The Relationship between User Location History and Interests in Products and Services

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Abstract. This study evaluated the use of location history as a predictor of user interests in products and services. Over a 1-month time period, subjects used a voicemail or email diary to report their visits to various establishments, such as shops and restaurants. At the end of the study, they completed questionnaires asking about their demographic characteristics, as well as their use of advanced mobile services and involvement in making decisions about the purchase or use of various products and services. A series of stepwise linear regressions showed that parameters derived from the diary data, when combined with demographic and mobile usage parameters, significantly improved predictions of product/service involvement, when compared to using the demographic and mobile usage predictors alone. These results suggest that location history measures could potentially be valuable components of algorithms for targeting commercial content to end users.

Keywords: Location history, targeting algorithms, consumer behavior, mobile commerce.

1 Introduction

While location-based services have been useful for providing context-sensitive functionality to users, other applications have focused on using context history to categorize user behaviors, interests and other characteristics [1]. These have included, for example, identifying users' social networks [2], determining their daily routines [3,4], categorizing their in-home activities [5] and inferring the purpose of their travels [6].

Another use of context history is to infer user interests in products and services, which could then help in targeting ads and other commercial content to users [7]. Historically, such targeting has been based on users' content preferences (e.g., favorite TV Shows), their prior product or service purchases using credit or loyalty cards, and their searching and browsing behaviors on the Internet. However, with context history, such interests could be estimated based on prior visits to retail shops, restaurants and other establishments.

Using context history in this way has some advantages over traditional approaches. It can provide information about users' interests even when there is no computer record identifying them with their purchases. This could happen if they do not make purchases using a credit or loyalty card, either because they pay with cash or because someone else pays for their purchases.

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Location history can also provide information about more general lifestyle interests, based on prior visits to schools, parks and other non-commercial establishments. Thus, if a user is a member of a retailer's loyalty program, such lifestyle data could potentially identify product or service interests that are not evident in the purchase history data that the retailer has for that user.

Finally, information about regularities in the user's travel and visit times (e.g., dining out every Saturday evening) can be used to anticipate purchases. This could enable more timely presentations of commercial content (e.g., every Saturday afternoon, presenting mobile ads that offer restaurant discounts), thereby increasing the relevance of the content to the user.

Aside from discovering users' product or service interests, location history could also be used to discover typical patterns of visits that large groups of users have in common. Then, through market research, it may be possible to find associations between such patterns and the predominant product or service interests for those groups. This approach could then promote collaborative filtering, where ads or special offers for such products or services can be presented to new users who exhibit similar patterns. This is analogous to approaches used in online shopping recommender systems, except that those systems rely on user Internet-based behavioral patterns, such as browsing patterns, for targeting ads or recommending products [8].

Product/Service Interests. In order to evaluate the use of location history as a predictor of product/service interests, the current study evaluated the relationship between patterns of visits to certain categories of establishments and one important measure of product/service interest: involvement in making decisions about the purchase or use of certain categories of products or services (Product/Service Involvement, or PSI). Following Zaichkowsky [9], involvement includes doing research and comparing brands, versions etc. of products or services. However, the current study also includes the frequency with which users make these decisions.

In evaluating location history as a predictor of PSI, the approach taken here is to assess whether it incrementally adds predictive capabilities above other traditional predictors. For example, there are well-known demographic differences in involvement for different types of products and services, including differences in gender, age and income. A strong test of the predictive capabilities of location history is whether it predicts variability in involvement that is not accounted for by these other variables.

Another potential predictor of involvement for certain products and services is the use of advanced mobile services, such as location-based and mobile Internet services. This variable is accessible to analytics systems that collect user mobile data, and Pagani [10] has shown that use of such services is associated with user segments, such as Innovators and Early Adopters, who tend to more readily adapt new technologies. Thus, use of advanced mobile services should be associated with greater involvement in making purchase and usage decisions regarding technology products and services.

