Recognising Activities at Home

Digital and Human Sensors

Jie Jiang

Riccardo Pozza

Kristrún Gunnarsdóttir

Nigel Gilbert

Klaus Moessner

HomeSense: digital sensors for social research

- The project will make it easier and more productive for social researchers to use the digital sensors that are becoming available as a result of the rise of the 'internet of things' and ubiquitous computing.

- The project will yield *guidelines* for and *examples* of the use of digital sensors, including consideration of technical, methodological and ethical issues.

Background

Social researchers

Self reporting

Digital sensors

Triangulating the data

- Time use data
  - Start and end times of activities may not be accurate
  - Activities may be recorded out of sequence
  - Some activities may not be recorded
- Sensor data
  - Activities may take place out of range of the sensors
  - Sensors do not observe activities, but only their physical effects (e.g. ‘cooking’ could be recorded as an increase in temperature and noise in the kitchen)
  - Hence there is a problem of inference: from sensor data to activity

Research question

How can we quantify the agreement between what we detect in sensor-generated data and what we know from self-reported data ?

Sensors: human sensors

UNIVERSITY OF SURREY

Time use diary

Time	Activity	Location	Appliances/Devices
17:50 – 18:00	Entertaining	Living room	Laptop
18:00 – 18:10	Cooking	Kitchen	Oven
18:10 – 18:20	Cooking	Kitchen	Oven
18:20 – 18:30	Dining	Living room	Laptop

HomeSense
digital sensors in social research

Sensors: digital sensors

Sensor box (egg)

