

Classifying Spending Behavior using Socio-Mobile Data

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ABSTRACT

Human spending behavior is essentially social. This work motivates and grounds the use of mobile phone based social interaction features for classifying spending behavior. Using a data set involving 52 adults (26 couples) living in a community for over a year, we find that social behavior measured via face-to-face interaction, call, and SMS logs, can be used to predict the spending behavior for couples in terms of their propensity to explore diverse businesses, become loyal customers, and overspend. Our results show that mobile phone based social interaction patterns can provide more predictive power on spending behavior than personality based features. Interestingly, we find that more social couples also tend to overspend. Obtaining such insights about couple level spending behavior via novel social-computing frameworks can be of vital importance to economists, marketing professionals, and policy makers.

I INTRODUCTION

People's social behavior has been shown to affect their obesity levels [6], reproductive fitness [2], productivity, software adoption [5], college choices, substance abuse, political affiliations [7], and health characteristics [6, 33]. In the last decades, many researchers in sociology, social psychology and cultural anthropology have also described the spending behavior as a social construct, pointing out that social influences play a large role in customer behavior. The basic idea is that a person's attitudes and behaviors are influenced by several levels of society, such as culture, subculture, social classes, reference groups, and face-to-face groups [39]. For example, in 1967 James Duesenberry [27] persuasively questioned one of the fundamental assumptions of consumer theory, namely that consumers behave independently of each other. Instead, Duesenberry empirically demonstrated that consumption patterns have a social character. Other theories have described shopping as a leisure activity [40, 41], and Daniel Miller in his book "A theory of shopping" [42] ethnographically inferred the role played by shopping in building relationships with

one's peers (e.g., family members, friends, and so on).

Recently, ubiquitous sensing and other social computing frameworks have been employed to study the links between the various facets of human behavior [8, 9], and also to influence human behavior in positive ways [4, 36]. While multiple efforts have employed ubiquitous sensing for monitoring health state [10], affect [11, 12], mobility [8, 13], social relationships [14, 50] and personality traits [15]. Our work extends these efforts to a new domain: spending behavior.

Specifically, we investigate whether the social behavior measured via face-to-face interactions, call, and SMS logs, can be used to predict the spending behavior for couples in terms of their propensity to explore diverse businesses, engage frequently with them, and overspend. An analysis of a dataset consisting of social interaction patterns and self-reported spending data for 52 adults (26 couples) living in a residential community for a year, shows that there are significant links between social behavior and spending patterns. These findings not only motivate a potentially new line of investigation into spending behavior via mobile sensing, but also demonstrate the feasibility of *passive* (i.e. those which do not require active user attention) methods for undertaking similar studies at a larger scale in near future.

Understanding which couples are likely to explore diverse businesses and engage frequently with them is vital information for marketing campaign managers. It affects two fundamental aspects of marketing: *customer acquisition* and *customer retention*. Similarly predicting which couples are likely to overspend can be a valuable insight for economists, credit unions, and policy designers. Further, an understanding of these results can help the individuals themselves to understand their long term spending profile both individually and with a partner.

The rest of this paper is organized as follows. We survey the related work followed by the description of the dataset employed. We present a

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method for characterizing spending behavior, and discuss the socio-mobile and spending features used to study the interconnections. The observed correlations are first explored separately. Next, multiple features are combined using a naïve Bayes method to predict the high (or low) propensity of couples to demonstrate a specified spending behavior. The observed results are compared with a baseline model and an alternative personality based approach. Lastly, we discuss some limitations of the current study and discuss the potential for much larger similar studies in future.

II RELATED WORK

In recent years, mobile sensing and reality mining approaches have been used to understand multiple aspects of human behavior. Some of these look at detailed sensing of the individual to understand measures like gaze, interest level, affect, stress and personality (e.g. [14, 22]). Others look at the communication and interaction patterns to study the spread of diseases, obesity, information, and product adoption [6]. Mobile phones in particular have been used to study patterns of human mobility both at a macro and an individual level [4, 8, 16].

Previous efforts at linking social behavior, as detected by ubiquitous sensing, with economic behavior have focused on two aspects.

First is the interconnection between social behavior and income levels. For example, Eagle et al. [16] found that localities (cell tower areas) with diverse network interactions tend to have higher economic development. Similarly, Pan et al. [3] have shown that people with higher diversity in social contacts tend to have higher incomes. A second line of investigation has focused on using homophily and social closeness to predict the products of interest to individuals. For example, [5] shows that users with high face-to-face interactions tend to install similar mobile apps. In fact, the key idea behind Amazon's collaborative filtering based product recommendation uses a similar idea [43].