Measuring Location History. The results reported here come from a study evaluating the use of location history to estimate the times of visits to establishments, and the validity of location history as a predictor of PSI. In this study, establishment visits were recorded using both GPS data and subjects' diary reports. However, the analyses in the current paper will focus only on the diary reports, because more visits could be identified from the diary entries than from the GPS results. This was due to both subject errors (e.g., subjects forgetting to bring the GPS data logger with them on a shopping trip) and technical problems (e.g., lack of a GPS signal in multi-level shopping malls). Furthermore, the diary data was considered to be a good substitute for the location data, since there was a significant relationship between 1) the rankings of subjects' preferred establishment categories derived from the diary reports of their establishment visits and 2) those same rankings derived from the GPS-based estimates of such visits [7].

In order to produce, from the diary data, a set of variables representing visit patterns, the study used Principal Components Analysis (PCA), a form of Factor Analysis. This approach extracts the common variance out of a set of correlated measures to produce a smaller number of more stable variables. Thus, if there is a tendency for users who visit one category of establishments (e.g., clothing shops) to visit others as well (e.g., accessories and beauty shops), there would be a relatively high correlation between visit frequencies across these categories. PCA would then derive one factor that represents this tendency, along with a factor score for each user representing the degree to which he or she prefers visiting these establishments. The factor analytic approach helps produce fewer and more stable variables for use as predictors in the models of PSI. Similarly, PCA was used to reduce the number of PSI variables, thus producing fewer, more stable dependent measures as well.

2 Method

A total 24 subjects (11 male and 13 female) participated in the study, ranging in age from 23 to 66 years. Individuals were selected to participate in the study if they 1) resided in Schaumburg, Illinois and adjacent towns and villages, and 2) reported being frequent shoppers having an annual household income exceeding $50,000. These criteria were used to increase the chances that they would engage in a relatively large amount of shopping during the course of the study.

The study itself consisted of two parts, a field study and a lab study. The field study involved collecting diary data regarding the users' visits to establishments during the 1-month time period of the study. The lab study included questionnaires on the subjects' basic demographics, their use of mobile services, and their involvement in commercially-relevant activities.

For their diary entries, the subjects were instructed to report on their visits to establishments each day by calling a toll-free number and leaving a voicemail message for the experimenter, or by sending an email message to the experimenter. They were instructed to include, in each report, their name, the name of each establishment they visited, the type of establishment, its location, the date and time they entered and exited, and the reasons for visiting that establishment.

2.1 Lab Study

After subjects had completed the field study, they were brought into the lab to complete some questionnaires. Two questionnaires that are relevant to the current report were the Demographics Questionnaire (DQ) and the Product/Service Questionnaire (PSQ). The DQ asked basic questions, such as subjects' age, gender and household income. It also asked about how frequently they use a mobile device to talk, access web sites, send or receive email and text messages, get GPS navigation instructions, and play games.

The PSQ measured involvement in making decisions regarding the purchase or use of certain products and services. For each product or service, subjects were asked two questions, an "Experience" question and an "Involvement" question. The Experience question asked about the frequency with which they purchased or consumed that item over a given time period. The Involvement question asked how involved they were in purchase or consumption decisions, which entailed doing research to learn more about the product or service, determining the best brand to buy or use, and deciding how much to pay for it. For consumption, involvement referred to making decisions about, for example, what TV programs to watch, meals to prepare, etc.

Product/Service Involvement. To analyze the PSQ results, the "Experience" and "Involvement" scores were combined together into one measure. However, the problem with the PSQ "Experience" items was that the response scales differed across items. The items asked how frequently subjects performed activities across various time spans, from weeks to years, depending on the activity. In order to create a standard scale for all PSQ items, the response of each subject, j, on each "Experience" item, i, was rescaled by computing a standard score, E_{ij}, for that item, using the following formula:

$$E_{ij} = \frac{x_{ij} - \bar{x}_i}{s_i} \tag{1}$$

where x_{ij} was the original response of that subject for this item converted to an integer scale, $\bar{x}_i$ was the average rating for the item, and s_i was the standard deviation of the ratings for that item.

Unlike the "Experience" items, responses to the "Involvement" items were already on the same 5-point scale, from "I have not been involved at all" to "I have been very involved". However, the problem with these items was in how subjects interpreted "being involved". Some subjects, for example, might have had a more liberal interpretation of this than others, so their overall responses could have been toward the top of this scale (i.e., "C", "D" or "E"), whereas others might have been more conservative, giving responses of mainly "A" or "B".

