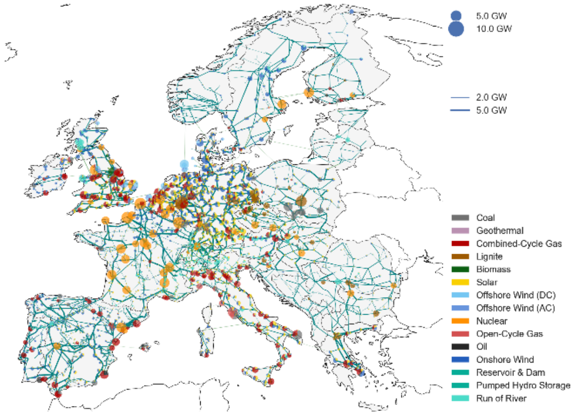
Energy System Modeling with Python



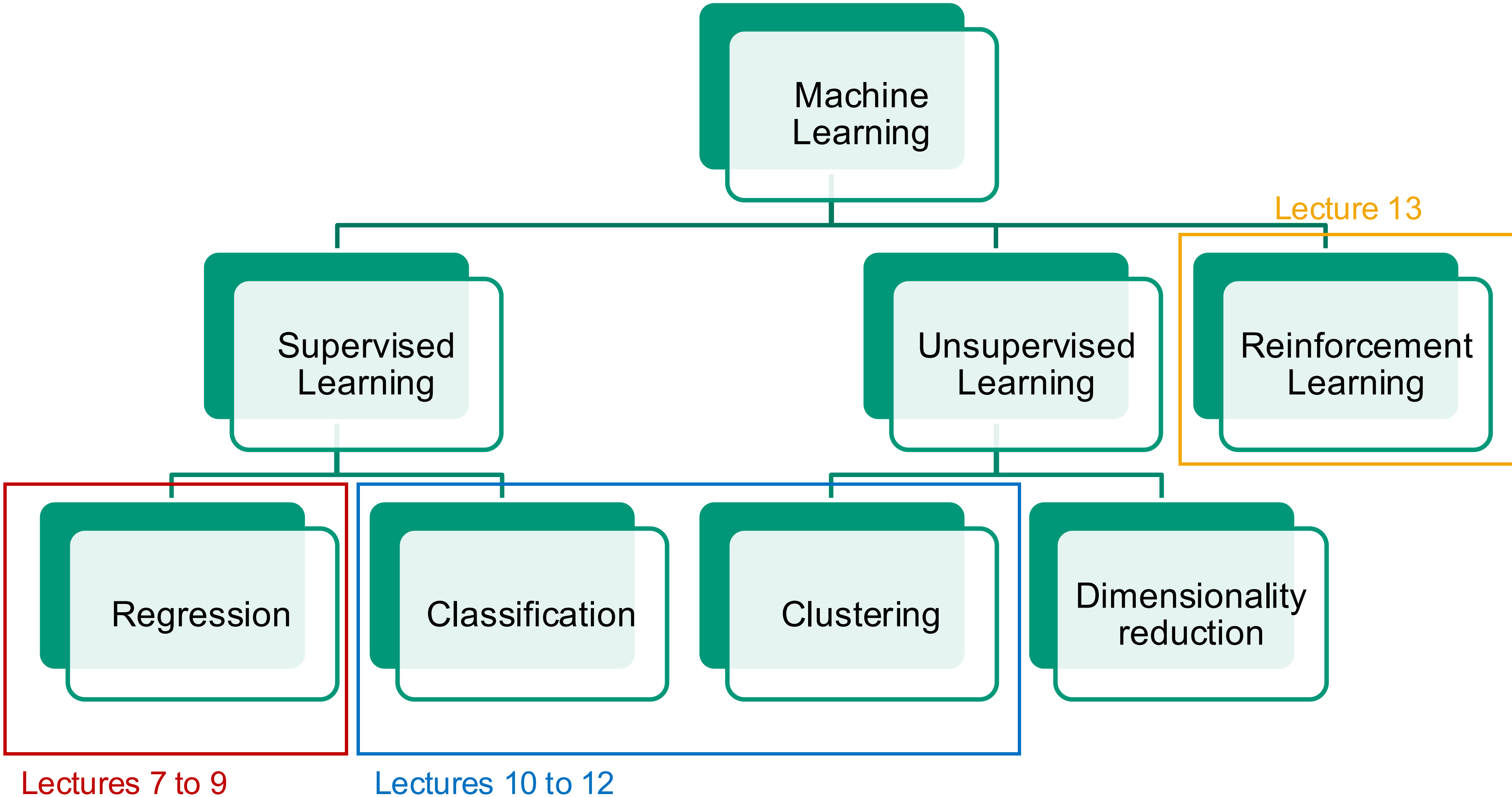
University of Freiburg (Germany) | Faculty of Engineering

