Smartphone-Based Estimation Of A User Being In Company Or Alone Based On Place, Time, And Activity

Conference Paper · March 2018

5 authors, including:

Anja Exler
Karlsruhe Institute of Technology

Kristina Mincheva
Karlsruhe Institute of Technology

Andrea Schankin
FOM Hochschule für Oekonomie & Management gGmbH

Michael Beigl
Karlsruhe Institute of Technology

Smartphone-Based Estimation Of A User Being In Company Or Alone Based On Place, Time, And Activity

Anja Exler, Marcel Braith, Kristina Mincheva, Andrea Schankin, and Michael Beigl

Karlsruhe Institute of Technology (KIT), TECO
76131 Karlsruhe, Germany
exler@teco.edu

Abstract. Whether a person is *in company* is an important indicator for several research fields such as monitoring a patient's mental health states in clinical psychology or interruptibility detection in experience sampling. Traditionally, social activity is assessed using self-report questionnaires. However, this approach is obtrusive. The best solution would be an automatic assessment. Smartphones are suitable sensing systems for this task. In this paper, we investigate relations between being *in company* and place types. First, we present results of an online survey taken by 68 persons. Within the survey, we assessed how likely users are to be *in company* at specific place types provided by the Google Places API. We identified that places such as night club, bar, movie theatre, and restaurant are primarily visited *in company*. Places such as post office, gym, bank, or library are visited rather *alone*. Some place types are undecidable and require additional context information. As a next step, we ran an in-field user study to gather enriched real-world data. We logged temporal features, user activity, place type, and self-reported company indicators as ground truth. We gathered data of 24 participants over a period of three weeks. Using information gain and χ^2, we identified that *place type* and *hour of day* correlate with being *in company* with statistical significance shown by Cramér's *V*. Using machine learning, we trained different classifiers to predict being *in company*. We achieved an accuracy of up to 91.1%. Our approach is a first step towards an automatic assessment of being *in company* as it is more accurate than pure guessing. We propose to enrich it with further context information such as transportation mode or a more accurate activity classifier.

Key words: Context Recognition; Place Type; Social Activity

1 Introduction

Context-aware systems, which adapt their functionalities to the current context without explicit actions of the user, are supposed to have a better usability and user experience. This is, in particular, the case for mobile devices which may adapt their functionalities with regard to the user's location, time or other properties of the environment.

The current social context, i.e. if a user is *in company* or *alone* might be another interesting contextual factor. For example, our social context influences our interruptibility and how we respond to smartphone notifications [14, 17]. Also, the social context or a change in social context might be useful to support the detection of states and state changes in bi-polar personality disorder or depression to perform an appropriate treatment [10, 18, 19].

Commonly, the social context is provided by the users themselves via self-reports at discrete and sparse points in time. However, automatic context-aware systems require continuously gathered information. In this paper, we explore if it is possible to detect whether a user is *in company* or *alone* based on (a) different place types, (b) temporal features, and (c) the user activity. First, we propose a relationship between different place types and the probability of being *in company* or *alone*. We test this hypothesis within an online survey. Second, we enrich location features with temporal features and activity, because activities change during the day according to our biorhythm and habits [2, 11]. This approach has been evaluated within a field study. Analyses include identification of feature importance and evaluating predictive models based on their accuracy.

2 Related Work

Many of these approaches rely on Bluetooth-based recognition of nearby devices [7, 12]. However, due to raising privacy-awareness and security reasons, the visibility of devices using Bluetooth was restricted by the mobile OS during the last years. Smartphones with active Bluetooth are only visible if the user is currently in the Bluetooth settings. Hence, this approach is no longer an option. Alternative approaches for social sensing collected location data and transfered it to a server [7]. Every phone who installed this app provides data and allows a comparison of the data so check if devices are nearby. In this paper, we focus on a group activity recognition approach that relies on data from one single device only and that does not share the data with any server but instead runs all processes on the device itself.