Thus, to assure that all subjects were on the same scale, each subject's responses to these items were standardized with respect to that individual's overall distribution of responses to the Involvement items. Thus, the standard score, V_{ij}, for Involvement item i and user j, was defined as

$$V_{ij} = \frac{x_{ij} - \bar{x}_j}{s_j} \tag{2}$$

where x_{ij} is the subject's response for this item converted to an integer scale, $\bar{x}_j$ is the average rating that the subject gave for all of the "Involvement" items, and s_j is the standard deviation of that subject's ratings for these items.

Once the responses to the "Experience" and "Involvement" items were standardized, they were combined together to produce the Product/Service Interest Index (PSII), using the following logistic function:

$$I_{ij} = \frac{1}{1+e^{-(E_{ij}+V_{ij})}} \tag{3}$$

As shown in Table 1, there were 2 product or service items for each of 15 categories: Autos (AUT), Entertainment (ENT), Food and Drink (FAD), Finance (FIN), Health (HEA), Household (HSD), Internet Services (ISP), Leisure (LEI), Print Media (PRM), Public Service/Nonprofit (PSN), Retail (RTL), Sports (SPO), Toiletries and Cosmetics (TAC), Technology (TCH), and Telecommunications (TEL).

Table 1. Products and services used in the Product/Service Questionnaire

CAT	ITEM 1	ITEM 2	CAT	ITEM 1	ITEM 2
AUT	Cars	Automobile Magazines	PRM	Magazines	Newspapers
ENT	Movies	Television Programs	PSN	Charities	Food Banks
FAD	Groceries	Meals prepared	RTL	Clothing	Jewelry
FIN	Stocks Traded	Checking Financial Markets on the Web	SPO	TV Sports Programs	Live Professional Sporting Events
HEA	Non-prescription remedies	Health Products	TAC	Hair Products	Creams and Moisturizers
HSD	Lawn/ Garden Maintenance	Home Repair/ Maintenance	TCH	Computers	Mobile Phones
ISP	Email Addresses	Web Hosting Services	TEL	Call Forwarding	Caller ID
LEI	Vacation/ Holiday Travel	Amusement Parks			

3 Results

Diary Data. There were 401 voicemail diary reports and 100 email diary reports during the course of the study, and a total of 1500 reported visits to establishments, or an average of 62.5 visits per subject (SD 39.8). Three subjects reported fewer than 20 visits, whereas 3 reported 120 or more.

For the analyses of the diary data, a visit was included if there was sufficient information about the name, location and entry and exit times for that visit. However, subjects sometimes left out important information or gave incorrect information about their visits. Out of the original 1500 diary entries, 1286 or 85.7% included sufficient information about the name and location, as well as entry and exit times. In some cases, it was possible to fill in missing or incorrect information by searching for establishments on the web using the information that was provided in the diary.

Categorizing the Diary Data. A list of 485 unique brands of commercial establishments were derived from the diary data. These brands were then divided into 21 categories. Among these categories, restaurants comprised the highest number of brands (124), followed by retail (e.g., department stores; 94 brands), food & drink (e.g., groceries; 35), health-related establishments (e.g., doctors office; 35), auto (e.g., auto service stations; 29), recreation (e.g., health clubs; 21), and toiletries and cosmetics (21). However, snack shops (e.g., donut shops) had the highest number of visits per brand (6.3), followed by food and drink (5.8 visits per brand), technology establishments (e.g., home electronics; 4), educational (e.g., schools; 3.4), retail (3.2), finance (e.g., banks; 3.2), household (e.g., hardware stores; 3.1), and print media (e.g., book stores; 3.1).

In order to reduce the number of categories, the diary results were subjected to a Principal Components Analysis, where the unit of analysis was the number of reported visits by each subject in each category. The version of PCA used here employed Varimax rotation and Kaiser Normalization. This transformation assured that the factors were maximally differentiated from each other, and that they accounted for a significant percentage of the variance.

Given the large number of variables, two analyses were performed in order to produce more stable models. The decision about which variables to include in which analyses was made based upon the Pearson Product Moment correlations among the variables.

The results of these analyses are shown in Table 2, which displays the factor loadings for each of the diary categories in each factor, and the percentage of variance accounted by each factor in the model. As shown in the Table, there were two analyses performed, each limited to 3 factors. The first analysis accounted for 76.6% of the variance and the second accounted for 79.6%.