Department of Sustainable Systems Engineering | INATECH

Chair for Control and Integration of Grids

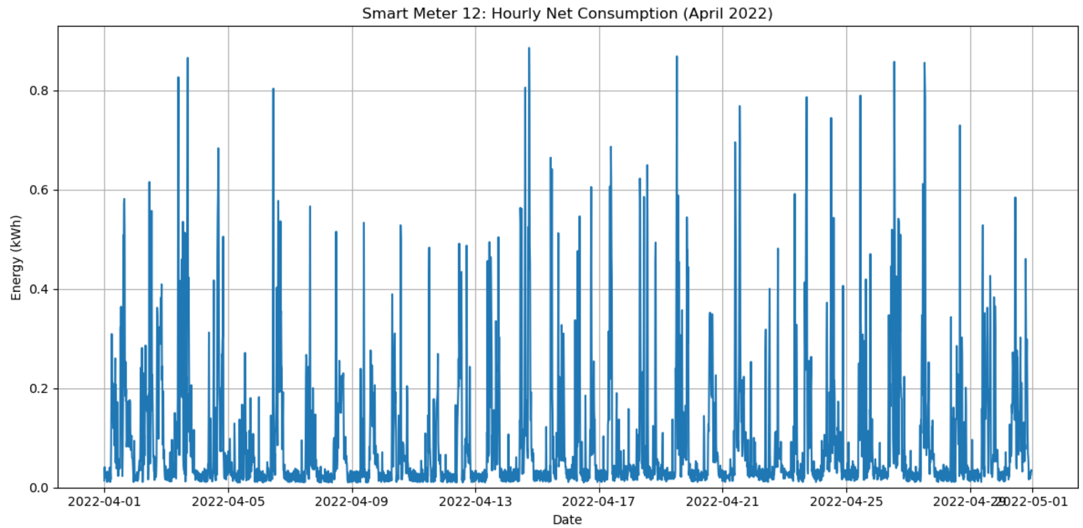
Tuesday, 3. June 2025

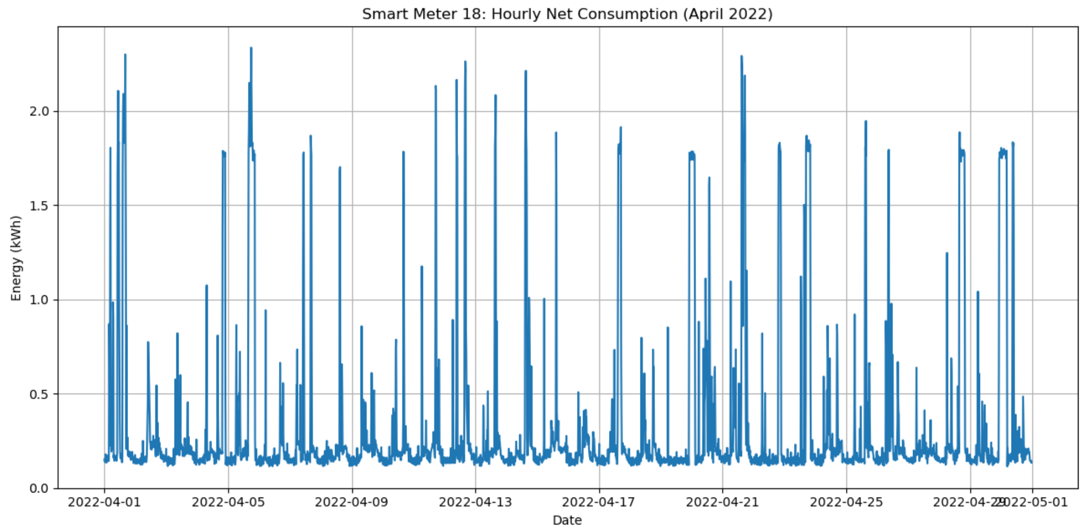
Branches of ML



Feature Engineering

What Can You Learn from This?





One household has an EV, another one is a baseline household. Which is which?

From Raw Curves to Insights: Feature Engineering

Raw Smart Meter Data

↓

Feature Extraction

↓

Machine Learning

- Supervised learning (e.g., forecasting)
- Unsupervised learning (e.g., clustering)

Why extract features?

- Reduce dimensionality (from thousands to a few dozen features)
- Make models faster, more robust, and easier to interpret
- Capture key properties: daily shape, variability, peak timing, etc.

What is a feature?

- A distinctive attribute or aspect of something
- A numeric descriptor summarizing one characteristic of the load curve
- Examples: *night/day ratio*, *midday dip*, *load skewness*, *peak-to-average ratio*

We'll explore two types: **domain-agnostic** and **domain-informed** features

Domain-Agnostic Features: Descriptors of Time Series

A **domain-agnostic feature** is a characteristic or attribute of data that is **not specific to any industry, task, or application area**, and can be effectively used across multiple domains. These features capture general patterns or structures that are broadly applicable, making them useful in building versatile machine learning models or systems.

Why use them?

- Work across any kind of time series
- Fast to compute, often highly informative
- Good baseline for clustering

Feature	What it Captures	DER Interpretation Potential
Mean, Std Dev	Central tendency and variability	General activity level, variability
Skewness, Kurtosis	Distribution shape and tail extremity	Detects rare spikes, consumption bias
Autocorrelation (Lag 1)	Short-term dependency / persistence	Operational cycles, device continuity
Autocorrelation (Lag 24)	Daily periodicity / routine	Regular habits, scheduled operations
Entropy	Signal complexity / unpredictability	Behavioral randomness, irregularity
Flat Spots	Periods of constant load (zero variance)	Device idling, standby detection

Autocorrelation: Temporal Smoothness

Autocorrelation measures how similar a time series is to itself at a shifted time (lag). It helps detect:

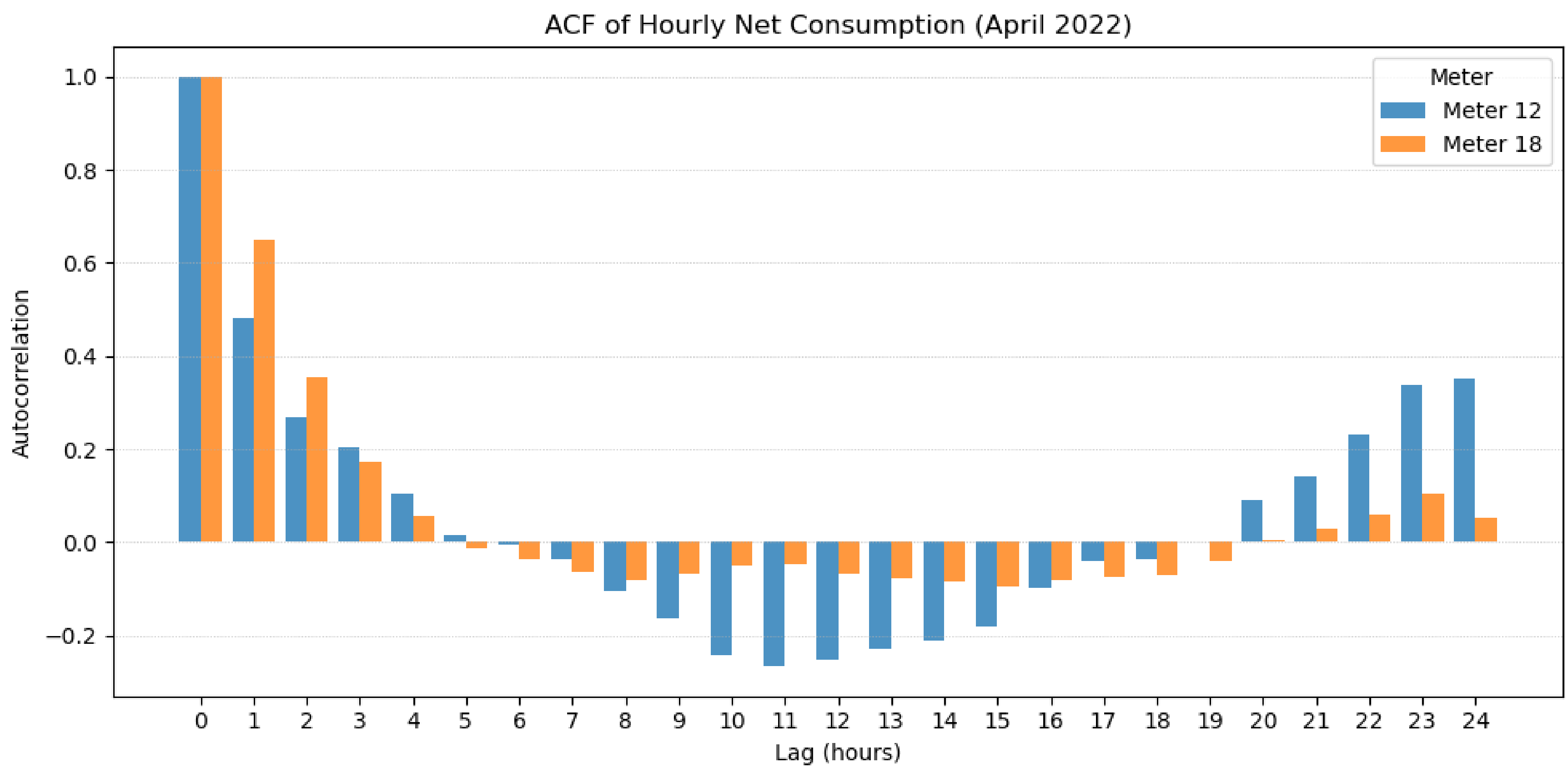
- Repeated patterns (e.g. daily cycles)
- Memory in the data (persistence)
- Seasonality or trend components

The autocorrelation at lag k is:

$$\rho_k = \frac{\sum_{t=1}^{N-k}(X_t - \mu)(X_{t+k} - \mu)}{\sum_{t=1}^{N}(X_t - \mu)^2}$$

Where:
$\boldsymbol{X_t}$: value of the time series at time t
$\boldsymbol{\mu}$: mean of the time series
$\boldsymbol{\sigma^2}$: variance of the time series
$\boldsymbol{N}$: number of observations

Autocorrelation: What can you spot?



Skewness & Kurtosis: Shape of the Distribution

Skewness (Asymmetry)

$$\text{Skewness} = \frac{1}{N}\sum_{t=1}^{N}\left(\frac{X_t - \mu}{\sigma}\right)^3$$

where:

$\boldsymbol{X_t}$**:** each value in the series

μ: mean

$\boldsymbol{\sigma}$**:** standard deviation

$\boldsymbol{N}$**:** number of observations

Kurtosis (Tailedness / Peakedness)

$$\text{Kurtosis} = \frac{1}{N}\sum_{t=1}^{N}\left(\frac{X_t - \mu}{\sigma}\right)^4$$

Often expressed as **Excess Kurtosis**:

$$\text{Excess Kurtosis} = \text{Kurtosis} - 3$$

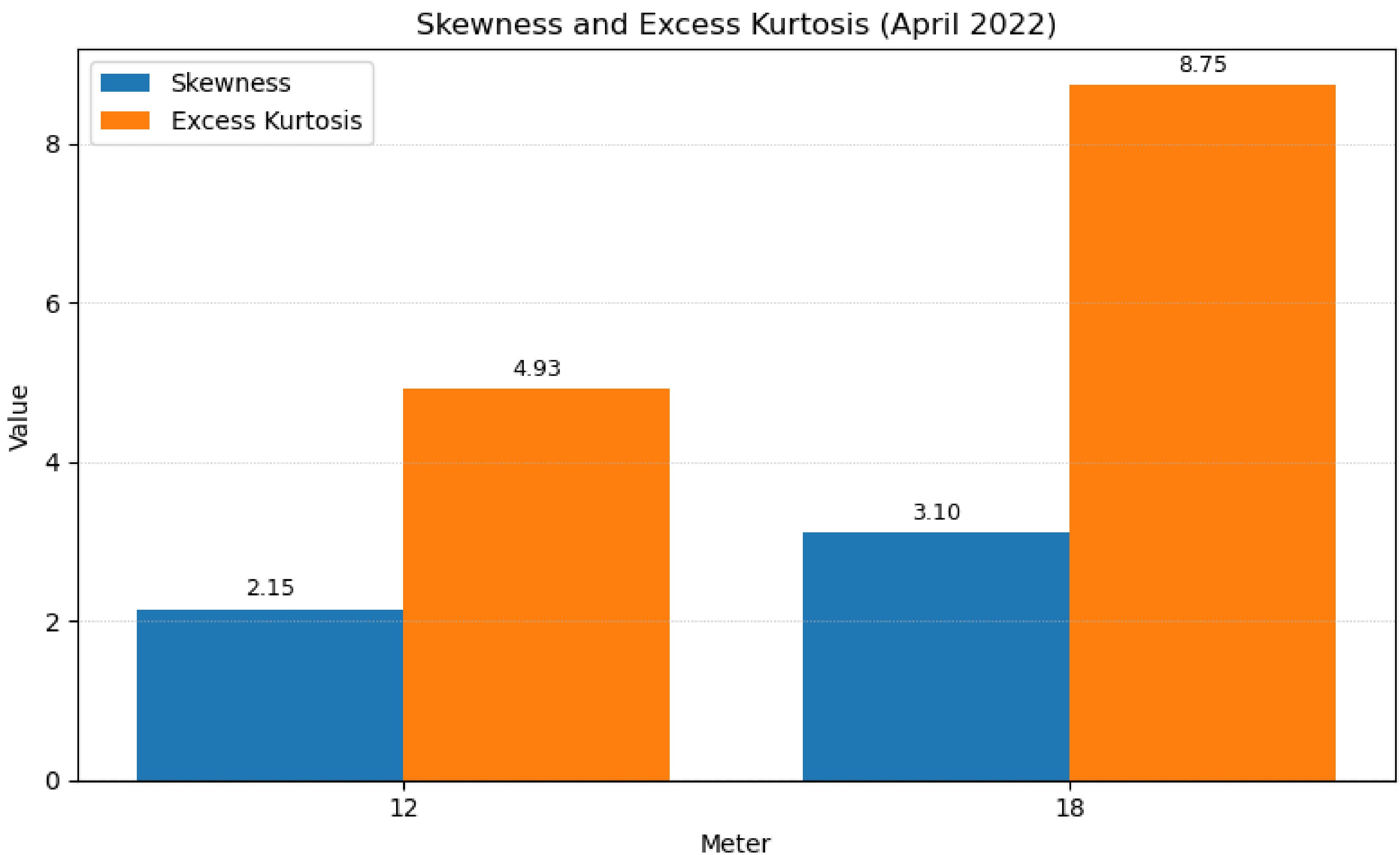
Interpretation:

- Positive skew (Skewness > 0) can signal infrequent large loads, like EV charging.
- Negative skew (Skewness < 0) can indicate net export periods from PV generation.

Interpretation :

- Excess Kurtosis ≈ 0: normal “bell curve” behavior
- Excess Kurtosis < 0: flatter peak → fewer extreme values
- High kurtosis (Excess Kurtosis > 0) might suggest occasional but extreme consumption or export spikes (e.g., EV charging, high solar feed-in).

Skewness & Kurtosis: What can you spot?



So, which is which?

Feature	Meter 12 ("Blue")	Meter 18 ("Orange")	Interpretation
Lag 1 ACF	0.4815	0.6482	Meter 18's high lag 1 reflects consecutive EV charging hours. Meter 12's appliances cycle more frequently.
Lag 24 ACF	0.3499	0.0512	Meter 12 has a strong everyday routine. Meter 18's charging occurs at varying times, so no daily repeat.
Skewness	+2.15	+3.10	Meter 18's distribution has fatter right tail (big EV-charging spikes). Meter 12 only has moderate right-tail events.
Excess Kurtosis	+4.93	+8.75	Meter 18 shows extremely heavy tails. Meter 12 has moderate tails from normal appliance peaks.
Lag 2–lag 4 behavior	Decays from 0.27 → 0.11	Decays from 0.36 → 0.05	Meter 18's multi-hour charging block keeps lag 2 elevated vs. Meter 12's faster decay.

Meter 12 is the regular household

- ACF shows a clear daily cycle (lag 24 near +0.35)
- only moderate skew/kurtosis

Meter 18 is the household with an EV

- It has a very high lag 1 (0.6482) because of multi-hour charging sessions
- almost zero lag 24 (0.0512) because charging times vary day-to-day
- very large skew/kurtosis (3.10, 8.75) due to those extreme charging spikes

Domain-Informed Features: Using Domain Knowledge

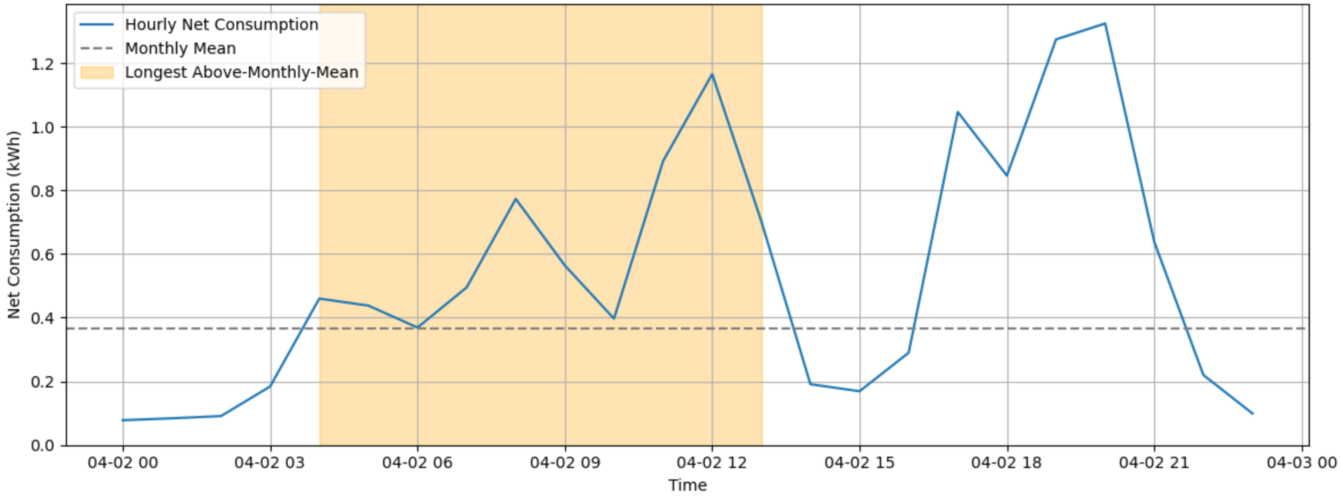
Definition:
"Features specifically designed to reflect energy use behaviors, patterns of DERs, or daily load structure."

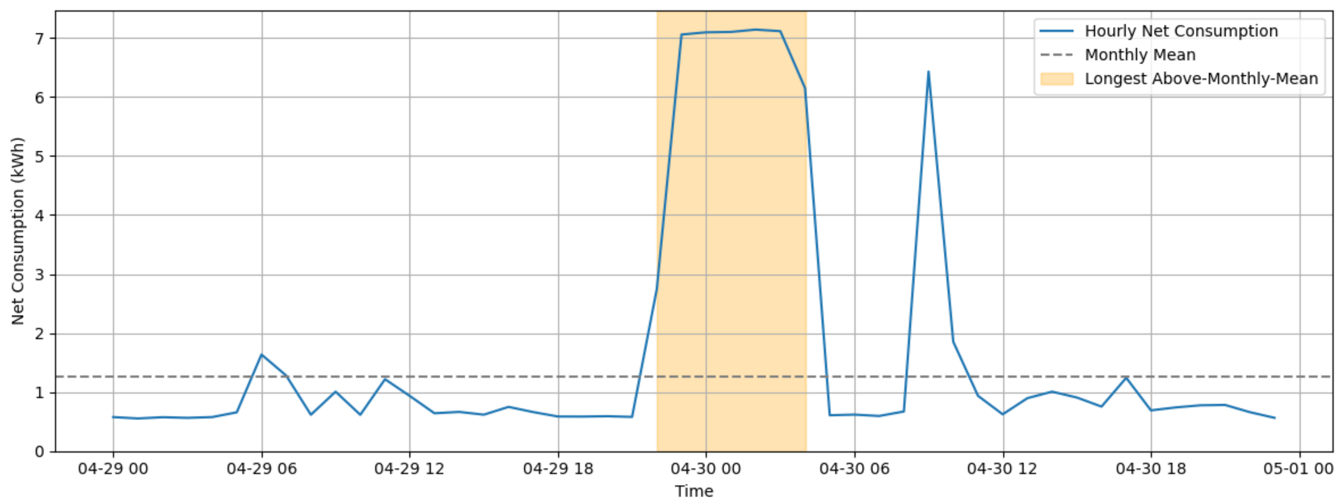
Why use them?