We focus on a third dimension. Rather than identifying user interest in specific products, we focus on understanding some fundamental *behavioral features* about user spending. Insights on a behavioral level (e.g. overspending, loyalty, and diversity) have much longer term validity and can explain certain fundamental aspects of human behavior. The roles of social features in identifying such behavioral characteristics have been alluded to in multiple social science efforts (e.g. [40, 41, 42]). However, to the best of our knowledge, this

paper is the first detailed study at predicting characteristic spending behaviors (overspending, loyalty, and diversity) using mobile phone based social interactions features.

Previous research on spending behavior comes largely from marketing science. One area of this research has focused on predicting customer attrition and retention using, for example, perceptions of quality [45], customer satisfaction [46], the company's marketing activities [47], promotional effects [48], and customer behavior [1], among other predictors. A less-extensively investigated area in marketing/resource allocation research is being able to identify potential high-value customers, or prospects. Easily available data on prospects, such as demographics and sociographic factors often have limited ability to predict future spending behavior [44]. Meanwhile, past customer behavior (often used to predict attrition and retention) cannot be used for prospect identification because past customer behavioral data only exists for people who are *already* customers. As such, existing research on how to choose which prospects to acquire are confined to the few businesses that collect data on individuals who are not yet customers; such a business could be an internet retailing company with clickstream data (e.g. [26]), or a business that has collected trial period data. However, the first approach focuses on using online behavior (as opposed to *real-world* behavior [9]) and the second requires costly surveys and trials for each new product.

An alternative approach, proposed here, is to use mobile phones to capture *real world* social behavior at scale. These data, with one time user consent, can be used to passively obtain and predict long term spending behavior.

This paper builds upon a six page conference version [49]. The current version provides more details and more thorough treatment. Specifically, it includes a section on the correlations observed between spending and socio-mobile features (Sec. IV), and provides results on the relative effectiveness of different sensing modalities (call, SMS, Bluetooth) for predicting spending behavior (Sec V.3).

III DATASET: A LIVING LABORATORY

For our work we use the *Friends and Family* dataset, first introduced by Aharony et al. [4]. The *Friends and Family* dataset is based on a year-long study, which used the "Funf" mobile phone platform, surveys, receipts/credit card statement, and a Facebook application, to collect an immensely rich and dense dataset on the lives of

the 64 families that participated. The participants were all members of a young-family residential living community at a major North American university. All members of the community were couples, in which at least one of the members was affiliated with the university. The community was composed of over 400 residents, approximately half of which had children. The community had many ties of friendship between its members.

Several facets of the *Friend and Family* study were opt-in. Submitting the spending data used in this study was one such facet. A total of 27 couples chose to participate. The results reported here come from 26 couples, as one of the 27 couples did not provide social behavior data. (Also note that 2 couples provided only partial data. We consider their data only in the features available.)

All participating couples in this study were of different genders and either married or in civil union; their mean age was 30 years; approximately half of the participants had kids, and at least one of the members of the couple was a graduate student at the above mentioned university. The participants belonged to more than 10 different nationalities.

Compared with previous social computing observatory studies (e.g. [9, 16, 17]), the Friends and Family community includes a more diverse subject pool and provides a unique perspective into a phase of life that has not been traditionally studied in the field of ubiquitous computing - married couples and young families.

1 SUBJECT PROTECTION, PRIVACY CONSIDERATIONS, AND INCENTIVES

The study undertaken was approved by the Institutional Review Board (IRB) and conducted under strict protocol guidelines. The protection of participant privacy and sensitive information was a key consideration. For example, data were linked to coded identifiers for participants and to not their real world personal identifiers. All human-readable text, such as phone numbers and text messages, was captured as hashed identifiers, and never saved in clear text. Collected data were physically secured and de-identified before being aggregated for analysis. Additionally, data collection was designed to be as unobtrusive to subject's daily life as possible.

As incentive, the participants were able to keep the phone at the end of the study, and were

compensated extra for every mandatory out-of-routine task, such as filling out surveys. Participation in interventions or sub-experiments (the current study included) was completely optional. The couples participating in the spending behavior study discussed here were incentivized by paying them a small amount for each submitted receipt, capped at \$50.

2 SOCIAL BEHAVIOR DATA

Each member of the couple was equipped with an Android-based mobile phone incorporating the Funf framework, a sensing software explicitly designed for collecting mobile data, such as Bluetooth of nearby devices, call and SMS logs, accelerometer, etc. This software ran in a passive manner, and did not interfere with the normal usage of the phone [4].

The data we analyze in this study consisted of: i) call logs; ii) SMS logs; and iii) proximity data. The proximity data were obtained from Bluetooth scans for nearby devices, made every five minutes (the five minutes sampling frequency prevents draining the battery while achieving a high enough resolution to detect social interaction). Knowing the Bluetooth identifiers of each smartphone in the study, we could thus infer when two participants' phones were in proximity. The logs of all the calls and SMS interactions by the users were also uploaded passively by the Funf software.

