Modeling Mobile User Activity Planning Targets

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Abstract. Modeling the information relevant to mobile users has primarily focused on the current activity location and occasionally the immediate next activity. We suggest a more forward-looking approach may provide additional insight as to what is relevant to a user beyond their immediate surroundings. We empirically demonstrate modeling what activities are currently being planned and the time frame for how far in the future the activity will be executed can be made with high precision and recall.

1 Introduction

Modeling what is relevant to a user has been an area of continual interest in recommender systems. Within mobile systems, the majority of models do not extend beyond the immediate environment except perhaps trying to predict the next location. Some works have had current context include data such as time availability, real-time weather or traffic updates and real-time events such as accidents [1–3]. These types of approaches overlook that while sometimes people make spur of the moment decisions on what to do next in the immediate area, for a large number of activities the decisions have been made hours or even days earlier through preplanning [4]. We believe benefit can be gained by extending these models to take into account this planning behavior.

We propose to predict what is currently being planned and for how far in the future, or the *planning target*. Recognizing that a plan is being made for a specific activity at a specific time window may provide information that results in a significant improvement of determining relevant immediate recommendations and thus improving the overall mobile user's experience beyond just considering their immediate surroundings.

2 Planning Targets/Horizons

An important aspect of planning targets is the length of time between when an activity is planned and its actual execution, referred to as the *planning horizon* [5]. Planning horizon can range from far in advance, such as a visit to the doctor planned several weeks ahead, to spur of the moment, such as an urgent stop to get gas. A typical person's day has a mix of routine and actively planned activities with a more finite planning horizon. For most people, plans are continuously made and finalized throughout the day for varying planning horizons [4]. For example, a person might be making reservations for dinner the next morning, followed by an impulsive decision to grab a snack, followed by making plans for meeting a friend for lunch in an hour.

3 Methodology

For this work, we assess how well a person's planning targets can be predicted at a point in time during a person's day against empirical data derived from the Computerized Household Activity Scheduling Elicitor (CHASE) survey conducted in Toronto in 2002-03 [6]. The CHASE survey captured a detailed accounting of the activity scheduling process of adult members of 271 households over a one-week period. This included capturing the time frame for when each activity was planned, in addition to observed activity attributes such as start time, end time, location, involved persons, and category of the activity. The activities were broken down into 11 categories: active recreation; drop-off/pick-up; entertainment; household obligations; meals; basic needs; other; services; shopping; social; and work/school. The planning time frame included routine, X number of days ago, more than 2 hours before, 1-2 hours before, less than one hour before, and just prior.

To model the planning targets for a participant the activities and their planning horizons were used to construct a time line for each day. The day was discretized into 6 time segments. For each of these time segments a series of possible planning target entries were created that consisted of the combination of a specific activity type and one of three planning horizons (1-2 hours prior, more than 2 hours prior, or 1-2 days before) for a total of 33 possible planning targets for each time segment. The data set was then encoded such that for each user, if one of the 33 possible targets was indicated it was marked as being active, otherwise it was encoded as a negative example. The current activity type and user demographics of age, employment status, and gender were then selected based on information gain to train C4.5 classifiers for whether for a given time a planning target for that activity was active. For measuring prediction performance, we use the information retrieval metrics of precision and recall to evaluate the identified planning target vs. the actual planning target.

4 Results

Below we compare the precision and recall across the activity types captured in CHASE for the various planning horizons. All results reported are based on a 10-fold cross validation methodology. As Figure 1 shows by training on each of the different planning horizons the planning activity can be predicted well across all of the activity types, ranging from .80 to just over .89 precision. Interesting to note are the activities types where a longer planning horizon was more precise,

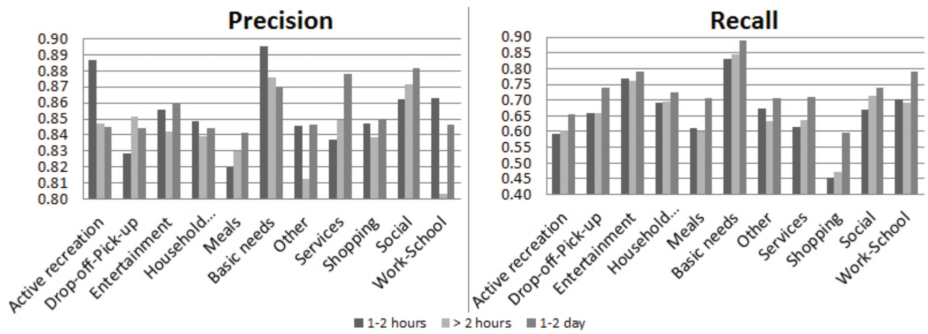

Fig. 1. Precision and recall of activity types across varying planning horizons

including 'services', 'meals', and 'social'. This is likely explained by the need for more coordination of these activities as they often involve other people, making the timing for when that coordination would occur more predictable. For example some service activities require appointments with others such as doctors, hair stylist, etc. which are more predictable when looking 1-2 days in the future.

Also interesting to note are activities such as 'basic needs' and 'active recreation' where precision was highest for the shortest planning horizon, but lower as the planning horizon became longer. A notable similarity between these activities is they often don't involve other people and require relatively little planning. The other trait observed in the C4.5 trees that stood out from other activity types was that these classifiers were more highly dependent on the immediately surrounding activities. This may reflect the planning of these activities being consistently occurring (if not triggered) after an activity type(s) occurs.

A somewhat unexpected pattern was observed for 'Work-School' that had a pronounced dip in precision in the mid-range ¿2 hour period, but higher precision in the short and longer horizons. This may reflect the haphazard way work plans made 2 hours in the future on the same day are made. However, additional investigation is needed to determine the cause for this difference with more confidence. Figure 1 displays the recall comparison of these same planning horizons.

Figure 1 displays the recall comparison of these same planning horizons. Across nearly all activity types, being able to recall a greater portion of planning activity was possible with a longer planning horizon. Intuitively this makes sense as being able to identify a higher proportion of the time when an activity type needs to be planned a day or two in the future seems easier than the same task within a day when considering the additional level of granularity being considered when windows as small as 1-2 hours are being considered.

5 Conclusions

Being able to anticipate when activities are being planned and the planning horizon for those activities may provide valuable insight in what data is the most relevant to the user. As the results demonstrate, with some basic information about the user and their current activity, the activities that are currently being planned can be modeled to identify these planning interests highly successfully. Of further interest, the predictability of this planning behavior varies across activity type and planning horizon. These findings and the potential reasons behind these differences advance the understanding of what may be relevant to a mobile user throughout the course of their activities and travels beyond just their immediate area. A broader implication of this work is that the field's current approach to identifying the information relevant to a mobile user is likely missing a significant opportunity to broaden the information returned while maintaining a high degree of relevancy. One potential way to leverage this data would be to combine the predicted activity and desired time frame with a weighting scheme based on the utility of adding different options to the user's plans through an approach such as that suggested by Horvitz et al. [7]. Because with mobile users it is rare that a single activity is considered in isolation due to travel times etc., in future work we plan to explore methods of recommending a bag/group of activities that match multiple predicted planning targets based on the combined utility of each activity need and convenience of combining trips.

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