

UMAP 2009. Selected Papers

PAWS Meeting 2009-09-08

Michael Yudelson

Paper 1. Bohnert, Zukerman

- Bohnert, F. and Zukerman, I. (2009). **Non-intrusive personalisation of the museum experience**. In Houben, G.-J., McCalla, G. I., Pianesi, F., and Zancanaro, M., (Eds.), 17th International Conference on User Modeling, Adaptation, and Personalization (UMAP 2009), pp. 197–209, Trento, Italy.

DOI: 10.1007/978-3-642-02247-0_20

Paper 1. Bohnert, Zukerman (cont'd)

- Topic: Mobile Recommendation
 - Collecting museum visitor log data
 - Build a collaborative [mobile] recommender
- Tool: Gecko-tracker
 - Mobile click-based system for pinpointing person's location on a pre-made map
 - Requires extra person – museum worker, the tracker

Paper 1. Bohnert, Zukerman (cont'd)

- Dataset: Melbourne Museum
 - April-June, 2008
 - 158 visitors' tracks recorded
 - Average visit 1:50:39, 1:31:09 viewing, 52.70 areas
- Assumptions
 - Viewing time is a reliable measure of interest
 - Use log-viewing time (log-normal distribution)

Paper 1. Bohnert, Zukerman (cont'd)

- Nearest-Neighbor Collaborative Filter
 - $v \in V = 1:m$ visitors
 - $i \in I = 1:n$ exhibits (items)
 - $r \in R = m \bullet n$ – normalized viewing times (z-scores), sparse matrix
- Predicting Viewing Time
 - Predict unobserved value r_{ai}^{\sim} of a visitor a from values in R

Paper 1. Bohnert, Zukerman (cont'd)

- Predicting Viewing Time
 - \bar{r}_a – a 's average normalized log viewing time
 - $N(a,i)$ – set of nearest neighbors
 - s_{av} – similarity between visitors a and v as Pearson correlation on log viewing times of a and v

$$\tilde{r}_{ai} = \bar{r}_a + \frac{\sum_{v \in N(a,i)} s_{av} (r_{vi} - \bar{r}_v)}{\sum_{v \in N(a,i)} |s_{av}|}$$

Paper 1. Bohnert, Zukerman (cont'd)

- Recommendation Procedure
 - Compute all s_{av} for all v that viewed exhibit i
 - Select all v , where s_{av} is above threshold
 - compute r_{ai}^- using weighted mean of deviations from each neighbor's viewing duration r_v^- .
(neutralize individual differences b/w visitors)
when there are at least 20 observations
 - Otherwise, use similarity-weighted mean of r_{vi} 's

Paper 1. Bohnert, Zukerman (cont'd)

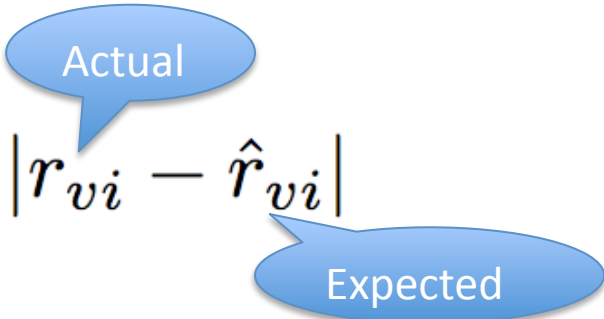
- Other tweaks
 - Similarity-weighting impossible (no neighbors)
 - Use un-weighted average of visitors of i
 - Significance weighting
 - Decrease the influence of neighbors with smaller set of co-visited exhibits
 - Shrinkage to the mean
 - Use MAE to improve statistical estimation

Paper 1. Bohnert, Zukerman (cont'd)

- Evaluation. Experimental setup.
 - Ignore b/w travel time, merge several views of the same item into 1
 - Leave-one-out training **1-vs-157**
- Evaluation experiments
 - Individual Exhibit – erase log view time & predict
 - Progressive Visit – iterative prediction of log view times as new visits added from log
 - Recommendation Potential – predict log view times of never visited exhibits

Paper 1. Bohnert, Zukerman (cont'd)

- Experiment. Accuracy measure – MAE
 - I_v – visitor v 's set of exhibits for which predictions computed

$$\text{MAE} = \frac{1}{\sum_{v \in V} |I_v|} \sum_{v \in V} \sum_{i \in I_v} |r_{vi} - \hat{r}_{vi}|$$


The diagram shows the MAE formula with two blue callout bubbles. One bubble points to r_{vi} and is labeled "Actual". The other bubble points to \hat{r}_{vi} and is labeled "Expected".