- **Temperature**
- **Humidity**
- **Light**
- **Movement**
- **Noise level**

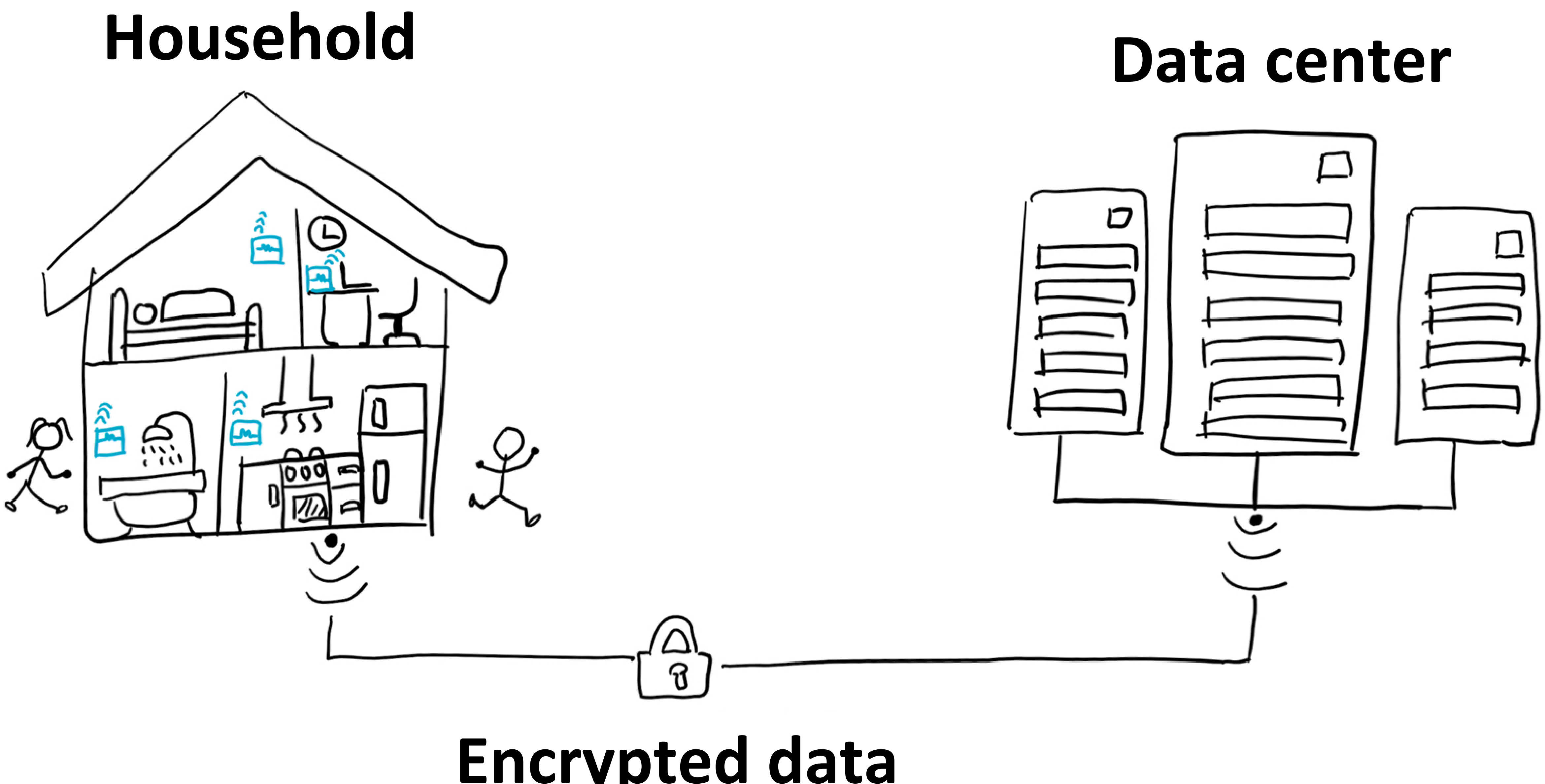
Energy monitor

- **Electricity consumption**

