# Energy Efficiency in Workplace Based on Occupant's Routine/Behavior

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## 1. ABSTRACT

In *t*oday's world, Offices are low on energy efficient because they don't have state of art intelligent systems. Which causes high energy consumption and wastage of energy. converting energy inefficient building into efficient one, can be an effective solution in terms of cost,which would result in reducing energy imports, and propagating environment conservation.
Energy-saving building and offices require automated system to control device intelligently for saving energy and at the same preserving occupant's comfort.As part of our project we are going to use this concept in our Robotics Lab (CSE Department, IITG). Best way to reduce energy consumption in lab is to: 1) Inspect on the use or flow of energy, resulting in identification the area or devices of work and 2) Monitoring such devices and activity around them by sensors.
Since Lab is equipped with various electronic devices, activity around these devices can be monitored so as to identify the flow of power through these devices and based on collected data, enough measure can be taken so as to control the devices intelligently.
**Keywords** : Data Collection, Activity Recognition, Activity Prediction, Energy Efficiency

## 2. INTRODUCTION

One *o*f the key input for saving energy in offices and building is activity information, which includes the physical behaviour of the person i.e. in time, out time etc. This information can be used to control appliances for saving energy while satisfying occupant's comfort. As part of our project below the milestones which we need to achieve are:

1. Collecting Lab's occupant activity related raw data.
2. Tagging the raw data with respective activity.
3. Modelling Activity recognition system.
4. Modelling Activity prediction system.

Our main goal of this project is to identify activities being performed in our Lab along with the prediction of activity sequences.
Activity recognition is a challenging work when it comes to human activity recognition from sensory data. After we have models for Activity prediction we can utilize planning algorithm to intelligently control the devices.
The system presented here aims to understand situations that take place in a multi-person office environment. Since lighting is one of the major consumption of energy, deploying sensors around workstation is one of the efficient way to reduce energy consumption and several other positions in lab.
We have also placed camera to identify activities. Then we built a model to identify activities and predict next activity that can be performed. For instance, If next activity is leaving system idle then probably we shall switch off monitor and lights.

Rest of the report is organized as follows. Part 3 discusses briefly about the literature review and different models used for the same. Part 4 gives insights of our methodology. In part 5, we have included our experiment along with data collection process and in part 6 results and discussions. Part 7 concludes our work and provides direction for future work.

## 3. LITERATURE REVIEW

The goal of activity recognition and prediction is to understand human behaviour and taking decision according to what we learnt. We can have energy efficient building having these learning and efficient planning of equipments.
This is well researched area, so we got so many work on this area [3][4][5][6][7]. A model depends on kind of data and environment setup. People used motion sensors, light sensors, ultrasonic sensors and now a days smart phones are used for this purpose [8][9].
Several researches used different models for AR/AP modelling. [10][11][12][13][14] used HMM model for activity recognition and pattern discovery. KNN is used in [15], [16][17] used Dynamic Bayesian Network . Fuzzy modelling approaches also used in [20][21][22]. Other methods used were based on decision tree [18] and neural network [19].

## 4. METHODOLOGY

In terms of implementation, first task is to collect the relevant data. Since we have selected our Robotics lab for implementation, all data has been collected from lab. There are various appliances configured in lab which run on electricity such as computers, lights, air conditioning etc. Here we are going work on the computer systems to lower down the energy consumption. We built and tested our model on bench-marked CASAS data-set.
Below are the major functionality that we have implemented in our project:

### 4.1 Collecting sensory Data

To start with data collection, our first task is to identify which kind of data we would require. The type data that needs to be collected depends upon the activities in which we are interested. As the appliance we have chosen is computer, we have monitored human activity around the computer systems alone. As part of activity recognition, after doing analysis on lab environment we came up with below four activities which are object vs system:

1. Position of person is Sitting on his/her computer desk and Monitor is in ON state.
2. Position of person is Sitting on his/her computer desk and Monitor is in OFF state.
3. Position of person is not Sitting on his/her computer desk and Monitor is in ON state.
4. Position of person is no Sitting on his/her computer desk and Monitor is in OFF state.

Next step in data collection includes deciding types of sensor required so that all above activities can be covered.

