

# Estimating Reduced Consumption for Dynamic Demand Response

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## Dynamic Demand Response

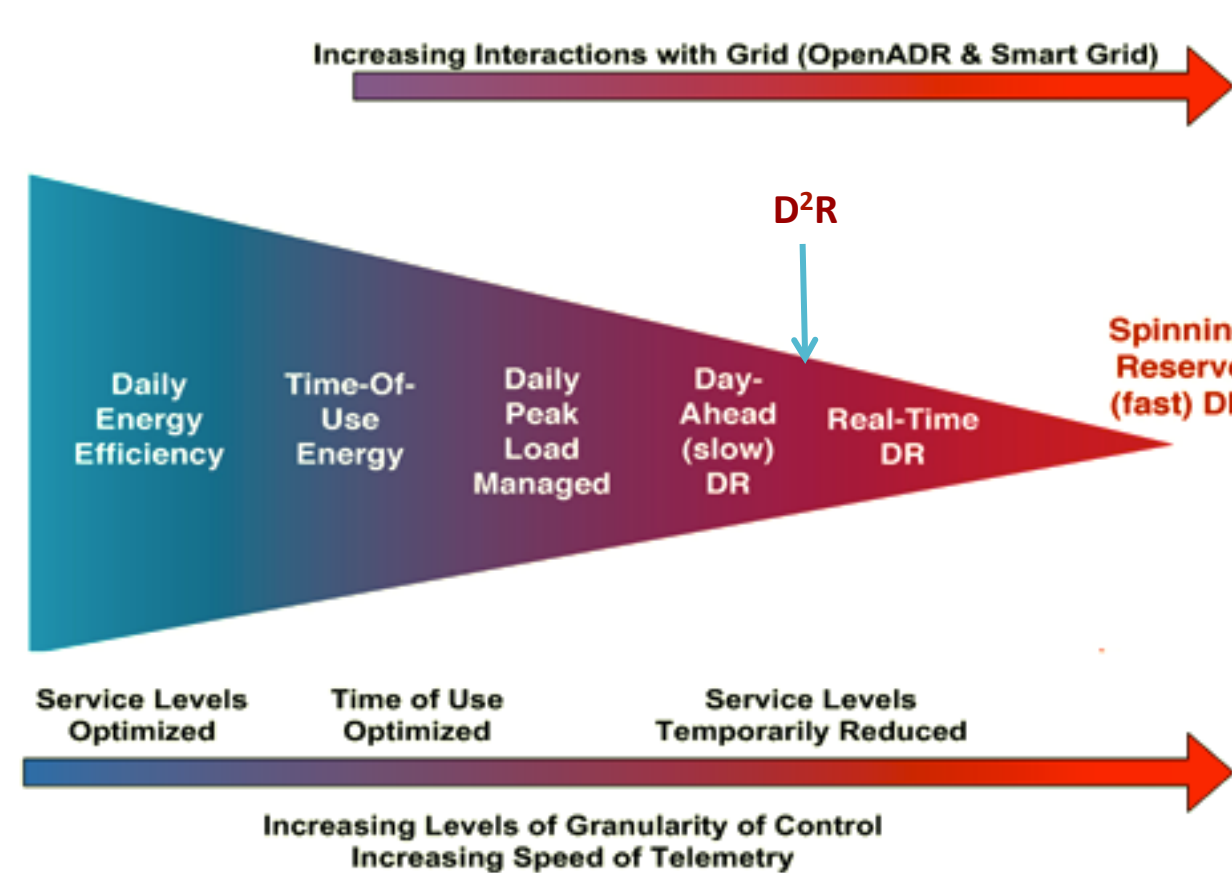
### Demand Response (DR)

Adjustment of electricity consumption during peak load periods in response to a signal from the utility, via

