

Comparing Mobility and Predictability of VoIP and WLAN Traces

Jeeyoung Kim, Yi Du, Mingsong Chen, Ahmed Helmy

Department of Computer and Information Science and Engineering, University of Florida

Email: { jk2, ydu, mchen, helmy } @cise.ufl.edu

1. INTRODUCTION

Realistic modeling of user mobility is one of the most critical research areas in wireless networks. Mobility data based on real human behaviors may give us the opportunity to improve wireless and mobile services for users in many ways. Currently, several mobility models are proposed based on the analysis of real WLAN traces [1,2]. However, the large collection of WLAN *usage* traces, seem to capture little *mobility* from the users.

In this paper, we focus on a subset of the wireless users, who use wireless VoIP devices. These users leave their devices *on* most of the time and the devices are light enough to carry and use while mobile. Hence, these users show a more mobile characteristic than laptop or other heavy device users while connected to the network. By analyzing these traces we aim to compare behavior of highly mobile VoIP users to the general WLAN users. This sheds light on the realism of WLAN trace-based models. We also aim to examine the effect of any differences on protocol performance, e.g., prediction protocols.

Particularly, we compare the mobility of VoIP user traces with whole WLAN traces (as used in previous studies) and also with some samples we have generated based on criterias that distinguish these samples as highly mobile compared to others. We compare these different sets of traces using several different predictors such as the Markov O(1), O(2), O(3) and also the LZ predictor. There has been work done with Wi-Fi mobility data using predictors [3] and work done on VoIP users [4] but to the best of our knowledge there has not been any work done using predictors to compare the mobility of users. Our experiments indicate that the number of access points (AP) visited has more to do with mobility than the actual area range the user has covered and also that the Markov O(2) is the predictor with the highest accuracy among the four predictors and the LZ has the lowest. Surprisingly, all predictors perform quite poorly with VoIP users compared to general WLAN users, prompting re-visiting of such algorithms for highly mobile users.

2. DATA SETS

The VoIP data set we use in this work is a subset of the WLAN trace of Dartmouth College [5] and consists of 97 users. Along with the VoIP data set we have generated test sets from the same trace in order

to validate our findings. There are three test sets used in this work and they are all considered to be highly mobile users. Sample 1 and sample 2 are both based on the number of APs visited. Sample 1 is a collection of users who have visited 200 APs or more during the length of the trace and sample 2 is a collection of users who have visited more than 170 APs but less than 200. Sample 3 is a collection of users who have covered the largest physical area during the length of the trace. This was done by studying the AP location file and calculating the area range that each user covered. All of these samples were carefully selected from the 3 year long Dartmouth movement trace from 2001 to 2004 [5] and each test set has approximately 100 users each.

3. PREDICTION COMPARISON

We have run the Markov O(1), O(2) and O(3) predictors along with the LZ [3] predictor for each of the test sets we have, and also for the VoIP trace set and the whole body of the WLAN trace. We also compared the accuracy of all four predictors with the VoIP trace data to see which one has the best performance. Accuracy is measured as percentage of correct predictions of the next AP to visit. As shown in Figs 1 through 5, the ***WLAN trace always had the best prediction accuracy for all the predictors with an average of about 60% accuracy. The VoIP trace, by contrast, had the worst prediction accuracy for all of the predictors with an average of approximately 25% accuracy.*** From these graphs we see that the best accuracy can be no more than 80% for VoIP users, while more than 95% accuracy for WLAN users¹.

When we were first conducting our experiment, we expected that the range of the physical area that each user covered would be a better criteria to measure mobility than the number of APs visited since we consider a person to be more mobile when that person covers more ground. Hence, we expected that sample 3 would return a very bad prediction accuracy. Surprisingly, sample 3 always exhibits performance between of the other two samples (1 & 2), which indicates that the users that covered larger areas physically most likely have visited an average

¹ Our further comparisons of WLAN and VoIP confirm these findings, and are omitted for brevity.

of 200 APs during their lifetime.

To explain this result, intuitively the sample of users which had visited less APs have a better prediction rate than that of the user who have visited more APs. The difference of the prediction accuracy between the two samples are always around 10% near the median.