digital sensors in social research

UNIVERSITY OF SURREY

Put into practice



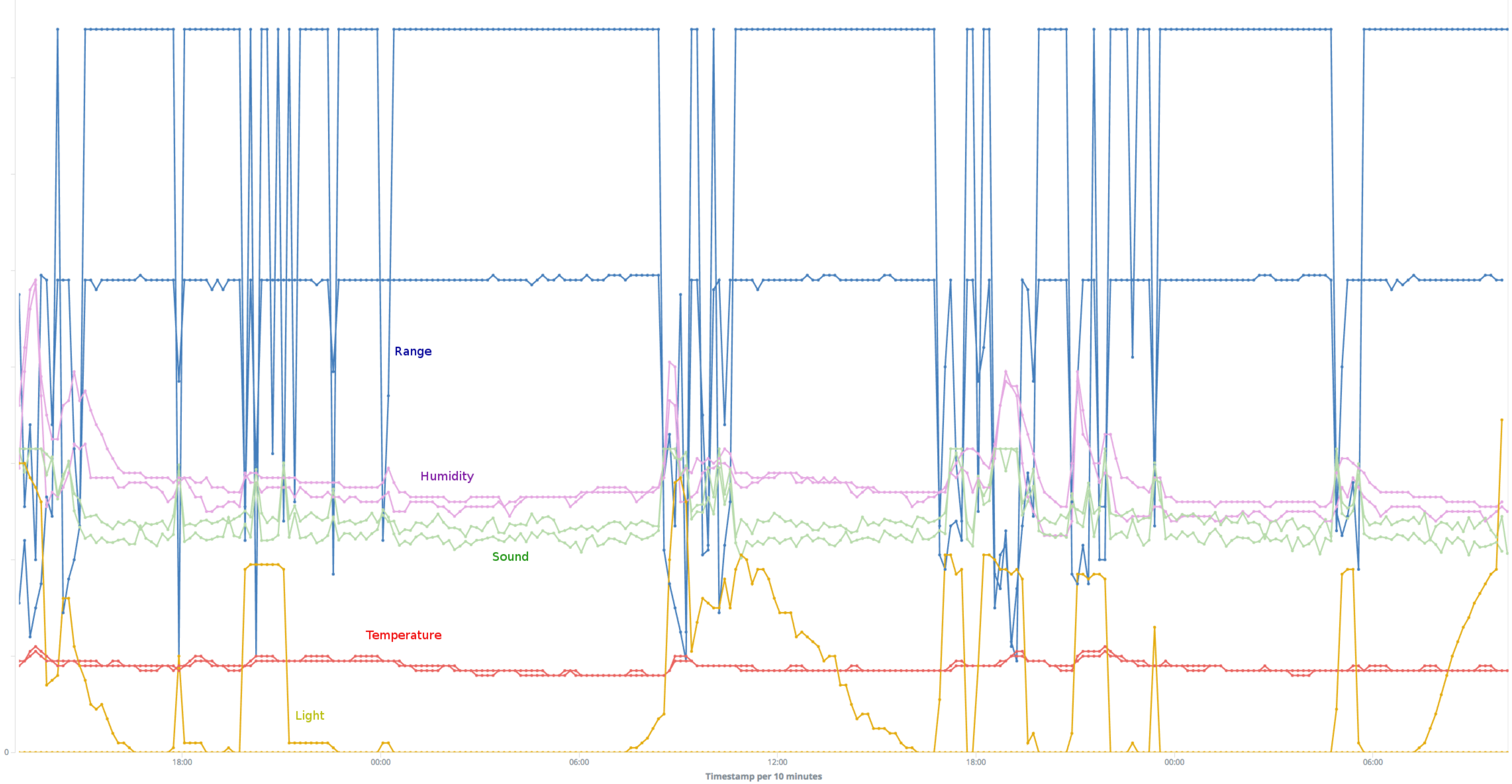
HomeSense
digital sensors in social research