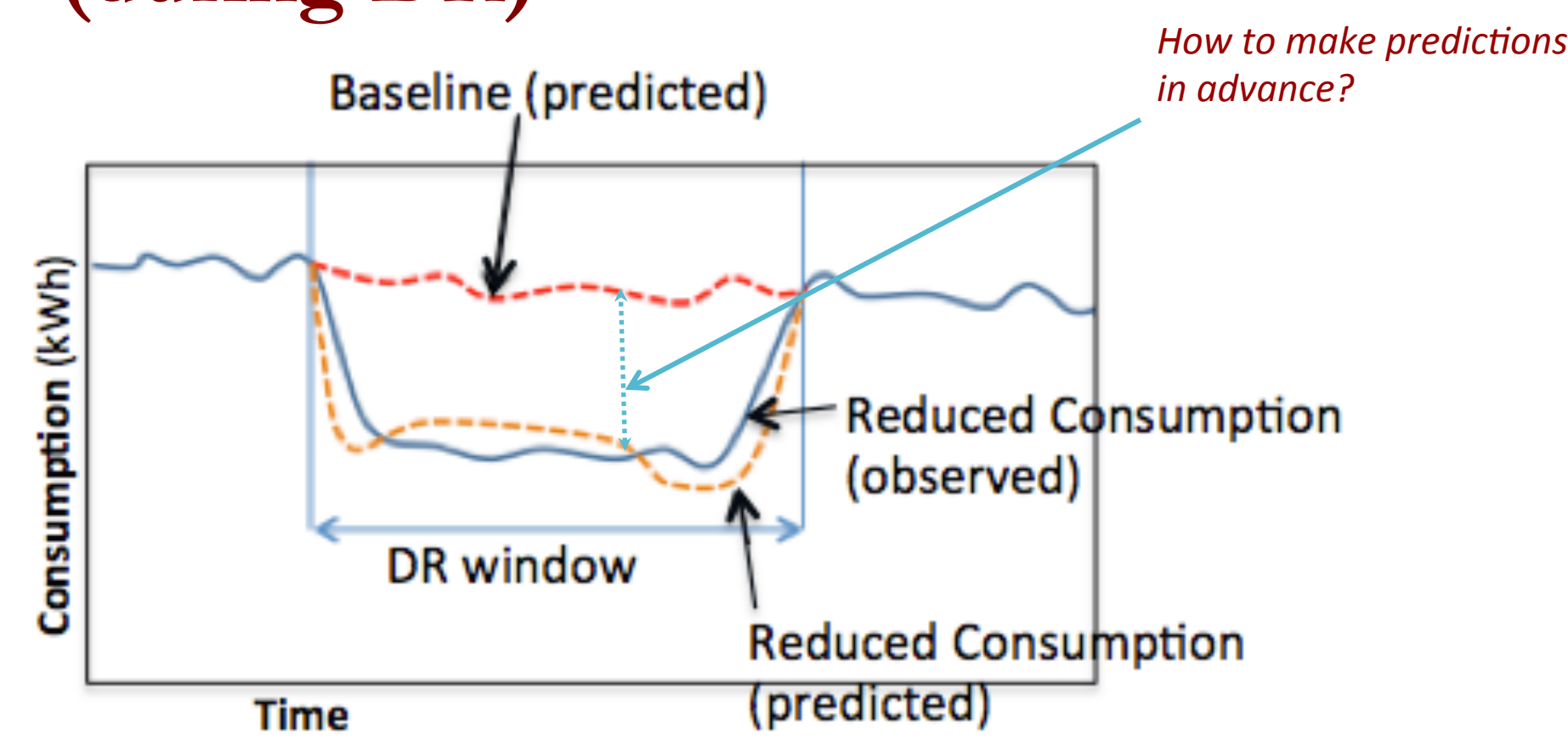
- direct control, or
- voluntary participation

### Dynamic Demand Response (D<sup>2</sup>R)

Deals with the decision making about **when**, by **how much** and **how** to reduce electricity use by the demand side.