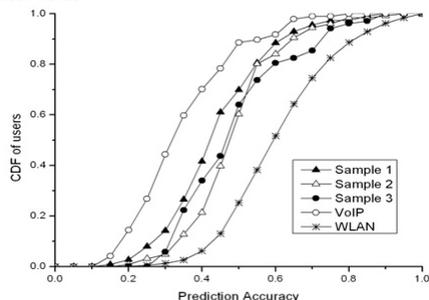


Figure 1. Accuracy of Markov O(1) Predictor

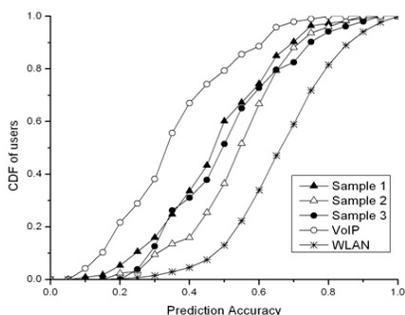


Figure 2. Accuracy of Markov O(2) Predictor

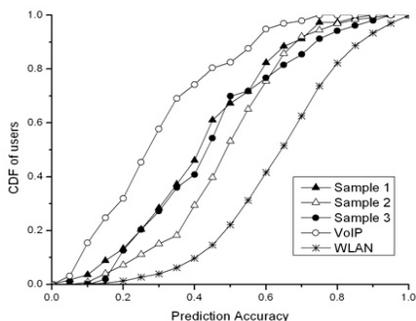


Figure 3. Accuracy of Markov O(3) Predictor

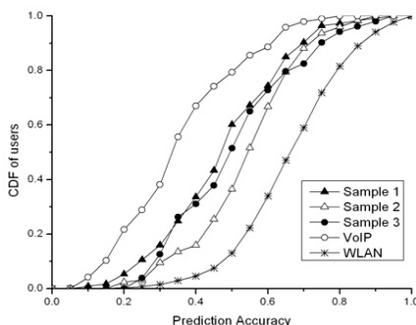


Figure 4. Accuracy of LZ Predictor

As for the comparison of the predictors on the VoIP data set, the LZ predictor showed the worst prediction rate and the Markov O(2) showed the best prediction accuracy by a very minimal difference from the Markov O(1). Markov O(3) did not show a good prediction and these results indicate that a larger data structure and higher complexity does not help in making better predictions. However, the four predictors that are used in this work do *not* provide good prediction for the VoIP data set.

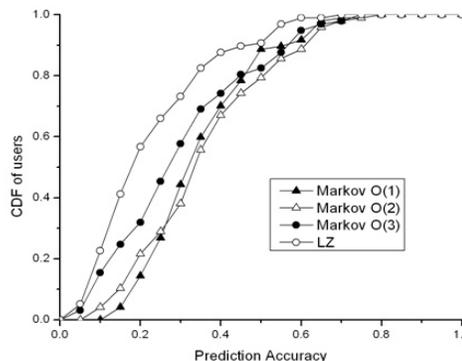


Figure 5. Comparison of Predictability on VoIP Trace

4. FUTURE DIRECTION

Our findings open the door for improved prediction and modeling of highly mobile users. We plan to design a better predictor for “highly mobile” users, especially the VoIP traces. Our plan includes investigating *domain-specific* knowledge, regressions, schedules and repetitive or preferential user behavior. We shall also examine the adequacy of WLAN trace based mobility models for highly mobile and VoIP users, that are likely to increase in the future.

5. REFERENCES

- [1] W. Hsu, T. Spyropoulos, K. Psounis, and A. Helmy, “*Modeling Time-variant User Mobility in Wireless Mobile Networks*”, Proceedings of IEEE INFOCOM 2007.
- [2] C. Tudece, T. Gross, “*A mobility model based on WLAN traces and its validation*”, Proceedings of INFOCOM 2005: Miami, FL, USA 664-674
- [3] L. Song, D. Kotz, R. Jain and X. He, “*Evaluating location predictors with extensive Wi-Fi mobility data*”, Proceedings of IEEE INFOCOM 2004.
- [4] M. Kim, D. Kotz, and S. Kim, “*Extracting a mobility model from real user traces*”, Proceedings of IEEE INFOCOM 2006.
- [5] <http://crawdad.cs.dartmouth.edu/>