- ✓ Capture patterns aligned with human activity (e.g., waking hours, night/day load balance)
- ✓ Reveal DER-specific markers (e.g., midday dip from PV, spikes from EV)
- ✓ More interpretable for grid planners and energy analysts

Feature	What it Captures	DER Interpretation Potential
Longest Period Above Mean	Sustained high consumption	Heat pump / EV
Longest Successive Increase	Structured ramp-ups	EV charging / manual load
Midday Dip	Solar PV export impact	PV detection
Night/Day Ratio	Load shifting between periods	Behavioral segmentation

Longest Period Above Mean: Sustained High Load





Feature Engineering: Summary

Domain-Agnostic Features

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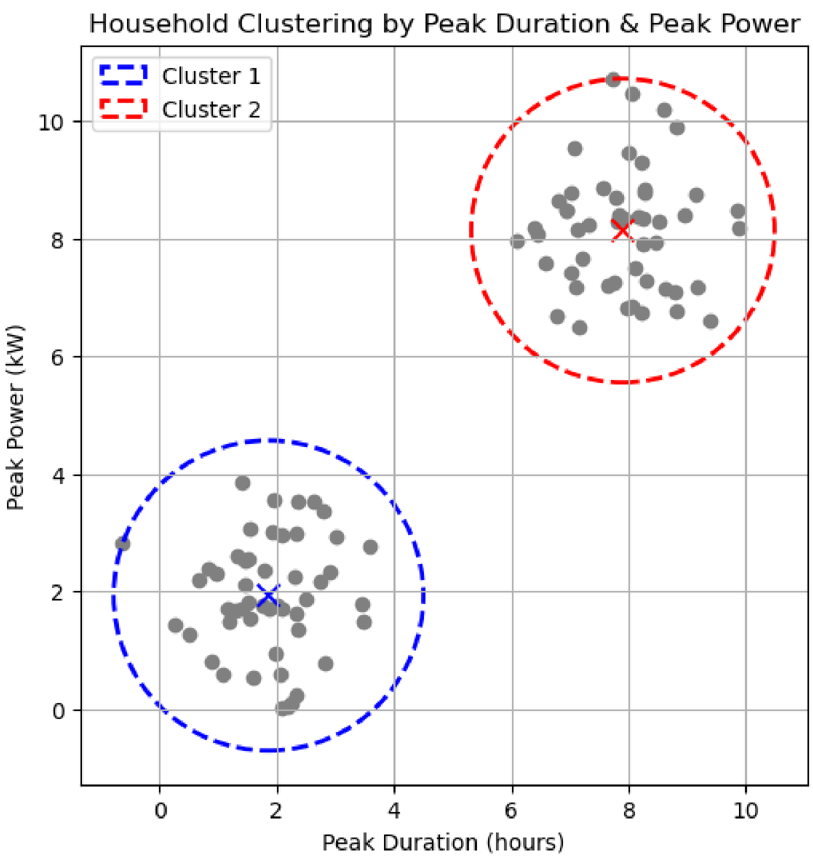
Clustering

Why Clustering? And What is Clustering?

- Manual comparison helped distinguish a few known profiles (e.g., EV vs baseline)
- But this doesn't scale to 1,000s of households
- We want to **group households automatically** based on extracted features
- We don't always know how many types (clusters) exist — sometimes it's known, sometimes not



Definition: The clustering consists in grouping a set of objects so that members of the same group (called cluster) are more similar.

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K-Means: Grouping by Proximity in Feature Space

Core idea:
Given data $\{x_i\}_{i=1}^{n}$, where $x_i \in R^d$, partition into k clusters $C_1, \ldots, C_k$ to minimize the **within-cluster sum of squares**:

$$\min_{C_1,\ldots,C_k} \sum_{j=1}^{k} \sum_{x_i \in C_j} |x_i - \mu_j|^2$$

Where μ_j is the **centroid** of cluster C_j:

$$\mu_j = \frac{1}{|C_j|} \sum_{x_i \in C_j} x_i$$

Algorithm:

1. Initialize $\mu_1, \ldots, \mu_k$ randomly

2. Repeat until convergence:

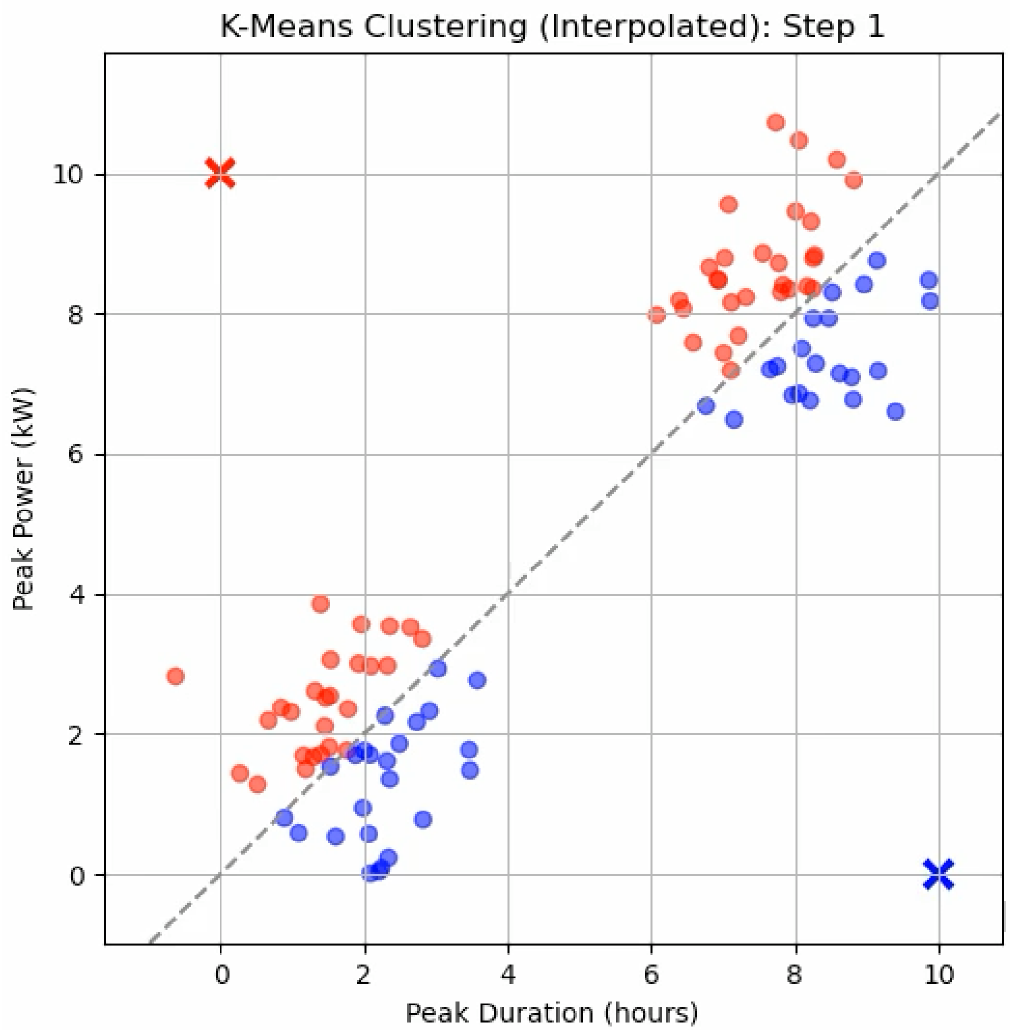
   - Assignment step:

$$c(i) = \arg\min_j |x_i - \mu_j|^2$$

   - Update step:

$$\mu_j = \frac{\sum_{i=1}^{n} \mathbb{1}(c(i) = j) \cdot x_i}{\sum_{i=1}^{n} \mathbb{1}(c(i) = j)}$$

K-Means: Grouping by Proximity in Feature Space



Ward's Method: Bottom-Up Clustering with Variance Minimization

Core idea:
Agglomerative clustering builds a **hierarchical tree** by **iteratively merging** the two closest clusters.

With **Ward linkage**, the "closeness" is defined by how much the total **within-cluster variance** would increase if two clusters are merged.

At each step, choose the pair (A, B) of clusters to merge that minimizes:

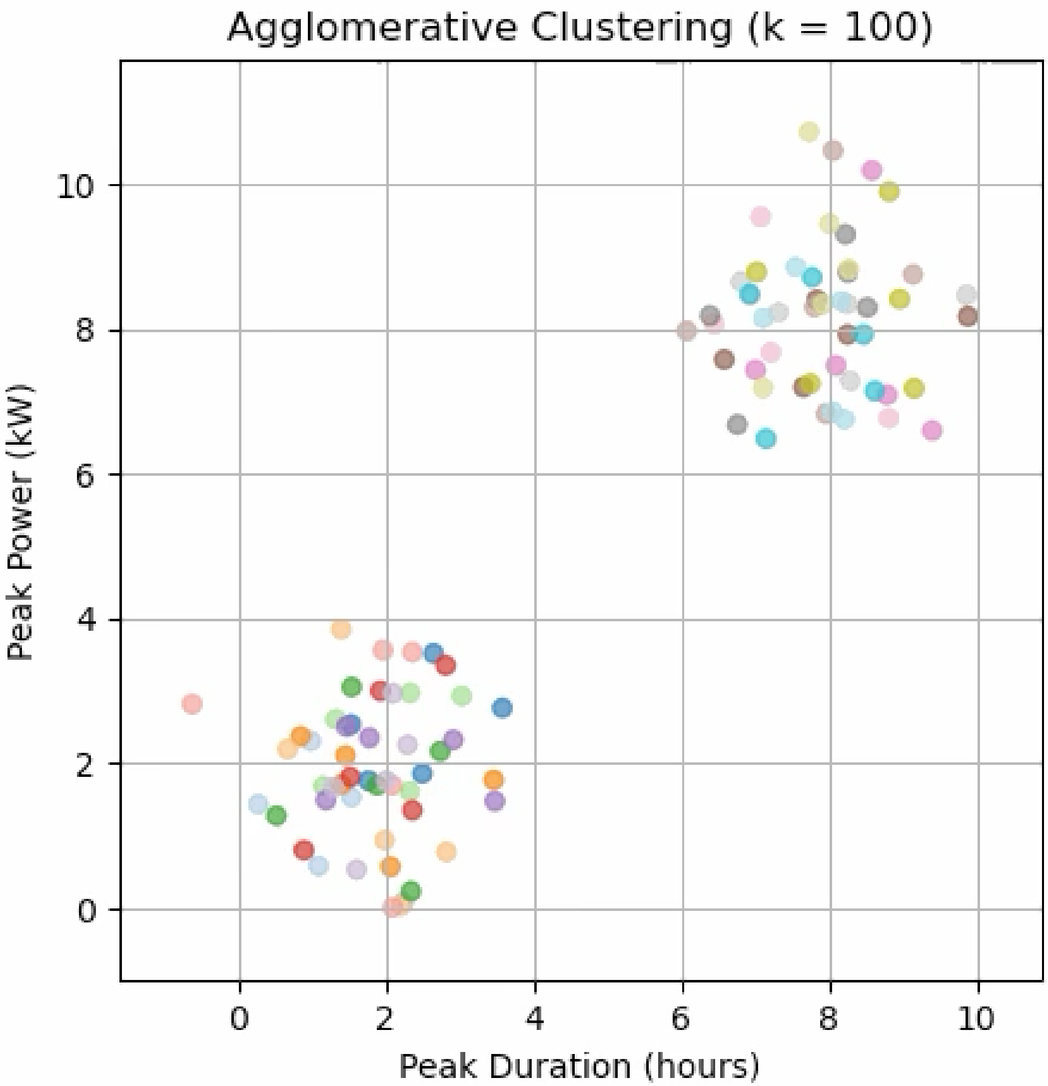
$$\Delta E(A,B) = \frac{|A| \cdot |B|}{|A| + |B|} \cdot |\mu_A - \mu_B|^2$$

Where:
$|A|, |B|$ are the sizes of clusters A and B
μ_A, μ_B are their centroids
ΔE is the increase in total within-cluster sum of squares

Algorithm:

1. Start with each data point as its own cluster.
2. Compute all pairwise cluster distances.
3. Merge the pair with the **smallest increase in variance**.
4. Repeat until a single cluster remains or desired number of clusters is reached.