## Reduced Consumption Prediction (during DR)

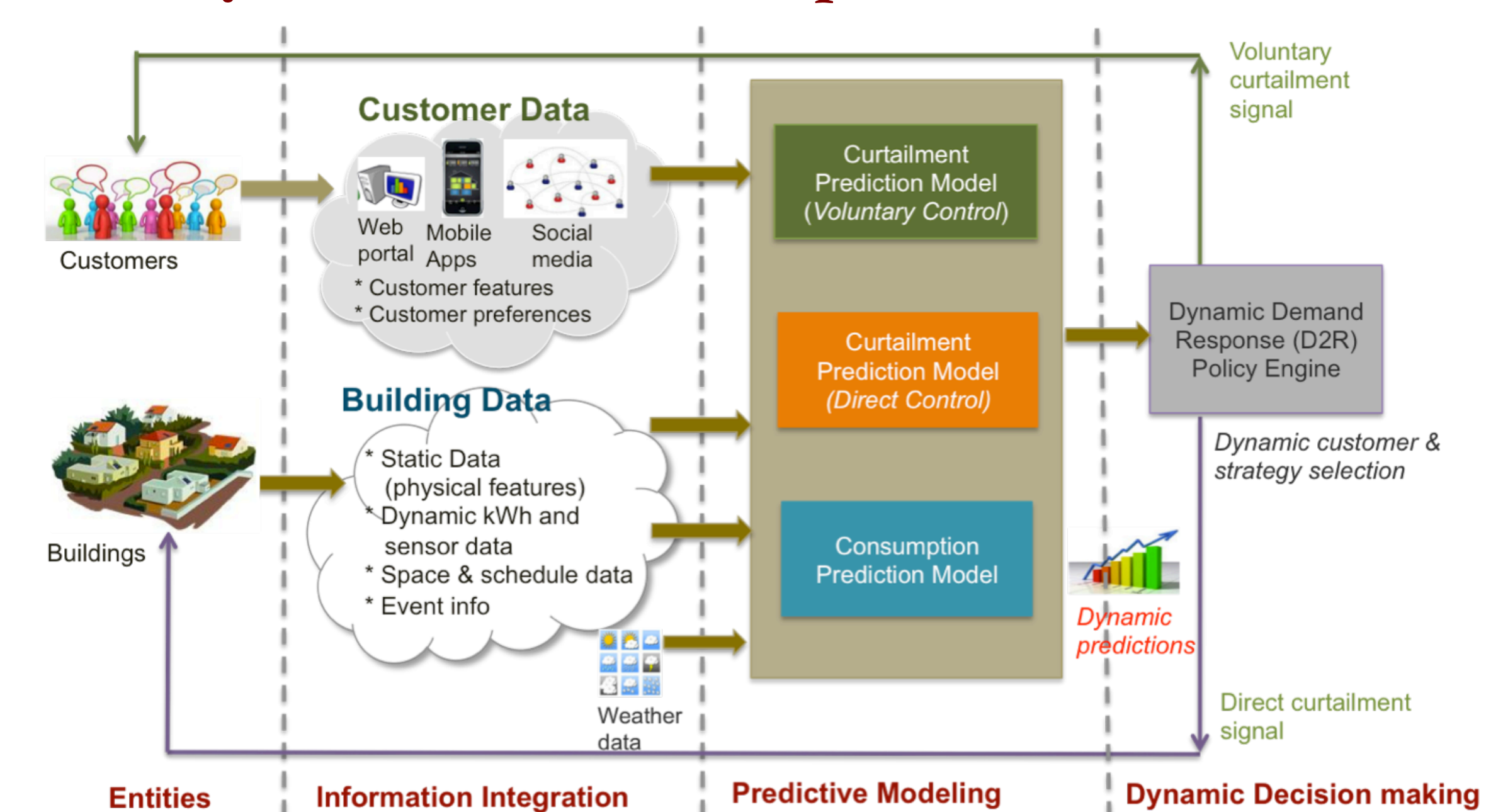


- Existing approaches focused on baseline prediction
- Sudden change in consumption profile
- DR events are not cyclic as they are scheduled when necessitated by energy demand or weather conditions