The usefulness of activity, location, or temporal features for group activity detection was already proved by related work. A common method is to extract information from videos and analyse it with the objective to differentiate activities which can later on be labeled as group or single activities [1, 4, 16]. Some of these approaches focused on the spatio-temporal evolution of crowd behavior, so-called crowd context [4] while others relied on temporal and spatial information [1, 16] – proving that spatio-temporal data is well-fitted for recognizing group activities. However, these approaches have the drawback that they use intrusive, non-privacy-aware, and high energy-consuming video techniques. It would be less energy-consuming and more privacy-aware to predict being *in company* based on automatically available and more abstract smartphone data and process this data directly on the phone itself – which is what we will do in this paper.

A connection between self-reported place types with social activity was already shown, e.g. to infer interruptibility [14]. Though, we focus on automatically detected location and place types as they are generalizable and do not require user involvement. In addition, place types are more abstract and hence more privacy-aware than raw GPS values. Our idea is to combine location data with temporal features and activity information. While related work focused on detecting groups and group activity we choose a more abstract approach and focus merely on recognizing being *in company*.

3 Exploring The Relation Between Place Types and Being in Company

We conducted an online survey to assess if users tend to visit a place rather *in company* or *alone*. We highlighted that being *in company* applies even if the user is only accompanied by one other person.

As mentioned before, locations were based on the place types that are offered by the Google Places API[1]. To reduce the number of questions within the survey the high number of over 120 place types[2] was reduced to 20 places as explained in [9].

In addition, we defined place categories to allow further abstraction of our results. Related work mostly focused on place categories for private [20] or business issues [12, 13, 15]. We intend to include both. We adapted the five categories proposed by Zheng et al. [20], namely: *Food & Drinks*, *Sports & Exercises*, *Movies & Shows*, *Shopping*, and *Recreation & Amusement*. We added the category *Work and Education* to cover both business matters and education.

For each place type we asked:

1. "In which category would you assign the currently displayed place type?" and offered the defined categories in form of *select many* checkboxes
2. "Do you visit the displayed place type rather alone or in company?" and offered a rating in form of a 5 point Likert scale ranging from "always alone" (1) to "always in company" (5)

The categories were assessed to be able to abstract the social activity to more abstract places. This might proof useful in the future as it allows to include new place types for which only the category but no probability for social activity is known. The answers to the Likert scale can be interpreted numerically as a likelihood of being *in company*, i.e. 1 being "always alone / never in company" and 5 being "never alone / always in company".

[1] `https://developers.google.com/places/`
[2] `https://developers.google.com/places/supported_types`

3.1 Participants

The survey was created with Google Forms and performed online. To recruit participants we spread the link to the survey via social media. 68 people answered the survey, 50% male and 50% female. The average age was 33 years (±12). Almost all participants had a school degree that qualified them for higher education. 63% even had a university degree which is a strong bias. The largest occupational category was information- and communication technology.

3.2 Results

The results of the survey are summarized in Table 1 and 2. Analyzing the place types (see Table 1), it is visible that users are usually *in company* when visiting night clubs, bars, movie theatres, restaurants, and cafés. In contrast, users tend to visit post offices and gyms preferably *alone*. In addition, there are some places which are visited *alone* as well as *in company*. Prominent examples for these are shopping malls, universities and meal takeaways. For these places more information about the users and their activities are required to decide whether they are *in company* or *alone*.

Table 1. Average answer per place type stating if a user visits a place rather *in company*(5) or *alone*(1).

Place Type	**Average**	**Standard Deviation**
Night Club	4.74	0.56
Bar	4.65	0.54
Movie Theatre	4.49	0.73
Restaurant	4.37	0.69
Café	4.08	0.71
Park	3.39	0.85
University	3.11	1.10
Shopping Mall	3.03	0.68
Meal Takeaway	2.87	0.75
Clothing Store	2.76	0.82
Parking	2.77	0.76
Store	2.69	0.62
Bus or Subway Station	2.60	0.65
Grocery Store	2.37	0.75
Bakery	2.29	0.55
Gas Station	2.28	0.76
Library	2.11	0.97
Bank	2.04	0.86
Gym	1.89	1.12
Post Office	1.77	0.64

Table 2. Likelihood of being *in company* per defined place category.

