users, it appears that in general, previous WLAN and GSM status details are of prime importance. LAN details were of little importance most of the time. The first user used only the LAN cable, both for LAN connection and charging purposes without using a separate charger. The relevance of LAN for him is very small compared to power. The obvious explanation in his case is, given the status of power, LAN status is implicit, but not the other way highlighting the fact that, in practice, whenever the USB cable is plugged, power status becomes available right after but for LAN status to become available, it takes some little more time for automatic configurations. Therefore, although the LAN status is obvious when the power status is given, power status is not completely shown by LAN status as the power status may have been available before (after) the LAN status becomes available (not available). Other users hardly used LAN cable and LAN availability was more an independent event from other variables. The third users "Time" relevance is absent as only evening data was used due to inconsistencies of log files as stated in the beginning.

To see the effects of these findings, we removed Bluetooth variable and GSM variable, one at a time and observed the probability differences caused on the predictions of 5 minute blocks ahead (as in section 4.1 last part). Ideally the differences without GSM should be more than that of Bluetooth according to above figures, as for all users GSM relevance is always higher than the Bluetooth relevance. The below diagram shows actual probabilities, predicted probabilities with all variables, same without Bluetooth and without GSM for a particular user in a particular day for order 1. (The mid of the graph where probability is constantly 1 is shrunk).

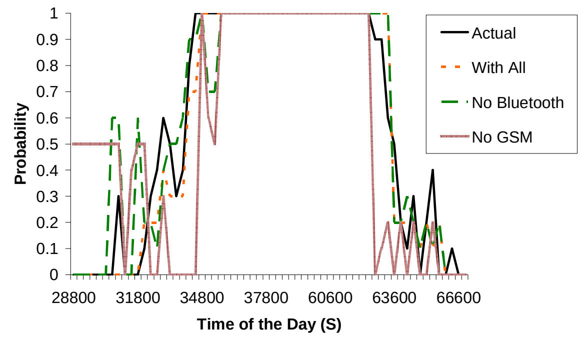

Figure 7. : WLAN availability probabilities.

And averaged prediction probability differences for all users for order 1 are as below.

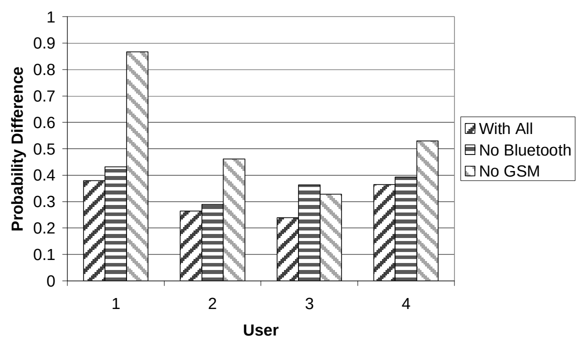

Figure 8. : Order 1 prediction probability difference.

We can see that removal of GSM affects prediction results in all users than Bluetooth except for third user. But still his GSM and Bluetooth effects appear to be close and this can be accounted for their relevance for both variables being very close. For user 2 and 4, the Bluetooth relevance is low (only 0.045 & 0.056 from the table 1) and we cannot observe a clear difference between "without Bluetooth" and 'with all variables" in both cases. For the order 2 model also, a similar check is applicable where in conditional independence check, the details of previous two states have to be considered.

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4.3 Parameter Tuning

The same conditional independence check can be used to tune parameters of the model. In our evaluation, we classified number of Bluetooth devices around, to two categories namely, “0” meaning it is below some number “n” and “1” for above that number. This “n” can be calculated in such a way that it produces maximum relevance in probabilities. We did the same check as in 4.2 without Bluetooth, when cutoff threshold is set to 1 up to 6, and found probability deviations from when all variables are considered and they were accumulated. The results are graphed below. The values are normalized by dividing from the maximum value encountered in the 1 to 6 range for each user.

