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“I want to … change”
Micro-moment based recommendations can change users’ energy habits

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At a Glance

<u>The facts:</u>

- **User behavior** is important in forming the household's energy footprint.
- Everyday energy-related **behavior** is:
  - Driven by the user **needs and desires**.
  - Influenced by **external factors** (outdoor temperature and humidity) and
  - Influenced by the user's common **habits** (e.g. switching the water heater on after arriving home)
- **Engaging users** to adopt more sustainable energy usage tactics is hard.

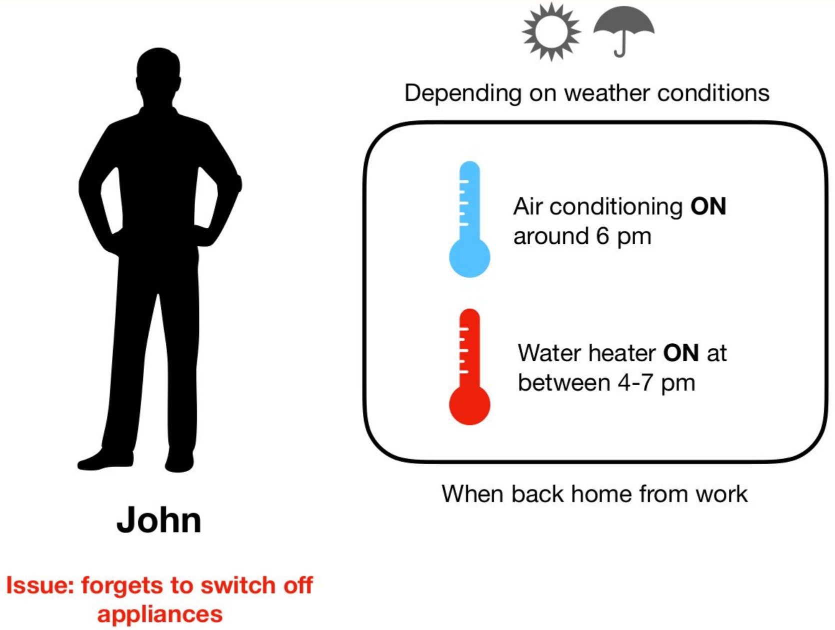
<u>The goal:</u> **Recommend actions** that will **reduce household energy consumption**

<u>The method:</u>

- Collect real-time information (consumption, environmental conditions, etc.).
- Define a framework for timely creating personalised energy-related recommendations.

Use Case Scenario

- Action: switch on ***water heater*** (for 30 minutes) to take a bath
- Conditions:
  - Time: as soon as he gets back home ***after work***, approx. at ***18:00*** in the afternoon
  - Temperature: the ***weather is cold***



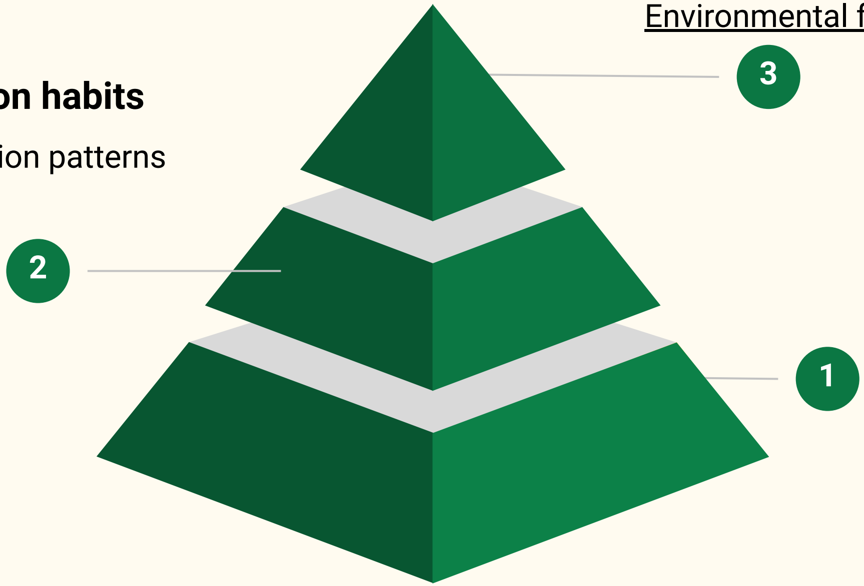
Methodology

Recommend the right energy-efficient action at the right Micro-moment

Use the extracted patterns to **predict** when the user's next action will happen.
Recommend the right action at the right moment, to change user's consumption habits.
<u>Environmental factors must be considered!</u>

Extract user consumption habits

Extract the user's consumption patterns in terms of devices' usage.



