

## Abstract

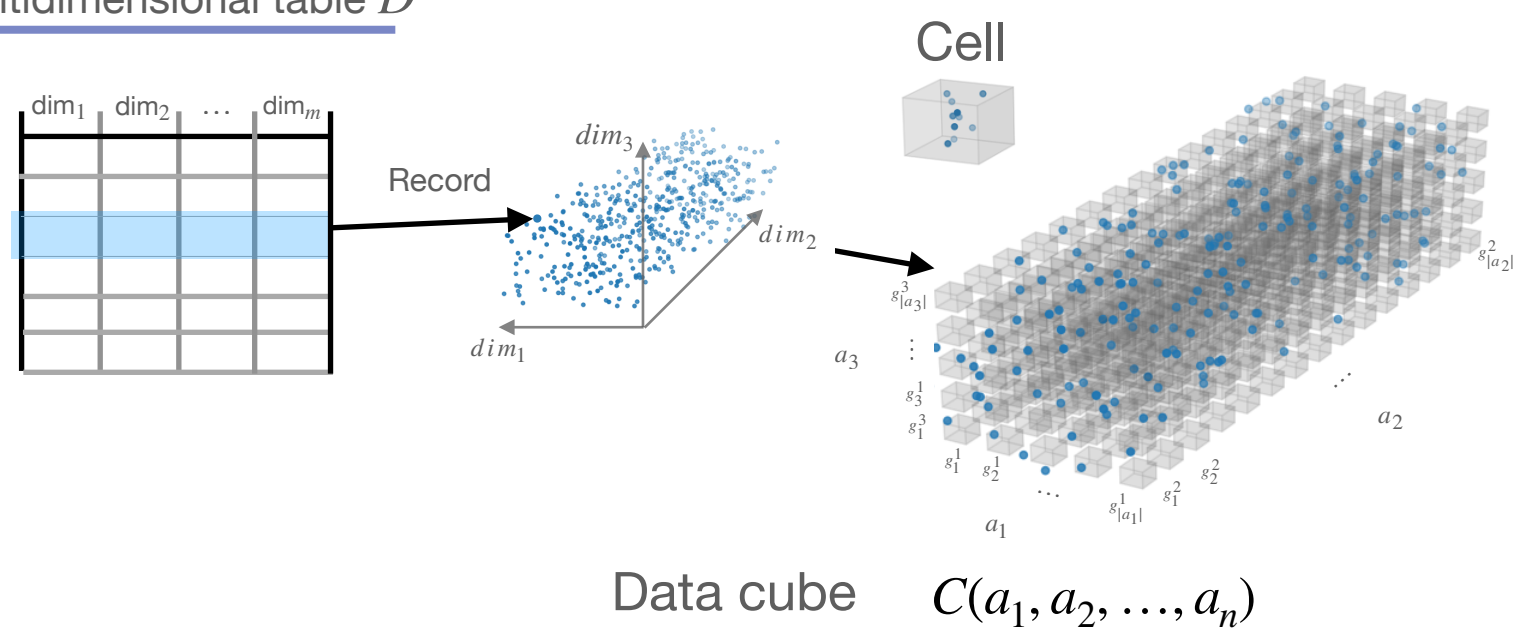
Efforts to reduce energy consumption in buildings are crucial for climate change concerns. In this sense, energy monitoring increases energy awareness and mitigates energy wastes. This study integrates machine learning models, advanced visualisations, and interactive tools to create an insightful energy monitoring dashboard. Novel contributions include a 2D map of daily energy demand profiles combining spatial encodings based on t-SNE, fluid aggregation, and filter operations via a data-cube framework, as well as visual encoding powered by morphing projections. This approach facilitates the decisions of end users regarding the optimisation of energy in residential facilities.

