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# Cognitive Health Prediction on the Elderly Using Sensor Data in Smart Homes

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## Abstract

The percentage of people living over 65 years has increased steadily over the last few decades, and with it is coming a rapid increase in cognitive health issues among the baby boomers. In order to address the issue of caring for this particular aging population, intelligent solutions need to be provided. It is our hypothesis that through the application of various data mining and machine learning approaches, we can analyze data from the sensors installed in smart homes in order to predict whether an elderly resident has cognitive impairments, which will hinder their ability to perform daily tasks. With the growing senior citizen population, it is imperative to detect and try to predict these kinds of behaviors because it can improve the quality and safety of the residents' home environment as well as provide aid and well-being for their caregiver. In this paper, we present our proposed approach, the real-world data set used in our experiments, and results from this study.

## Introduction

According to the United States Census Bureau (Ortman et al. 2014), 13 percent of the U.S. population in 2013 was of the age 65 and over. This is estimated to rise to more than 20 percent by the year 2030 due to the aging baby boomer generation. Although more of the U.S. population is living longer, that does not imply that they are at optimal health. In a 2016 report by the Alzheimer's Association (Association and others 2016), people over the age of 65 are prone to various degrees of cognitive disabilities that can limit their ability to perform day-to-day activities, requiring them to be dependent on caregivers. Alzheimer's disease and other forms of dementia are prominent among the elderly population and is estimated to affect 5.2 million people above the age of 65 (Association and others 2016). Elderly people are at a higher risk of developing mild cognitive impairment (MCI) which is a potential precursor to Alzheimer's disease and other dementias. In addition, with a rise in the elderly population with MCI comes the need for more caregivers which creates growing issues surrounding helping those with cognitive issues (Association and others 2016).



Smart home sensor systems can provide aid to elderly residents, especially those who are suffering from MCI, and their caregivers (Martin et al. 2008). Various intelligent systems such as smart homes have been used to provide aid in health-care monitoring (Cook et al. 2013) (Martin et al. 2008). The sensors set up throughout the home can collect information about a resident's everyday activities without interfering with their routines. These homes can also prompt users to perform particular activities, such as reminding a resident to take their medicine (Wilson, Hargreaves, and Hauxwell-Baldwin 2015). With the use of smart homes, the daily activities and behavioral patterns of residents can be monitored through sensors embedded within various areas in the home. This allows the residents to be more independent as well as providing aid to their family and caregivers. In 2016, the total annual costs associated with the care of patients with Alzheimer's was estimated at $236 billion for health-care, long-term care, and hospice care, and is estimated to increase to over $1 trillion in 2050 (Association and others 2016). The hope is to use smart homes to reduce this cost by alleviating some responsibilities on care providers and reducing medical emergencies.

It is our hypothesis that through the application of various machine learning approaches, we can analyze data from the sensors installed in smart homes in order to detect anomalous behavior that might be predictive of the onset of dementia. For example, a sensor can detect a resident being in a particular room for an extended amount of time which could indicate that the resident has fallen or other health risks have occurred. According to Galvin and Sadowsky (Galvin and Sadowsky 2012), some warning signs of Alzheimer's disease, which is the most common form of dementia, are memory loss, difficulty performing familiar tasks, misplacing things, and changes in behavior. These traits can be used to define anomalous behavior among residents. Using anomaly detection methods to analyze residents' daily functions can provide insight into whether they are experiencing a decline in cognitive abilities. This paper aims to use machine learning algorithms to analyze and predict whether a resident may be developing cognitive disabilities by finding abnormal patterns in their behavior.

The layout of this paper is described as follows: first, we present related work in the area of investigating elderly behavioral patterns in a smart home environment, followed by a description of the data, information about the residents living in smart homes, and data preprocessing. This is then followed by a description of the methodology used, experiments, and results. We then conclude with some observations and our proposed future work.

## Related Work

With the growing elderly population, research in elderly living and well-being has been aimed toward medical analysis and supporting independent living of elderly people. Most researchers aim to improve the living of people with medical issues, such as diabetes and cognitive disabilities, through analyzing behavior of residents within sensor-based environments. The types of intelligent systems used to analyze behavior ranges from wearable sensor technology to sensors installed within a resident's home. The following describes some research regarding the analysis of behavior and health monitoring among elderly people.