Collect data

Collect device consumption data, weather data, and occupancy data using smart meters and sensors.

Why Recommendation Systems?

1. They provide personalised recommendations to users.
2. They recommend energy-saving actions to the users.
3. They raise energy awareness and change users' energy habits.
4. They affect household's energy footprint.

What are Micro-Moments?

A marketing term (re-)invented by Google to represent moments in daily life, when users seek for specific type of information, using their smartphones

Micro-moments are the best moments to recommend an action to the user

I want-to-know moments

I want-to-go moments

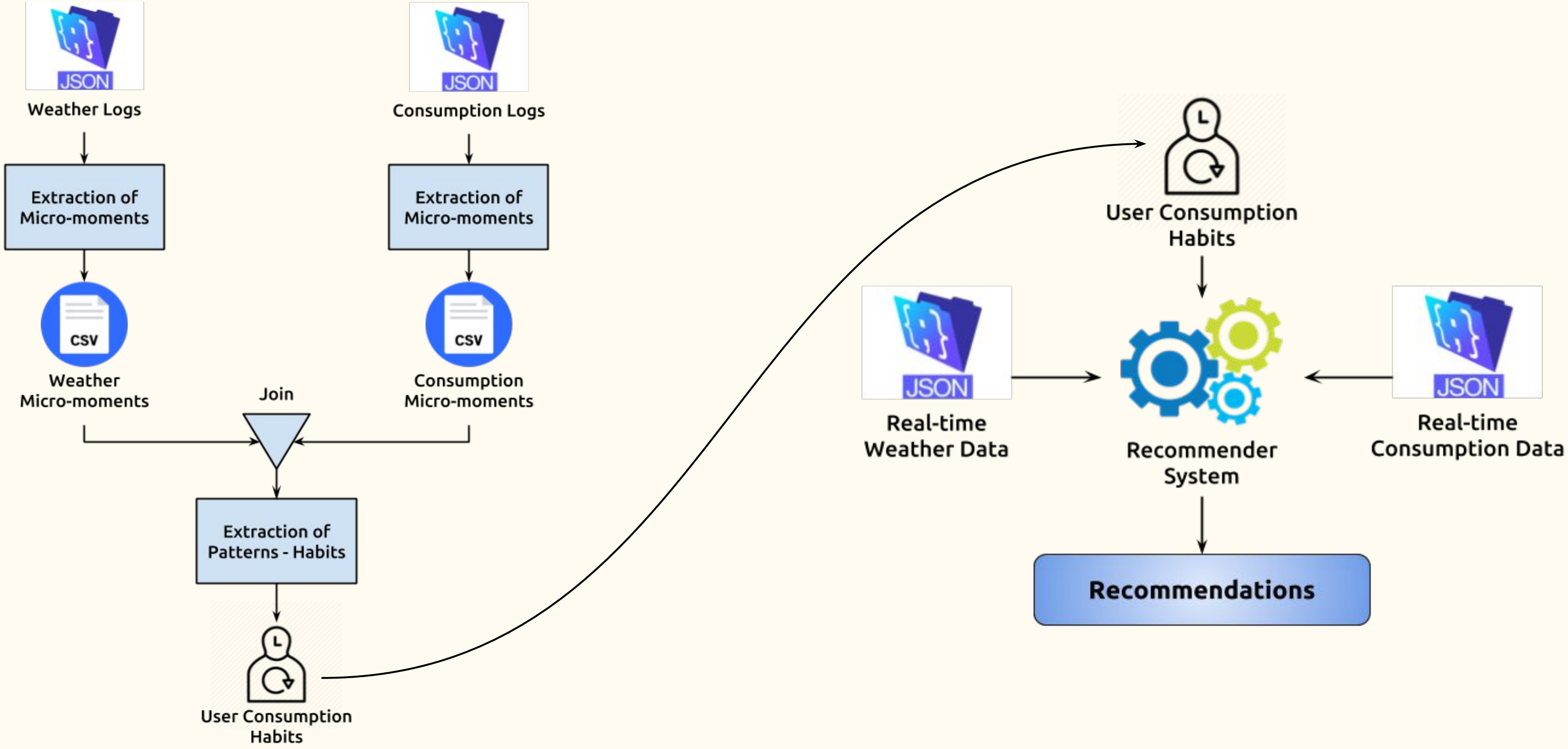