## Data-Cube framework

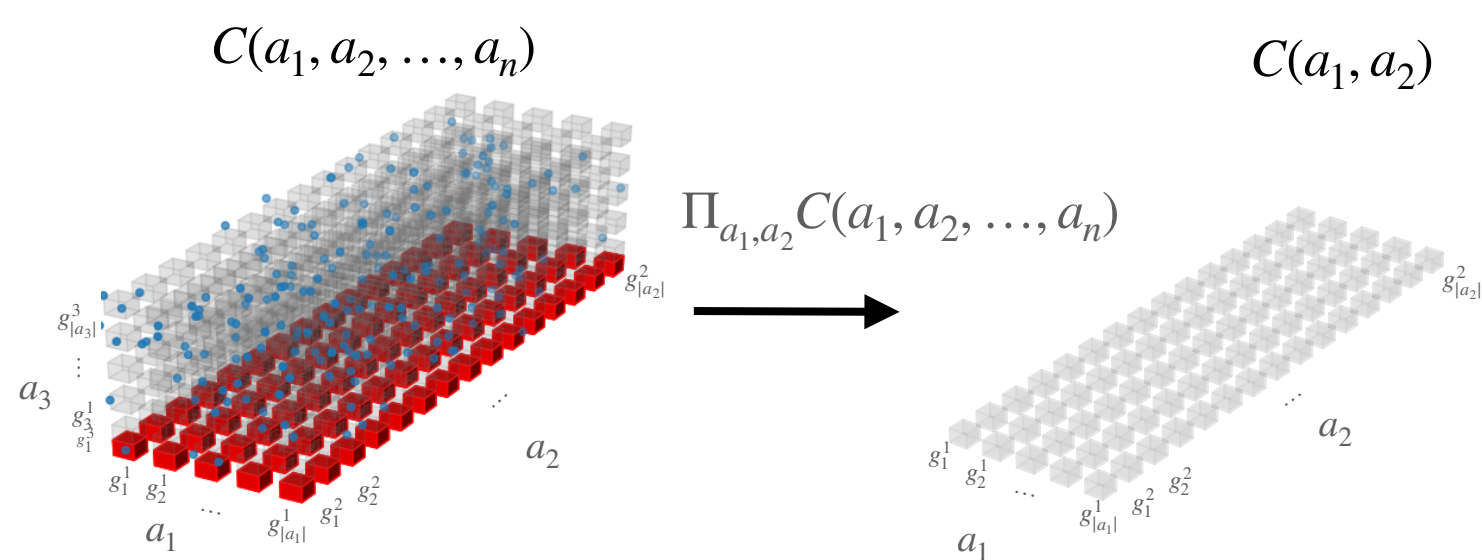
The **data cube** model speeds up filter and aggregation operations by efficiently indexing data into a hypercube, allowing users to decompose energy analysis into meaningful sub-problems. For instance, users can refine their analysis by filtering based on time of day or aggregating the energy demand by different time intervals (i.e. daily, weekly or monthly profiles).

The data cube structure, denoted as  $C(a_1, a_2, \dots, a_n)$ , consists of cells with coordinates  $(g^1, g^2, \dots, g^n)$ , where all records in  $D$  are arranged.