In the first analysis, the first factor, “RecHealth”, combined the recreation and health categories together. The second factor, “AutoPrint”, combined Auto and Print Media, and included also Retail, which had a negative loading for in this factor. The last factor, “Leisure”, combined Travel and Dining, as well as “Food & Drink”, which had a negative loading on this factor.

In the second analysis, the first factor, “SnackHouse”, combined the Snack category (which included coffee and donut shops) with the Household category (including home repair, lawn/garden maintenance, etc.). The second factor, “Entertain”, revolved around entertainment activities and hobbies. The final factor, “TechToys”, incorporated toys, games and technology.

Note that the categories and factor solutions presented here do not necessarily constitute the only way of dividing the space of establishments. Furthermore, other approaches, such as cluster analysis, are likely to yield different results. However, the solution here produced sensible factors that accounted for a large-enough percentage of variance in the data to justify using the factor scores derived from these analyses to predict product/service involvement.

Table 2. Results of factor analyses of the diary data

Item	Component 1 RecHealth	Component 2 AutoPrint	Component 3 Leisure	
Recreation	**0.91**	0.12	-0.10	
Health	**0.84**	-0.14	-0.23	
Auto	-0.42	**0.83**	0.19	
Print Media		**0.80**	-0.17	
Retail	-0.39	**-0.77**		
Travel			**0.87**	
Dining	-0.21	0.23	**0.79**	
Food & Drink		0.35	**-0.72**	
% of Variance	30.4	23.7	22.5	Total = 76.6

Item	Component 1 SnackHouse	Component 2 Entertain	Component 3 TechToys	
Snack	**0.89**			
Household	**0.86**	0.25	-0.12	
Entertainment		**0.90**		
Hobbies	0.29	**0.82**	-0.14	
Toys & Games	-0.23		**0.86**	
Technology		-0.25	**0.85**	
% of Variance	27.8	26.7	25.1	Total = 79.6

PSQ Results. In order to reduce the number of variables in the PSQ, the PSII scores were submitted to three Principal Components Analyses, each with Varimax Rotation and Kaiser Normalization. As shown in Table 3, four orthogonal factors were identified in the first analysis, 4 in the second, and 3 in the third. The first analysis accounted for 78% of the variance, the second accounted for 76.3% and the third accounted for 79.4%. Four of the PSQ items, Amusement Parks, Automobile Magazines, Books and Mobile Phones did not load significantly on any factor.

The factors in the first analysis revolved around the themes of Homemaker, Sundries, Entertainment and Technology. The "Homemaker" factor incorporated items relating to family care and self-grooming, while the "Sundries" factor contained items relevant to accessories and self-grooming. The "Entertainment" factor included movies and vacation/holiday items, as well as food shopping and preparation. Finally, the Technology factor ("Tech") incorporated computers and web hosting services.

The first factor in the second analysis, "EmailCar", had items relevant to autos and email addresses. The "Telecom" factor items related to telecommunications services, and the "Financial" factor included Internet financial services and investment in stocks.

In the third analysis, the "HomeCare" factor incorporated items relating to home and lawn/garden maintenance. The "SportsTV" factor included spectator sports and TV watching items. The third factor, "Charity", included donating to charities and food banks.

Table 3. Results of factor analyses of the PSQ.
(Top: Analysis 1, Middle: Analysis 2, Bottom: Analysis 3)

Item	Component				
	Homemaker	Sundries	Entertain	Tech	
non-prescription remedies	**0.80**			0.23	
visited an amusement park	**0.73**		0.38	0.41	
gone shopping for groceries	**0.65**	0.21	**0.51**	-0.24	
hair products	**0.64**	**0.48**		-0.15	
shopped for jewelry		**0.87**		0.32	
Clothing		**0.79**	0.23		
face creams, body creams . . .	**0.48**	**0.73**		-0.24	
Movies			**0.87**	0.11	
traveled on vacation	0.13	**0.47**	**0.77**		
prepared a meal	**0.52**		**0.66**	0.25	
web hosting services	0.11	-0.13	-0.12	**0.91**	
Computers		0.24	0.35	**0.74**	
Percentage of Variance	37.6	17.4	11.9	11.2	Total = 78.0