(Lotfi et al. 2012) investigated elderly residents living independently in real home environments who were diagnosed with dementia. They applied neural networks (Echo State Network ) to predict sensor activity in order to inform the caregiver of any anomalous behavior that can be expected in the future. However, this worked better for residents with more routine activities such as senior citizens rather than younger residents. (Jakkula and Cook 2011) used one-class support vector machines (SVM) using Sholkopf algorithms to improve detecting anomalous behavior in a smart home data. (Novák, Biňas, and Jakab 2012) used self-organizing maps for classification. They added artificial anomalous behavior based on the duration of an activity like unusually long inactivity or changes in daily activity to their dataset. They used a first level Markov model to detect 75% of the artificially added anomalies.

(Helal, Cook, and Schmalz 2009) used a smart home based health monitoring system to analyze the behavior of diabetes patients. They designed two types of assessment programs to monitor patients' behavior: using sensors for activity recognition in order to aid a patient's caregiver in keeping track on the patient's well-being; as well as using video to analyze a patient's chewing motions to keep track of their dietary habits. They used a hidden Markov model to classify the patients' activities. They concluded, however, that there are still issues with individual behavioral monitoring algorithms and for future work will use target populations to validate the accuracy of their algorithms. (Zhu, Sheng, and Liu 2015) used anomaly detection on wearable sensors to provide an intelligent living environment for elderly residents. They based their anomalies on location, time, duration, type of activity, and the transition of activities. The experiments consisted of a semi-supervised learning approach using maximum-likelihood estimation and Laplace smoothing. Though their results showed a promising anomaly detection system, they tested their experiment in a mock apartment environment.

(Dawadi, Cook, and Schmitter-Edgecombe 2016) created a Clinical Assessment using Activity Behavior (CAAB) approach to predict clinical assessment scores of the smart home residents in hopes to help clinicians make decisions regarding diagnosing patients. However, in this case, most of the 18 residents analyzed were cognitively healthy. (Cook, Schmitter-Edgecombe, and Dawadi 2015) used smart home and wearable sensors to collect data from older adults while they performed complex activities of daily living. They used various machine learning techniques and concluded that it was possible to automatically recognize a difference in behavior between healthy, older adults versus adults with parkinson's disease. However, while we only had access to features from sensors to classify the residents, they were able to add additional features such as smart sensors, wearable sensors, day out tasks (DOT), age, and activities.

In this paper, we address the problem of learning from smart home sensor data without including any medical information about the resident. Just using sensor data can be very valuable to any smart home scenario where medical information would not normally be available. In order to be comprehensive, we will select from a diverse set of machine learning techniques, and demonstrate the potential effectiveness of such techniques to classify cognitive impaired residents among elderly people in a smart home environment.

## Dataset

The dataset used for analysis is provided by Washington State University's CASAS program (http://casas.wsu.edu/). CASAS (Center for Advanced Studies in Adaptive Systems) aims to provide aid to residents through smart home technology. They use real-time data from sensors to analyze and monitor residents' health and behavior to improve future smart home living (Cook et al. 2013).

### Resident Information

For the purposes of our analysis, we chose a dataset from the CASAS repository that consists of ten elderly residents from a retirement community. Each of the smart homes has a single resident between the ages of 80 and 91. Five out of the ten residents are diagnosed with MCI, while the other five are considered cognitively healthy. Since the behavior will vary among each individual, we will analyze the data through different approaches, discussed in more detail later in this paper, in order to discover patterns and trends based on a resident's cognitive health. Our hypothesis is that this would allow medical personnel to be better able to predict whether a resident is in the stages of developing cognitive disabilities. Since the sensor data taken of each resident spans over months, our objective with this work is to detect any signs of changed behavior or activity patterns which are signs of having MCI (Galvin and Sadowsky 2012) (Ortman et al. 2014) (Petersen et al. 1999).

### Smart Home and Sensor Information

The sensors set up throughout the house detect the activity of a resident such as if they are in the bathroom or if they open the refrigerator door. The types of sensors installed are light sensors, infrared motion sensors, wide-area infrared motion sensors, temperature sensors, and magnetic door sensors.