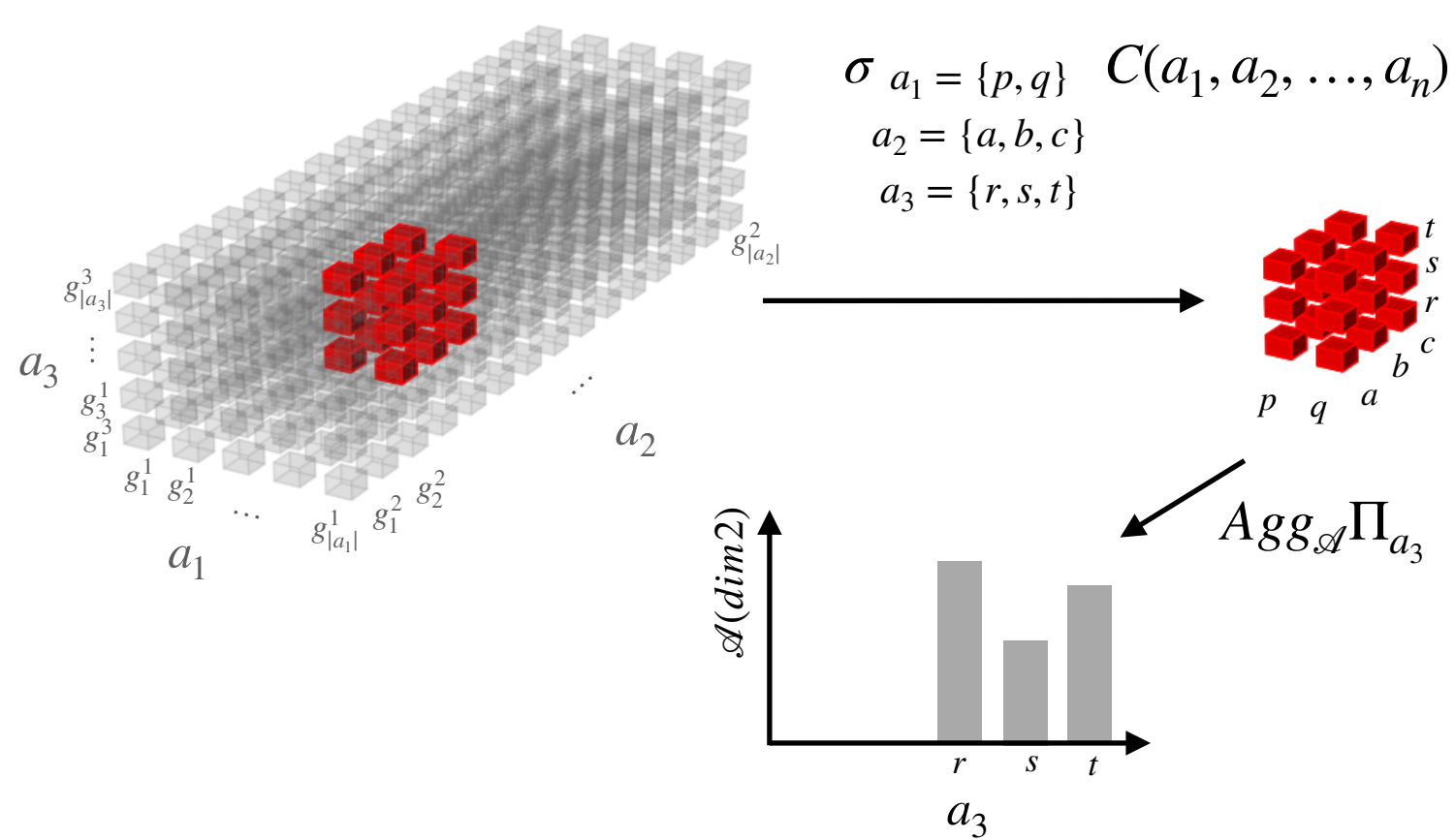
### Multidimensional table $D$



**Projection operation** restricts the multivariate analysis to a few attributes selected by the users:



**Filter and aggregation operations** entail selecting specific groups in one or more attributes of the cube and summarise the information:



## Visual encoding and morphing projections

The aggregated profiles are presented to end users in a 2D map as **sparklines**. Their position in the map is derived by the cells' index in the data cube. Coordinates or **spatial encoding  $\mathbf{P}^i$**  is assigned to the groups of the attributes  $a_i$  by means of a lookup table:

$$\begin{array}{c|ccc} a_i & g_1^i & g_2^i & \dots & g_{|a_i|}^i \\ \mathbf{P}^i & \mathbf{p}_1^i & \mathbf{p}_2^i & \dots & \mathbf{p}_{|a_i|}^i \end{array}$$

