Computer and Information Science and Engineering Department
UNIVERSITY OF FLORIDA

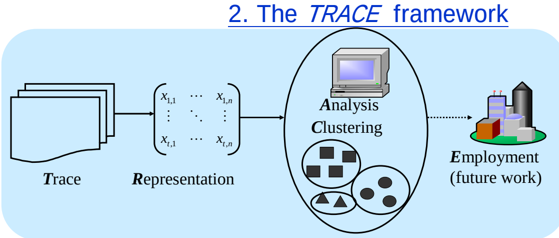
Mining Behavioral Groups in Large Wireless LANs

Wei-jen Hsu[1], Debojyoti Dutta[2], Ahmed Helmy[1]
[1]Dept. of Computer and Information Science and Engineering, U. of Florida, [2]Cisco Systems, Inc.
wjhsu@ufl.edu, dedutta@cisco.com, helmy@ufl.edu http://nile.cise.ufl.edu/MobiLib

1. Introduction

- Wireless devices and infrastructures are ubiquitous and have wider impact than mere advances in technology on our lives
- Portable personal wireless devices provide an opportunity for the study of human behavior
- We leverage WLAN traces to discover distinct behavioral groups (in terms of mobility)
  - USC WLAN trace[2] (2006 spring, 94 days, 5000 users)
  - Dartmouth WLAN trace[3] (2004 spring, 61 days, 6582 users)

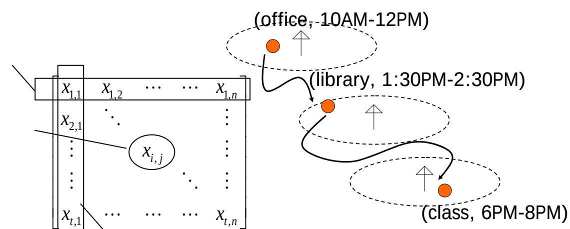
2. The *TRACE* framework



Contribution: Application of unsupervised learning techniques (clustering) with carefully selected features to identify groups

3. Preliminaries: Representing User Associations

- Use a *normalized association vector* to represent summary of user mobility in each day
- Elements in the vectors quantify the relative importance of a location to the user
- Location preference is one of the distinguishing feature of social groups
- *Association matrix* keeps long-run behavior of a user



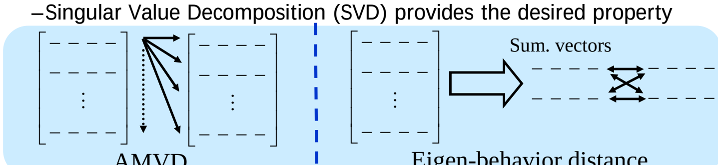
Association vector:
(library, office, class) =(0.2, 0.4, 0.4)

4. Comparing Similarity between Users' Association Matrices

- Average Minimum Vector Distance (AMVD)
  - For each association vector (row) of user *i*, find the closest vector of user *j* and take average of $|a_{jd'} - a_{id}|$ over all days *d*
  - Intuition: for every daily association vector of *i*, if there is a similar association vector for *j*, then (*i,j*) have similar behavior
- Drawback: expensive to compute $O(N^2d^2)$ and exchange. Includes noises.
- Require meaningful summary for the association matrix
  - Asso. matrices: multi-modal row vectors, but low dimensionality
  - Summary vector Y that captures the most variation in row vectors Xi's

$$SIG(Y) = \sum_{i=1}^{d} |X_i \cdot Y| \Big/ \sum_{i=1}^{d} \|X_i\|_1$$

  - Singular Value Decomposition (SVD) provides the desired property

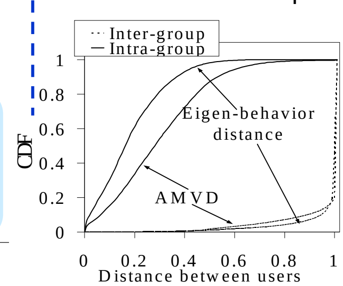


- Eigen-behaviors: The vectors that describe the maximum remaining power in the association matrix

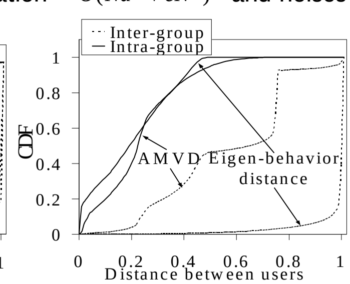
$$u_1 = \arg\max_{\|u\|=1} \|X \cdot u\|,\quad u_k = \arg\max_{\|u\|=1} \left\| (X - \sum_{i=1}^{k-1} X u_i u_i') \cdot u \right\| \quad \forall k \geq 2$$

with quantifiable importance $w_k = \sigma_k^2 \Big/ \sum_{i=1}^{Rank(X)} \sigma_i^2$

- Eigen-behavior Distance calculates similarity of users by weighted inner products of eigen-behaviors.
  - $Sim(U,V) = \sum_{\forall i,j} w_i w_j |u_i \cdot v_j|$
- Benefit: Reduced computation $O(Nd^2 + cN^2)$ and noises



USC



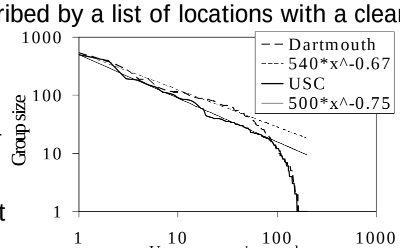
Dartmouth

5. Interpretation of Behavioral Groups

- The existence of distinct behavioral groups (~*hundreds*)– each group has unique group eigen-behavior

Significance score of top eigen-behavior for	USC	Dartmouth
Its own group	0.779	0.727
Other groups	0.005	0.004

- Skewed group size distribution – the largest 10 groups account for more than 30% of population on campus. Power-law distributed group sizes.
- Most groups can be described by a list of locations with a clear ordering of importance
- We also observe groups visiting multiple locations with similar importance – taking the majority or average of association vectors from a user is not sufficient



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6. Potential Usage and Future Direction

- Profile-casting[4] - Fast evaluation of similarity between nodes facilitates de-centralized packet forwarding decisions targeted at specific groups
- Better mobility model (with group size distribution and vectors describing their mobility preferences)
- Establishing norm of mobility characteristics of users
  - Abnormality detection, targeted advertisement
- The *TRACE* framework could be applied to different *representations* (e.g. encounter vector)

[1] Longer version of technical report available at http://arxiv.org/abs/cs/0606002
[2] W. Hsu and A. Helmy, MobiLib USC WLAN trace data set. Download from http://nile.cise.ufl.edu/MobiLib/USC_trace/
[3] D. Kotz, T. Henderson and I. Abyzov, CRAWDAD data set dartmouth/campus/movement/01_04 (v. 2005-03-08). Downloaded from http://crawdad.cs.dartmouth.edu/dartmouth/campus/movement/01_04
[4] W. Hsu, D. Dutta, and A. Helmy, "Profile-cast: Behavior-Aware Mobile Networking," MOBICOM 2007 poster and SRC.