## 4.2 Segmentation and Feature Extraction

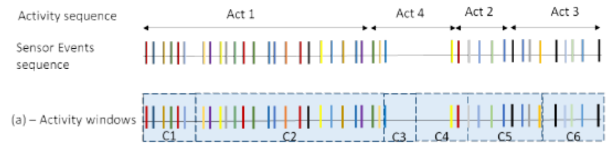
After collecting the data from Robotics lab, we started working on models for activity recognition and prediction. To test our model, we wanted to have some benchmark data, so that we can correctly evaluate our model. Also we wanted the data set which is close to our collected data. A good number of projects are going on in different universities. We used Washington State University's CASAS data-set.
We have referred a paper for feature extraction provided by the university [23].

This evaluation approach segments the data into separate sequences for each activity occurrence. Each activity occurrence has a specific beginning and ending and is treated as a whole unit. Please refer figure given below.

```
2009-06-10 03:20:59.087874 M006 ON Night_wandering begin
2009-06-10 03:21:01.038931 M002 ON
2009-06-10 03:21:03.001745 M002 OFF
2009-06-10 03:21:03.092281 M006 OFF
2009-06-10 03:21:04.000884 M002 ON
2009-06-10 03:21:05.009842 M002 OFF
2009-06-10 03:21:08.033939 M009 ON
2009-06-10 03:21:10.027285 M009 OFF
2009-06-10 03:21:52.005397 M002 ON
2009-06-10 03:21:55.046858 M002 OFF
2009-06-10 03:22:13.008367 M011 ON
2009-06-10 03:22:14.000398 M012 ON
2009-06-10 03:22:18.063157 M011 OFF
2009-06-10 03:22:18.078709 M012 OFF
2009-06-10 03:22:19.001209 M022 ON
2009-06-10 03:22:24.015902 M022 OFF
2009-06-10 03:25:19.059284 M012 ON
2009-06-10 03:25:19.086432 M011 ON
2009-06-10 03:25:24.054674 M011 OFF
2009-06-10 03:25:24.070558 M012 OFF Night_wandering end
```

Let us consider [E1, E2, ..., EN] a sequence of sensor events collected from a one resident smart home. Each event sensor is associated with date and time, sensor ID, sensor status and activity. Sensors IDs starting with M are motion sensors and IDs starting with D are door sensors.

We used following features




1. `SENSORS_USED`: This feature is array of sensors which stores the count of each sensor event during that activity.
2. TIME: Time of activity. It can take value from 0-23. Array of 24 values storing the time at which activity happened
3. `DAY_OF_WEEK`: The day (Monday - Sunday) on which the activity happened.
4. `PREVIOUS_ACTIVITY`: Activity performed before this activity. We can have range of previous activities too. Used the array for this.
5. `ACTIVITY_LENGTH`: Duration of activity which is measured as number of sensor events also plays role in identifying activities. There are activities such as 'Leave Home' that are defined by rapid firing of a small set of while at the other end is the activity 'Bed that continues for hours, but typically leads to occasional firing of one or two sensors.

## 4.3 Algorithm

Our problem is temporal in nature which deals with states over a period of time. We have time series data. To model activity recognition we used classification approach of machine leaning and used Hidden Markov and Naive Bayes model to achieve it.
We modelled activity prediction using HMM.

### 4.3.1 *Naive Bayes:*

Naive-Bayes works on the assumption that each feature is conditionally independent of each other.
**Calculating Prior beliefs for activity:** We calculated prior beliefs of each activity using Maximum Likelihood Estimate approach.
$\mathrm{Pr}(\mathrm{Activity_i}) = \mathrm{Count}(\text{Number of Sensor events for Activity}_\mathrm{i})/\mathrm{Count}(\text{ Sensor events})$
**Calculating Likelihood:** We have calculate the evidences using Maximum Likelihood Estimate.
$\mathrm{Pr}(\text{evidence}|\mathrm{Activity_k}) = \text{alpha} * \mathrm{Pr}(\text{evidence, Activity}_\mathrm{k})$
If evidence is feature vector <e1, e2, e3......>
so,
$\mathrm{Pr}(\text{evidence}|\mathrm{Activity_k}) = \text{alpha}*\mathrm{Pr}(\text{evidence,Activity}_\mathrm{k})$

$$= alpha * \prod_{i}^{n} Pr(e_\mathrm{i}|A_\mathrm{k})$$

Both above is the parameters for model and leaned while training.
**Naive Bayes Classification:**

Predicted Activity A =

$$\underset{k=1,2,\ldots,K}{\text{argmax}}\ Pr(A_\mathrm{k}) * \prod_{i}^{n} Pr(e_\mathrm{i}|A_\mathrm{k})$$

Following is the loss Function that needs to be minimized while classification.

$$L = -(log(Pr(A_k). \sum_{n=1} log(Pr(e_i|A_k)))$$

Activity which minimizes this loss function is assigned as recognized activity

### 4.3.2 Hidden Markov Model:

We need to find out following three parameters for HMM from given data set.