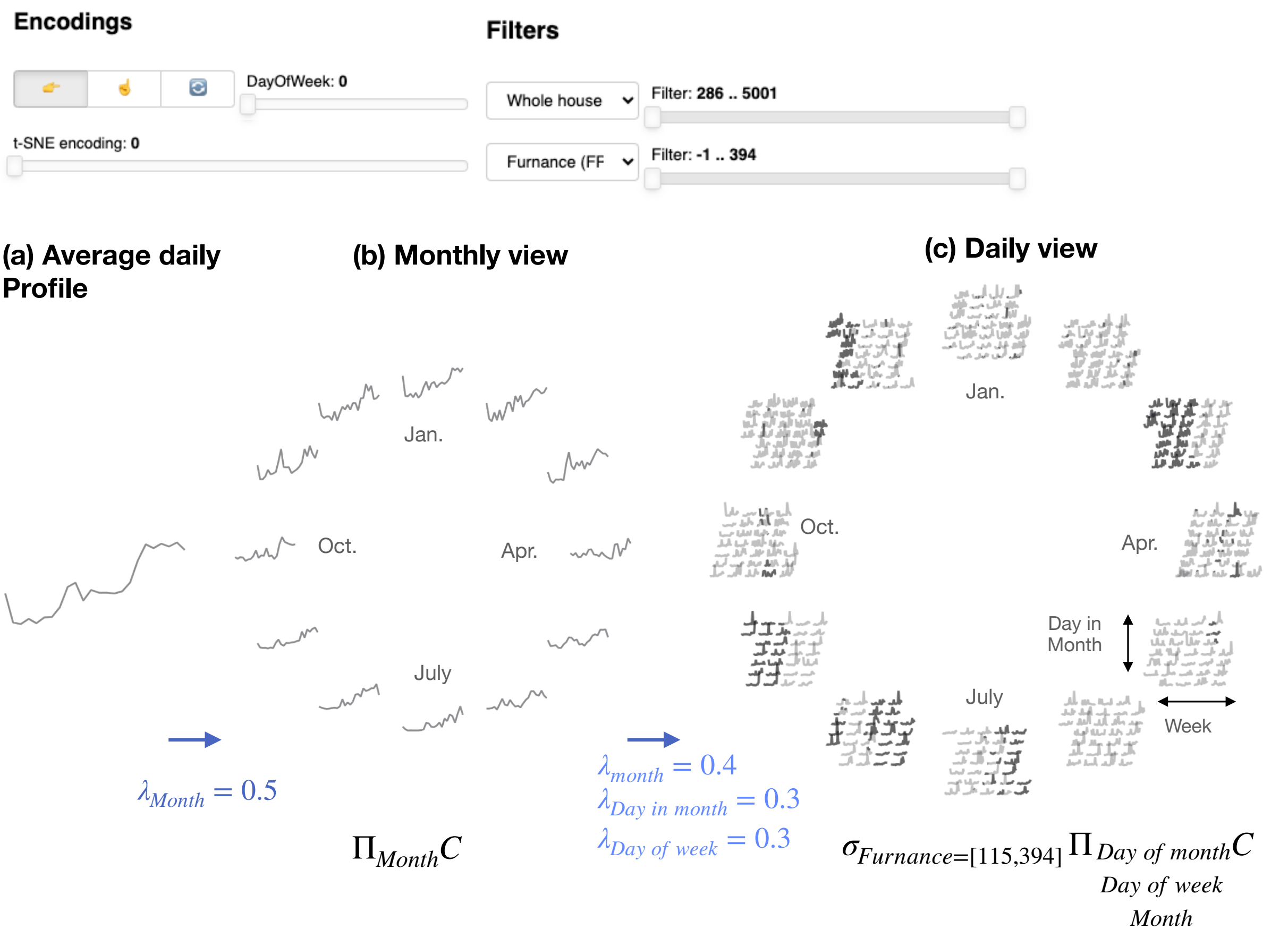
The spatial encodings per attribute are efficiently mixed to obtain a final set of coordinates  $\mathbf{P}^\lambda = \{\mathbf{p}_k^\lambda\}_{k=1,2,\dots,K}$  by the **morphing operation**:

$$\mathbf{p}_k^\lambda = \sum_{i=1}^p \lambda_i \mathbf{p}_k^i$$

where  $K = |a_1 \times a_2 \times \dots \times a_p|$  is number of active cells,  $p$  is the number of active encodings and  $\lambda_i$  are the attribute importance coefficients and typically  $\sum_i \lambda_i = 1$