Such data were collected for more than a year in the study. The long term data collection is pertinent as we focus on longer term behavioral features rather than one off transactions. An overview of the socio-mobile data captured is presented in Table 1. As can be seen we employ a rich collection of socio-mobile data, which exceeds 10 million data points.

Table 1: Dates and number of samples available for each social interaction data type employed:

| Data type | Duration | N |
|-----------------|---------------------|------------|
| Calls | Mar 2010 – Jul 2011 | 105,281 |
| SMS | Mar 2010 – Jul 2011 | 53,363 |
| Bluetooth scans | Mar 2010 – May 2011 | 10,877,546 |

3 SPENDING DATA

Following the observations by several prominent economics researchers (e.g. [28]), we collected spending data at the “household,” or couple, level. This eliminates the often impossible task of disentangling the spending of the different family members, who too often share money and act on behalf of one another. Hence, this study does not focus on identifying the relative role (e.g. who buys more often? who makes spending decisions more often?) played by the two partners within the couple. Rather it focuses on couple level variables both in the social and the spending behavior to understand their interconnections.

Participating couples were asked to submit receipts or credit card statements of their purchases. Paper receipts were translated to digital transaction logs by a research assistant. Each entry in the credit card statements was considered a separate receipt.

Although participants were asked to submit receipts throughout the study, we focus on a period of 6 months (Mar 2010 - Aug 2010), during which all 26 couples actively and consistently submitted receipts (mean number of receipts per month = 448; standard deviation = 56).

The average amount spent by each couple during this period was \$704 per month and the average amount spent per receipt was \$41. The majority of expenses (around 65%) of the receipts came from restaurants, cafés, pubs, groceries, and entertainment. So, the spending behavior we are targeting is largely related to social activities.

4 SURVEY DATA: DISPOSABLE INCOME AND PERSONALITY

A one-time survey administered at the start of the study was used to determine self-reported disposable income, and personality traits. Disposable income was used to calculate overspending (explained in the next section). Personality traits were used to create a comparative model to predict spending, against which we compared our model-of-interest (based on social behavior measures). This was motivated by multiple studies, which have shown that personality variables can explain differences in spending behavior. For example, Norvilitis et al. [17] found that an ability to delay gratification was a predictor for debt accrued by college students.

Similarly, Salmela [18] found that extroversion was predictive of people’s attachment to luxury goods, and Nyhus et al. [19] showed that emotional stability, autonomy, and extraversion were robust predictors of saving and borrowing behavior.

For this study, we use the Big Five personality questionnaire developed by John et al. [20] to characterize participant’s personalities. The Big Five questionnaire owes its name to the five personality dimensions it measures, which together can be used to distinguish between personality types. For each couple we obtained five features capturing the couple’s average level of *extraversion*, *agreeableness*, *conscientiousness*, *neuroticism*, and *openness*, and another five capturing the couple difference on those five features. This resulted in 10 personality based features for each couple.

The Big Five method is a well-studied and widely-used method in psychology. Moreover, several personality traits measured by the Big Five Model have been found to be related to a variety of financial decisions. For example, Brandstätter [21] has found that the three dimensions, ‘emotional stability’, ‘introversion’ and ‘conscientiousness’, are related to a variety of financial decisions. Similarly, empirical evidence has shown that extraversion is associated with lower saving [23].

IV CHARACTERIZING SPENDING AND SOCIAL BEHAVIOR

To study spending behavior of couples, we focus on three important behaviors: **exploration**, **loyalty**, and **overspending**. The aim is to identify the couples that tend to explore diverse business, engage repeatedly and frequently with certain businesses, and/or spend higher amounts of money.

To quantify these three facets we used three different variables. For exploration, we calculated the **diversity** in vendors frequented. The exact method for calculating diversity scores is explained in the next section. For loyalty, we considered how frequently couples **engage** with their favorite businesses. Specifically, we calculated the percentage of transactions (out of a couple’s total transactions), that were made at their top three frequented businesses. Lastly, to quantify **overspending**, we calculated the ratio of the amount of money spent by a couple to their self-declared discretionary spending budget.

1 SPENDING VARIABLES

1.1 DIVERSITY VENDOR

Diversity quantifies exploration. The diversity score is a measure of how evenly a couple's purchases are distributed between different vendors. A couple with low diversity distributes their spending unevenly across businesses, whereas a couple with high diversity spends evenly across many businesses.