I want-to-do moments

I want-to-buy moments

I want-to-change moments

Methodology

From consumption and weather data to energy action recommendations

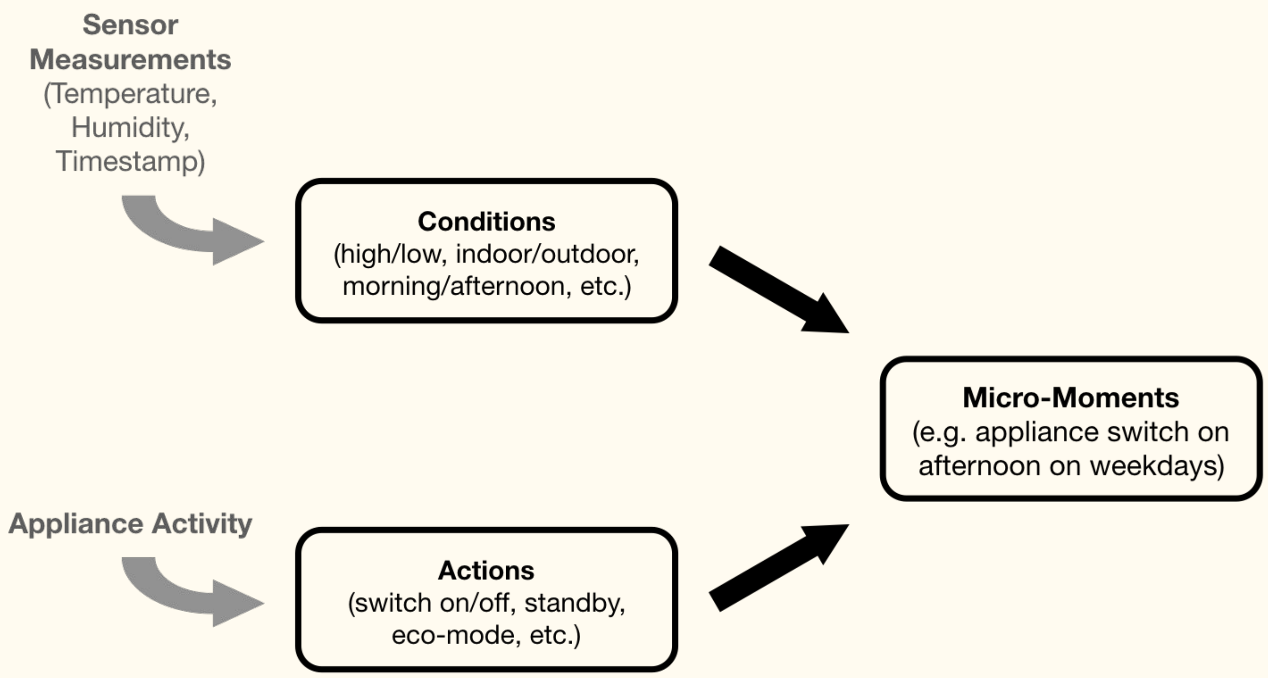


Data Acquisition

~~Two~~ Three types of information:

- Consumption Logs
  - WiFi-enabled smart plugs/outlets equipped in the most frequently used appliances to collect the energy consumption of each device in a minute window.
- Weather Logs
  - Sensing modules are used inside and outside of the user's household to record contextual information (e.g. temperature, humidity, and occupancy).
- Room occupancy data
  - They allow us to detect unnecessary usage of devices (e.g. lights) 