Ward's Method: Bottom-Up Clustering with Variance Minimization



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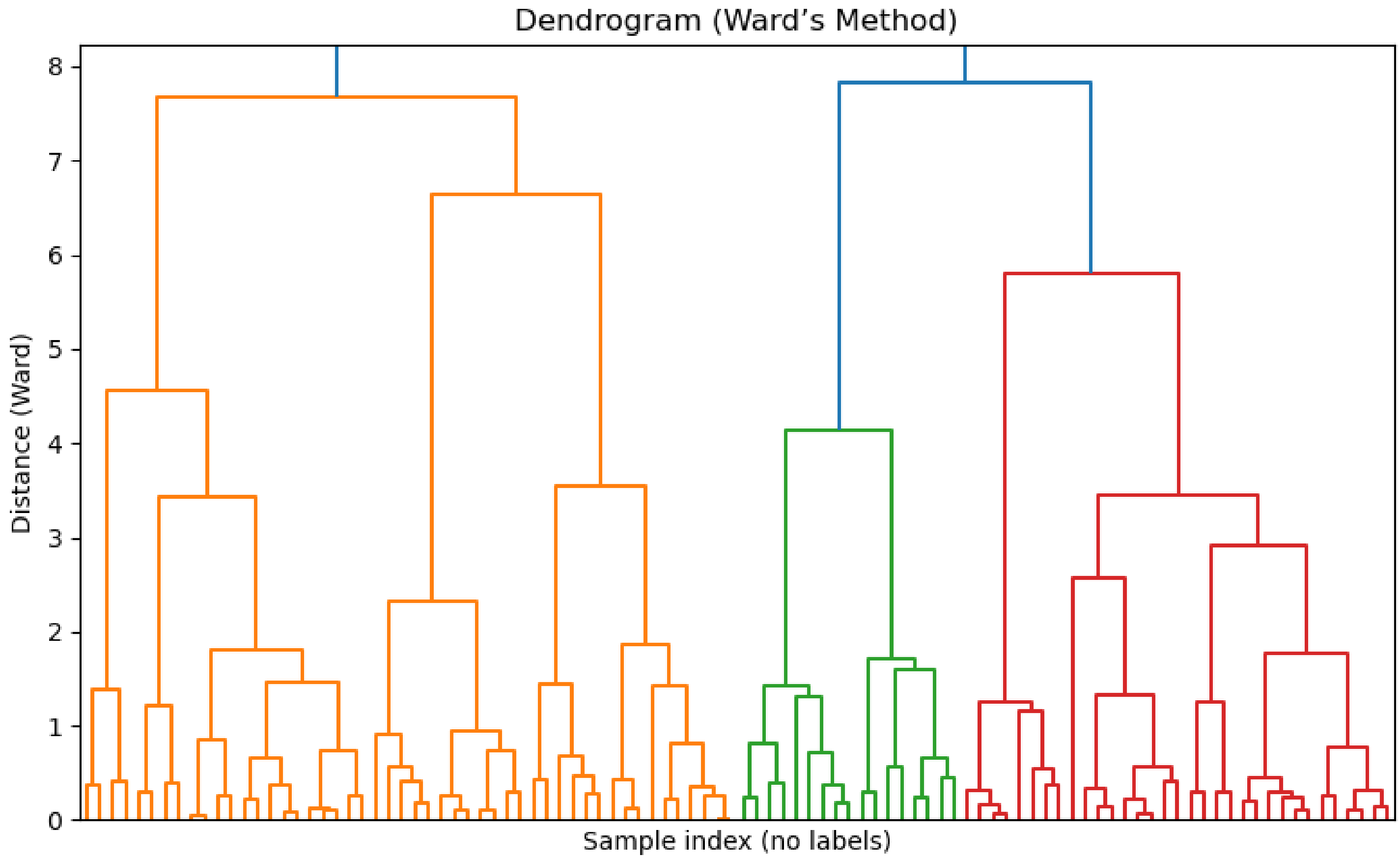
Ward’s Method: Dendogram



A **dendrogram** is a tree-like diagram that shows how data points or clusters are merged (or split) during **hierarchical clustering**.

It's a **visual map of the clustering process** — showing how each point starts in its own cluster and how clusters get merged step by step until only one cluster remains.

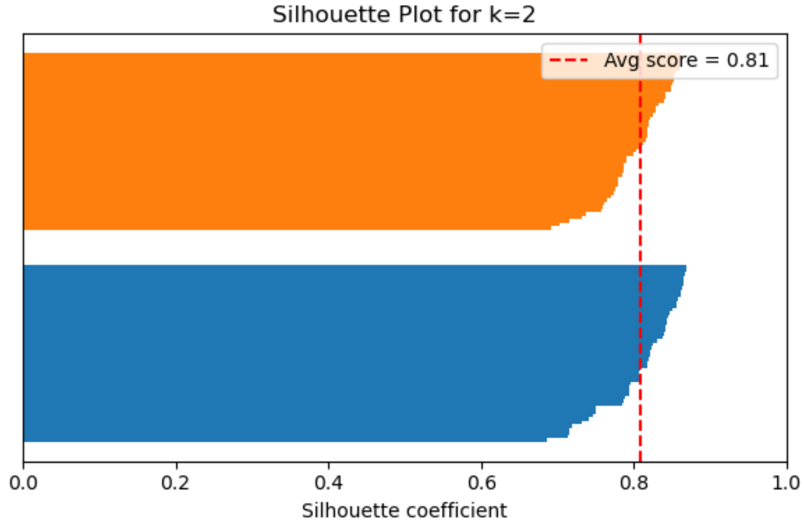
Choosing a Clustering Method: Trade-Offs