Paper 1. Bohnert, Zukerman (cont'd)

- Experiment. Results
 - Individual Exhibit:
 - MAE total **.75-.86**, by museum area **.55-.81**
 - Compare with (Corbett & Anderson 1995) MAE .10-.16
 - Recommendation Potential
 - 23-29 new unvisited exhibits predicted

Corbett, A. T. and Anderson, J. R. (1995). Knowledge tracing: Modeling the acquisition of procedural knowledge. *User Modeling and User-Adapted Interaction*, 4(4):253–278.

Paper 1. Bohnert, Zukerman (cont'd)

- Discussion. Predict->Recommend
 - Do not recommend what visitor is going to visit anyway
 - Form list 1 – global exhibits of interest
 - Form List 2 – location/proximity based exhibits
 - **Merge** lists (magic happens here)
 - Use “sure” exhibits to build trust, recommend exhibits likely to be overlooked but still interesting

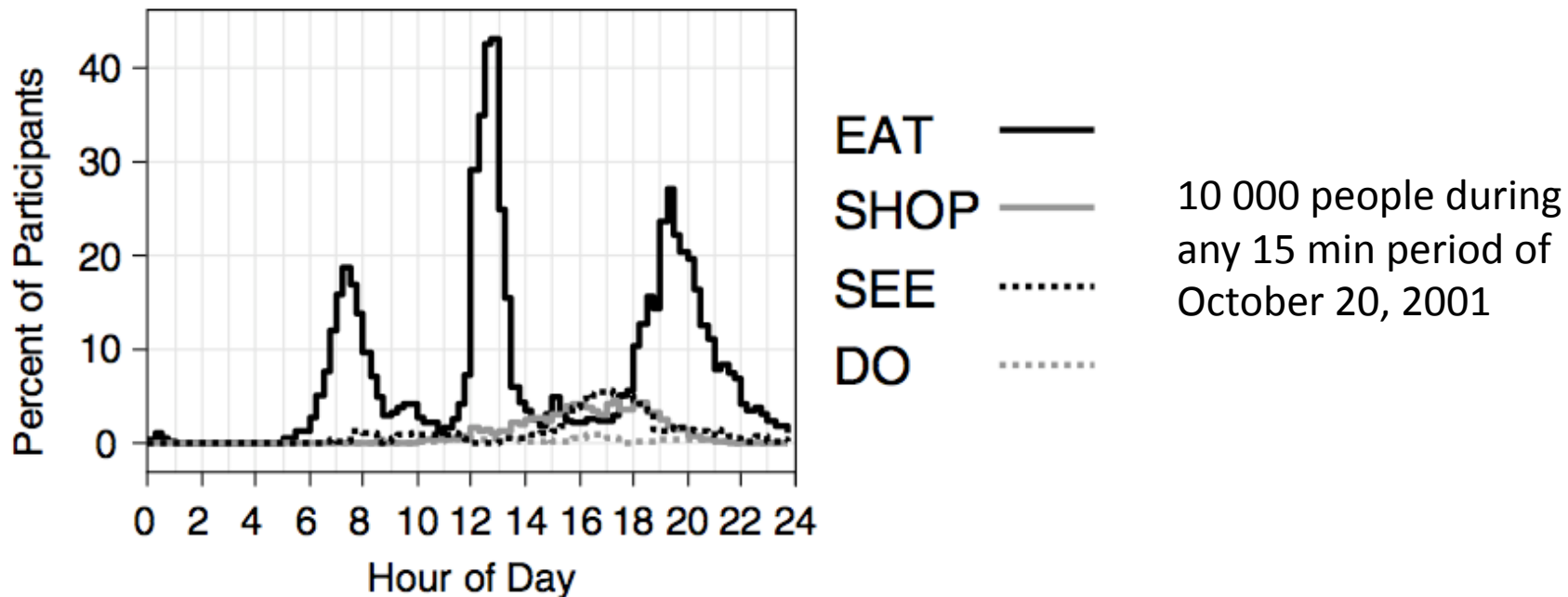
Paper 2. Partridge, Price

- Partridge, K. and Price, B. (2009). **Enhancing mobile recommender systems with activity inference**. In Houben, G.-J., McCalla, G. I., Pianesi, F., and Zancanaro, M., (Eds.) 17th International Conference on User Modeling, Adaptation, and Personalization (UMAP 2009), pp. 307–318, Trento, Italy.