Data set: digital sensors

- Data streams from the sensor boxes
  - A limited number of physical measurements in a limited number of locations
    - Every 3 - 5 seconds
    - 5* 300K data points
- Data streams from the energy monitors
  - Electricity usage of individual appliances monitored
  - Plus total household electricity consumption
    - Every 5 minutes
    - 3*10K data points

Data set: digital sensors

in the kitchen



Data set: human sensors

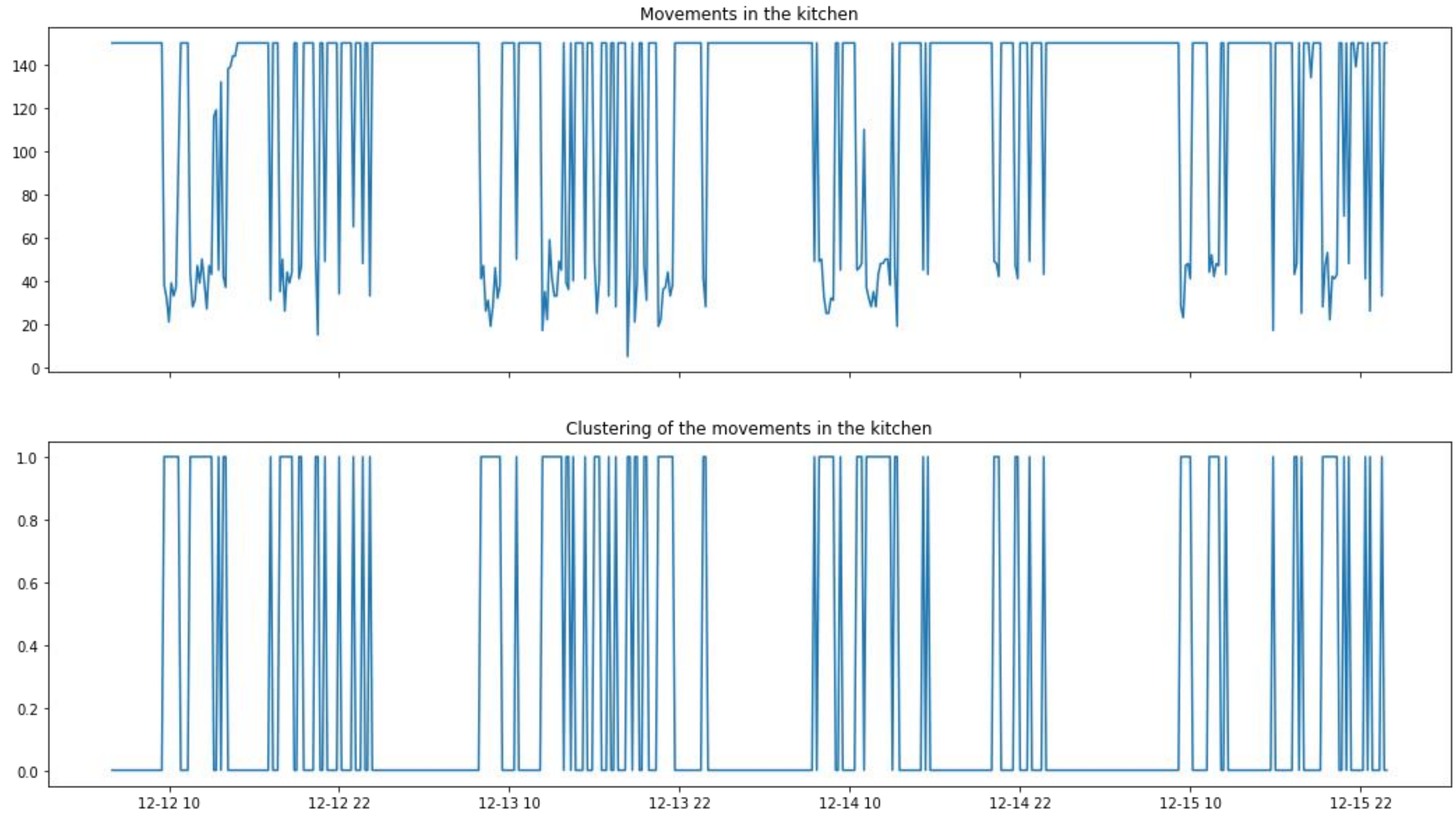
- Time use diaries
  - Self-assigned descriptors of activity
    - Every 10 minutes for four days
    - 540 data points