Diversity scores were computed following the definition used by Eagle et al. [16] where diversity, D , for a given couple, i , is given by:

$$D(i) = \frac{-\sum_{j=1}^k P_{ij} \log(P_{ij})}{\log(k)} \quad \dots (1)$$

In the equation above, j represents a vendor in couple i 's repertoire, or "contact" list (i.e. the set of j values represents the set of vendors by name); and k is the total number of i 's contacts. P_{ij} is the proportion of interaction i makes with contact j out of i 's total interaction volume with any contact:

$$P_{ij} = \frac{V_{ij}}{\sum_{j=1}^k V_{ij}} \quad \dots (2)$$

where V_{ij} is the number of interactions between i and j , and k is the total number of contacts for i .

For spending behavior each receipt was considered as evidence of one interaction. For the social behavior, (see next section), each call, SMS, or face-to-face meeting was considered as one interaction.

1.2 ENGAGEMENTTOP3

Engagement quantifies loyalty. For this measure we calculated the percentage of each couple's total purchases that were made at their three most frequented vendors.

$$L(i) = \frac{\sum_{j=1}^3 V_{ij}}{\sum_{j=1}^k V_{ij}} \quad \dots (3)$$

The notations i , j , and k are used in the same way as in Equation 1.

1.2 MONTHLY OVERSPENDING

Overspending was measured as the ratio of actual monthly spending to the self-reported discretionary

spending (obtained from a one-time survey administered early in the study asking *individuals* for their individual discretionary spending).

$$MonthlyOver = \frac{4 * AveWeeklySpending_{couple}}{Discretionary_{p1} + Discretionary_{p2}} \quad \dots (4)$$

where *MonthlyOver* stands for monthly overspending.

The median values for the three spending variables were 0.9041, 0.3297, and 3.8696 respectively. The corresponding standard deviations were 0.0763, 0.1185, and 4.7287 respectively.

2 SOCIAL BEHAVIOR VARIABLES

2.1 INTERACTION MODALITIES

We consider user interactions via three modalities: Bluetooth, calls, and SMS logs. Each of these interaction modalities captures a different mode of human interaction.

- **Bluetooth scans:** captured the physical collocation between participants. Such scans were undertaken every five minutes and provided an estimate of the face to face interactions happening between the participant and other individuals.
- **Call logs:** captured distant, synchronous interactions. Hence the interacting individuals could be at different locations but were communicating at the same time.
- **SMS logs:** captured the distant, asynchronous, textual interactions. Unlike calls, and face-to-face interaction, in this interaction mode the users could be separated in both space and time.

2.2 FEATURES FOR EACH MODALITY

We use four social behavior features for each couple, which were computed independently for each of the three modes of interaction (Calls, SMS, Bluetooth):

1. **NumEvents:** Total count of all interaction events (e.g. number of calls made).
2. **NumContacts:** Total number of different contacts interacted with. For example, if a user

made 100 calls to 7 different people, then, NumEvents=100 and NumContacts=7.

3. **InteractionDiversity:** A measure of diversity in the user's communication pattern. Using the call log data, SMS, and Bluetooth face-to-face proximity data collected via phone sensors, we computed this value as shown in Equation 1. The diversity score measures how evenly an individual's time is distributed among others. It is important to note that high diversity does not necessarily correspond to high call volumes or large number of unique contacts.
4. **EngagementTop3:** A measure of how engaged a user is with his/her favorite contacts. This measures the percentage of all interactions that involve only the three most frequently interacted contacts. This was computed using Equation 3.

2.3 FEATURES ON COUPLE (DIS)SIMILARITY

Each of the four features mentioned above was averaged and differenced over each couple to obtain 8 features per modality. The difference based features were included to consider the impact of dissimilar social behaviors in a couple on their spending patterns.

Table 2: Features for characterizing social behavior

| | Couple Average | Couple Difference |
|------------------|--|-------------------|
| Bluetooth | <ol style="list-style-type: none"> 1. NumEvents 2. NumContacts 3. InteractionDiversity 4. EngagementTop3 | |
| Call | | |
| SMS | | |
| | | |

As shown in Table 2 we obtained a total of 24 sociability features for each couple (3 modalities * 2 varieties * 4 variables) for each couple.

V PRELIMINARY ANALYSIS: CORRELATIONS BETWEEN SPENDING AND SOCIO-MOBILE FEATURES

Using the Pearson's coefficient to explore the data, we found some of the pairwise linear correlations between spending features and the socio-mobile features to be significant (p -

$value < 0.05$). We list the correlations observed in this section. Note that we focus only on correlations, and leave the causality effects outside the scope of our current discussion.