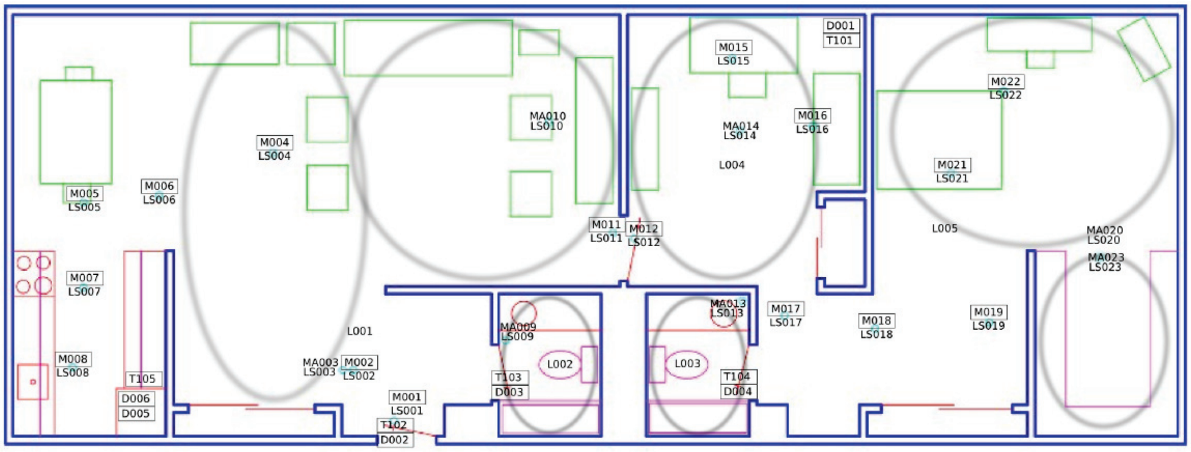


Figure 1: CASAS smart home floor plan and sensor layout (Dawadi, Cook, and Schmitter-Edgecombe 2016)

Light switches and sensor battery levels are also included as part of the sensor data.

CASAS website provides sensor data (both the raw dataset and the annotated dataset). The raw dataset contains the date (yyyy-mm-dd), time (HH:MM:SS), sensor identification (e.g. "M009" represents a motion sensor and the number "009" indicates a particular area in the home), and sensor type (e.g. sensors like motion and door that have binary states of ON/OFF or OPENED/CLOSED, or battery sensors that have a number to indicate battery levels). This information is also included in the annotated dataset, including an additional attribute that signifies the activity type (e.g. Sleep= "begin", Sleep= "end", Eat_Lunch= "begin", Watch_TV= "end"). CASAS researchers used an activity recognition algorithm to label activities based on what sensors were activated. First, these activities are labeled by human annotators to provide a ground truth and then the algorithm is used to label the remaining activities (Dawadi, Cook, and Schmitter-Edgecombe 2016). An example of the layout of a resident's house with sensors is shown in Figure 1. Since the layout of the homes varies for the residents and human behavior varies throughout a home, the data is analyzed by the activity type in the annotated dataset rather than analyzing whether a sensor from a specific location in the house was activated.

## Data Preprocessing

First, we convert the data into comma separated files (CSV) for ease of parsing. For our analysis, we will use the activity type to categorize the different activities of the residents throughout the day. Figure 2 shows a snippet of the annotated data of one of the residents and the cleaned CSV data file. Most of the activities in the dataset fall under the set of eight Instrumental Activities of Daily Living (IADL) (Lawton and Brody 1970), where competence in IADL activities is required for independent living. Based on a resident's ability to perform these activities, clinicians can characterize their daily behavior and find out whether they have cognitive or physical difficulties.

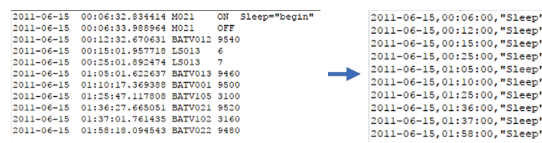


Figure 2: Resident's data snippet, annotated dataset (left), cleaner dataset (right)