1. Prior Beliefs for each hidden state (activities) : $\mathrm{Pr}(\mathrm{Activity}_i)$
2. Transition Model : $T_{ij} = \mathrm{Pr}(\mathrm{Activity}_j | \mathrm{Activity}_i)$
3. Observation Model $P(E_t|\mathrm{Activity}_t)$

**Training:** We have fully observed data so, used MLE estimation for estimating parameters of HMM by counting and normalization.

$\mathrm{Pr}(\mathrm{Activity}_i) =$
Count(Number of Sensor events for $\mathrm{Activity}_i$)/ Count(Number of Sensor events)

To calculate the probability of each evidence, we assumed that each feature value is independent of each other.

$\mathrm{Pr}(\mathrm{evidence}|\mathrm{Activity}_k) =$
Count(evidence, $\mathrm{Activity}_k$)/Count($\mathrm{Activity}_k$)
and calculated as described in NB approach.

Transition model is also obtained using MLE.
$T_{ij} = \mathrm{Pr}(\mathrm{Activity}_j | \mathrm{Activity}_i) =$
Count($\mathrm{Activity}_i$ -> $\mathrm{Activity}_j$)/ Count($\mathrm{Activity}_i$)

**Activity Recognition:**
For activity recognition we used Viterbi algorithm to recursively calculate the likelihood of activity given evidence. Activity with highest likelihood will be assigned to that evidence.

$$PredictedActivityA = \underset{k=1,2,\ldots,K}{\mathrm{argmax}}\ Likelihood(A_k)$$

We also updated the prior belief at each time t with max likelihood achieved at time t using viterbi.

$$PriorProbabilityPr(A_t) = Pr(A_t)$$

**Activity Prediction:** The task of prediction can be seen simply as filtering without the addition of new evidence.
We have calculated the likelihood of each activity at time t. Then we can use these likelihood to predict activity at time (t+1) using following:

$\mathrm{Pr}(A_{t+1}) = \mathrm{Pr}(A_{t+1}|e_{1:t})$

$$= \sum_{a_t} Pr(A_{t+1}|a_t).Pr(a_t \vee e_{1:t}))$$

$$PredictedActivityA = \underset{k=1,2,\ldots,K}{\mathrm{argmax}}\ Pr(A_k)$$

# 5. EXPERIMENT AND RESULTS

## 5.1 Data Collection

In order to proceed with data collection, our first task is to identify which kind of data we need which is critical to our main goal i.e. Activity Recognition. As far as Activity recognition is concerned we monitored the activity of lab occupants i.e. their timings of coming in and going out of lab along with normal activities that take place in multi-person environment. To do this we have deployed many sensor around workstation and several other places in lab. Based on all the above classified activities we came up with the requirement of below sensors:
**Types of sensor:**
Following are the sensors which will be helpful in activity recognition phenomenon:
**PIR Sensor**: The PIR sensor is used for object detection. In our project we are using PIR for human detection. Waves generated by PIR differs in case of human and other objects. This information will help us in differentiating between human and other objects.
**Ultrasonic**: Ultrasonic sensor used for measuring distance to an object by using ultrasonic waves. So this sensor will tell us about the distance of the object from workstation. This will help us in determining the activities going around the workstations for eg- whether person is moving or idle.
**Light Sensor**: Light sensor is used to detect light. We are using this sensor to keep track of monitorâĂŹs status.
**Barometer**: This sensor is used for measuring atmospheric pressure. In our project we are using this sensor to measure temperature.

