You Are What You Use: Usage-based Profiling in IoT Environments

Manan Choksi
mcho6881@uni.sydney.edu.au
The University of Sydney
Sydney, NSW, Australia

Dipankar Chaki
dipankar.chaki@sydney.edu.au
The University of Sydney
Sydney, NSW, Australia

Abdallah Lakhdari
abdallah.lakhdari@sydney.edu.au
The University of Sydney
Sydney, NSW, Australia

Athman Bouguettaya
athman.bouguettaya@sydney.edu.au
The University of Sydney
Sydney, NSW, Australia

ABSTRACT

Habit extraction is essential to automate services and provide appliance usage insights in the smart home environment. However, habit extraction comes with plenty of challenges in viewing typical start and end times for particular activities. This paper introduces a novel way of identifying habits using an ensemble of unsupervised clustering techniques. We use different clustering algorithms to extract habits based on how static or dynamic they are. Silhouette coefficients and a novel noise metric are utilized to extract habits appropriately. Furthermore, we associate the extracted habits with time intervals and a confidence score to denote how confident we are that a habit is likely to occur at that time.

CCS CONCEPTS
• Human-centered computing → Ubiquitous computing.

KEYWORDS
Habit Extraction, Electricity Consumption Data, Clustering, Smart Homes

ACM Reference Format:
Manan Choksi, Dipankar Chaki, Abdallah Lakhdari, and Athman Bouguettaya. 2022. You Are What You Use: Usage-based Profiling in IoT Environments. In Proceedings of the 2022 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp/ISWC ’22 Adjunct), September 11–15, 2022, Cambridge, United Kingdom. ACM, New York, NY, USA, 3 pages. https://doi.org/10.1145/3544793.3560360

1 INTRODUCTION

Today IoT is one of the most ubiquitous terms used in tech as its value and popularity have risen over the past decade. IoT refers to the web of interconnected devices that can provide insights and automate many services. Given its popularity, concepts like smart homes and smart campuses are becoming pioneering applications in this domain. Smart homes help provide users with detailed information about their energy consumption while providing avenues to automate services like turning devices on in response to known user habits. To provide this level of convenience, we need to develop a sophisticated technique to detect user habits. A habit refers to a set routine or task a user performs at a particular time. Examples of habits include eating breakfast, watching television, showering, or exercising. We need to discern certain activities’ start and end times to detect these patterns and analyze habits. Despite various techniques to extract habits, methods related to identifying definite habit start and end times are mainly unaddressed. Many papers rely primarily on pre-setting arbitrary time bounds for certain activities or using time bounds that are not precise [1, 2, 5]. We believe that identifying precise time intervals with some confidence level can be much more helpful if we want to use habit extraction methods for developing personalized services in the future. As a result, this paper aims to introduce a novel way of identifying habits using an ensemble of unsupervised clustering techniques to cluster activities’ start and end times. Since some user behaviors may be more static than others, we use different clustering algorithms like k-means, hierarchical clustering, and density-based clustering to profile different usage behaviors of people. For example, one may predict that habits like eating breakfast are more likely to occur during the morning. However, habits like watching television are more prone to be random (i.e., people may watch television in the morning, afternoon, or evening). This makes it essential to employ different clustering techniques to capture different usage behavior patterns.

2 PROPOSED METHODOLOGY

2.1 K-means and Agglomerative Clustering

We aim to build a model to profile typical start and end times for particular user habits. To do this, we systematically implement
different clustering algorithms and settle on a clustering pattern in accordance with two metrics: silhouette coefficient and a novel noise metric. To begin, we pass our tuples denoted by \((t_{\text{start}}, t_{\text{end}})\) for one activity to be clustered by the k-means and agglomerative clustering algorithms. Then, we denote the number of clusters as \(k\) and run both algorithms from \(k = 2\) to \(k = 6\) as any maximum value that can be specified arbitrarily by the user, increasing the value of \(k\) by one and calculating the silhouette score each time. Finally, we pick the clustering arrangement with the highest silhouette score (closest to 1) as it represents the most compact and well-separated clusters.

### 2.2 Novel Noise Metric

Once we find the optimal number of clusters and the favored clustering technique using this method, we propose a noise metric to measure the sparsity of each cluster. First, we find the euclidean distance between every combination of two tuples in every cluster generated. We can denote the distance between any two tuples as \(d(t_{\text{up}_1}, t_{\text{up}_2})\) where \(t_{\text{up}_n}\) represents a single tuple for a start and end time of activity in a day. Then, for each cluster, we find the mean of all \(\frac{n(n-1)}{2}\) distances generated where \(n\) represents the number of tuples in a cluster. We can denote this mean value as \(P_r\), where \(r\) uniquely identifies each generated cluster.

\[
P_r = \frac{\sum_{0 \leq i < j \leq n} d(t_{\text{up}_i}, t_{\text{up}_j})}{n}
\]

### 2.3 DBSCAN

Given that the value \(P_r\) generated for all clusters falls below a certain threshold, we can finish our process and calculate our results. On the contrary, if any \(P_r\) value for a cluster exceeds a set threshold, the clusters display too much variability. In this case, we turn to a density-based clustering method called DBSCAN. Before we perform DBSCAN, we must decide on an \(\epsilon\) value that specifies the maximum distance between two points in one cluster. On top of this, we must specify any number \(v\), which denotes the minimum number of points to form a cluster. We can set the value for \(\epsilon\) using the elbow method in DBSCAN. After performing DBSCAN, we can test the validity of the clusters by calculating their \(P_r\) values. If they still exceed our thresholds, we can reduce our \(\epsilon\) value, but if not, we can proceed to extract habits.