1 DIVERSITY IN BUSINESSES EXPLORED

We noticed that the diversity in vendors patronized by a couple is significantly correlated with the difference in social behaviors between the two members of the couple. Specifically, we observed positive correlations between the spending diversity feature and the difference in number of Bluetooth contacts ($r = 0.54$, $p-value = 0.005$), difference in the number of SMS contacts ($r = 0.42$, $p-value = 0.034$), and the difference in the percentage of SMS communication undertaken with top three contacts ($r = 0.46$, $p-value = 0.019$).

One possible interpretation of these correlations is that when the two partners in a couple have different social circles and social preferences, they may be exposed to different businesses explaining the observed spending diversity. Conversely, the users who regularly visit different businesses may come in contact with different people, and develop different social behavior.

2 LOYALTY TO BUSINESSES

The engagement of the couples in terms of the percentage of their shopping occurring within their top three frequented businesses was found to be correlated negatively with multiple measures of sociability, including the average number of call contacts ($r = -0.42$, $p-value = 0.034$), number of SMS contacts ($r = -0.48$, $p-value = 0.014$), and diversity of SMS contacts ($r = -0.47$, $p-value = 0.014$). We also find that the engagement is correlated negatively with the difference in the social behaviors including the difference in the number of Bluetooth contacts ($r = -0.44$, $p-value = 0.024$), difference in the number of SMS contacts ($r = -0.40$, $p-value = 0.045$), and the percentage of SMS communication with the top three contacts ($r = -0.44$, $p-value = 0.023$) for the couple.

These observations may suggest that users with lesser social activity (low number of contacts and low interaction diversity) also have a propensity to focus only on fewer business establishments. Also, if the divergence within the couple is low, they do not get exposed to too many places (as

also seen in previous section), and tend to focus on fewer businesses.

3 OVERSPENDING

Monthly overspending by couples was found to be correlated with higher social activity, including number of face-to-face interactions ($r=0.58$, $p\text{-value}=0.002$), number of face-to-face contacts ($r=0.44$, $p\text{-value}=0.025$), number of call contacts ($r=0.56$, $p\text{-value}=0.003$), call diversity ($r=0.43$, $p\text{-value}=0.028$), SMS contacts ($r=0.49$, $p\text{-value}=0.011$), and SMS diversity ($r=0.39$, $p\text{-value}=0.049$). Monthly overspending was also negatively correlated to the difference in the social behaviors of the two partners in terms of number of face-to-face contacts ($r=-0.48$, $p\text{-value}=0.013$).

These observations may suggest that more social couples tend to have larger social circles that may expose and/or include them in more spending opportunities. It also seems that overspending occurs when the two partners have similar social behavior profiles. We leave a deeper exploration of this link and its interpretation to future work.

We also noticed some interesting trends in variables for which no significant correlations were observed. For example while the number of call contacts and SMS contacts were both significantly correlated with the loyalty variable, the actual number of calls ($r= -0.25$, $p\text{-value} = 0.222$) and the number of SMS messages exchanged ($r=-0.31$, $p\text{-value} = 0.130$) were *not* found to be significantly related. In fact, while we found 10 different features related to the number of contacts to be significantly correlated; only 1 significant correlation was found with the number of interaction events. This indicates that the number of different people a couple interacts with may be a more significant predictor of their spending behavior than the number of interaction events.

Table 3: Trends in interconnection between social behavior and spending behavior. Each + or - sign indicates the directionality of the correlation found for the variables belonging to that category

| Spending behavior | Average Sociability | Divergence |
|-------------------|---------------------|------------|
| Diversity | | +++ |
| Loyalty | --- | --- |
| Overspending | +++++ | - |

We also see certain general trends in the correlation observed as shown in Table 3. Diversity in spending is positively correlated with divergence in the couple. Loyalty to businesses is inversely correlated to both sociability and divergence. Overspending is positively correlated with sociability.

To understand the ability of these correlations to collectively explain the respective spending tasks, we computed the adjusted R-square via piecewise linear regression for each of the three spending variables and we found values of 0.4110, 0.5414, 0.4732 respectively. We consider this to be preliminary evidence that socio-mobile features can reasonably capture the variance in the spending behavior. We further explore the predictive power of the socio-mobile features in the classification tasks described in the next section.

VI AUTOMATIC CLASSIFICATION OF SPENDING BEHAVIOR VARIABLES

We turn now to investigate the predictive power of the socio-mobile features at classifying spending variables. The motivation here is to investigate the ability of mobile phone based features to correctly classify couples as those with high or low propensity to (i) explore diverse businesses, (ii) become loyal customers, and (iii) overspend. We split each spending variable into two classes using the 50th percentile (*median*, as listed in section IV) value for each variable as the threshold. This resulted in two classes with equal frequency for each spending variable.