Place Type	**Likelihood**
Movie & Shows	84.8 %
Recreation & Amusement	67.2 %
Food & Drink	61.7 %
Work & Education	40.2 %
Shopping	39.0 %
Sports & Exercise	33.3 %

Considering categories (cf. Table 2) we computed a likelihood for being *in company* while being in such places. Attending *Movies & Shows* is usually done *in company*. According to the place categories, *Recreation & Amusement* and *Food & Drinks* locations are visited *in company* in 2 out of 3 cases. *Sports & Exercises* are performed *in company* only in 1 out of 3 cases, probably depending on the kind of sport. *Work & Education* and *Shopping* are not decidable. The decision probably depends on the purpose of the business (e.g. having a meeting vs. writing a paper) or the shopping purpose (e.g. doing the weekly shopping vs. buying new clothes).

Overall, it becomes clear that location alone is not a distinct feature to differentiate between being *in company* and *alone*. It is necessary to investigate its combination with further contextual data such as activity or time. Thus, we conduct a user study to collect and analyze data.

4 In-Field User Study

4.1 Study Design

The purpose of the study was to gain insight about the context in which people are *in company* or *alone*. The time frame for the study was set to take place in February 2017 and to last three weeks.

There was an initial meeting with the participants in which we described the purpose of the study. Participants were free to ask questions about the study. We informed them that they were free to drop out of the study if they feel uncomfortable at any time. Afterwards, we asked them to sign a consent form to confirm their participation and to allow us using their personal data anonymously and for scientific purposes only. Next, we installed our app on their smartphone. We asked the participants to keep the location service enabled and only switch it off if they need to, for example to save battery, if they do not want a place to be recorded, or when they are outside the country and needed to prevent network access. We explained to them how to respond to notifications and how to add data later on using the retrospective log functionality of our app. After three weeks, we met again to export the recorded data and to ask the participants for feedback, such as problems or difficulties.

4.2 Participants

We recruited 30 participants, of which 24 started the study. The others had exclusion criteria, such as not having a cellular connection for large parts of the study or finally decided not to participate in the study because of privacy concerns. The participants were between 19 and 31 years old with an average of 24 years. 10 participants were female and 14 male. There was an equal distribution of students and working population.

4.3 Data Assessment App

Sensor Measurements We developed an Android app to assess the desired features: place types (via Google Places API), user activity (Google Activity Recognition API), and temporal features (via system time).

To assess the location, we send longitude and latitude to the Places API which returns a collection of *PlaceLikelihood* objects, one for each probable place the user could currently be at. For simplicity, we visualized the structure of such a result returned by the API in JSON notation (see Figure 1). We decided to always consider the most likely place and the first (i.e. most suitable) place type.

```
{
   "likelyPlaces": [
      {
         "likelihood": 0.4,
         "place": {
            "name": "ZKM Karlsruhe",
            ...
            "placeTypes": [66, 5, 1013]
         }
      },
      {
         "likelihood": 0.12,
         "place": {
            "name": "Filmpalast",
            ...
            "placeTypes": [64, 34]
         }
      },
      ...
   ]
}
```

Fig. 1. Simplyfied representation of objects returned by the Google Places API in JSON notation.

The Activity Recognition API relies on data from physical sensors such as accelerometer and gyroscope, but also GPS. It returns the most probable activity and the confidence of the classifier.

For temporal features, the app stores the internal system time as a unix timestamp. From the timestamp, we can derive features such as hour of day, day of week, or workday.

Subjective User Feedback (Ground Truth) Whenever a location change happens, i.e. the app detected a new place type, the user is prompted for feedback by a smartphone notification. The user has the choice to respond now or add the information later using the retrospective log functionality. Whenever reacting to the response, promptly or later on, the user is confronted with questions similar to the following example:

1. Are you currently at this place? *University*
2. *If yes:*
   a) Are you *in company* at this place?
      → push either *in company* button or *alone* button
3. *If no:*
   a) At which place are you currently?
      → select place type out of a drop down list
   b) Are you *in company* at this place?
      → push either *in company* button or *alone* button

The retrospective log function of the app presented a list of all places that a user visited that day. Each row showed the time of arrival and departure as well as the detected place type. Only visits of the same day were shown. A longer period would require to show dates as well and would eventually bloat the list with a lot of entries. In addition, retrospective bias or memory gaps might have occurred. A click on a list entry started the same interface that was used in case a user responds to a feedback prompt. This ensured that the user did not have to learn a new design but was already used to the same feedback interface.