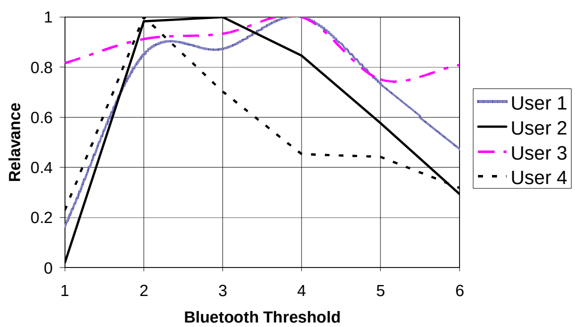

Figure 9. : Bluetooth relevance against Bluetooth threshold

From the above diagram, we can see that for user 1 and 3, the maximum occurs on threshold 4 whereas for 2nd and 4th users they are 3 and 2. It is actually these thresholds that we used in our previous analysis. To see the effect on prediction probability difference from actual, we calculated average prediction probability differences for optimum threshold and for threshold 1 for each user. The below column graph shows the results for order 1 model.

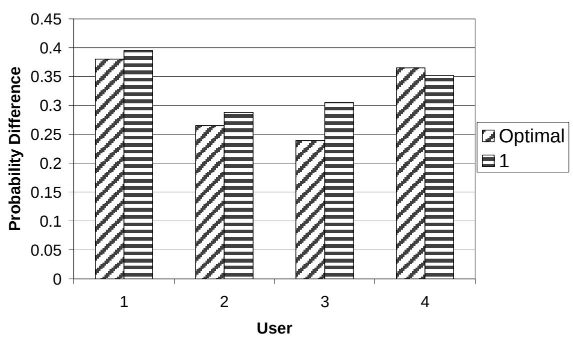

Figure 10. : Order 1 prediction probability difference for different Bluetooth thresholds.

We can clearly see in most of the users that we get the least probability difference from actual, with optimal threshold except in user 4. We looked into that user’s results on each evaluation day and found that the difference is caused by the first evaluation day results where the matrices contained information of only limited number of log files due to the fact that Bluetooth interface goes down over continuous running for more than few days as stated in the beginning. For him, the optimal threshold gave better results when the matrix was learnt gradually on latter days.

We checked the predicted probability differences from actual when the threshold is optimal and 1, for order 2 model as well and found that they are compliant with our method although we considered only the previous state’s variables there and not previous two states’. Figure 11 shows above results for order 2 for all users.

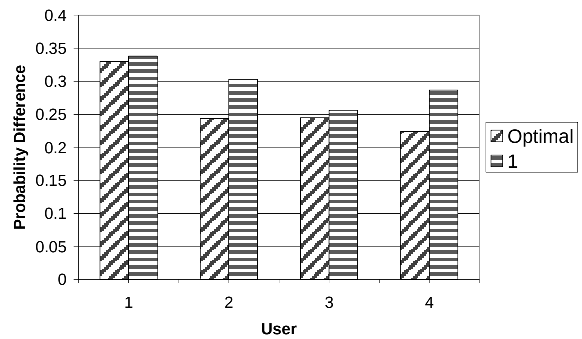

Figure 11. : Order 2 prediction probability difference for different Bluetooth thresholds.

5. CONCLUSION AND FUTURE WORK

Network availability prediction helps to optimize wireless resource utilization of a mobile device in a heterogeneous network environment. We have shown with real user data collected in our experiments that the WLAN availability can be predicted using any available context information of the device with a Semi-Markovian state model, without using any domain specific knowledge. Our results show that predicting WLAN availability status over next 5 minutes blocks performs nearly perfectly when WLAN status is not changing. Even in changing situations, the WLAN availability probability difference between actual and predicted goes up only to 26% on average. Also, the presented method to rank context variables according to their importance in predictions found to be realistic and with that, unimportant variables can be removed saving power and processing of the device without much (or at least known) effect on the quality of predictions. It was further shown that the same method can be used for optimizing parameters of the model, again justified by results.

We will look into incorporating more context information for predictions with refined models and with more user data. Further, we will work on extending the same methods to predict network QoS parameters as well together with availability, followed by introducing the prediction knowledge in a mobile device to utilize wireless resources optimally.

6. ACKNOWLEDGMENTS

This work has been performed in the context of NICTA’s CAMP project, which is funded by Ericsson. We would like to thank the developers of NiceTrack and RilTest software, which were used for GSM data collecting purposes. We would also like to thank NICTA staff volunteers who helped in our experiments.

Digital Object Identifier: 10.4108/ICST.MOBIQUITOUS2008.3563
http://dx.doi.org/10.4108/ICST.MOBIQUITOUS2008.3563

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