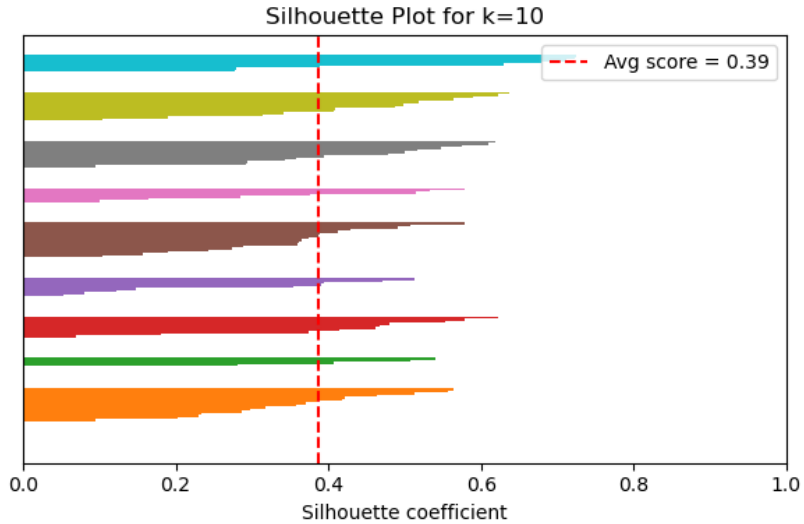
Aspect	K-Means	Agglomerative (Ward)
Cluster shape assumption	Spherical, equal-sized clusters	Any shape, hierarchical structure
Input requirement	Must specify number of clusters	No need to specify number of clusters upfront (optional cutoff later)
Distance metric	Euclidean (squared L2 norm)	Increase in within-cluster variance (Ward linkage)
Scalability	Fast on large datasets	Slower and memory-heavy
Output structure	Flat clusters only	Hierarchical tree (dendrogram)
Determinism	Random init → results may vary (use multiple runs)	Deterministic
Interpretability	Easy to visualize centroids	Reveals structure at multiple scales
Use case fit (for DER)	Clear household types known (e.g. EV, PV, baseline)	Unknown number/types of behaviors; exploratory profiling

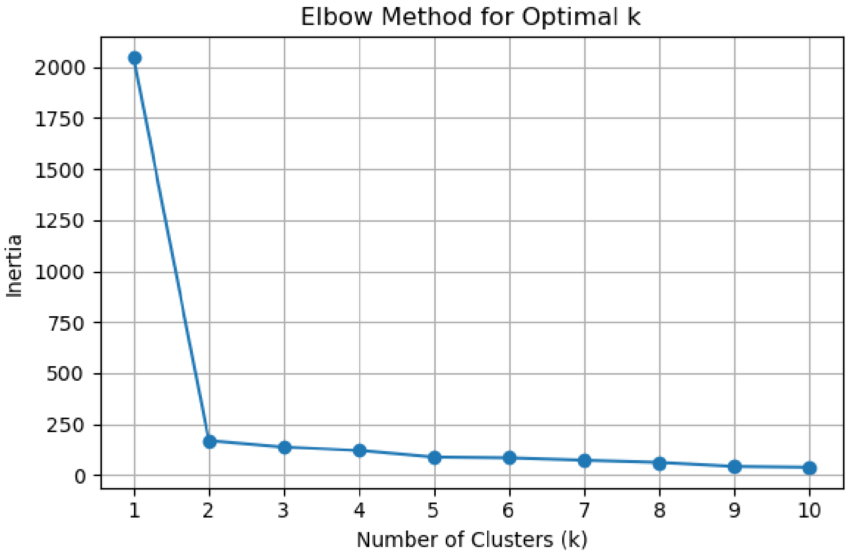
How Do We Know If Clustering Worked?

Aspect	Definition / Equation	Purpose	Key Notes
Silhouette Score	$s_i = \frac{b_i - a_i}{\max(a_i, b_i)}$ a_i: intra-cluster distance b_i: nearest-cluster distance	Measures cluster compactness and separation	Values close to 1 = good clustering Near zero = misclassified
Elbow Method	Plot inertia score vs. number of clusters Inertia $= \sum_{i=1}^{k} \sum_{x \in C_i} \lvert x - \mu_i \rvert^2$: sum of squared distances between each point and the centroid of its assigned cluster	Identify optimal number of clusters	Look for "elbow" — point where additional clusters give diminishing returns
t-SNE	Nonlinear dimensionality reduction Preserves local neighborhoods; not distances	Visualize clusters in 2D	For **visualization only**, not cluster assignment Layout may change on re-run

How Do We Know If Clustering Worked?







Coffee Break

Time to put everything into code

What You'll Do in Code Today

Goal:

Use smart meter data to extract meaningful features, apply clustering, and explore how different types of households group together based on their electricity usage.

Main Steps:

1. **Load and explore** the dataset of household electricity profiles.
2. **Extract features** that summarize daily and weekly consumption patterns.
3. **Standardize** the features to prepare them for clustering.
4. **Visualize** the data structure using dimensionality reduction.
5. **Apply clustering** using two different algorithms and compare the results.
6. **Interpret** the discovered clusters and connect them to possible DER types.

Takeaways

- ✓ Raw smart meter data is high-dimensional and hard to interpret directly — we need feature engineering to extract meaningful patterns.
- ✓ Domain-agnostic features offer general, statistically grounded insights; useful for broad structure detection.
- ✓ Domain-informed features capture behaviorally or technically relevant characteristics (e.g., PV dips, EV ramps).
- ✓ Clustering methods like K-Means and Ward help group households with similar load behavior — even without labeled data.
- ✓ Evaluation tools such as silhouette scores and t-SNE plots help assess and interpret clustering outcomes.

Further Questions to Think About

- ➢ Which features are most relevant for detecting specific DERs like heat pumps or batteries?
- ➢ How sensitive are clustering results to the feature set or scaling method used?
- ➢ How might time-of-day or seasonal effects influence feature extraction or clustering quality?