5 Descriptive Data Analysis

The final dataset consisted of 1745 instances from 24 different participants. There were more instances in the dataset of class *in company* (993) than *alone* (752). A common comment was that the participants sometimes felt it was difficult to decide whether to declare a situation as being *in company* or *alone*, because there were other people present but the degree of social interaction was low.

Place types were also imbalanced and distributed very unevenly. As Table 3 shows, only 13 places had more than 10 occurrences. Some places, on the other hand, were strongly represented, e.g., "at home" with almost 700 instances.

A frequent observation was that places were often detected incorrectly and required correction by the user. Also, some place types were detected multiple times although no change of place had happened. Both errors are probably caused by GPS drifts or inaccuracies of the Places API.

Table 3. Number of recorded visits for each place type ordered by decreasing occurrence.

Place Type	**Occurances**	**% in Company**
Movie Theatre	1	100.00
Bar	22	95.45
Fast Food Store	12	91.67
Work	72	90.28
Restaurant	41	87.80
Café	27	85.19
Clothing Store	12	83.33
Gym	11	81.82
Other	48	77.08
Shopping Mall	18	61.11
Department Store	12	58.33
Grocery Store	39	51.28
At Home	697	50.65
Bakery	6	50.00
Bank	3	33.33
Bus / Train Straion	77	29.87
Gast Station	7	28.57
Park	8	12.50
Parking Lot	8	12.50
Post Office	1	0.00

Precision of the Google Places API To evaluate how well the place recognition itself worked, we compared the place types detected by the Google Places API with the place types provided by the participants (ground truth). It is calculated how often the users rejected the suggested place and picked a different one. If the user labeled the place as "at home", "on the way", "work", or "other" the datum was not counted, because those places were not detectable by the Google Places API. Based on the ground truth, the service achieves a precision of 73%. This result is significantly better than guessing. Results might be enhanced by considering more place types than only the most probable one that is returned by the Google Places API. We only considered the place type that, had the highest probability. However, the Google Places API returns a list of suitable place types with probabilities. Elhamshary and Youssef already showed that considering the top 5 venues is advisable: their approach yielded a 99% precision for the actual venue to be in the top 5 candidate list [8]. For future studies, a weighted approach considering the five most probables places should be considered.

Analysis of Place Type, Time, and Activity Figure 2 presents the distribution of being *in company* or *alone* plotted against all considered place types and the hour of day. "Bars" and "restaurants" were frequently visited *in company*. In contrast, "bus or train stations" were mostly visited *alone*. The distribution of being *in company* or *alone* was rather balanced for places such as "at home", "on the way", "other", and "university".

Focusing on the hours of the arrival times (y axis) it can be seen that firstly, place and arrival time were dependent and secondly, that at night many places were visited *in company*. Though, there was not very much data with this pattern.