### 2.4 Habit Extraction

In the habit extraction process, we calculate the average of every single start and end time in a singular cluster. After this, we calculate the standard deviation of the start and end times in each cluster to associate possible times an activity could begin. Furthermore, we will associate a confidence score as a probability to represent how often we believe the user will carry out the activity at the clustered time interval. We can represent this as a probability using \(\frac{n}{q}\), where \(q\) denotes the total number of tuples in a cluster, and \(n\) represents the total number of tuples for the entire activity across all clusters.

### 3 EXPERIMENTS

The majority of the data used to test the methods in this paper come from the University of Washington’s CASAS household data set and REFIT electrical loads management data set [3, 4]. A significant difference between the data sets was their presentation of ON and OFF states. While CASAS pre-processed the voltage data to signify ON and OFF states, REFIT required analyzing the voltage readings and determining a threshold to represent an ON or OFF state for the device. Based on the ON times for devices presented in the data, we represented how long a device/activity was ON for as a two-dimensional tuple \((t_{\text{start}}, t_{\text{end}})\) where \(t_{\text{start}}\) is the start time for a device and \(t_{\text{end}}\) is the end time.

In the results of our experiments, we found that k-means and hierarchical clustering were optimal in profiling usage behaviors for more regular activities. For example, figure 2a represents the data clustering to do with eating breakfast. We obtained four common times for this user to eat breakfast: 8:30am ± 18 minutes - 8:38am (18% confidence), 9:52am ± 18 minutes - 10:03 am (24% confidence), 10:53am ± 14 minutes - 11:04am (44% confidence) and 11:54 am ± 14 minutes - 12:14am (13% confidence). On the other hand, hierarchical clustering on the television watching habits of a user suggested that common television watching times were 5:51 pm ± 276 minutes - 7:02 pm ± 285 minutes (97% confidence) and 12:32 am ± 37 minutes - 12:37 am ± 37 minutes (3% confidence). The results for the clustering of this activity can be viewed in figure 2b. The clusters in figure 2b cannot be viable because our noise metric score of 7.46 far exceeded our threshold for \(P_r\), which was 4. Figure 2b represents a prime example of the necessity of introducing our noise metric. While we believe the silhouette score works well most of the time, a major component of the score lies in how well separated the data is. While this is important in measuring the feasibility of clusters, since our
data do not possess high dimensionality and work on a relatively small axes size (24-hour time), we need a measure to quantify the compactness of clusters to support the silhouette score. Thus, our noise metric can measure how distinct clusters are and help detect when either hierarchical or k-means clustering struggles to output viable clusters due to the sparsity of data. Figure 2c shows the results of DBSCAN on the usage data from figure 2b. As we can see, many of the noisy points have been pruned, and the clustering generated is far more compact and precise, which is supported by the fact that all 5 clusters for figure 2c possessed a noise metric that fell below our threshold of 4.

4 CONCLUSION AND FUTURE WORK
This paper proposes a method to extract habits’ start and end times using a group of unsupervised clustering algorithms. Furthermore, we introduce a novel noise metric to address the deficiencies related to measuring the fitness of clusters. In addition, we associate extracted habits with some confidence scores and upper and lower time limits. In the future, we plan to use our methods to develop a more extensive framework for detecting changes in habits.

ACKNOWLEDGMENTS
This research was partly made possible by LE220100078 and LE180100158 grants from the Australian Research Council. The statements made herein are solely the responsibility of the authors.

REFERENCES
[1] Hadi Banaee, Gibson Chimaniwa, Marjan Alirezaie, and Amy Loutfi. 2020. Explaining Habits and Changes of Activities in Smart Homes. In Artificial Intelligence for Health, Personalised Medicine and Wellbeing (HELIPLINE), in conjunction with ECAI 2020, Santiago de Compostela, Spain (Digital Conference), August 29-September 8, 2020.
[2] Dipankar Chaki and Athman Bouguettaya. 2020. Fine-grained conflict detection of iot services. In 2020 IEEE International Conference on Services Computing (SCC). IEEE, 321–328.
[3] Diane J Cook, Aaron S Crandall, Brian L Thomas, and Narayanan C Krishnan. 2012. CASAS: A smart home in a box. Computer 46, 7 (2012), 62–69.
[4] David Murray, Lina Stankovic, and Vladimir Stankovic. 2017. An electrical load measurements dataset of United Kingdom households from a two-year longitudinal study. Scientific data 4, 1 (2017), 1–12.
[5] Pingquan Wang, Hong Luo, Xinming Li, Zhongwen Zhao, et al. 2016. A new habit pattern learning scheme in smart home. Journal of Applied Science and Engineering 19, 1 (2016), 83–94.