Indian Institute of Technology, Guwahati

CS-561 Project Presentation

Energy Efficiency in Workplace Based on Occupant's Routine

Presented By:
Group 26 – Team Alphabet

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Outline

- Motivation
- Methodology
  - Segmentation and Features
  - Activity Recognition (Using Naïve Bayes and HMM)
  - Activity Prediction (HMM)
- Experiment and Results
- Demo
- Conclusion and Future work

Motivation

- Energy-saving workplaces require autonomous and optimized control of integrated devices and appliances with the objective of saving energy while preserving the comfort of occupant.

- A state of art artificial intelligence system can be built to control equipment to reduce energy consumption.

- Learning user activities and behavior can help us identify the planning to control equipment for better usage.

Approach

- Building data set for the location
- Activity Recognition based on context information
- Activity Prediction
- Combining AI Planning - We haven’t attempted this. Can be done in future.

Methodology: Data Collection and Tagging

- Identifying equipment, location and user activities.

  Identified Equipment: Workstation, Overhead Lights
  Activities: User presence, absence and usage of computer system

- Collecting sensory data based on user activities identified.

- Tagging the data with activities.

  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.

Methodology: Activity Recognition

- This is very well researched area and several researchers used different model for the same like: HMM, KNN, Decision Tree, LSTM neural net etc.

- We used HMM and Naïve Babes models for AR and used HMM for AP.

- Naïve Bayes

$$\text{Activity A} = \underset{k=1,2,\ldots,K}{\text{argmax}}\, Pr(A_k) * \prod_{i}^{n} Pr(e_i|A_k)$$

  - We minimized following loss function to get the activity

$$L = -\left(log\, \Pr(Ak) . \sum_{i=1}^{n} \log\left(\Pr(ei|Ak)\right)\right)$$

Methodology: Activity Recognition

- Hidden Markov Model

  - Used Viterbi Algorithm to get the most probable sequence and used this activity sequence to get the likelihood of activity at time t as below.

  - Given prior belief, transition model and observation model calculated Likelihood of activity given current evidence.

$$Liklihood(a(t)) = \Pr(a(t)|e(1{:}t) = \alpha P(e(t)|a(t)) \sum_{a(t-1)} \Pr(at|a(t-1)) \, Likelihood(a(t-1))$$

$$\text{where,} \quad \mathrm{Likelihood}(\mathrm{a}(\mathrm{t}=0)) = \mathrm{Prior}\ Probability\ (a)$$

Methodology: Activity Recognition

- Hidden Markov Model
  - Recursively updated the belief of an activity at each time t with likelihood Pr(At) calculated above.

$$Prior\ Probability\ \Pr(At) = Likelihood(At)$$

Methodology: Activity Prediction

- Hidden Markov Model
  - We used prediction model of HMM to predict next activity for time t+1 given evidence e $_{(1:t)}$

$$Likelihood(At+1) = \Pr(At+1 \mid e1{:}t) = \sum_{at} \Pr(At+1 \mid at) \,.\, \Pr(at \mid e1{:}t)$$

$$Predicted\ Activity\ A = \underset{k=\{1,2,\ldots,K\}}{\operatorname{argmax}} \ \mathrm{Likelihood}(Ak).$$

Experiment: Dataset

- We have worked on two data sets.
  - Collected sensory data in Robotics Lab
  - Online Benchmark dataset – CASAS

Experiment: Dataset Collection and Tagging

- Collected sensory data from our lab using following sensors:

  PIR, Ultrasonic, Light Sensor, Barometer

- Used Raspberry Pi and libraries to collect and process the data.