First to address reduced consumption prediction problem

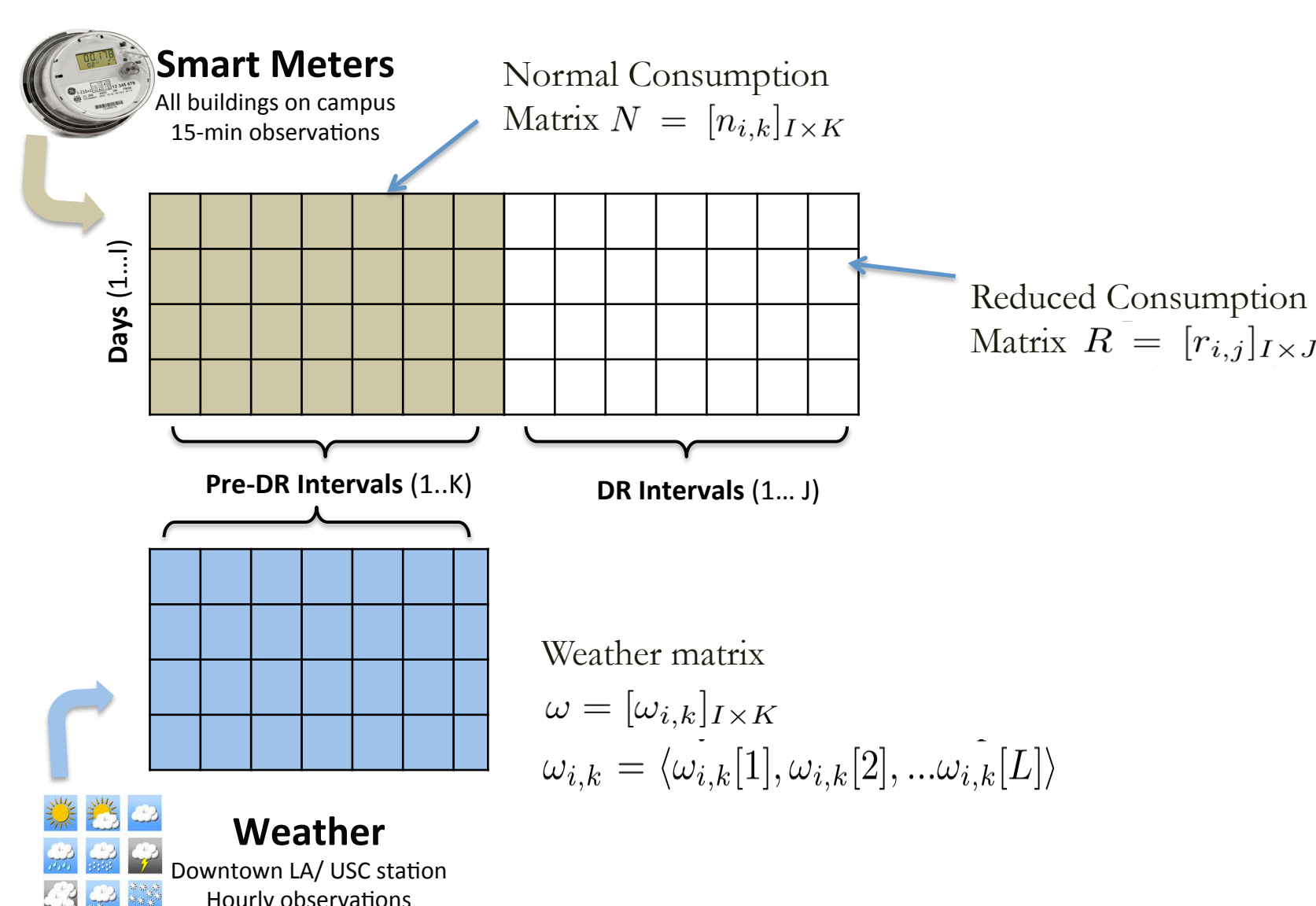
Traditional time series methods are not applicable

## Dynamic Demand Response Framework



- Reduced consumption prediction is used to estimate curtailment in energy consumption during DR
- Estimates help in planning for DR
- Used to select buildings and strategies for DR
- Useful for assessing success of a DR event

## Problem Formulation and Approach



### Historical Averaging - *HistAv*

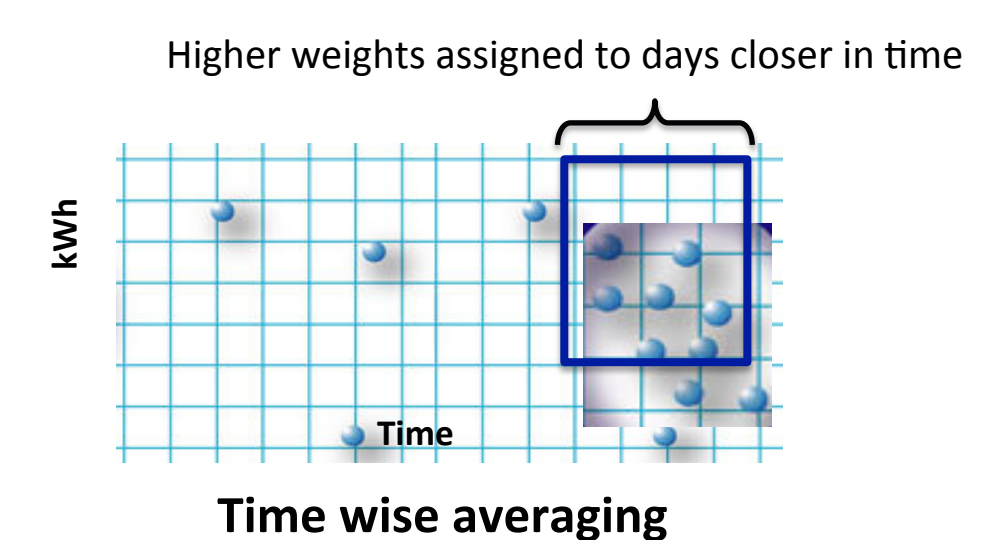
- Predicted Values during DR period are equal to the average of all historical values
- Motivation: Not enough DR events for each <building, strategy> combination. Hence, an averaging of all events is a practical approach.