In addition, we derive several features that may prove useful in the discovery of patterns. For instance, we calculate a *duration* required for each activity by looking at a resident's activity start time and end time. In addition, instead of using an explicit date time, we will generate extra features like *month of the year*, *weekday or weekend*, *time of the day* (early morning, morning, afternoon, evening and night), and *hour of the day*. We decide to derive these features because it will provide us with valuable insight on a resident's behavior, such as if there are any patterns of normal or unusual behavior based upon whether it is early or later in the day, if there is any variant behavior during the days of the week verses the end of the week, or perhaps during summer and winter months (just to name a few scenarios). In addition, a person with MCI can be wandering, getting confused, committing frequent mistakes or not completing an activity. We calculate *number of times the motion sensor activated* while doing a specific activity and the *time to next activity* to learn if the resident is wandering and taking a lot of time to complete the activity. (Beaulieu-Bonneau and Hudon 2009) and (da Silva 2015) found that sleep disturbances could indicate signs of MCI. To represent these behaviors, we generate additional features like *preceded by* and *followed by*, which tells us what activity precedes and follows the current activity. For example, if the resident's activity "toilet" is preceded and followed by "sleep" then we can then probably infer that the resident woke up from sleep to go to toilet, indicating a sleep disturbance. A total of 17 features are generated. Table 2 shows the list of features and their description. Table 1

| Class | Dataset 1 | Dataset 2 |
|---|---|---|
| Healthy | 33,252 (5 resident) | 10,004 (4 resident) |
| MCI | 9,093(5 resident) | 9093 (5 resident) |
| **Total** | **42,345 (10 resident)** | **19,097 (9 resident)** |

Table 1: Dataset detail

| Features | Description |
|---|---|
| Month | Month of the year |
| Activity | Resident activity |
| Precede by | Activity performed before current activity |
| followed by | Activity performed after current activity |
| Activity start time | Time at which resident starts the activity |
| Activity end time | Time at which resident ends the activity |
| Duration | Time required to do the activity |
| Time to Next Activity | Time taken to start next activity |
| Hour of day | Hour of day |
| Start time of day | Activity start part of the day |
| End time of day | Activity ending part of the day |
| Day of week | Day of a week |
| Is weekend | Flag for weekday or weekend |
| Motion sensor count | Number of motion sensor activated |
| Light sensor count | Number of light sensor activated |
| Light on count | Number of light turned on |
| Light off count | Number of light turned off |

Table 2: Features used and their description

shows the detail of datasets considered for experiments.

## Methodology

In order to represent a cross-section of the most common machine learning techniques, both supervised and unsupervised, we will experiment with the following approaches:

- Logistic Regression
- Linear Discriminant analysis (LDA)
- Decision Tree
- Support Vector Machine (SVM)
- K-Nearest Neighbor (KNN)
- Random Forest
- Ada Boosting
- One-Class SVM

This will provide us with a comprehensive analysis of traditional machine learning techniques for predicting mental cognitive impairments among elderly people in a smart home environment.

All of our experiments are done in python using the sci-kit learning tool's. We use label encoding to encode the categorical values, i.e., converting each value in a column to a number between 0 and $num\_of\_classes - 1$. The label encoded data is then passed through data scaling, where the distribution of each feature is "shifted" to have a mean of zero and a standard deviation of one (unit variance), where the range of values in the raw data varies widely. And if we have the classifier that calculates the distance between two points, and there is a feature with broad range of values, the distance will be governed by this particular feature. Therefore, the range of all features will be scaled so that each feature contributes approximately proportionately to the final distance. Once label encoding and scaling are done, the algorithm is run on the scaled data using 10 fold cross validation.

| Algorithm | Accuracy | Precision | Recall | F1-Score | AUC |
|---|---|---|---|---|---|
| Logistic Regression | **.77** | .69 | .77 | **.79** | .51 |
| LDA | **.77** | .70 | .77 | .71 | .52 |
| KNN | **.77** | **.75** | **.78** | .76 | .60 |
| Random Forest | .74 | .74 | .75 | .74 | **.66** |
| Decision Tree | .70 | **.75** | .71 | .72 | .63 |
| Ada Boost | .70 | .71 | .71 | .71 | .57 |
| SVM | .76 | .72 | .76 | .73 | .56 |
| One-Class SVM | .52 | .55 | .53 | .53 | .54 |

Table 3: Performance of all algorithms in Dataset 1

| Algorithm | Precision | Recall | F1-Score |
|---|---|---|---|
| Healthy | .83 | .91 | .86 |
| MCI | .47 | .30 | .37 |
| Average | .75 | .78 | .76 |