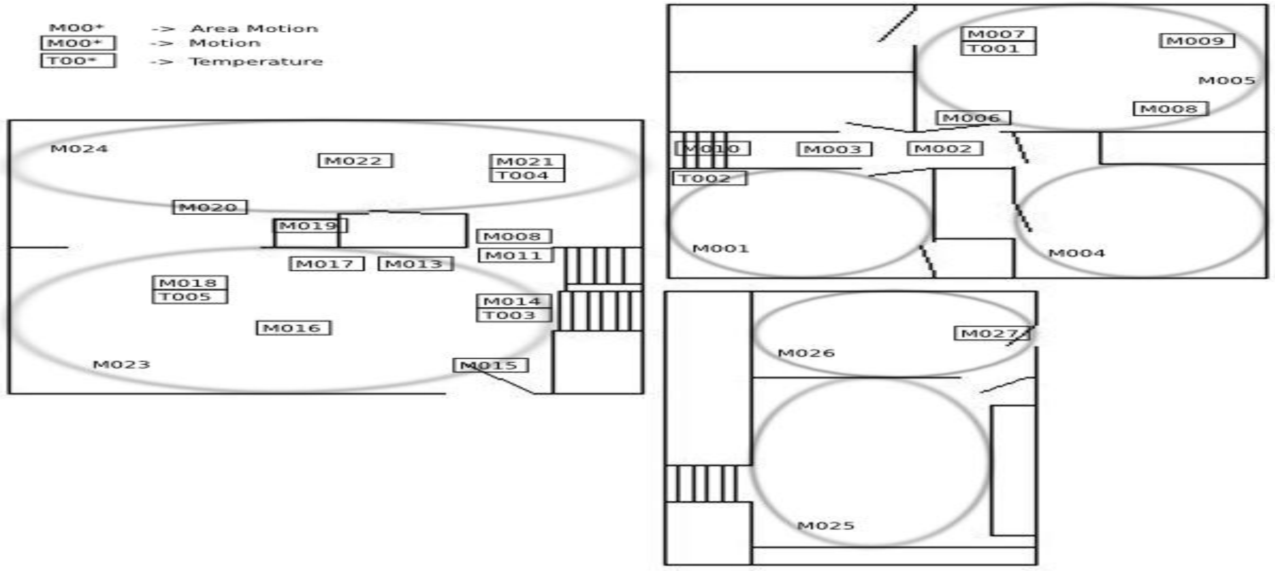
Format: <Date Time, PIR, Ping, Light, Temperature, Pressure, Activity-Tag>

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

Experiment: Online Dataset and Feature Extraction

- CASAS dataset was used, which contains sensor data that was collected in the home of a volunteer adult resident and a dog.

- 27 Motion sensors were used to record activities.



Experiment: Online Dataset and Feature Extraction

- Activities Identified:

{Bed_to_toilet, Breakfast, Bed, C_work, Dinner, Laundry., Leave_home, Lunch, Night_wandering, R_medicine}

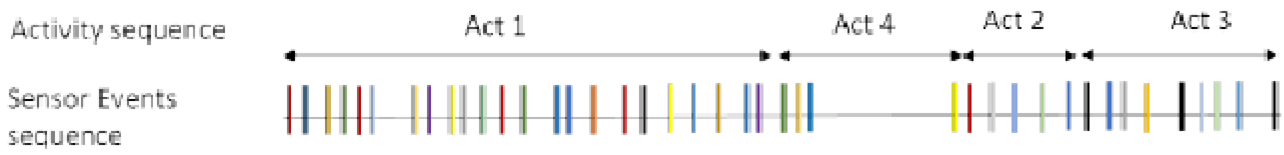
- Data format:

<Date(yyyy-mm-dd), Time, Sensor_Id, Sensor_State, Activity, Begin/End>

```
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
```

Experiment: Online Dataset and Feature Extraction

- Segmentation: Data was segmented into separate sequences of activity occurrences.



- Features Extracted:

  1. Sensors Used
  2. Time of Use
  3. Day of Week
  4. Previous Activity
  5. Activity Length

Experiment: Algorithm Evaluation

- We used earlier described annotated data set to train the system.
- Used Maximum Likelihood Estimation (MLE) technique to estimate parameters for both Naïve Bayes and HMM model.
- Training Parameters for Naïve Bayes Model
  - Prior Beliefs Pr(Activity) =

    (#Sensor Events for Activity)/ (# Total Sensor Events)
  - Observation Pr(Ei|Activity) =

    (#Ei in sensor events for the activity)/ (# Total Sensor Events for Activity)

Experiment: Algorithm Evaluation

- Training Parameters for HMM Model
  - Prior Beliefs Pr(Activity) =

    (#Sensor Events for Activity)/ (# Total Sensor Events)

  - Observation Pr(Ei|Activity) =

    (#Ei in sensor events for the activity)/ (# Total Sensor Events for Activity)

  - Transition Tr(Aj -> Ai):

    Pr(Ai|Aj) =

    (# of times Aj -> Ai)/ (# Occurrences of Activity Aj)

Experiment: Results

- We predicted activity with our model and compared with tagged activity. If activity tag is A and predicted activity is A', updated entry in matrix Freq(A,A‘).