1 FEATURE SELECTION

A known problem in classification tasks is to find strategies to reduce the dimensionality of the feature space in order to avoid over-fitting. In our experiment, we used the Information Gain approach in order to evaluate the importance of a feature.

This method evaluates the worth of an attribute by measuring the information gain with respect to the class. This method is used with a Ranker search method and the features are ranked according to the square of the weights assigned to them. Hence, the first feature is the most relevant for the

classification task at hand and the last feature of the least relevant one.

For reasons of space and clarity of presentation, we do not report all the feature rankings produced, but present a subset of them in the next section.

2 EXPERIMENTAL SETUP AND RESULTS

For our classification experiments, we choose to use the Naïve Bayes method. Naïve Bayes is simple probabilistic classifier that applies Bayes theorem and assumes that the presence/absence of a particular feature of a given class is unrelated to the presence/absence of any other feature. Despite the simplified feature independence assumption, Naive Bayes classifiers have worked quite well in many complex real-world situations [37]. Further, the independence assumption reduces the likelihood of over fitting the data [38]. Finally, Naïve Bayes requires only a small amount of training data to estimate the parameters (means and variances of the variables) necessary for the classification.

For each classification task (overspending, loyalty, diversity), we executed 10 classification runs, each exploiting a subset of the features aggregated according to the ranking provided by the Info-gain approach. We started from the single feature experiment using the first ranked feature, then executed the 2-feature experiment with the first two ranked features, and so on.

A leave-one-out cross validation strategy was employed in this study. Hence, 26 models for each classification task (overspending, loyalty, diversity) were trained on 25 instances (couples), evaluating them against the remaining ones and finally averaging the results.

Table 4 reports, for each classification task, the feature combination producing the highest accuracy value. The socio-mobile features based approach could correctly classify spending diversity, loyalty, and overspending 69%, 69%, and 77% of times respectively. The *precision*, *recall*, and *f-score* measures for the diversity prediction task were 0.69, 0.69, and 0.69 respectively. Corresponding values for the loyalty classification and overspending classification tasks were 0.78, 0.54, 0.64, and 0.82, 0.69, 0.75 respectively. Given the balanced size of the two classes we focus on the accuracy values for the remainder of the paper.

Table 4: Prediction results for the three classification tasks: Best accuracy observed and the corresponding feature set.

| Prediction Task | Accuracy | Features employed |
|-----------------|----------|--|
| Diversity | 69% | { diff_SMS_top3, avg_call_top3, avg_SMS_events, diff_SMS_diversity, avg_call_diversity, avg_call_contacts } |
| Loyalty | 69% | { avg_SMS_top3, avg_call_top3} |
| Overspending | 77% | { avg_bt_events } |

The average accuracy of classification across the three spending features was 72%. The size of the feature set varied across tasks, but it was interesting to observe that overspending classification task obtained 77% accuracy using just one feature.

3 COMPARISON WITH ALTERNATIVE APPROACHES

We compare our approach with two different approaches. One is a baseline ‘Zero-R’ approach, which simply classifies all data into the largest category. The second approach is based on using personality variables, which have been shown by multiple efforts to be related to spending behavior [20, 21, 23].

Given the equally distributed classes, the baseline approach simply resulted in 50% accuracy for all the classification tasks. As can be seen in Figure 1, the socio-mobile features perform much better than baseline methods for classification of the spending behavior. On average the socio-mobile features could correctly classify the spending category 72% of the times, which mark a 44% relative improvement over the baseline method. The second alternative approach considered was based on personality driven features. Consistent with the approach adopted for socio-mobile approach, we undertook a feature ranking using the Info Gain method and ran multiple rounds of experiments with different sizes for feature sets. We report the best results obtained for the cross-validated leave-one-out approach in Figure 1.

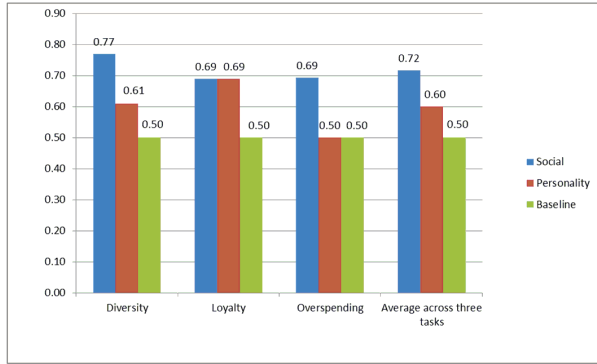


Figure 1: Correct classification percentage for the 3 spending behavior features. The figure also shows the average of the values found across the 3 tasks.