Table 4: Performance of KNN in Dataset 1

### Supervised Approach

For our proposed supervised approaches, we choose from a range of different machine learning techniques: logistic regression, a Bayesian classifier using LDA, ensemble methods like random forest and ada boosting, and non-linear classifiers like KNN and decision tree. We apply all of the supervised algorithms on Dataset 1, with the results shown in Table 3. Considering the results, out of the chosen eight algorithms, KNN has the best performance in terms of accuracy (77%), precision (75%), and recall (78%), logistic regression has the best F1-score (79%) and accuracy (77%), and random forest has the best auc (66%). The AUC curve comparing the performance of all algorithms is shown in figure 3. Based on these results, we can conclude that KNN has the best performance among all of the algorithms. However, breaking down the performance of KNN for healthy and MCI class (shown in table 4), the recall for an MCI resident is low (only 30%) while recall for the healthy class is 91%. This indicates healthy residents are easier to recognize, possibly as a result of having more data points in Dataset 1 for healthy residents (MCI to healthy ratio $\approx$ 1:4).

Since, the goal of our research is to correctly identify a cognitively impaired resident, the recall of 30% is not a good result. Since the model is biased towards the healthy class, resulting in low recall for MCI, we decided to run another experiment on a balanced dataset. We randomly removed the data of one (arbitrary) healthy resident and created Dataset 2 consisting of 9 residents that have almost an equal number of data instances for both the healthy and the MCI class (MCI to healthy ratio $\approx$ 1:1). Table 5 shows the performance of all the supervised algorithms on Dataset 2. As shown, the overall accuracy, precision, recall and F1-score for all algorithms drops by a few percentage points, but the AUC increases for all of them. Random Forest has the best performance (highest value for accuracy, precision, recall, F1-score and AUC) among all algorithms. Breaking down the performance of

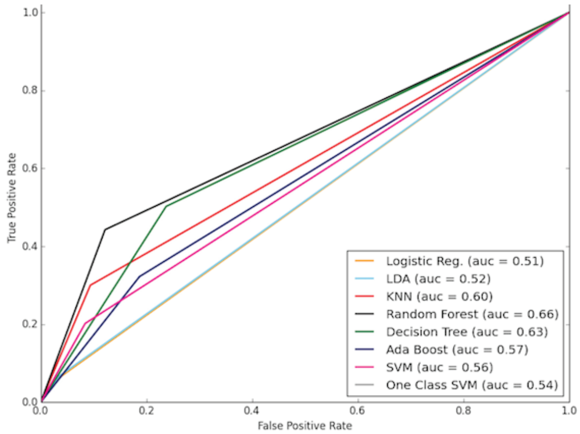


Figure 3: AUC curve using Dataset 1

| Algorithm | Accuracy | Precision | Recall | F1-Score | AUC |
|---|---|---|---|---|---|
| Logistic Regression | .64 | .65 | .65 | .65 | .65 |
| LDA | .64 | .65 | .65 | .65 | .65 |
| KNN | .67 | .68 | .67 | .67 | .66 |
| Random Forest | **.73** | **.74** | **.73** | **.73** | **.72** |
| Decision Tree | .68 | .68 | .68 | .68 | .68 |
| Ada Boost | .65 | .66 | .66 | .66 | .66 |
| SVM | .71 | .71 | .71 | .71 | .71 |

Table 5: Performance of supervised algorithms in Dataset 2

random forest on Dataset 2 (Table 6), we can see a significant increase in recall of the MCI class (from 30% to 60%). Though the overall performance decreases, we are still able correctly identify a higher number of instances of residents with MCI.

### Unsupervised Approach

The CASAS smart home dataset is a labeled dataset. However, it is not always possible to have access to labeled datasets, which would necessitate the use of unsupervised approaches. We choose to use a one-class SVM as our unsupervised algorithm. One-class SVMs are a special case of support vector machines. Our problem is to classify healthy and cognitively impaired residents, which can be done by mapping it as a one-class SVM problem. By providing the normal (healthy resident) training data, the algorithm can create a (representational) model of healthy data. Then, if newly encountered data is significantly different from this model, according to some measurement, it is labeled as out-of-class - which in our case, we infer as MCI.