**Data collection through PI:** We have mounted all these sensor on raspberry pi circuit and placed at different workstations. To get good measures of activities we have collected data for few days. As the collected data from all sensors was raw data, our next task was to annotate the data or tag the data.We have used Ada-Fruit Library API to collect Data from PIR Sensor, Light Sensor, Gas Sensor and Barometer.Furthermore Gas sensor and Barometer are analog devices so we have used analog to digital converter as well to collect are the data in digital form. After gathering all the sensors and installing required libraries we ran our program on raspberry to start collecting the values from sensors and writing it to the .csv file with below format:

<Date Time, PIR, Ping, Light, Temperature, Pressure, Activity-Tag>

We are collecting data for 18 hours a day and then the program stops collecting data for next 6 hours. We are stopping the data collection for these 6 hours because of absence of all the lab occupant in this duration.
Below is the sample untagged data:

**Tagging Data:**
Once we have all the raw data with us, we have started tagging the same. To identify the activities happening in duration of 18hr we have deployed the cameras which covers the whole area of lab. With the help of camera recorded data, actual sensor data is tagged for four activities and their corresponding codes are as follows:

| | | | | | | |
|---|---|---|---|---|---|---|
| 2017-03-29 10:21:35.978083 | 14036 | 4101.5950441361 | 22388 | 23.8 | 100535 | |
| 2017-03-29 10:21:37.328279 | 14612 | 4.9925208092 | 22379 | 23.8 | 100536 | |
| 2017-03-29 10:21:38.936853 | 14817 | 4105.1973462105 | 22390 | 23.8 | 100535 | |
| 2017-03-29 10:21:40.277285 | 14936 | 4.9925208092 | 22400 | 23.8 | 100529 | |
| 2017-03-29 10:21:41.883308 | 13616 | 4112.4305725098 | 22395 | 23.8 | 100536 | |
| 2017-03-29 10:21:43.230644 | 13304 | 4.9557209015 | 22390 | 23.8 | 100536 | |
| 2017-03-29 10:21:44.842752 | 13847 | 4148.4495043755 | 22339 | 23.8 | 100540 | |
| 2017-03-29 10:21:46.190569 | 13432 | 5.1642537117 | 22332 | 23.8 | 100536 | |
| 2017-03-29 10:21:47.836307 | 13669 | 4080.0548315048 | 22301 | 23.8 | 100538 | |
| 2017-03-29 10:21:49.172666 | 14474 | 5.1478981972 | 22291 | 23.8 | 100533 | |
| 2017-03-29 10:21:50.780240 | 14815 | 4085.1618409157 | 22285 | 23.8 | 100538 | |
| 2017-03-29 10:21:52.122341 | 15044 | 4.972076416 | 22310 | 23.8 | 100533 | |
| 2017-03-29 10:21:53.727910 | 12531 | 4084.270465374 | 22273 | 23.8 | 100541 | |
| 2017-03-29 10:21:55.075827 | 14194 | 5.0047874451 | 22273 | 23.8 | 100538 | |
| 2017-03-29 10:21:56.693655 | 14261 | 4084.6834421158 | 22265 | 23.8 | 100540 | |
| 2017-03-29 10:21:58.014129 | 13282 | 5.094742775 | 22248 | 23.8 | 100540 | |
| 2017-03-29 10:21:59.621351 | 13233 | 4094.1001296043 | 22270 | 23.8 | 100541 | |
| 2017-03-29 10:22:00.969568 | 14425 | 5.1438093185 | 22263 | 23.8 | 100546 | |
| 2017-03-29 10:22:02.579412 | 13785 | 4091.6304469109 | 22226 | 23.8 | 100544 | |
| 2017-03-29 10:22:03.927891 | 13588 | 4.9557209015 | 22229 | 23.8 | 100543 | |
| 2017-03-29 10:22:05.541007 | 13364 | 4134.1956734657 | 22227 | 23.8 | 100543 | |
| 2017-03-29 10:22:06.891659 | 14554 | 4.9557209015 | 22217 | 23.8 | 100540 | |
| 2017-03-29 10:22:08.508819 | 13483 | 4062.0106101036 | 22213 | 23.8 | 100541 | |
| 2017-03-29 10:22:09.859490 | 13365 | 4.9761652946 | 22207 | 23.8 | 100543 | |
| 2017-03-29 10:22:11.214243 | 13956 | 120.9244966507 | 22214 | 23.8 | 100536 | |
| 2017-03-29 10:22:12.829308 | 13693 | 4073.9296913147 | 22210 | 23.8 | 100543 | |
| 2017-03-29 10:22:14.151178 | 14841 | 5.0783872604 | 22180 | 23.8 | 100544 | |
| 2017-03-29 10:22:15.764163 | 13266 | 4052.7370333672 | 22221 | 23.8 | 100543 | |
| 2017-03-29 10:22:17.109627 | 14269 | 4.9925208092 | 22179 | 23.8 | 100538 | |
| 2017-03-29 10:22:18.721322 | 12935 | 4095.2654600144 | 22185 | 23.8 | 100539 | |

| ACTIVITY | TAG |
|---|---|
| Person is sitting and monitor is on | 0 |
| Person is sitting and monitor is off | 1 |
| Person is not sitting and monitor is on | 2 |
| Person is not sitting and monitor is off | 3 |

