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# A Health Care Service Model using Human Activity Patterns


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## Abstract

The people's shift from rural to urban areas is increasing highly all over the world. Due to this change, people are affected by normal human behaviors. This leads to a greater effect in human health. The increasing research challenge incurred due to this is the Health care service. Millions of people in urban areas are equipped with the usage of smart devices. Smart devices produce a very high potential data and this massive volume can be used for analysis purposes. The analyzed results will be of much higher input to many servicing applications. Health care application is of major concern in using this analyzed result. We propose a model that can be utilized for analyzing smart devices data and discovering new patterns that can significantly target basic human activities. It also registers the changes in user's behavior. The usage of appliances for a day is mapped to human activities. This mapping is done by frequent pattern association mining and clustering. Finally the associated patterns are classified using SVM classifier for predicting the human usual and unusual behavior. Individuals' habit can be discovered by checking their everyday routines. Difficulties in performing a particular task can be analyzed from these routines. Data from smart meters are undergone with recursive mining and the results are used to identify human activity patterns. The paper presents the activity predictions with greater accuracy levels.

**Keywords**

Activity patterns, Frequent Pattern, Human Activity Prediction, K-Means, SVM Classifier, Healthcare model.

## INTRODUCTION

In due course, almost 3/4$^{th}$ of the world population will be living in urban areas. The migration of people from rural to urban areas poses a serious challenge for many health care applications. Due to this change, all the urban areas are in position to have a concern over the health of these people. This arise a need for new challenges to cities to invest in digital transformation to support sustainable urban communities, and provide healthier environment. In urban areas, most of the homes will be occupied with many automatic smart appliances that can be used to collect data for many service applications. The data can be analyzed for supporting health care applications. The usage of appliances by individuals in smart home may be associated with generating patterns and discovering their regular activities. Monitoring these patterns will help us to identify sudden abrupt changes in the individuals well being. The relation identified between the usage of appliances with respect to day-to-day activities can be used for many health care service applications for monitoring health of the individuals. The system would be able to automatically find out normal and unusual activities of the individuals. The paper assumes that security measures are implemented to avoid detection of illegal activities of the people. Readings from smart meters are used to recognize the human activities and the changes in their behavior. The measures are related to the normal activities of human beings. For example, if TV is in ON state, this can be associated with the human activity of “Leisure”. Also if microwave oven is in ON state, it can be associated with the activity of “Food preparation”. The time associated with the appliance can also be mapped with respect to what kind of food is prepared. For example, if the oven is in ON state and the time denotes evening, then it can be inferred that dinner is prepared. Similarly, activities can also be done in a group. Activities such as “Food preparation” and “Listening to Music” can be associated together when both oven and music system is in ON state in the same time. In this way, multiple appliances usage with respect to time can be used to predict what kind of operations are done together. For detecting the appliance-appliance usage and appliance-to-time association, we propose mining schemes that continuously mine the data for segregating the associations. We utilize SVM classifier, a popular classification model, to predict the use of multiple appliances and household energy consumption. The model that is proposed will make predictions with respect to time and days of the week. The main contributions to this paper can be summarized as follows: We propose a human activity pattern based on appliance usage variations in smart homes. The model utilizes frequent pattern mining algorithm for pattern recognition and K-means clustering algorithm is capable of identifying associations between appliances and time. The resulting patterns can be utilized by health care services for monitoring patients well being. We apply a SVM classification model for activity prediction based on individual and multiple appliance usage.

## II. RELATED WORK

Many technologies have been proposed for predicting human activities using massive amount of data that is generated from smart devices. The actual aim of the model is to discover individuals’ behavior and predict human activities specifically for those that would be a sign of health issue. This part is meant for literature review of existing works that utilize data from smart devices for analyzing human behavior. In [1], the authors propose Semi Markov Model for predicting the activities of humans. They also introduce an impulse based method which is used to detect common activities in a daily living. Temporal analysis of activities is done to detect activities that are happening together. The work proposed in [2] predicts the activities of elderly people for monitoring their health. The authors use sensors for data collection and propose a classification model to relate the activities.