DOI: 10.1007/978-3-642-02247-0_29

Paper 2. Partridge, Price (cont'd)

- Topic: Mobile Recommendation
 - Using data from Japan Statistics Bureau
 - Build mobile activity recommender – Magitti
 - 5 activity categories: eat, shop, see, do, read



Paper 2. Partridge, Price (cont'd)

- Models
 - PopulationPriorModel – mine the JSB dataset
 - PlaceTimeModel – use time & location to build distributions of activities, all venues are classified as primary activity
 - eat – default, shop – in the afternoon, when in shopping area – shop is default, see – around movies and performance halls

Paper 2. Partridge, Price (cont'd)

- Models (cont'd)
 - UserCalendarModel
 - Parse calendar for information (“Lunch at 11”)
 - Predictions are stored in the model’s calendar
 - Actual calendar events are given priority
 - Negations taken into account (“can’t meet for dinner”)
 - LearnedInteractionModel
 - User’s typical activity for a given time
 - Explore mobile device interaction patterns
 - Recommendation overrides of the are logged and used later

Paper 2. Partridge, Price (cont'd)

- Models (cont'd)
 - LearnedVisitModel
 - Learning from indirectly labeled data
 - Using database of venues and GPS data (10m precise)
 - Utilize proximity for recommendation
 - $\Pr(A|L,T) = \alpha \sum_V \Pr(L|V) \Pr(V|A) \Pr(A|T)$
 - Also learn/mine context-specific user preferences

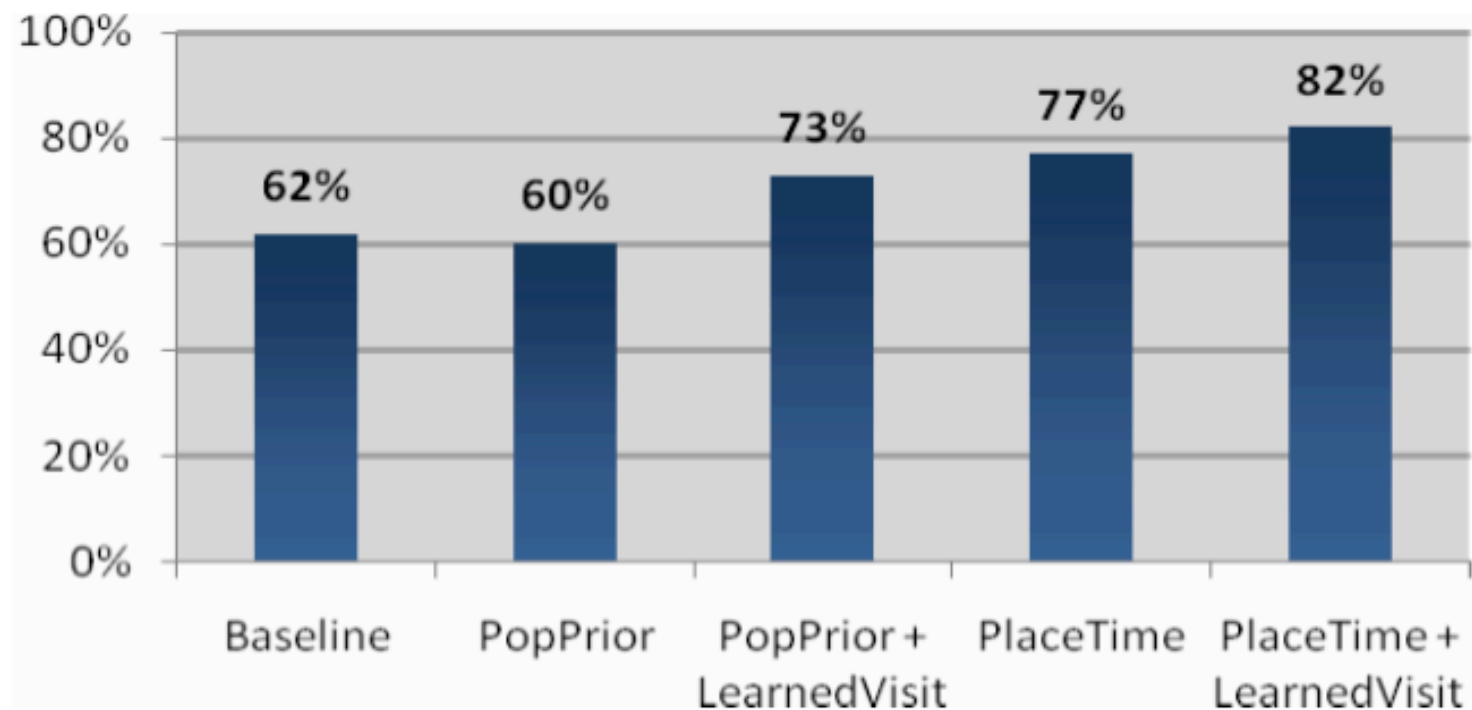
Paper 2. Partridge, Price (cont'd)

- Study
 - 11 participants (researchers, administrative staff)

Activity Predictor	Inputs	Outputs
Baseline	None	Always EAT
PopulationPriorModel	Day of Week, Time of Day, Weather	Most common activity from fixed tables
PopulationPriorModel + LearnedVisitModel	Day, Time, Weather, User ID	Prod. of prior probabilities and per-user table prob.
PlaceTimeModel	Day, Time, Weather, GPS Locations	Activity determined by place-specific rules
PlaceTimeModel + LearnedVisitModel	Day, Time, Weather, GPS Locations, User ID	Product of placetime priors and per-user table prob.