After the completion of data tagging next step is to build algorithms for activity recognition. Below is the sample data after tagging:

| | | | | | | |
|---|---|---|---|---|---|---|
| 2017-03-29 10:21:35.978083 | 14036 | 4101.5950441361 | 22388 | 23.8 | 100535 | 1 |
| 2017-03-29 10:21:37.328279 | 14612 | 4.9925208092 | 22379 | 23.8 | 100536 | 1 |
| 2017-03-29 10:21:38.936853 | 14817 | 4105.1973462105 | 22390 | 23.8 | 100535 | 1 |
| 2017-03-29 10:21:40.277285 | 14936 | 4.9925208092 | 22400 | 23.8 | 100529 | 1 |
| 2017-03-29 10:21:41.883308 | 13616 | 4112.4305725098 | 22395 | 23.8 | 100536 | 1 |
| 2017-03-29 10:21:43.230644 | 13304 | 4.9557209015 | 22390 | 23.8 | 100536 | 1 |
| 2017-03-29 10:21:44.842752 | 13847 | 4148.4495043755 | 22339 | 23.8 | 100540 | 1 |
| 2017-03-29 10:21:46.190569 | 13432 | 5.1642537117 | 22332 | 23.8 | 100536 | 1 |
| 2017-03-29 10:21:47.836307 | 13669 | 4080.0548315048 | 22301 | 23.8 | 100538 | 1 |
| 2017-03-29 10:21:49.172666 | 14474 | 5.1478981972 | 22291 | 23.8 | 100533 | 1 |
| 2017-03-29 10:21:50.780240 | 14815 | 4085.1618409157 | 22285 | 23.8 | 100538 | 1 |
| 2017-03-29 10:21:52.122341 | 15044 | 4.972076416 | 22310 | 23.8 | 100533 | 1 |
| 2017-03-29 10:21:53.727910 | 12531 | 4084.270465374 | 22273 | 23.8 | 100541 | 1 |
| 2017-03-29 10:21:55.075827 | 14194 | 5.0047874451 | 22273 | 23.8 | 100538 | 1 |
| 2017-03-29 10:21:56.693655 | 14261 | 4084.6834421158 | 22265 | 23.8 | 100540 | 5 |
| 2017-03-29 10:21:58.014129 | 13282 | 5.094742775 | 22248 | 23.8 | 100540 | 5 |
| 2017-03-29 10:21:59.621351 | 13233 | 4094.1001296043 | 22270 | 23.8 | 100541 | 5 |
| 2017-03-29 10:22:00.969568 | 14425 | 5.1438093185 | 22263 | 23.8 | 100546 | 3 |
| 2017-03-29 10:22:02.579412 | 13785 | 4091.6304469109 | 22226 | 23.8 | 100544 | 3 |
| 2017-03-29 10:22:03.927891 | 13588 | 4.9557209015 | 22229 | 23.8 | 100543 | 3 |
| 2017-03-29 10:22:05.541007 | 13364 | 4134.1956734657 | 22227 | 23.8 | 100543 | 3 |
| 2017-03-29 10:22:06.891659 | 14554 | 4.9557209015 | 22217 | 23.8 | 100540 | 3 |
| 2017-03-29 10:22:08.508819 | 13483 | 4062.0106101036 | 22213 | 23.8 | 100541 | 3 |
| 2017-03-29 10:22:09.859490 | 13365 | 4.9761652946 | 22207 | 23.8 | 100543 | 3 |
| 2017-03-29 10:22:11.214243 | 13956 | 120.9244966507 | 22214 | 23.8 | 100536 | 3 |
| 2017-03-29 10:22:12.829308 | 13693 | 4073.9296913147 | 22210 | 23.8 | 100543 | 3 |
| 2017-03-29 10:22:14.151178 | 14841 | 5.0783872604 | 22180 | 23.8 | 100544 | 3 |
| 2017-03-29 10:22:15.764163 | 13266 | 4052.7370333672 | 22221 | 23.8 | 100543 | 3 |
| 2017-03-29 10:22:17.109627 | 14269 | 4.9925208092 | 22179 | 23.8 | 100538 | 3 |
| 2017-03-29 10:22:18.721322 | 12935 | 4095.2654600144 | 22185 | 23.8 | 100539 | 3 |