Prediction of human activities using NALM and DS theory is proposed in [3]. Few machine learning algorithms are applied on the data collected from homes for predicting the appliance usage. The major activities are then isolated. The paper has an issue in performing the model in two steps for segregating the major activities. Research towards various appliance usage and identification of abrupt changes in the human behavior are presented in [4]. The paper is specifically addressed for people suffering from Parkinson and Alzheimer disease. Classification technique is used to identify unusual behavior [5],[6],[7]. Besides data collected from smart meters, IoT devices are also identified as a source for providing data to analyze the behavioral patterns. These patterns are used for many health care services for monitoring patients. Prediction of abnormalities in human behavior using data analytics for monitoring patient's health in remote areas is discussed in [8] and [9]. The authors of [8] analyze the traces of human activities within a short time span from group of appliances that are used together. They propose hierarchical probability based model for identifying jarring behavior. Critical behaviors that require immediate attention is predicted from this model. The authors of [9] propose an investigational revelation for identifying and measuring the usage of appliances. This study identifies patterns to provide a series of activities of an elderly individual independently living at home. These patterns are mined for analyzing urgent health conditions of elderly individuals. The model proposed in [10] is based on Naïve Bayesian classification where the human activities are analyzed from the data collected from smart devices. The pattern prediction is done based on single appliance usage and this is not applicable for real world problems. Decision tree method of classification is used in [2], [4] for predicting appliances usage with multiple classifying labels with respect to time. The paper limits to only 24-hour time period with sequential associations. A temporal pattern recognition using clustering algorithm is suggested in [11] to identify human behaviors. The paper does not include the usage of appliances for considering the patterns. Since appliance usage is also a major concern in predicting human behaviors, this method is not applicable. Hierarchical clustering algorithms are used in [12] considering the ON-OFF status of the appliances. The status is used to detect usage pattern but the paper failed to consider the duration of the usage of particular appliance. A graphical algorithmic model is developed by authors in [13] for predicting human behavior. It uses Bayesian method for predicting patterns related to multiple usages of appliances. But appliance to time level usage is not discussed. The experiments are conducted with sample dataset and though there may be many similarities in the techniques used in the proposed work and the already existing work, we claim for the greater level of accuracy in accordance with SVM classifier model.

## III. EXTRACTING FREQUENT PATTERNS OF HUMAN ACTIVITIES

The paper proposes a model that uses frequent pattern mining to find associations between appliances and to identify appliances that are operating together. As the second process clustering algorithm is used to associate appliances with respect to time. Finally the associations are combined for predicting patterns that identify human behaviors. These predictions can be consumed by health care service applications for tracking individuals' health. The main objective of the proposed model is to learn patterns that simulate human activities from a large set of massive data collected from smart meters. Regular activities such as washing clothes, using laptop, listening to music, preparing dinner etc., can be used as the training data patterns. The proposed model identifies these patterns which can be used by health care service applications for identifying abnormal changes in individual's behavior. For the model to have proper accuracy levels, we assume appliances for 30 minutes time duration to be active appliances. The readings from smart meters are related to different levels of human activities such as "leisure", "working", "preparing food" etc., Figure 1 gives an example for relating usage of appliances with respect to human activities.

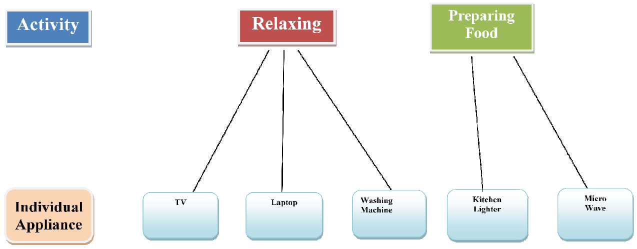


Figure 1. Relating appliance usage with human activity

Individual appliance usage and the association between two appliances are considered for discovering the patterns of daily activities of human. We use frequent pattern mining algorithm that uses divide and conquer technique for discovering the appliance to appliance association. This would help us in identifying the patterns that are simultaneously performed. The working of frequent pattern mining algorithm is done for a day and is accumulated over a period of a week. The progressive measurement would help us in accurate extraction of the associations. Let T be the set of all n item sets. $T = \{t_1, t_2, \ldots. t_n\}$. Here the itemsets are the appliances that are considered active. We measure the support and confidence of the itemsets for frequent pattern mining. Support value will be the number of transactions that contain all itemsets and minimum support is defined with some threshold value. Frequent patterns are identified by comparing the number of transactions that has the support count greater than the minimum threshold value. Confidence is the measure of number of transactions that has both the itemset in consideration. Based on the support and confidence measures, frequent patterns are generated and association rules are framed. The following algorithm sketches the overall process of frequent pattern mining.