Item	Component				
	EmailCar	Telecom	PrintNews	Financial	
cars have you owned	**0.88**	0.29	-0.11		
email addresses	**0.88**	-0.31	0.12	0.17	
caller ID		**0.88**	-0.15		
call forwarding		**0.72**	0.46	0.20	
news magazines	-0.20	-0.24	**0.78**		
Newspapers	0.19	0.26	**0.75**		
check markets on the Internet		0.18	0.21	**0.88**	
traded stocks	0.34	-0.18	-0.22	**0.76**	
Percentage of Variance	21.7	20.7	18.9	18.0	Total = 79.4

Item	Component			
	HomeCare	SportsTV	Charity	
home repair/maintenance	**0.86**	0.26		
maintaining lawn & garden	**0.85**	-0.23		
donating to charities	**0.68**		**0.59**	
sport(s)-related programming	-0.13	**0.86**	0.13	
live professional sporting events	0.33	**0.79**	-0.25	
hours of television	-0.11	**0.73**	0.39	
vitamins, supplements, etc.		0.20	**0.86**	
donating to food banks			**0.81**	
Percentage of Variance	25.8	25.7	24.8	Total = 76.3

Regression Analyses. The final analyses focused on whether diary factors provided significant incremental improvements in predictions of PSQ factors over using the demographic and mobile usage variables alone. The first step was to fit linear regression models using Gender, Age Range, and Income as predictors, and the PSQ factors as dependent measures. Then the next step was to add the mobile context variables to the models. For these analyses, the Gender variable was coded 1 for male and 2 for female, and Age-Range was coded according to the 5-point scale used in the study: "1" for under 20 years, "2" for 21 to 30, "3" for 31 to 40, "4" for 41 to 50, and "5" for over 50.

Tables 4 and 5 shows the results of modeling the PSQ factors using the demographic predictors alone, and then adding the mobile context variables. For the first three models, the dependent variable was the Sundries factor. The first of these models included, as the predictor, only the Leisure factor derived from the diary data. Subjects with greater involvement in Leisure-relevant products and services more frequently

Table 4. Results of regression analyses using factor scores derived from the diary data as predictors and factor scores derived from the PSQ data as the outcome measures [1]

Prod. Invmt. Factor		Demographic Variable			Context Variable 1				Context Variable 2			
		Name	Coef.	Adj. R^2	Label	Coef.	Adj. R^2	Incr. R^2	Label	Coef.	Adj. R^2	Incr. R^2
Sundries	1	[none]			Leisure	0.51	0.23	0.23				
	2	Gender**	0.90	0.18	Leisure	0.50	0.42	0.24				
	3	Income**	0.02	0.22	Leisure	0.49	0.44	0.22				
Sports-TV	1	[none]			Mobile	-0.39	0.17	0.17	Tech-Toys	0.42	0.32	0.15
	2	Gender*	-0.64	0.07	Mobile	-0.41	0.24	0.17				
Home-Care	1	[none]			Snack-House	0.49	0.30	0.30	Rec-Health	0.45	0.48	0.18
Email-Car	1	[none]			Leisure	-0.43	0.15	0.15	Auto-Print	0.43	0.30	0.15
	2	Gender*	-0.68	0.08	Leisure	-0.43	0.24	0.15				
Print-News	1	[none]			Mobile	-0.42	0.14	0.14	Auto-Print	0.43	0.29	0.16
	2	Age Range**	-0.35	0.09	Auto-Print	0.43	0.25	0.15				

[1] Note that, except where "[none]" is indicated, each regression included one demographic variable. The context variables were added in via stepwise regression, with a variable added as long as $p < .05$, and removed when $p > 0.1$. All regressions are statistically significant at $p < .05$, all context predictor variables are significant at $p < .05$, all demographic predictors with an asterisk (*) are nearly significant at $p < 0.1$, and all demographic predictors with a double asterisk (**) are significant at $p < .05$.

reported visiting restaurants and travel-related establishments, but less frequently reported visiting grocery stores and similar establishments. This model produced a statistically significant fit, but accounted for only 23% of the variance.