- Freq(i, j) = Frequency or number of times actual activity Ai predicted as activity Aj.

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

- We used Java 8 and NetBeans IDE for implementation of model.

Experiment: Results

- Naïve Bayes

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

Experiment: Results

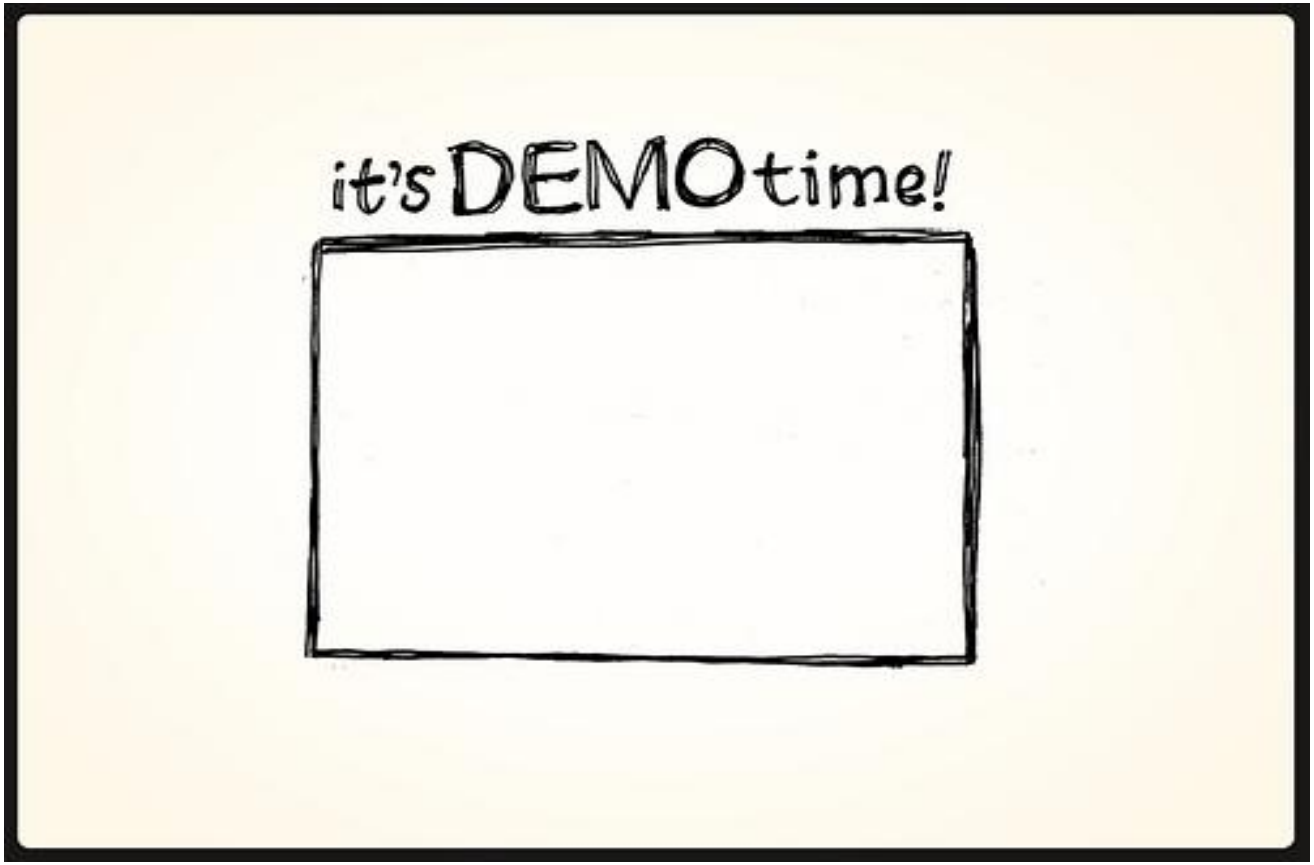
- Hidden Markov Model

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

Demo



Conclusion and Future Work

- We collected data from robotics lab.
- Applied AR and AP on benchmark data with accuracy around 70%.
- We worked on prediction of activity for time (t+1). It can be extended to find next activity sequence (t+k). HMM model can be used to do so.
- 'Internet of Things' (IoT) concepts can be applied to make equipments intelligent and able to communicate over a network.
- Protocols and messages need to be built for these communication models.
- AI Planning algorithms can be used to intelligently control equipments for energy efficiency.

Thank You