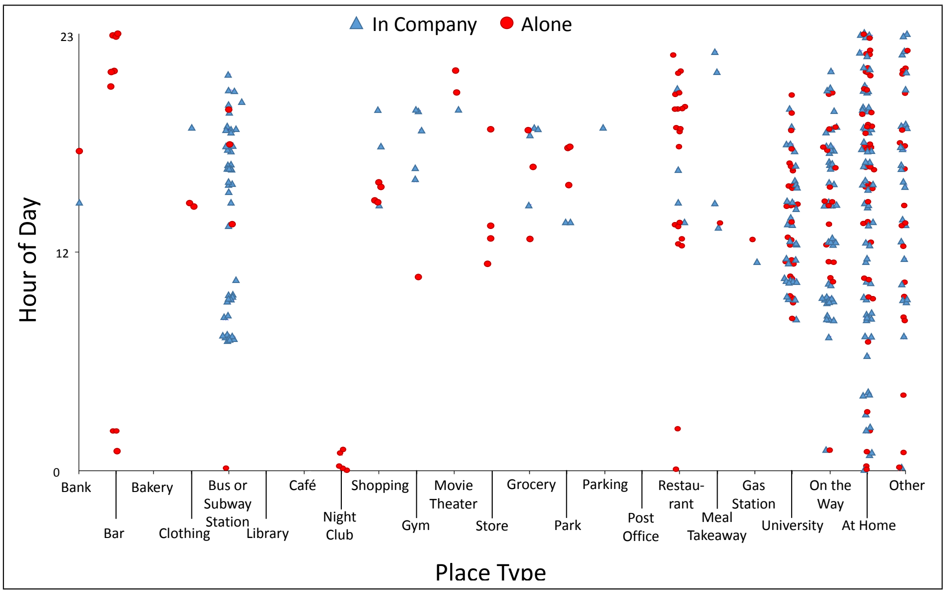

Fig. 2. Distribution of being *in company* (blue triangles) or *alone* (red circles) while being at a specific place typ (x axis) at a specific hour of day (y axis).

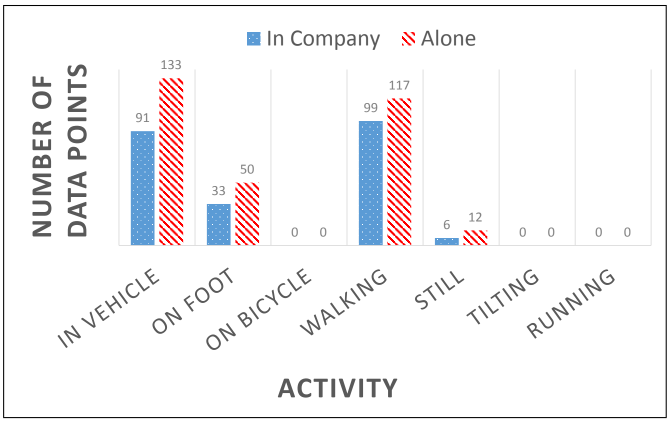

Fig. 3. Distribution of being *in company* (blue) or *alone* (red) per physical user activity.

It is visible that there were more records of activities performed *alone* than *in company*. This phenomenon might be biased by the labeling process. If a participant labeled data only in case of being *alone* and never while being *in company* – for example, because it would be impolite to use the smartphone while being with others – such an imbalance could occur. In addition, the definition of being *in company* was strongly dependent on the participant's interpretation. According to the user feedback it was also hard to judge where being *in company* began and where it ended. One example for this it "at home" where it was not easy to tell if the fact of living in a shared apartment or with a partner always counted as being *in company* or only when performing joint activities. For "at home" and "university", it happened that participants were *in company* but not actually involved in a common activity. This is obvious for such place types as there might be individual activities performed in the presence of other people. In these cases the place seems to be no useful indicator for social activity.

User activities per se were also not very separating as shown in Figure 3. There were almost no patterns between the activities and being *in company* or *alone*. The closest explanation would be that the shares of activities were not sufficient to discriminate between the classes, and time sequences play a large role there.

6 Feature Analysis

To assess the quality of our features we calculated the information gain and χ^2 with Cramér's V. Those numbers reveal how the features perform and how they compare to each other. However, they do not reveal how combinations of the features might be correlated to being *in company*, but give a tendency. The combination of features is measured with the performance of the classification.

6.1 Information Gain

Information gain is a measure of how much the entropy of the class distribution is reduced when only considering the different values of a feature. A reduction of entropy is desirable. For example if the data is separated by place type, it would be beneficial if within each place the class value would either be mainly *in company* or *alone*. The stronger the social activity indicator leans to one side, the lower the entropy. Information gain cannot be calculated on numeric attributes. Therefore, we binarized numeric attributes, i.e. transformed the attribute into the values zero and non-zero.

Table 4 shows the information gain for each feature. Place is by far the best feature according to this metric. Temporal features perform not as good but still have some gain. User activity however provides marginal information gain.

Table 4. Overview of the information gain for each feature of the mixed dataset for predicting being *in company* or *alone*.

Feature	Information Gain
place	0.11481
weekday	0.02976
hourOfDay	0.02678
activity	0.00113

Table 5. Overview of χ^2 values for each feature and its significance in form of p-values and Cramér's V.