**Algorithm**: Frequent Pattern Mining
**Input:** Transaction database (*DB*)
**Output:** Frequent Patterns – FreqPat
1: **for all** Transactions database *DB*
**do**
2: Determine the size of the database
3:Compute Frequent Patterns FreqPat using FreqPat growth algorithm
4: **for all** Frequent Patterns FreqPat in the Frequent Pattern Database (FPD)
**do**
5: Find a frequent pattern FreqPat in FPD
6: **if** Frequent Pattern found **then**
7: Update frequent pattern in FPD
8: **else**
9: add a new Frequent Pattern FreqPat to FPD
10: **end if**
11: **end for**
12: For all Frequent Patterns in FPD increment the size of the database.
13: **end for**

## IV. CLUSTERING ANALYSIS BY K MEANS

Analysis of the activity patterns on a daily basis requires associations between appliances and also association between appliances with respect to time. This section deals with clustering algorithm that is used for discovering association of appliances with time. Appliances that are active for about 30 minute duration are registered. These readings are mapped with four different time scenarios such as Morning, Afternoon, Evening and Night. Further individual days are also registered for a week. We propose K-Means clustering algorithm to form a cluster of appliances that are used simultaneously. Clustering is the process of identifying groups from a collection of data where members within a group have similar properties and members of different groups are with different properties. The cluster size depends on the number of members present within a cluster. Clustering is an unsupervised algorithm and provides added advantage to the proposed process. The main goal of K-Means algorithm is to find groups represented by a variable 'k'. The algorithm works recursively for each data point to be assigned to one of the "k" cluster.

**Algorithm:** K-Means Clustering
1. Initialize a variable "k" with some random values
2. **for** a given number of iterations
**do**
3. for each of the items in the iteration
4. Compute the mean value that is closest to the item.

5. Assign all the remaining items depending upon the mean
6. Update mean

Clustering algorithm works with both Euclidean distance and also Manhattan distance measure. We use Euclidean distance measure for clustering appliance to time associations. The function of Euclidean distance between two given points (x,y) and (a,b) is computed by $distance((x,y),(a,b)) = \sqrt{(x-a)^2 + (y-b)^2}$.

## V. SVM CLASSIFICATION

This section discusses the integration of the frequent patterns and appliance-to-time associations using SVM classifier. Support Vector Machines (SVMs) are supervised learning models used mainly for classification and regression analysis. SVM is mostly used in classification problems. In this algorithm, we plot each data item as a point in n-dimensional space (where n is number of features) with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiates the two classes very well. In other words, the support vector machine searches for the closest points which it calls the "support vectors". Once it has found the closest points, the SVM draws a line connecting them. It draws this connecting line by doing vector subtraction (point A - point B). It then declares the best separating line to be the line that bisects and is perpendicular to the connecting line. Let x (x € □$^n$) be a feature vector which is the input for SVM. This feature vector is got from cluster and associations got from the previous modules. y be the class. w and b be the parameters of SVM. We need to learn w and b using the training set. SVM aims at two basic requirements.

1) It should maximize the distance between two decision boundaries. (ie) distance between the hyperplane $w^T x + b = -1$ and the hyperplane $w^T x + b = 1$ should be $\frac{2}{|w|}$.
2) It should correctly classify all $x^{(i)}$ which means $y^{(i)}(w^T x^{(i)} + b) \geq 1$ for i=1 to N.

The sample training data derived from clustering and frequent pattern analysis for a specific duration is utilized by the SVM classifier for determining active appliances. The training From the historical evidences collected from appliance-to-time associations and appliance-to-appliance associations, we predict appliances that are operating simultaneously.