Personality based features could classify the Diversity variable correctly 61% of the time, loyalty correctly 69% of the time, and overspending only 50% of the time. On average it obtained 60% accuracy across the three tasks. This indicates a relative improvement of 20% over the baseline method. This is consistent with the marketing research on personality deriving from the possibility that individuals, in spite of their uniqueness, may possess a given trait or type in common with each other (e.g., extraversion); such groupings (typologies) might then become the basis of separate market segments and justify special marketing action.

However, the availability of rich mobile sensing (e.g. Bluetooth scans every 5 minute, every call, and SMS sent), now allows for creation of much more precisely defined models for each individuals behavior. We see that the socio-mobile method performs much better than the personality based approach for two of the three tasks, and achieves an overall accuracy rate of 72% as opposed to 60% obtained by the personality variables. These results suggest that socio-mobile feature based models might be able to capture behavioral traits that go beyond the personality variables at explaining the spending behavior. Further investigation with larger samples is needed to confirm this initial evidence.

3 PERFORMANCE USING DIFFERENT SIGNAL MODALITIES

To understand the role the different modalities play in predicting the spending behavior of the users, we undertook the same classification task using a subset of features – those derived from single modality (call, SMS, or Bluetooth). We

used the same experimental settings as discussed earlier (Info Gain, best subset, leave one out cross validation) for the 8 features defined for each modality as discussed earlier and obtained the prediction accuracy results shown in Figure 2.

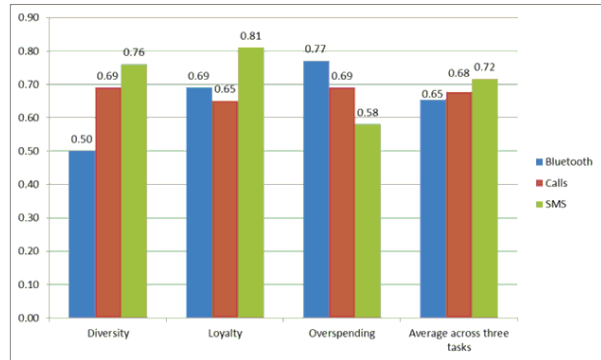


Figure 2: Correct classification percentage for the 3 spending behavior features using different modalities. The figure also shows the average of the values found across the 3 tasks.

We observe that SMS based features yielded best classification results for two tasks (diversity and loyalty). Overspending on the other hand was best predicted using face to face interaction (Bluetooth) signals. It was interesting to note that just using the SMS based features yielded 76% and 81% correct classifications for the first two tasks, which is higher than those obtained by using all the signals. A possible explanation for this is that the subset of features selected for SMS may have leveraged some interaction effects between the variables. This requires further investigation and also motivates the use of late-fusion techniques [25] for combining results across modalities. However, given the small data size, we conservatively focus here on Info Gain driven Naïve Bayes approach which assumes each feature to be independent and does not make any assumptions about classification method to be adopted while undertaking the feature selection.

In fact the strong results obtained for SMS modality are a very positive finding for undertaking similar experiments using feature-phones (those without Bluetooth capability) in the near future.

4 IDENTIFYING SPOUSES VIA SOCIAL INTERACTION SIGNALS

While all the socio-mobile features used in this study were obtained via *passive* sensing, spousal relationship (obtained via surveys) was a key connector in the analysis.

While spousal information is often available to mobile service providers (via ‘family plans’, or through billing addresses), derivation of spousal relationship through passive sensing may also be useful in multiple situations. Hence we decided to investigate the feasibility of identifying the couple relationship purely based on socio-mobile signals. We used a simple hypothesis to evaluate this: *the most frequent Bluetooth contact for the less social member of the couple was likely to be their spouse.*

We proceeded to test this hypothesis as follows. We first identified the most frequent face-to-face contact for each user. If two participants had each other as the most frequent contact, they were assigned as couples. If the most frequent contact for a participant (say A) was B, but B’s most frequent contact was C, the participant with lower tie strength at its maximum contact was considered to be more ‘socially reserved’ and his/her values were used to assign partner values to both the participants. Such a process was repeated for each participant.

While clearly non-optimal, we found that this simple approach yields correct couple assignment in 69% of the cases. Note that the baseline random allocation yields only 2% accuracy.

While the recognition performance can be improved with more sophisticated techniques, we consider this to be reasonable evidence that spousal and close couple relationships can also be derived using social interaction signals.

VI DISCUSSION, LIMITATIONS, AND PRACTICAL IMPLICATIONS

This work demonstrates the interconnection between socio-mobile features and spending behavior. In socio-economic literature there have been multiple efforts that use personality variables to understand the spending behavior of people [17, 18, and 19]. Our work, however, shows that socio-mobile features can often be better predictors of spending behavior than personality features.