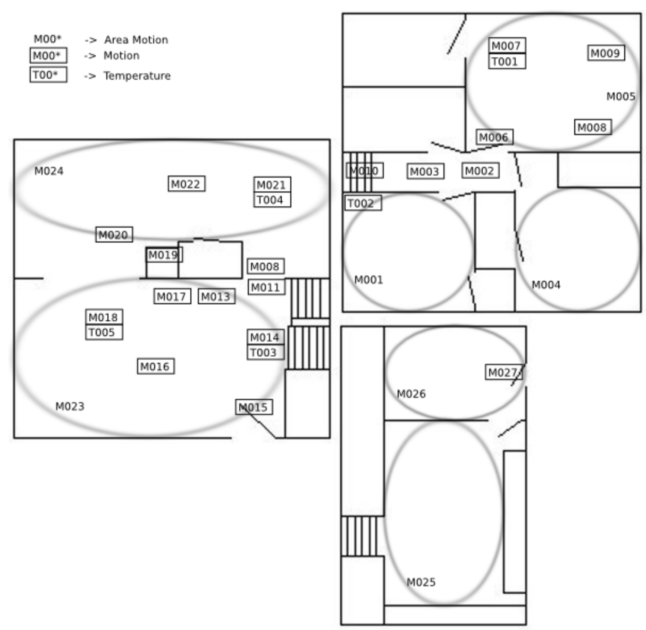
## 5.2 Benchmark Data Set

We have taken CASAS data set which contains sensor data that was in the home of a volunteer adult resident and a dog. Infrared based motion sensors are used for collecting the data for a smart home. Video cameras are used to monitor and recognize the activities as we did while collecting data in our lab. This data set has similar tagging pattern as we did for our lab. The following activities are annotated within the data-set.
Bed_to_toilet, Breakfast, Bed, C_work, Dinner, Laundry, Leave_home, Lunch, Night_wandering, R_medicine
Following is the snapshot of data collected.

```
<Date, Time, Sensor_Id, Sensor_Value, Activity_Label,
Begin/End>
```

```
2009-06-10 01:28:39.066357 M005 ON
2009-06-10 01:28:40.065879 M005 OFF
2009-06-10 03:20:59.087874 M006 ON Night_wandering begin
2009-06-10 03:21:01.038931 M002 ON
2009-06-10 03:21:03.001745 M002 OFF
2009-06-10 03:21:03.092281 M006 OFF
2009-06-10 03:21:04.000884 M002 ON
2009-06-10 03:21:05.009842 M002 OFF
2009-06-10 03:21:08.033939 M009 ON
2009-06-10 03:21:10.027285 M009 OFF
2009-06-10 03:21:52.005397 M002 ON
2009-06-10 03:21:55.046858 M002 OFF
2009-06-10 03:22:13.008367 M011 ON
2009-06-10 03:22:14.000398 M012 ON
2009-06-10 03:22:18.063157 M011 OFF
2009-06-10 03:22:18.078709 M012 OFF
2009-06-10 03:22:19.001209 M022 ON
2009-06-10 03:22:24.015902 M022 OFF
2009-06-10 03:25:19.059284 M012 ON
2009-06-10 03:25:19.086432 M011 ON
2009-06-10 03:25:24.054674 M011 OFF
2009-06-10 03:25:24.070558 M012 OFF Night_wandering end
2009-06-10 03:45:16.046068 M009 ON Bed_to_toilet begin
2009-06-10 03:45:21.054413 M005 ON
2009-06-10 03:45:25.025127 M005 OFF
2009-06-10 03:45:25.063127 M005 ON
```

Data collected from 2009-06-10 01:28:39 to 2009-08-05 23:36:05 comprising total 647487 events. Here is the layout of the house which was used.