## VI. RESULTS AND DISCUSSION

The proposed model is evaluated with a simulated dataset arrived from REDD [15]. REDD consists of whole-home and circuit/device specific electricity consumption for a number of real houses over several months' time [15]. The main objective of the model is to detect the usage of appliances to predict human activity patterns. The patterns can be used as input to health care applications for further process. As a first process, association between appliance usage is extracted. It is seen that between 2:30 and 5:00 pm Kitchen lighter, Laptop, Microwave are used together with highest concentration during the weekend. Also, the Microwave and Laptop are simultaneously used between 8:30 am and 10:00 am. Table 1 shows the result of appliance to appliance association.

| Appliance | 00:01-00:29 | 01:00-01:29 | 02:00-02:29 | …. | 10:00-10:29 | 11:00-11:29 |
|---|---|---|---|---|---|---|
| 1 | 50 | 50 | 50 | …. | 50 | 50 |
| 2 | 25 | 25 | 25 | …. | 25 | 25 |
| 3 | 15 | 15 | 15 | …. | 15 | 15 |
| 4 | 20 | 20 | 20 | …. | 20 | 20 |
| 5 | 10 | 10 | 10 | …. | 10 | 10 |

*1- Kitchen Lighter, 2 – Laptop, 3 – TV, 4 – Microwave, 5 – Washing Machine

Table 1. Appliance-to-Appliance association

The experimental result is calculated for two houses with few hundreds of the dataset. The strongest association made out of this experiment is occupants' wishes to relax while preparing food. Similar samples are collected from various types of appliances and the proposed model is used to discover abrupt changes in the individuals' behavior from the normal human behavior. Figure 2 and 3 denotes the association of appliances with respect to time and with respect to week day respectively. The prediction model utilizes associations between appliances and association of appliances with respect to time for predicting multiple concurrently operating appliances. The proposed model attains combined accuracy of 81.82%. This clearly shows that smart meter data can be used to identify human activity patterns in a better way.

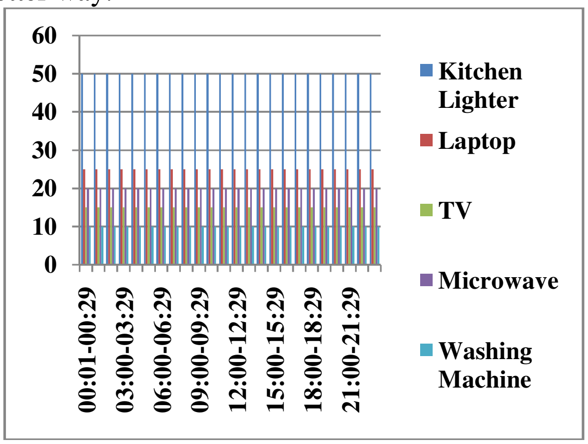


Figure 2 – Association of appliances with respect to time

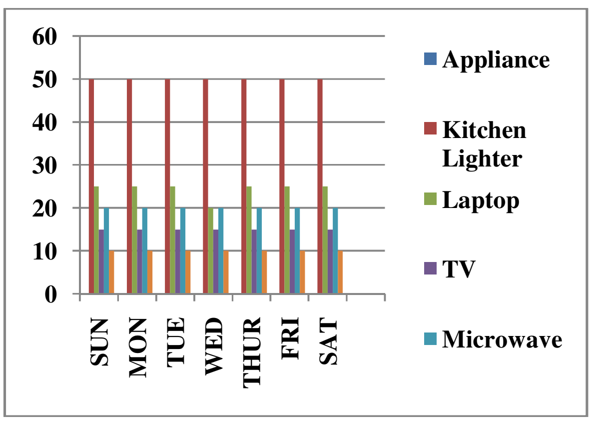


Figure 3 – Association of appliances with respect to weekday

## VII. CONCLUSION AND FUTURE WORK

The proposed paper portrays a mining model that identifies human normal activities in day to day routine. The data collected from smart meters are used to identify such patterns. The human activities performed in a day and accumulated for a week can be of greater significance for applications such as health care services. These applications use the patterns for monitoring the health of individuals especially those who are living independently or with limited conditions. Associations generated from appliance to appliance usage and appliance to time associations provides major activity patterns. Frequent pattern mining algorithm followed with k-means clustering algorithm provides a framework for generating associations. SVM classifier is then used for predicting the human normal and abnormal behaviors. Experimental results show that the proposed model can be used to correctly predict the behaviors with higher level of accuracy. The future scope of this work will be with various other algorithms for pattern mining and classification. In the other direction this work can be extended for processing of big data with some deep learning algorithms.

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