Activities	Number of occurrences	Percentage of time
Cooking	12	10.74%
Dining	6	3.89%
Entertaining	13	31.85%
Sleeping	5	33.33%

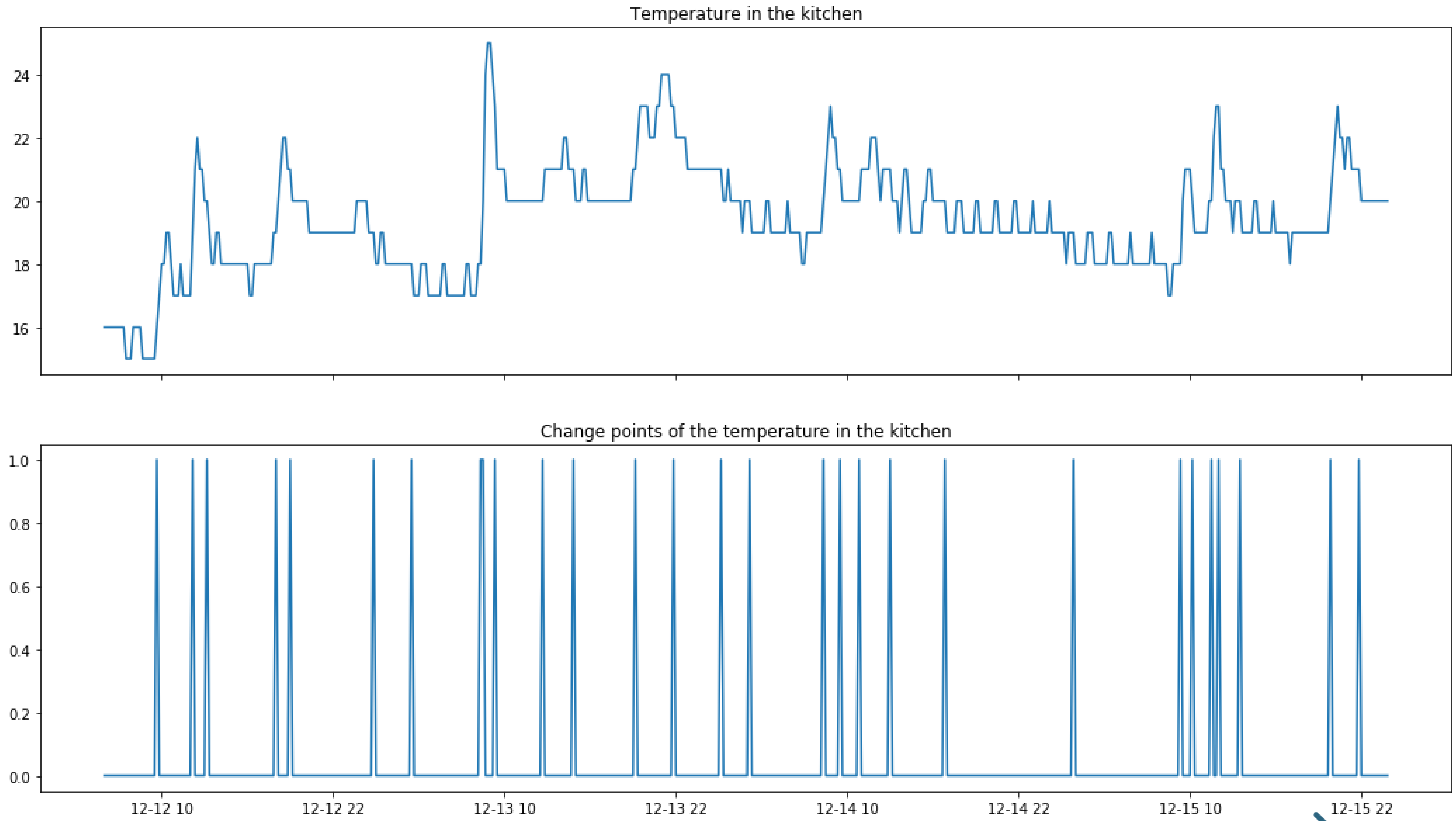
Recognising activities

1. Pre-process data
   - Maximum or minimum
   - Resampling
2. Construct features
   - Mean shift clustering
   - Change point detection
3. Recognise activities
   - Hidden Markov Modelling