### Weighted Averaging - *WtdAv*

- Predicted values during DR period are equal to the weighted average of all historical values

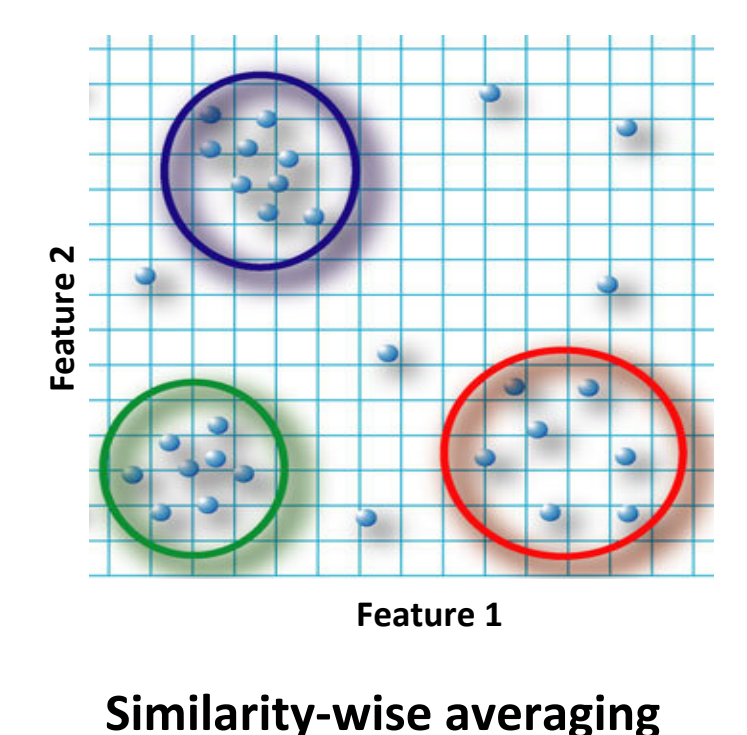
### Time-wise Weighted Averaging - *WtdAvTi*