Feature	χ^2	p-value	significant	$\widetilde{V}$
place type	104.42	¡ 0.00001	yes	0.2446
hour of day	38.777	0.02099	yes	0.1491
weekday	5.708	0.04567	yes	0.05719

6.2 χ^2 and Cramér's V

χ^2 is a metric to test distributions of variables for independence. It is calculated by the sum of squared differences between observations. If the corresponding p-value, which indicates the likelihood that the difference in the observations is caused by statistical error, is smaller than the significance level α of usually 0.05 then the variables are dependent. The purpose of the test in the present case is to see if the selected features are actually dependent on being *in company* and, most importantly, if the results are significant despite the low amount of data.

Cramér's V is a measure of association between two variables and is based on χ^2. It shows the strength of the correlation between the variables. Equation (1) shows a bias-corrected version of Cramér's V which is used to ensure comparability between features that differ in the number of values [3]. The measure is used to judge which features are worth investigating further and which are neglectable.

$$\widetilde{V} = \sqrt{\frac{max(0, \frac{\chi^2}{n} - \frac{(k-1)(r-1)}{n-1})}{min(k-1, r-1)}} \tag{1}$$

Table 5 shows χ^2 values for all features compared with the class attribute, i.e. being *in company*. It also displays if there is a significant correlation between the feature and the class attribute, determined by the p-value. If true, Cramér's V is presented to indicate the strength of the correlation. The place type seems certain to be an indicator for being *in company* with a clear correlation expressed by a V of about 24%. Hour of day is also significantly correlated with a V of about 15%. According to Cohen [5] both qualify as a weak effect size. The weekday has no apparent significance which might be caused by the inhomogenity of the sample as students and working population have different schedules for each day.

Since place type and all temporal features are not only significant but also qualify for a small effect size, they are considered useful in classification.

7 Prediction of Being in Company

7.1 Preliminary Considerations

To evaluate the features that have been picked and to measure the potential of the approach for real world applications, a predictive model is built using machine learning. The result of our classification model is binary: a participant is either *in company* (1) or *alone* (0). Pure guessing would result in 50% accuracy on average. However, there are more instances in the dataset of class *alone* than *in company*. Always choosing *in company* would result in 57% accuracy on average. This value represents the baseline for the recognition accuracy of our predictive model. One question is which accuracy would be optimal. However, this heavily depends on the use case. For an ambulatory assessment with a socio-psychological component information about social activities, i.e. being *in company* or *alone*, are highly relevant and high recognition accuracies are required; misclassification might lead to misdiagnoses and wrong treatment. For context-dependent notifications lower accuracies might be more acceptable as missing a notification or being notified one time more might not have that severe consequences.

7.2 Classification

Based on the identified features, we evaluated different classification algorithms from the Weka[3] toolkit and compared them in terms of recognition accuracy, i.e. the ratio of correctly classified instances and total number of instances. Accuracy is a good measure if the detection of both classes is equally important. It is used due to its neutrality as no specific use case is evaluated at this point. It is also already appropriate for a scenario such as counting the number of moments per month a participants was *in company*. In addition, we calculated precision, recall, and F1 measure.

For each classifier a 10-fold cross-validation was performed. That means the dataset is randomly split into 10 parts of equal size and the tested 10 times, each time with 9 parts being trained and one used for testing. The results are then averaged to give a final accuracy. All classification algorithms have reasonable default parameters. We did not perform any parameter tuning during this evaluation.

The selected classifiers are popular representatives from different types of classification methods. We considered J48 (C4.5) and Random Forest as tree-based methods, IB1 (1-Nearest-Neighbor) as a lazy learning method, SMO (Support Vector Machine) with polynomial kernel, Multilayer Perceptron as an Artificial Neural Network, Naive Bayes and Bayes Net as probabilistic methods, Logit Boost with Decision Stump to include a method with logistic regression, and VFI (Voting Feature Intervals) [6] as an alternative.

[3] `http://www.cs.waikato.ac.nz/ml/weka/`

Table 6. Overview of the classification results.