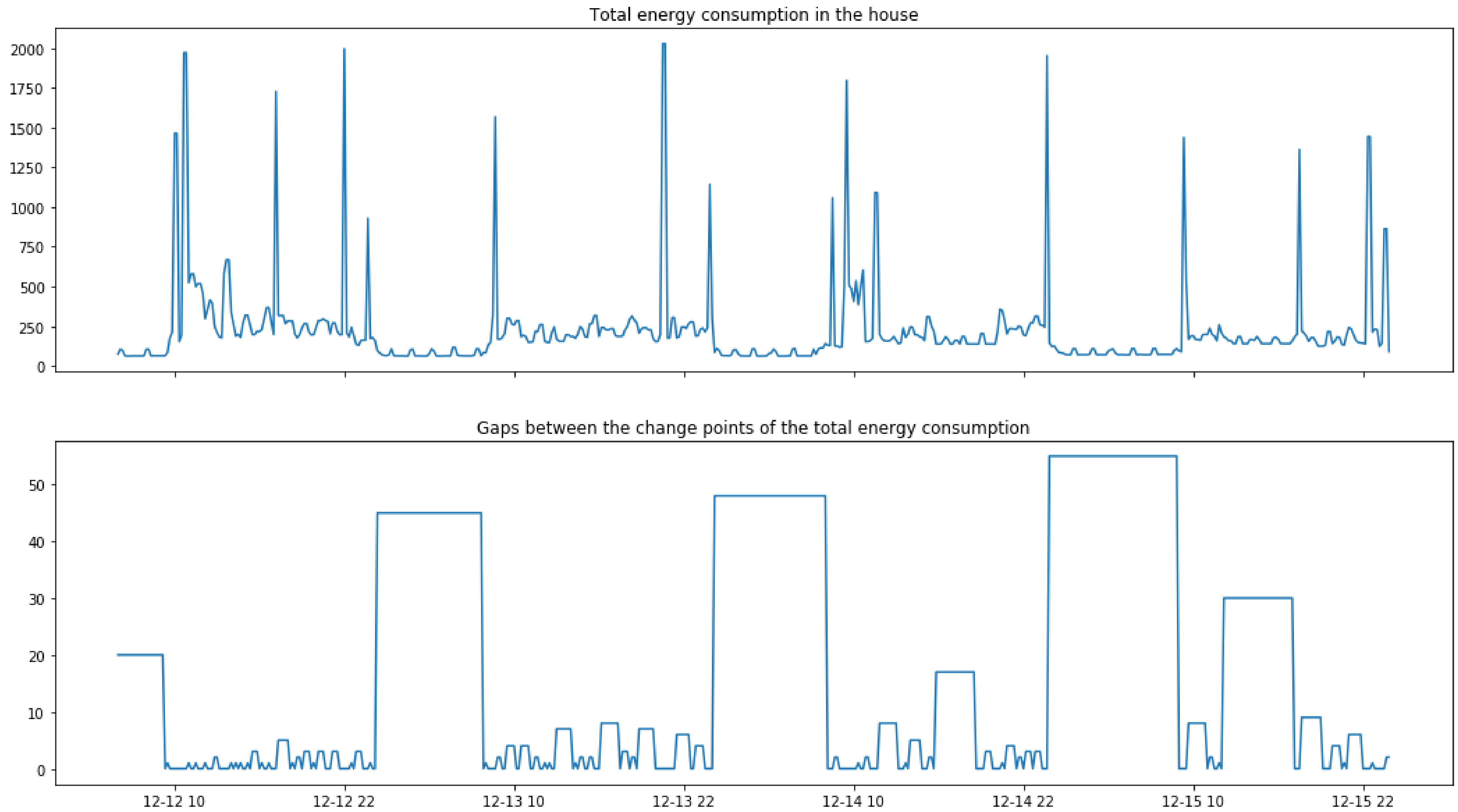
Mean shift: example output



Change point: example output



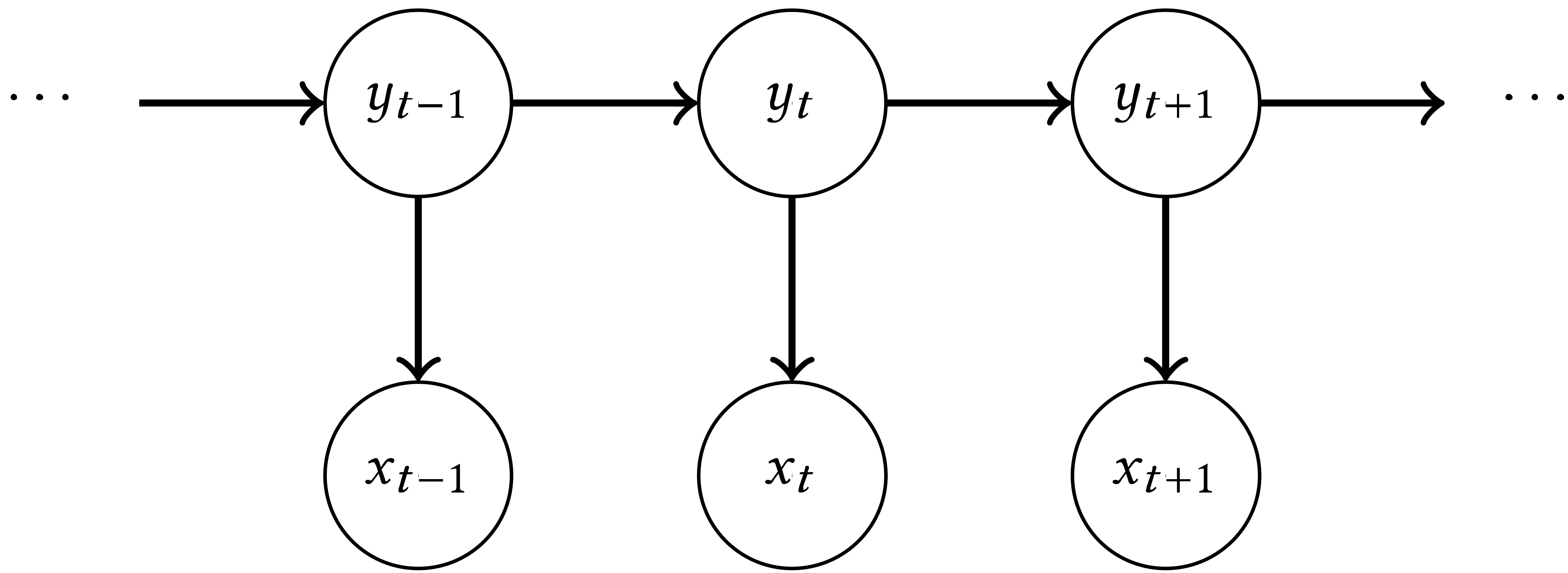
Change point: example output



Activity inference

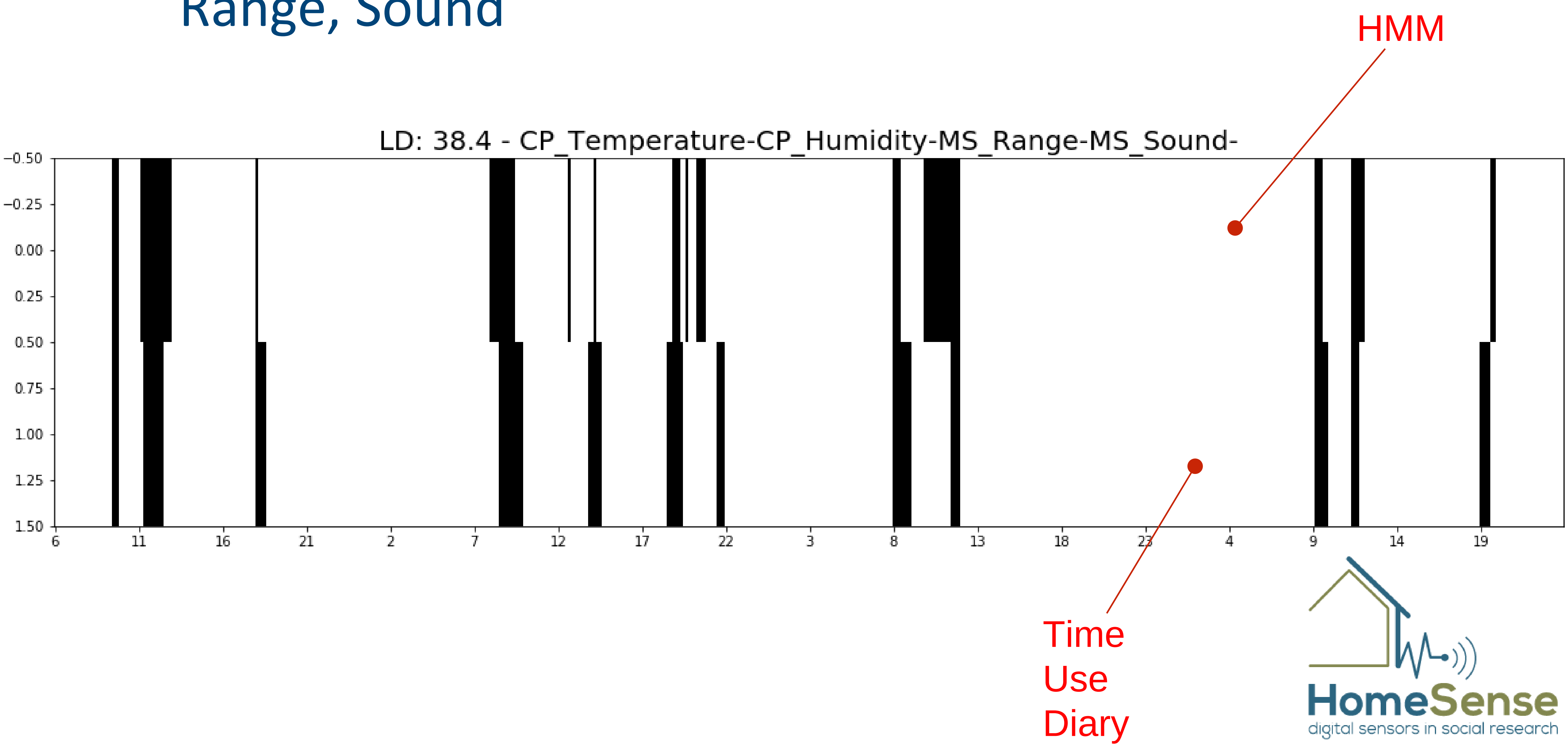
- The household members are carrying out some activities. These activities result in data that the sensors can detect. And one of the members fills in a Time Use Diary that records the activities and gives them names.
- The activities correspond to states that are ‘hidden’ or ‘latent’ but which generate observable sensor data and observable marks in the Time Use Diaries. We want to reveal the hidden activities and label them.
- Use a Hidden Markov Model (HMM)