## 5.3 Results

We used the annotated data set to train the system using MLE approach as described above. We also used the labelled test data set to evaluate our model.
For each given evidence over time t, we predicted activity

with our model and compared with labelled activity tag. If activity tag is A and predicted activity tag is A', updated entry in matrix Freq[A][A'].
Following is matrix shown which has rows as Actual Labels and columns as Predicted Labels.
Freq(i, j) = Frequency or number of times actual activity i predicted as activity j.

$$Accuracy = Freq(i, j) / \sum_{n=1}^{n} Freq(i, j)$$

### 5.3.1 HMM Activity Recognition

| Actaul/Class Label | Bed_to_toilet | Breakfast | Bed | C_work | Dinner | Laundry | Leave_home | Lunch | Night_wandering | R_medicine | Accuracy |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Bed_to_toilet | 18 | 0 | 5 | 0 | 0 | 0 | 0 | 0 | 7 | 0 | 0.6 |
| Breakfast | 0 | 14 | 2 | 0 | 26 | 0 | 0 | 6 | 0 | 0 | 0.29166666 |
| Bed | 6 | 0 | 182 | 7 | 1 | 0 | 7 | 0 | 4 | 0 | 0.87922704 |
| C_work | 0 | 0 | 9 | 32 | 0 | 0 | 5 | 0 | 0 | 0 | 0.6956522 |
| Dinner | 0 | 9 | 0 | 0 | 29 | 0 | 0 | 4 | 0 | 0 | 0.6904762 |
| Laundry | 0 | 0 | 0 | 0 | 0 | 9 | 1 | 0 | 0 | 0 | 0.9 |
| Leave_home | 0 | 0 | 0 | 0 | 0 | 0 | 69 | 0 | 0 | 0 | 1.0 |
| Lunch | 0 | 10 | 1 | 0 | 19 | 0 | 0 | 7 | 0 | 0 | 0.1891892 |
| Night_wandering | 13 | 0 | 11 | 0 | 0 | 0 | 6 | 0 | 37 | 0 | 0.5522388 |
| R_medicine | 0 | 0 | 14 | 0 | 0 | 0 | 18 | 0 | 1 | 11 | 0.25 |

Result:

Right 408
Wrong 192
Average accuracy is 0.68

### 5.3.2 NB Activity Recognition

| Actaul/Class Label | Bed_to_toilet | Breakfast | Bed | C_work | Dinner | Laundry | Leave_home | Lunch | Night_wandering | R_medicine | Accuracy |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Bed_to_toilet | 22 | 0 | 5 | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 0.73333335 |
| Breakfast | 0 | 12 | 5 | 0 | 24 | 0 | 0 | 5 | 2 | 0 | 0.25 |
| Bed | 3 | 0 | 149 | 1 | 0 | 0 | 0 | 0 | 54 | 0 | 0.7198068 |
| C_work | 0 | 0 | 17 | 25 | 0 | 0 | 0 | 0 | 4 | 0 | 0.54347825 |
| Dinner | 0 | 5 | 7 | 0 | 24 | 0 | 0 | 5 | 1 | 0 | 0.5714286 |
| Laundry | 0 | 0 | 0 | 0 | 0 | 7 | 1 | 1 | 1 | 0 | 0.7 |
| Leave_home | 0 | 0 | 0 | 0 | 0 | 0 | 69 | 0 | 0 | 0 | 1.0 |
| Lunch | 0 | 7 | 3 | 0 | 16 | 0 | 0 | 10 | 1 | 0 | 0.27027026 |
| Night_wandering | 0 | 0 | 3 | 0 | 0 | 0 | 0 | 0 | 64 | 0 | 0.95522386 |
| R_medicine | 0 | 6 | 3 | 0 | 0 | 0 | 0 | 1 | 1 | 33 | 0.75 |

Result:

Right 415
Wrong 185
Average accuracy is 0.69166666

## 6. CONCLUSION AND FUTURE WORK

We have worked on recognition and collection of data from our Robotics lab. In future work can be doe on building benchmark data-set which can be used in different modelling purposes.
We have built model for predicting next activity given current activity and evidence. For more efficient model, work can can be done in the direction of finding next activity sequence. HMM model can be used to do so. Knowing activity for a day or at least couple of hours will also help in controlling devices efficiently.
Further 'Internet of Things' (IoT) approaches and smart firmwares can be deployed to make equipments intelligent and able to communicate over a network. Planning algorithms can be used to efficiently plan the usage of these equipments. Protocols and messages can be built for these communication models.

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