Classifier				
	Accuracy	**Precision**	**Recall**	**F1 Measure**
J48	91.90%	92.00%	91.90%	91.90%
Random Forest	91.90%	92.00%	92.00%	92.00%
IB1	91.50%	91.70%	91.50%	91.60%
SMO	77.60%	76.80%	77.60%	76.70%
Multilayer Percertron	86.20%	86.20%	86.30%	86.20%
Naive Bayes	76.10%	75.50%	76.10%	75.70%
Bayes Net	76.80%	76.60%	76.90%	76.70%
Logit Boost	77.70%	77.10%	77.70%	76.00%
Vote	68.60%	47.10%	68.70%	55.90%
Average	82.03%	79.44%	82.08%	80.30%

Table 6 shows the results. Tree-based methods, Nearest Neighbor classification, and Multilayer Perceptron perform best on our dataset. All others yield mediocre results. All classifiers perform significantly better than guessing and also much better than picking the majority class.

We considered the cardinalization of the place type feature in form of an a priori probability calculated from the results of the survey. However, it was found to be harmful for classification results except for Naive Bayes, a probabilistic approach. Hence, we neglected the a priori probabilities as a feature.

8 Conclusions

Automatically assessed indicators for being *in company* or *alone* are a desired feature in many areas of social sciences and computer science. Smartphones, as personal wearables and ubiquitous sensor system, are a suitable platform for an automatic assessment of this feature. Several researches investigated how to infer group activity based on sensor measurements such as audio data, video, detected bluetooth devices or GPS locations. However, none is known that relied on the place types provided by the Google Places API in a data protective and opportunistic manner.

8.1 Online Survey – Conclusion

As a first step towards a location-aware detection system we ran an online survey to assess a basic separability of being *in company* or *alone* based on the place type. We identified that place types with a high frequency of being *in company* usually belong to the *Recreation & amusement* category, e.g. "night clubs", "bars", or "movie theatres", or belong to the *Food & Drink* category, e.g. "restaurants" or "cafés".

In contrast, users tend to visit place types on their own if they are assigned to the place category *Sports & Exercise*, e.g. visiting the "gym". For some place types and categories a differentiation is not possible without further information. Example place types are "universities", "parks" or "shopping malls". We assume that temporal features such as time of day, weekday or information about the physical activity might improve the differentiation between being *alone* or *in company* at a specific place type.

8.2 User Study – Conclusion

These results encouraged us to run a user study to gather real world location data in combination with activity and time. The study lasted three weeks and was taken by 24 participants.

The gathered data consisted of place, temporal features such as day of week and hour of day, and the user activity. We calculated information gain and χ^2 in combination with Cramér's V to rate the feature importance. Both showed a significance for place, with a medium effect V value of 0.37, and temporal features, with a small effect V value between 0.21 and 0.23.

Based on these features, we built and evaluated different classifiers using the Weka toolkit. Results of up to 91.9% recognition accuracy are above the baseline of 50% (guessing) or 57% (predicting the most frequent class), respectively. Still, this recognition accuracy is pretty high, but still has room for improvement which is required for the classifier to be applicable for example in social sciences where accurate predictions of social activity is important. Though, it is also considerable to have a classifier that works automatically and only asks for user feedback in case its confidence is below a threshold.

Some place types showed to be reliably separable, such as "restaurants" and "bus or subway stations". For other place types the distribution seems random, e.g. "universities". For those places, further information is required.

The imbalance in the dataset and specifically the sparse data for some places impacted the results negatively. Some places might be very well distinguishable in terms of being *in company* or *alone*, but correlations, for example with hour of day, were indicated but without confirmable statistically significance.

8.3 Summary and Future Work

In summary, our research showed that smartphone-based features possess the power to support automatic distinction between being *in company* and *alone*. We identified significant relevance of spatio-temporal features. Classification models trained on study data achieved a higher recognition accuracy than the baseline. However, the models need further improvement to be suitable for real-world application.

Within this paper, we investigated generalized models due to two reasons: First, because the online survey was performed on a wider range of participants. Second, because the location sample from the user study was fairly sparse and we would not have had sufficient samples per place type per person. However, in future work, personalized models should be investigated stronger. The online survey already suggested that there are either interpersonal differences or external factors that influence the decision of being *in company* or *alone* at a specific place. Hence, further context and sensor sources, e.g. enhanced activity classifiers, calendar information, or device usage statistics, should be considered.