Hidden Markov Models



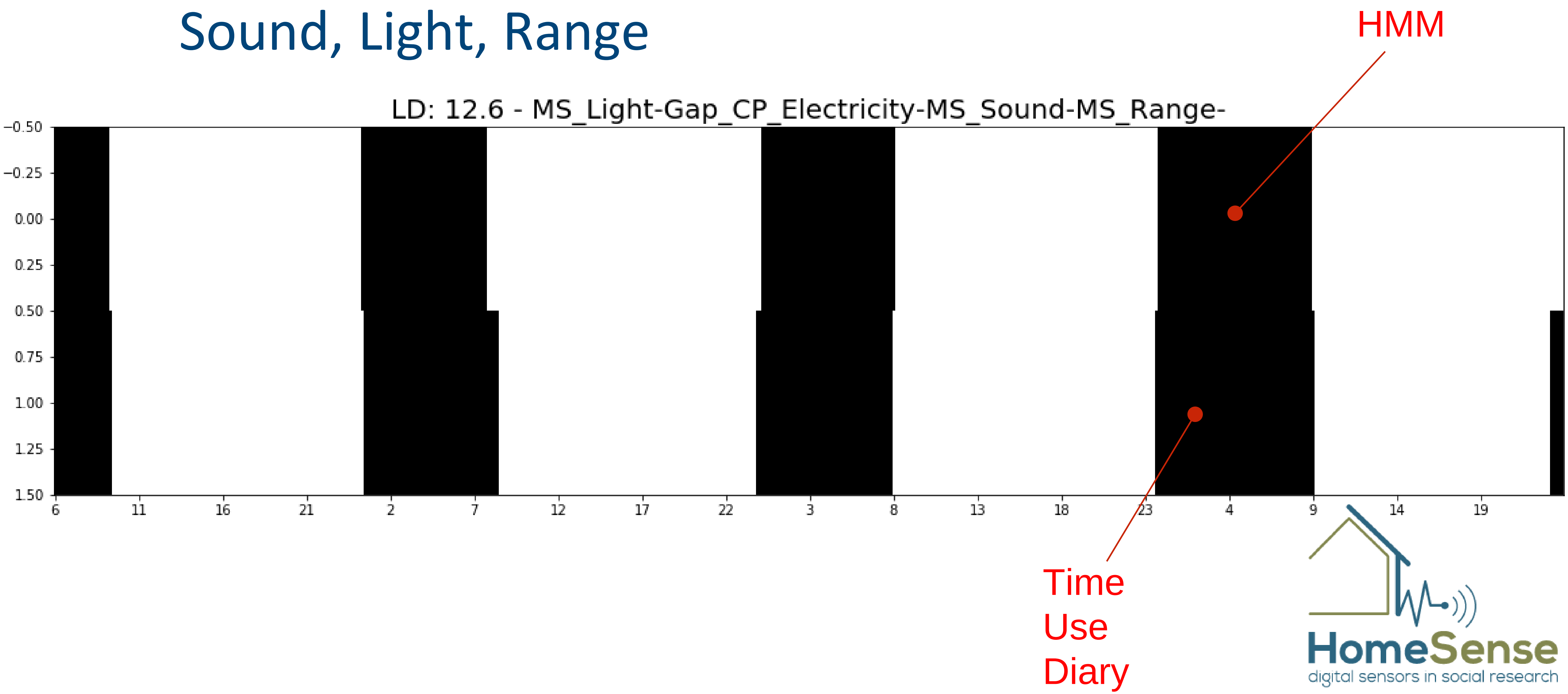
Hidden Markov Model: example output

- Cooking: using data from the sensor box in the kitchen
- Significant data streams: Temperature, Humidity, Range, Sound



Hidden Markov Model: example output

- Sleeping: using data from the sensor box in the bedroom and the energy monitor attached to the electricity mains
- Significant data streams: Whole house electricity, Sound, Light, Range



Agreement evaluation

- Cause of differences
  - Time shifts
  - Missing values
- Levenshtein distance
  - Minimum number of insertion, deletion or substitution operations needed to transform one sequence into the other.
  - The weights of different operations are tuned to counter the exaggerated effect of time shifts and missing values.

Agreement evaluation: results

Activities	Sensor location	Features	Levenshtein distance
Cooking	Kitchen	CP_Temperature CP_Humidity MS_Range MS_Sound	38.4
Dining	Living room	CP_Sound Gap_CP_Electricity	36.0
Entertaining	Living room	MS_Electricity MS_Sound MS_Light MS_Range	61.1
Sleeping	Bedroom	Gap_CP_Electricity MS_Sound MS_Light MS_Range	12.6

Conclusions

- A mixed-methods approach of combining computational and qualitative types of non-provoked data: sensor-generated data and time use diary.
- An evaluation method for measuring the agreement between sensor-supported activity recognition algorithms and the human constructed diary.
- An on-going research investigating the use of digital sensors for social research.

HomeSense project

- Pilot sample of 20 households in South-East England, each participating for 3 months
  - Six households of one occupant;
  - Eight households of two or more adults;
  - Six households of parent(s) with dependant(s) 0-16yrs.

  (roughly corresponding to the proportions in the UK population) facebook.com/sensoresearch/

@CRESS_HomeSense

HomeSense

digital sensors in social research