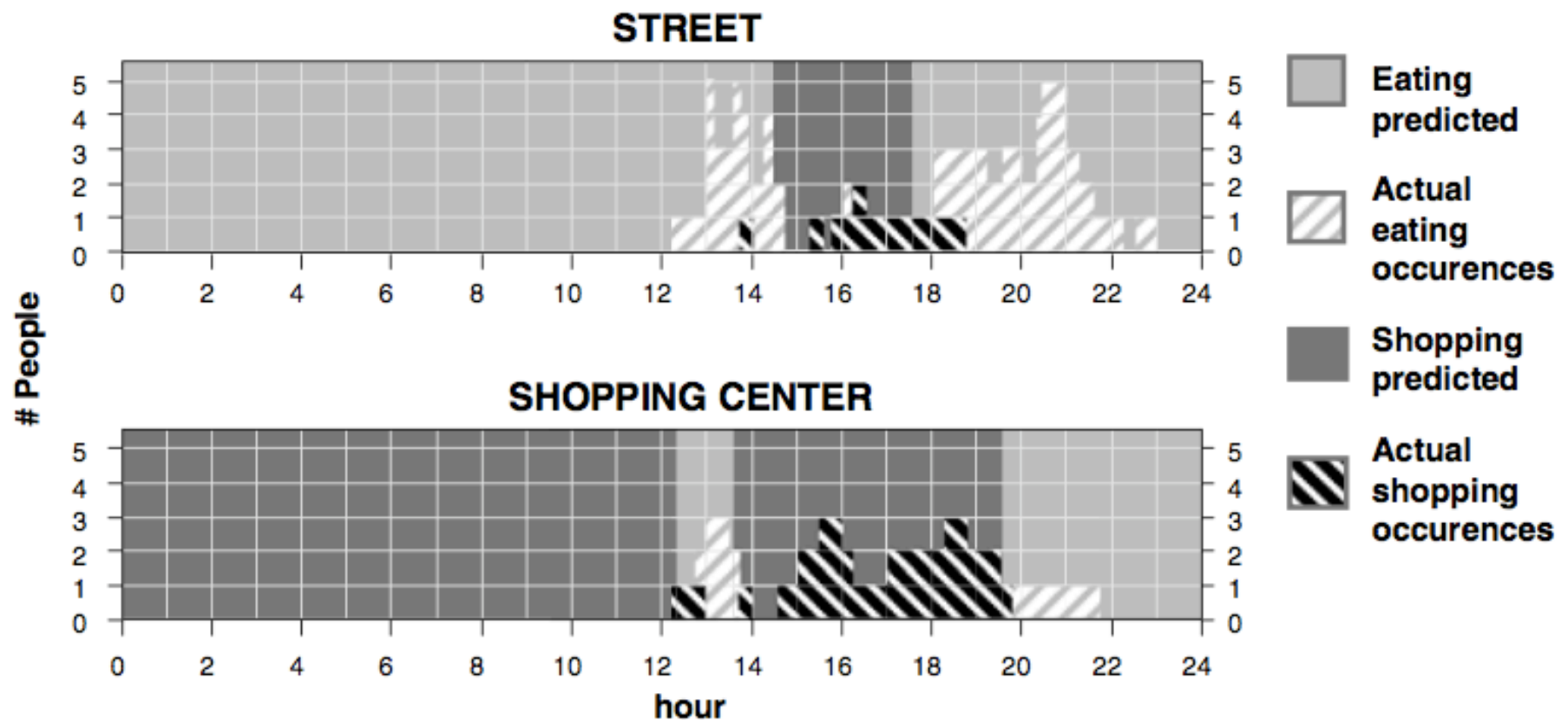
Paper 2. Partridge, Price (cont'd)

- Study Results



Paper 2. Partridge, Price (cont'd)

- Study Results: PlaceTime priors – EAT & SHOP



Paper 2. Partridge, Price (cont'd)

- Discussion
 - Categories: visit museum – SEE or DO?
 - Mixed-initiative interface, still needs “manual” interaction
 - Data could be richer (purchase records, pooling collaborative data)

Thank You!