Presuming that smartwatches become more widespread, more complex activities could be detected without specialized hardware or laboratory setups. Furthermore, there is potential in recognizing long-term patterns and routines of individual persons, such as regular sport events or working hours.

References

1. M. R. Amer, D. Xie, M. Zhao, S. Todorovic, and S.-C. Zhu. Cost-sensitive top-down/bottom-up inference for multiscale activity recognition. In *European Conference on Computer Vision*, pages 187–200. Springer, 2012.
2. A. Bachmann, C. Klebsattel, M. Budde, T. Riedel, M. Beigl, M. Reichert, P. Santangelo, and U. Ebner-Priemer. How to use smartphones for less obtrusive ambulatory mood assessment and mood recognition. In *Adj. Proc. of Ubicomp'15*, pages 693–702. ACM, 2015.
3. W. Bergsma. A bias-correction for Cramér's and Tschuprow's. *Journal of the Korean Statistical Society*, 42(3):323–328, Sept. 2013.
4. W. Choi, K. Shahid, and S. Savarese. Learning context for collective activity recognition. In *Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on*, pages 3273–3280. IEEE, 2011.
5. J. Cohen. *Statistical Power Analysis for the Behavioral Sciences*. Hillsdale, New Jersey, 2 edition, 1988.
6. G. Demiroz and A. Guvenir. Classification by voting feature intervals. In *9th European Conference on Machine Learning*, pages 85–92. Springer, 1997.
7. N. Eagle and A. S. Pentland. Reality mining: sensing complex social systems. *Personal and ubiquitous computing*, 10(4):255–268, 2006.
8. M. Elhamshary and M. Youssef. Checkinside: A fine-grained indoor location-based social network. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, pages 607–618. ACM, 2014.
9. A. Exler, M. Braith, A. Schankin, and M. Beigl. Preliminary investigations about interruptibility of smartphone users at specific place types. In *Adj. Proc. of Ubicomp'16*. ACM, 2016. To appear.
10. M. Faurholt-Jepsen, M. Frost, M. Vinberg, E. M. Christensen, J. E. Bardram, and L. V. Kessing. Smartphone data as objective measures of bipolar disorder symptoms. volume 217, pages 124–127, 2014.
11. F. Halberg, Y. L. Tong, and E. Johnson. Circadian system phase - an aspect of temporal morphology; procedures and illustrative examples. In *The cellular aspects of biorhythms*, pages 20–48. Springer, 1967.
12. G. Liang, J. Cao, and W. Z. 0004. CircleSense: A pervasive computing system for recognizing social activities. 2013.

13. L. Liao, D. Fox, and H. A. Kautz. Hierarchical Conditional Random Fields for GPS-Based Activity Recognition. *ISRR*, 28(Chapter 41):487–506, 2005.
14. V. Pejovic and M. Musolesi. InterruptMe: Designing Intelligent Prompting Mechanisms for Pervasive Applications. 2014.
15. D. Riboni and C. Bettini. OWL 2 modeling and reasoning with complex human activities. *Pervasive and Mobile Computing*, 7(3):379–395, June 2011.
16. M. Ryoo and J. Aggarwal. Stochastic representation and recognition of high-level group activities. *International journal of computer Vision*, 93(2):183–200, 2011.
17. G. H. Ter Hofte. Xensible interruptions from your mobile phone. In *MobileHCI'07*, 2007.
18. T. J. Trull and U. Ebner-Priemer. Ambulatory assessment. *Annual review of clinical psychology*, 9:151, 2013.
19. T. J. Trull and U. W. Ebner-Priemer. Using experience sampling methods/ecological momentary assessment (esm/ema) in clinical assessment and clinical research: introduction to the special section. 2009.
20. V. W. Zheng, Y. Zheng, X. Xie, and Q. Yang. Collaborative location and activity recommendations with GPS history data. In *International World Wide Web Conference 2010*, New York, New York, USA, 2010.