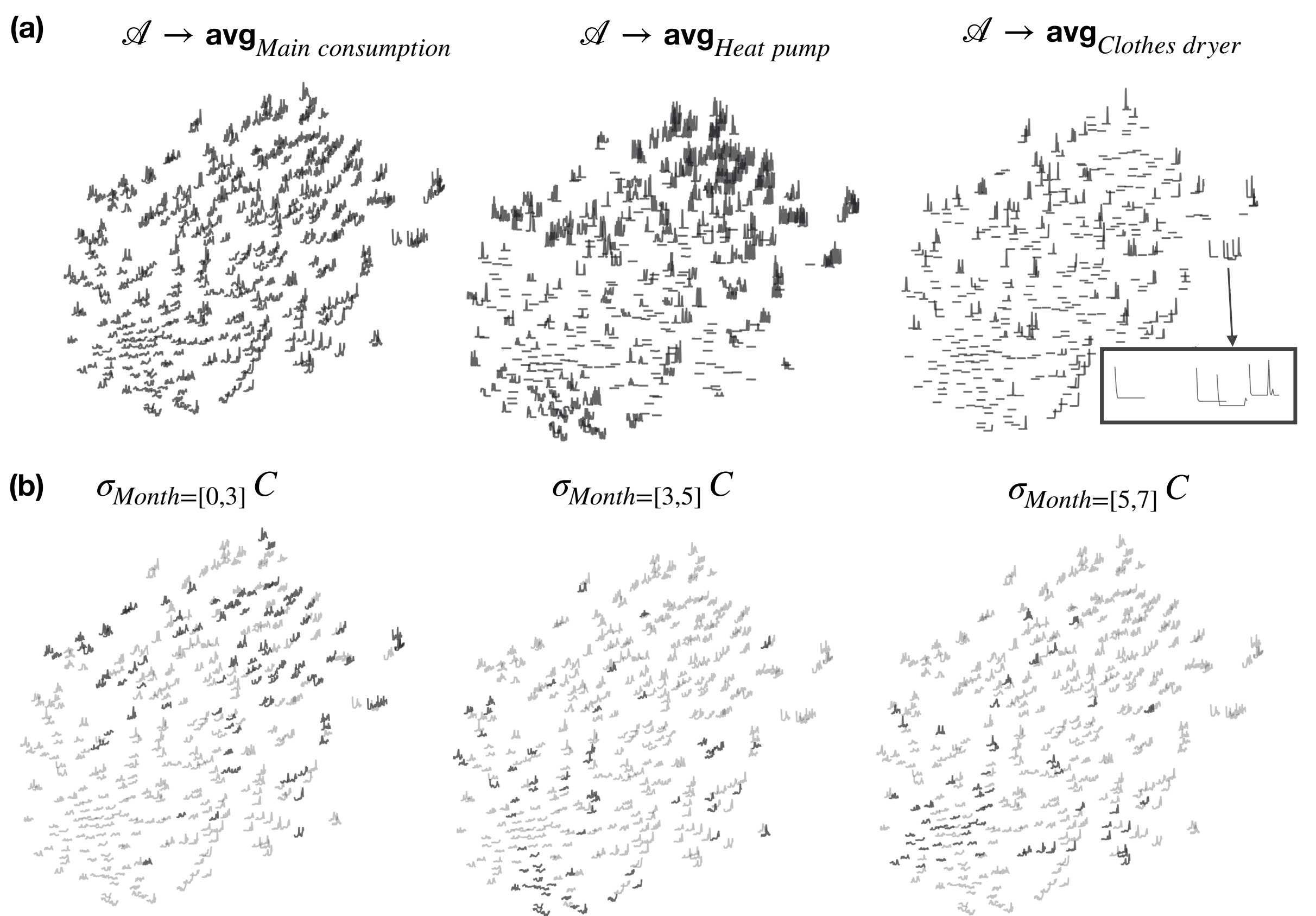
## Experimental set-up and dashboard

The proposed method is tested using one year of electric energy demand data from the **publicly available dataset, the Almanac of Minutely Power dataset (AMPd)**. Importance coefficients  $\lambda_i$  are attached to sliders in the final dashboard by which the user can smoothly switch between views and modify the projection operation at the same time.



## ML-based spatial encodings

User-defined encodings distribute the groups of the cube using basic layouts, such as vertical, horizontal or circular arrangements. Our approach also offers spatial encodings computed by applying a **dimensionality reduction model** to the energy demand records, such as **t-SNE**.



## Conclusions

- Our method exhibits results on the analysis of energy demand patterns in residential facilities.
- Morphing projections along with the data cube operations facilitate the analysis and exploration of energy demand records, increasing the energy awareness.
- The integration of ML-based spatial encodings into the analysis helps users to correlate ML-based maps with specific appliance usage patterns
- Our approach not only enhances comprehension but also facilitates informed decision-making regarding energy usage

## Demo online