Raw Data ⇒ Micro-Moments



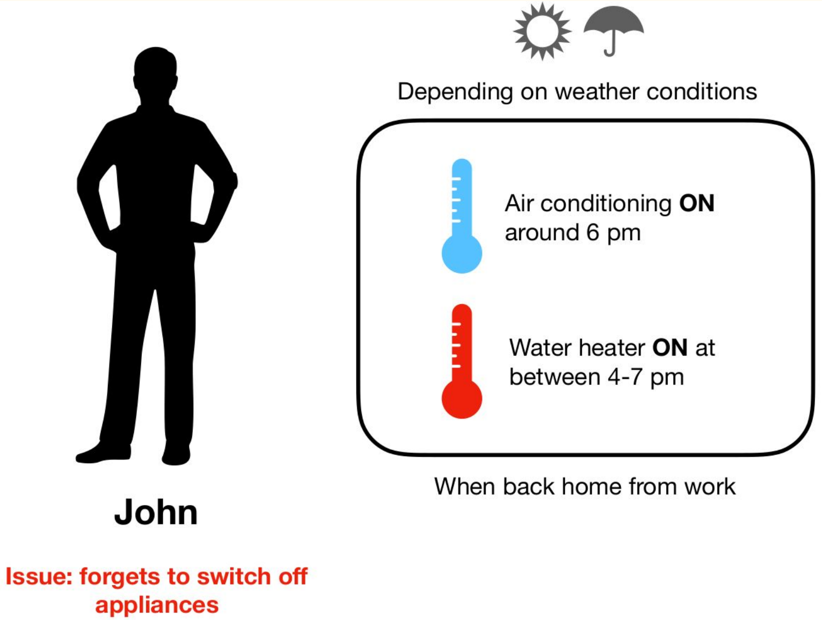
Repeated Micro-Moments ⇒ Habits

- The analysis of micro-moments leads to frequent consumption patterns (i.e. device usage patterns).
- Actions are associated with weather conditions and other temporal parameters (e.g. time of day, day of the week etc.).
- An association rule mining algorithm (a-priori):
  - is applied to user's micro-moments data (consumption and weather conditions)
  - finds frequent co-occurring itemsets (i.e. combinations of conditions and associated actions) in the micro-moments logs
  - generates association rules of the form:

antecedent ⇒ consequent

appliance, spatial/time/environment conditions ⇒ user action

Use Case Scenario... Revisited



Target user habits

Recommend small changes

work to home, afternoon, cold, turn on heater ⇒ turn off heater earlier

(e.g. in 28 minutes i.e. 95% of the normal time)

Experimental Evaluation

- A power consumption dataset from a ***single household*** was downloaded by the University of California Irvine dataset repository*.
- 2,075,259 measurements of a house in Paris France, spanning a ***4 years period*** (12/2006-11/2010).
- The measurements concern the ***aggregated energy consumption*** (in watt/hour of active energy) of ***three rooms***:
    - the kitchen (which contains mainly a dishwasher, an oven and a microwave),
    - the laundry room (which contains a washing-machine, a tumble-drier, a refrigerator and a light)
    - and a set of energy consuming devices which correspond to an electric water-heater and an air-conditioner.

*https://archive.ics.uci.edu/ml/datasets.php/datasets/datasets/Individual+household+electric+power+consumption

Data Disaggregation and Event Detection

- Data disaggregation
  - The dataset contains aggregated consumption data from 3 or 4 devices in each room.
  - We computed consumption changes between consecutive 1-minute and 5-minutes periods.
  - We isolate consumption change events (i.e. appliances have been turned on/off)
- Event detection
  - We applied k-Means clustering on the power consumption changes for each room and associate each cluster to a combined switch on/off action of the appliances in the room.

Micro-Moments Extraction

- We process the user activity data file and abstract the timezone and day of the week for each activity.
- We map each activity to the two-hours time-slot that it occurred (e.g. 1-3 am, 3-5 pm, etc.).
- Resulting in a series of switch on and off actions for each device.