- Weights decrease exponentially with time

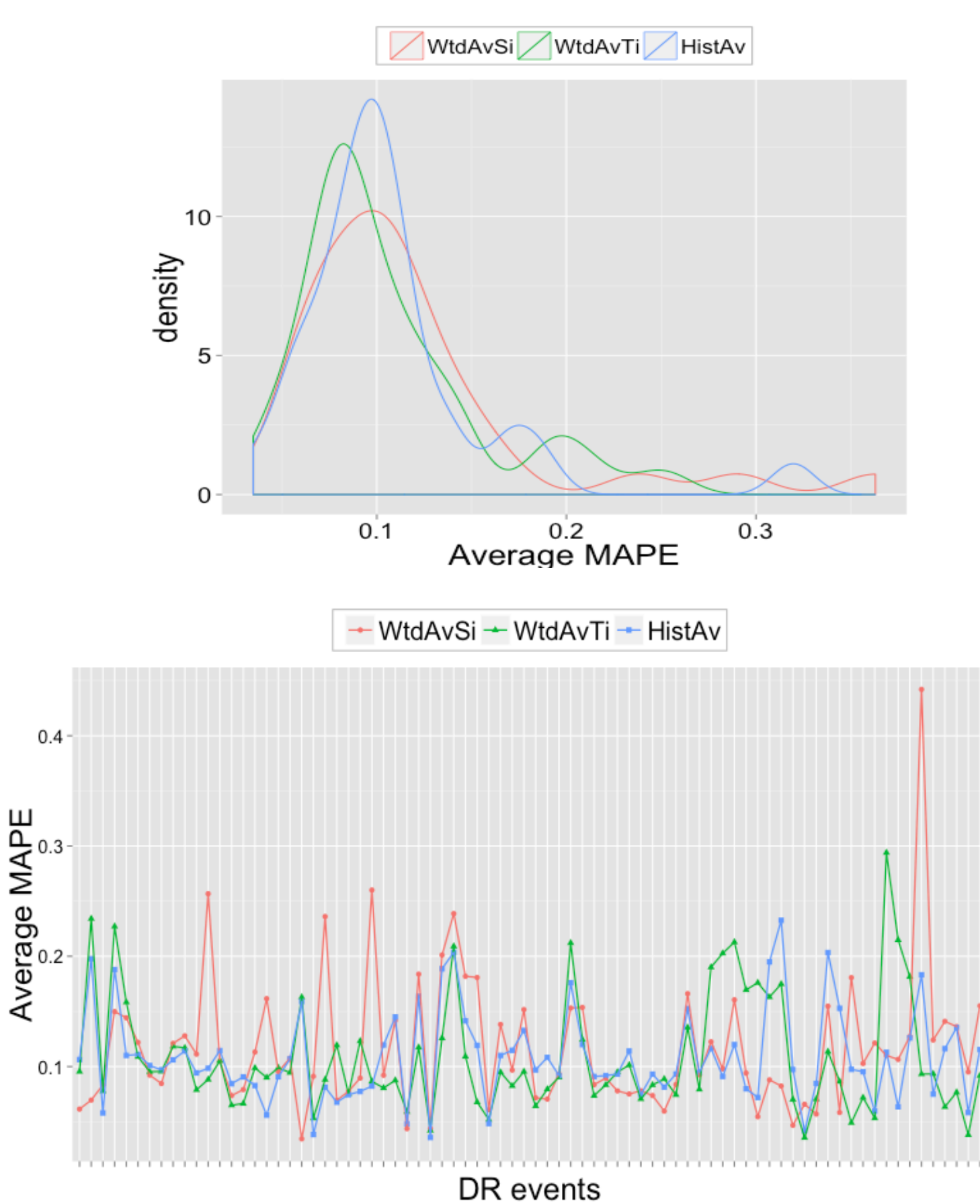


### Similarity-wise Weighted Averaging - *WtdAvSi*

- Each day is represented as feature vector (kwh, weather, calendar)
- Similarity is defined as distance between feature vectors
- Weights decrease exponentially with decreasing similarity

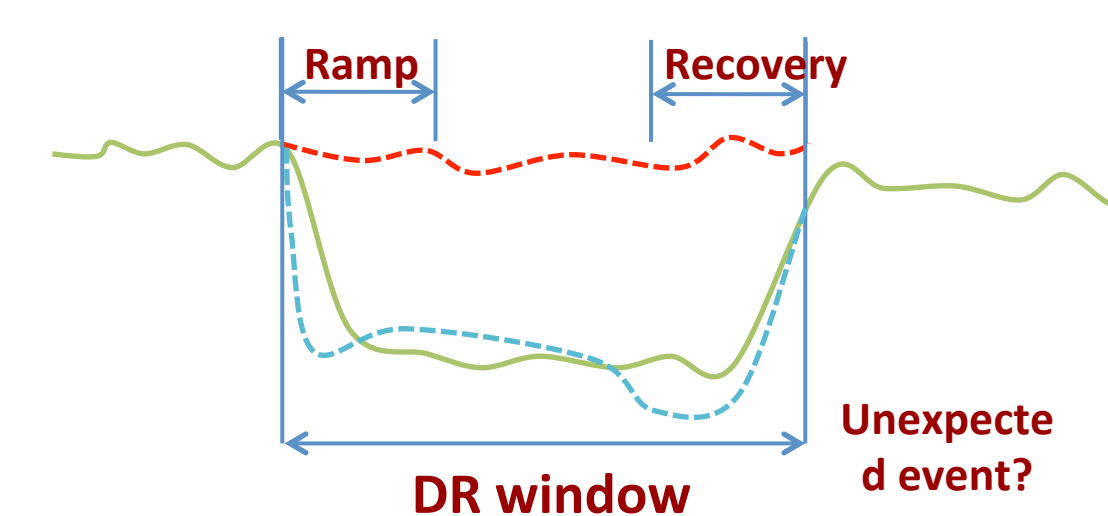


## Experiments and Results



## Challenges

- Small number of historical observations
- Volatile and irregular consumption profiles
- Small shifts in usage affect curtailment
- Ramp period: Abrupt change for each customer starts at different times after a DR is initiated
- Recovery period: Abrupt change towards the end of DR also varies for each customer
- Unexpected events: e.g., automatic restart of HVAC units due to temp rising over a pre-defined threshold
- Reduction in consumption varies:
  - per customer for a DR event day
  - per DR event for each customer



## Future Work

- Explore similarity based on more important features.
- Use dimensionality reduction to identify important features and then select similar days for averaging
- Combine models in an ensemble for better performance
- From micro-grid to city-scale: Apply reduced consumption prediction methods for individual consumers in the city of Los Angeles.

## ACKNOWLEDGEMENT



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