A key aspect of this study was to explore couple’s as social and spending *units* – how do spouse’s social behaviors *combine* to form a single unit with distinctive spending characteristics. While the effects of spousal similarity have been studied in

economic research on assortative matching (similar users form couples [34]), the relationship between spousal *dissimilarity* (especially in social behavior) and spending behavior has not yet been explored. Our work demonstrates the potential of exploring this further to allow couples to better understand themselves and plan their long term spending profile both alone and with their partner.

The proposed approach adopts **passive sensing**, which allows for faster, cheaper data capture and also mitigates some of the differences between ‘real’ and ‘perceived’ behavior [9]. The adopted approach also shows graceful degradation to feature phone capabilities. This demonstrates the feasibility of undertaking similar studies at the scale of billions of users in near future.

In this study overspending was found to be positively correlated with sociability. This finding however does not imply that people with more social connections are likely to be worse off financially. For example, [5, 6, 16, 33] have indicated that highly social people are also likely to earn higher wages, find better jobs, and live healthier lives. Hence there is growing evidence that social behavior is a fundamental human characteristic that affects multiple aspects of human life.

The current study also has some limitations. First is the homogeneity of the sample. While this limitation prevents us from generalizing the findings to larger populations, it also allowed us to focus on a relatively un-studied population in ubiquitous sensing (namely, young families). Moreover, the homogeneity allowed us to isolate social behavior as a predictor. Previous research efforts have identified multiple factors, such as life-cycle stage, social network structure, occupation, income level, and personality, as potentially impacting spending behavior. The homogeneity of our sample mitigates the effect of many of these potentially confounding factors. Here we are able to focus on one group and predict **relative** variation in their spending behavior as a function of their social behavior. A second limitation is the relatively small sample size - only 52 adults (26 couples). Taking into account these two limitations, we will be cautious in generalizing the correlations found to larger populations until the results are verified at scale.

Despite these limitations, this study is the first of its kind. To our knowledge there have been no previous studies undertaken that analyze the link between spending behavior and socio-mobile

behavior with such detailed and rich a dataset (>10 million data points). The obtained results are encouraging, and have demonstrated the ability of socio-mobile signals at predicting spending behavior of couples.

This work has tremendous implications for marketers, economists, mobile phone service providers, and social policy designers. For example it is possible for mobile phone service providers (e.g. ATT, Verizon, Telefonica, Virgin and so on) to use the detailed social interaction user behaviors to predict the spending behavior for different users. These could be used by marketing professionals for better customer acquisition (e.g. identifying which couple is likely to try newer restaurants), and customer retention (e.g. modeling which couple is likely to become a loyal customer).

Predicting and understanding overspending is also of critical importance to banks, credit unions, and policy makers. The banks may use the overspending propensity information to better estimate customer credit scores. Banks may also use these newer methods to define the credit worthiness for the currently unbanked customers. Presently more than 5 billion users have a mobile phone but a large portion of them do not use a banking facility (and therefore have a limited credit history). Use of mobile phone based behavioral data can be used to estimate credit scores for this population and drive applications like micro-finance. Similarly, policy designers can study the correlations to implement policy decisions that encourage balanced family spending.

Longer term, we hope that similar studies can be extended to understand spending behavior at societal and country levels. This is of critical importance, as spending behavior, austerity measures, and spending cuts have been major contentious issues in US, Europe and multiple parts of Asia during the recent years.

To summarize, we believe that the real merit of this work lies in grounding and motivating a new line of investigation that may allow us to study the spending behavior of users based on detailed socio-mobile sensing. Using mobile phones to understand spending behavior can fundamentally impact the way we study consumer behavior, how marketing decisions are made, and how policy makers study loans and credit-worthiness.

VII CONCLUSIONS AND FUTURE OUTLOOK

This work is the first systematic study that connects spending behavior with social behavior observable via mobile phones. Social interaction patterns studied via Bluetooth, call, and SMS logs show that more social couples tend to spend more. Further, the dissimilarity in a couple's social behaviors is correlated with spending diversity, customer loyalty, and overspending. We also found social features to be better predictors of spending behavior of a couple than personality variables. There exists tremendous scope to extend this work to study larger number of participants in diverse settings. The proliferation of spending log apps, such as Mint, Xpenses, Cashish, and Pennies, and collaborations, such as that of American Express with Twitter [35] indicate that more and more spending data will be available electronically soon to understand mobility, sociability, and spending behavior. We also plan to undertake more detailed analysis on couples as spending, and social units of behavior in societies. Studying couple dynamics (e.g. who has more purchasing agency based on gender, social role, and financial role) by using rich minute-by-minute ubiquitous sensing techniques has tremendous potential in enhancing our understanding of how couples function and make their decisions.

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