Date	timezone	daytype	room	appliance	action
2006-12-17	5-7am	weekend	kitchen	microwave	on
2006-12-17	5-7am	weekend	kitchen	oven	on
2006-12-17	5-7am	weekend	kitchen	oven	off
2006-12-17	5-7am	weekend	kitchen	microwave	off
2006-12-17	5-7am	weekend	kitchen	dishwasher	on
2006-12-17	5-7am	weekend	kitchen	oven	on
2006-12-17	5-7am	weekend	kitchen	microwave	on
2006-12-17	5-7am	weekend	kitchen	oven	off
2006-12-17	5-7am	weekend	kitchen	dishwasher	off

User Habits (Frequent Actions) Extraction

- The 29,255 on/off actions that have been recorded in the 47 months period for the three devices of the kitchen and the time-zones they occured (an average of 10 interactions per day).
- Each on action is followed by an off action, so values in the table count pairs of on/off actions.
- These form the user's frequent actions.

Appliance	Timezone	Times per month
oven	7-9 am	5.96
	9-11 am	9.2
	11-1 pm	16.84
	1-3 pm	12.71
	3-5 pm	10.83
	5-7 pm	11.22
	7-9 pm	32.21
	9-11 pm	19.6
	11-1 am	5.33
microwave	7-9 am	6.0
	9-11 am	9.61
	11-1 pm	17.79
	1-3 pm	12.67
	3-5 pm	10.81
	5-7 pm	11.9
	7-9 pm	33.13
	9-11 pm	19.07
	11-1 am	4.64
dishwasher	9-11 am	4.09
	11-1 pm	8.62
	1-3 pm	5.87
	3-5 pm	4.99
	5-7 pm	4.78
	7-9 pm	14.15
	9-11 pm	8.26

Sample Association Rules

- The association rules extracted for the kitchen devices that have a support bigger that 0.02 (happen more than 12 times per month).
- The rules extracted have an ‘on’ or ‘off’ action at the right hand side, an appliance and an associated day and time-zone at the left hand side

LHS	RHS	Supp
7-9 pm, microwave, weekday	on	0.04
7-9 pm, oven, weekday	on	0.03
7-9 pm, microwave, weekday	off	0.03
7-9 pm, oven, weekday	off	0.03
9-11 pm, oven, weekday	off	0.02
9-11 pm, microwave, weekday	off	0.02
9-11 pm, oven, weekday	on	0.02
9-11 pm, microwave, weekday	on	0.02
7-9 pm, microwave, weekend	off	0.02
7-9 pm, microwave, weekend	on	0.02
11-1 pm, microwave, weekend	on	0.02
11-1 pm, microwave, weekend	off	0.02
7-9 pm, oven, weekend	off	0.02
7-9 pm, oven, weekend	on	0.02
11-1 pm, oven, weekend	on	0.02
11-1 pm, oven, weekend	off	0.02
7-9 pm, dishwasher, weekday	on	0.02

Evaluation of the Extracted Habits

80%

Data used for training

- 3.3 years
- The remaining 20% for testing

17

Micro-moments extracted

- All in the evening zone (7 pm - 1 am)

36%

Match the remaining 6,000 of the test actions

- 46.3% partially match (i.e. all but one of the antecedent conditions apply)

Conclusions

- We identify that the users' everyday energy-related behavior is driven by their needs and desires.
- Almost ⅓ ***of the actions is subject of a repetitive behavior*** that is driven by external factors, such as outdoor weather conditions or common energy consumption habits (micro-moments).
- Such ***micro-moments are useful for transforming users' energy profile*** towards efficiency.

Frequent Actions + **Association Rules** → **Rules for Generating Recommendations.**

What is next?

- The dataset we used for evaluation contains only consumption data.
- We will evaluate our methodology on the AMPds dataset* (21 power meters, 2 water meters, 2 natural gas meters, weather data as well as billing data from utility companies)
  - We will further test our disaggregation module and the use of weather conditions in our rules.
- We are currently building our own dataset that contains, consumption data, indoor and outdoor weather conditions and room occupancy data.
  - We will perform habit extraction based on weather conditions and user presence in a room.

*https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi%3A10.7910/DVN/FIE0S4%20

Thank you!

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