As Sundries model 2 shows, when Gender was the lone predictor, the model accounted for 18% of the variance, whereas when both Gender and Leisure were the predictors, the model accounted for 42% of the variance. Similarly, when Income and Leisure were the predictors, the model accounted for 44% of the variance. Thus, the best predictors for the Sundries factor was 1) being female, 2) having a larger income, and 3) visiting establishments that provide Leisure-relevant services (i.e., travel and dining), but not visiting grocery stores and related establishments.

When "SportsTV" was the dependent variable, the best-fitting model, accounting for 32% of the variance, included Mobile and "TechToys" as predictors. Subjects who watched more sports and TV were less likely to use mobile services and more likely to visit toy and technology stores. In the second "SportsTV" model, accounting for 24% of the variance, the key predictors were being male and not using mobile services.

With "HomeCare" as the dependent variable, the significant predictors were "SnackHouse" and "RecHealth". For this model, which accounted for 48% of the variance, those subjects who more often reported visiting snack shops (e.g., donut and coffee shops), household-relevant establishments (e.g., stores selling supplies for home and garden care and maintenance), and recreation- and health-related establishments (e.g., health clubs) were more likely to be involved in making decisions about purchasing and using home, lawn and garden maintenance products and services, and were also more likely to be involved in deciding what charities to contribute to.

Table 5. Summary of regression results

Subjects who…..	**were more likely to….**	**were less likely to….**
watched more TV and watch more live/televised sports ("SportsTV")	…visit toy & games stores and technology stores …be male	…use advanced mobile services
had more involvement in home, lawn, garden maintenance and donations to charity ("HomeCare")	…visit snack shops, and household supplies stores (including home repair, lawn & garden care & maintenance) …visit recreation & health related establishments, e.g., health clubs …be involved in deciding what charities to donate to	
had more involvement in purchase decisions about email services, auto products & services	…visit bookstores, auto products and services establishments …be male	…visit restaurants, travel establishments, clothing and grocery stores.
had more involvement in purchasing decisions about newspapers & news magazines	…visit bookstores, auto products and services establishments …be younger	…use advanced mobile services

The significant predictors of "EmailCar" were Leisure and "AutoPrint". Thus, the subjects who were more involved in decisions regarding email services and automotive products and services were 1) less often visiting restaurants, travel-related establish- ments, and clothing and grocery stores, and 2) more often visiting book-stores and establishments selling automotive-relevant products and services. Furthermore, "EmailCar" model 2 shows that males were more involved in making these decisions.

The final set of models showed that the use of fewer mobile services and more frequent visits to bookstores and automotive-relevant establishments were both significantly associated with greater involvement in making purchase decisions about newspapers and newsmagazines. Furthermore, as "PrintNews" model 2 shows, younger individuals were more likely to be involved in making these decisions as well.

4 Discussion

The results of this study demonstrate the potential for using location history as an indicator of user interest in products and services. These results also suggest that location history could add significant value to more traditional measures (e.g., demographic measures) as predictors of user interests. Adding the location history factor scores as predictors significantly improved the predictive capabilities of the regression models, when compared to using demographic variables and a measure of mobile usage alone. The implication is that visit patterns are a significant component in models for targeting ads and other commercial communications.

One limitation, however, was the small sample size. It is likely that a larger sample would have produced more significant prediction models. Furthermore, a longer data collection period would have produced more accurate estimates of visit patterns. There was likely some bias since, in the 1-month time period of the study, the observed patterns were probably influenced by the season during which the study was conducted.

Another limitation was the lack of purchase history data for the subjects. Many targeting algorithms rely on such data to make inferences about user product interests. Incorporating purchase history would also have improved the model predictions.

Finally, it was clear from the data that some subjects were better than others at reporting their establishment visits. Despite this, there were more visits identified in the diaries than in the GPS data [7], due to the technical and human-error issues discussed above. Perhaps some of the technical problems might be overcome by using both GPS and Wi-Fi to estimate location [11].

Overall, the results presented here demonstrate that use of location history for targeting could potentially support location-based and m-commerce services that rely on analytics, advertising and sales as sources of revenue. If future research supports the validity of location history as a predictor of PSI, then the next steps should include evaluating whether targeting based on location history can significantly increase consumer basket size and other outcome variables that are important for retailers.

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