In order to simulate unlabeled data, we remove the class label from Dataset 1. We then divide the data set into training and test sets. The experiment for the unsupervised approach is done on Dataset 1 because of the higher number of instances of the healthy class will provide more information to build a model for the healthy class. We randomly split the data set 80-20% for training and testing. Since one-class SVM is trained using the normal (healthy) data, splitting is done in such a way that the training set will only have data from healthy residents. For these experiments, we will use the default parameters for the RBF kernel. The results of one-class SVM is shown in Table 3. As shown, one-class SVM performs only slightly better than 50% for all metrics (i.e., about the same as flipping a coin). Though the results are not satisfactory, using more data, adding extra information about the resident and tuning parameter for the algorithm can help improve the performance, which we would like to explore in future.

| Algorithm | Precision | Recall | F1-Score |
|---|---|---|---|
| Healthy | .70 | .84 | .77 |
| MCI | .78 | .61 | .68 |
| Average | .74 | .73 | .73 |

Table 6: Performance of random forest in Dataset 2

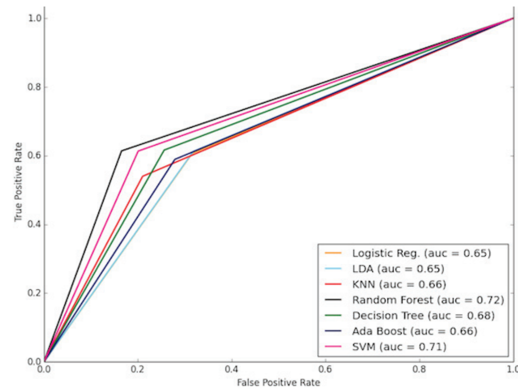


Figure 4: AUC curve using Dataset 2

## Results and Discussion

We formulated the problem as both a supervised and unsupervised learning problem. Table 3 shows the final results for both supervised and unsupervised algorithms using dataset 1. Out of the chosen eight algorithms, KNN has the best performance in terms of accuracy (77%), precision (75%), and recall (78%). Logistic regression has the best F1-score (79%) and accuracy (77%) and random forest have the best auc (66%). KNN shows the best performance to all other algorithms in dataset 1. However, dataset 1 has low recall for MCI class because of data being more biased toward healthy class. The low recall can be increased by making dataset more balanced. Random forest in dataset 2 which is a balanced dataset has the best performance with recall of 61% for MCI class and recall of 84% for healthy class.

We are using segments of sensor values of each residents as one data point. This can introduce bias while using 10 fold cross validation because training and testing data will have data point from the same resident. In future we would like to use leave-one-subject-out (training on 9 residents and testing on the $10^{th}$) cross validation to deal with such bias. Also all the experiment are performed using default parameter for all algorithms. Some form of parameter tuning could increase the performance which we would like to do in future.

## Conclusion

There has been much research focused on improving independent living for cognitively impaired residents through sensor-based smart home environments. Smart home environments aim to not interfere with the normal activities of the residents and hope to reduce the cost of health care associated with caring for the resident. Understanding human behavior through sensor data can prove to be challenging and by using machine learning tools on data collected on residents' activities can help categorize the movement of residents in order to determine their behavior.

Our objective was to see if we can use automated machine learning techniques in smart home data to predict the cognitive health of resident. Based on our experiments, we see positive results, where supervised approaches easily outperform unsupervised approaches. Among all the algorithms, KNN has the best accuracy, precision, and recall, logistic regression has the best F-1 score, and random forest has the best AUC on Dataset 1. The low recall for the MCI class in Dataset 1 can be increased by making the dataset more balanced. Balancing the data, random forest has the best recall for the MCI class, with almost comparable performance to KNN. In a smart home environment, where it is not always possible to get medical information, by just analyzing the resident behavior using smart sensor data we have shown that machine learning can provide a physician and health care worker with valuable insights on resident mental health.

In future work, since it is not easy to get a labeled dataset, we would like to focus more on improving the performance of our unsupervised approach. The accuracy of a one-class SVM is not the best, but it does show the potential of an unsupervised approach. We believe we can do better in the future if we have more data. The sensor activity in the CASAS testbed have sets of sub-activities and each of the activities have an associated score indicating how well the resident did while performing the activity. In the future, we would like to include these sub-activities and their associated scores. We also plan to investigate unsupervised graph-based approaches in order to discover anomalous activities and movements that can be used to report unusual, out-of-the-norm, behavior by a resident - a possible sign of the onset of dementia. In addition, we hope to involve a clinician as a domain expert so that we can validate our results.

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