

Behavioral Energy Profile Analysis based on Mixed Model and Causal Network Estimation

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Motivation

Occupant behavior and related energy consumption are important inputs to the control and simulation of smart buildings. With a predictive occupant model, the prediction of energy consumption can be further refined, and the stochastic flexibility of the model also provide a hint for occupancy scheduling. Further, the estimation of the **interaction between occupancy behavior and device networks** will not only give us energy consumption for each individual in a disaggregated manner, but also can serve as “characters” of certain individual, and inspire possible control strategies.

The difficulties are the *nonhomogeneous nature* of occupant activities with time evolution, and the *asymmetric nature* of the relationship between Occupant behavior and devices.

Main Objectives

The analysis of behavioral energy profile involves three main modeling aspects:

Occupancy Model

Model individual activity as well as group dynamics
Find possible association among occupancies

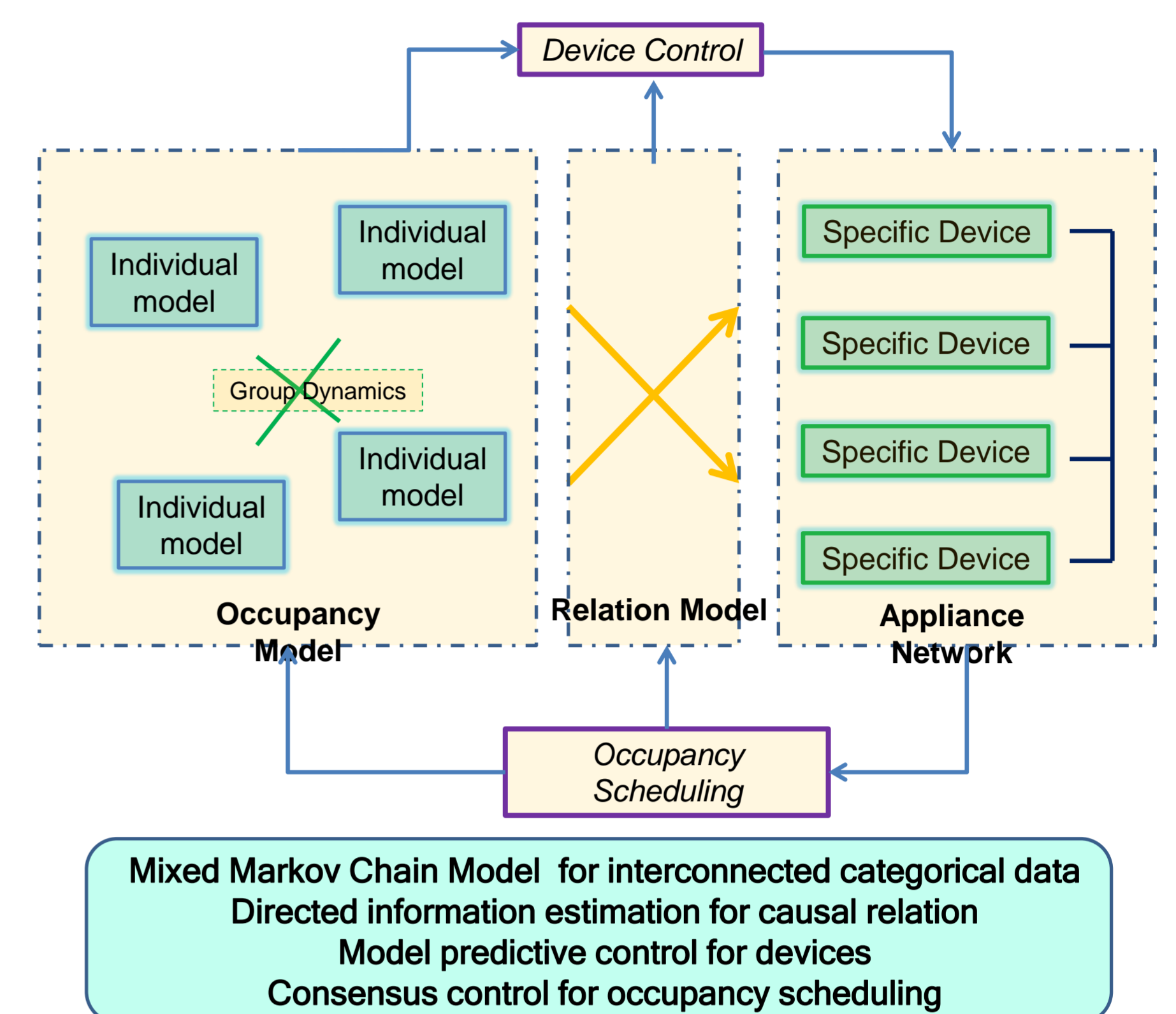
Relation Model

Estimate quantified relation between individual activities and appliance usage. Build a network model.
Address occupant energy profile in a disaggregated way

Device network control model

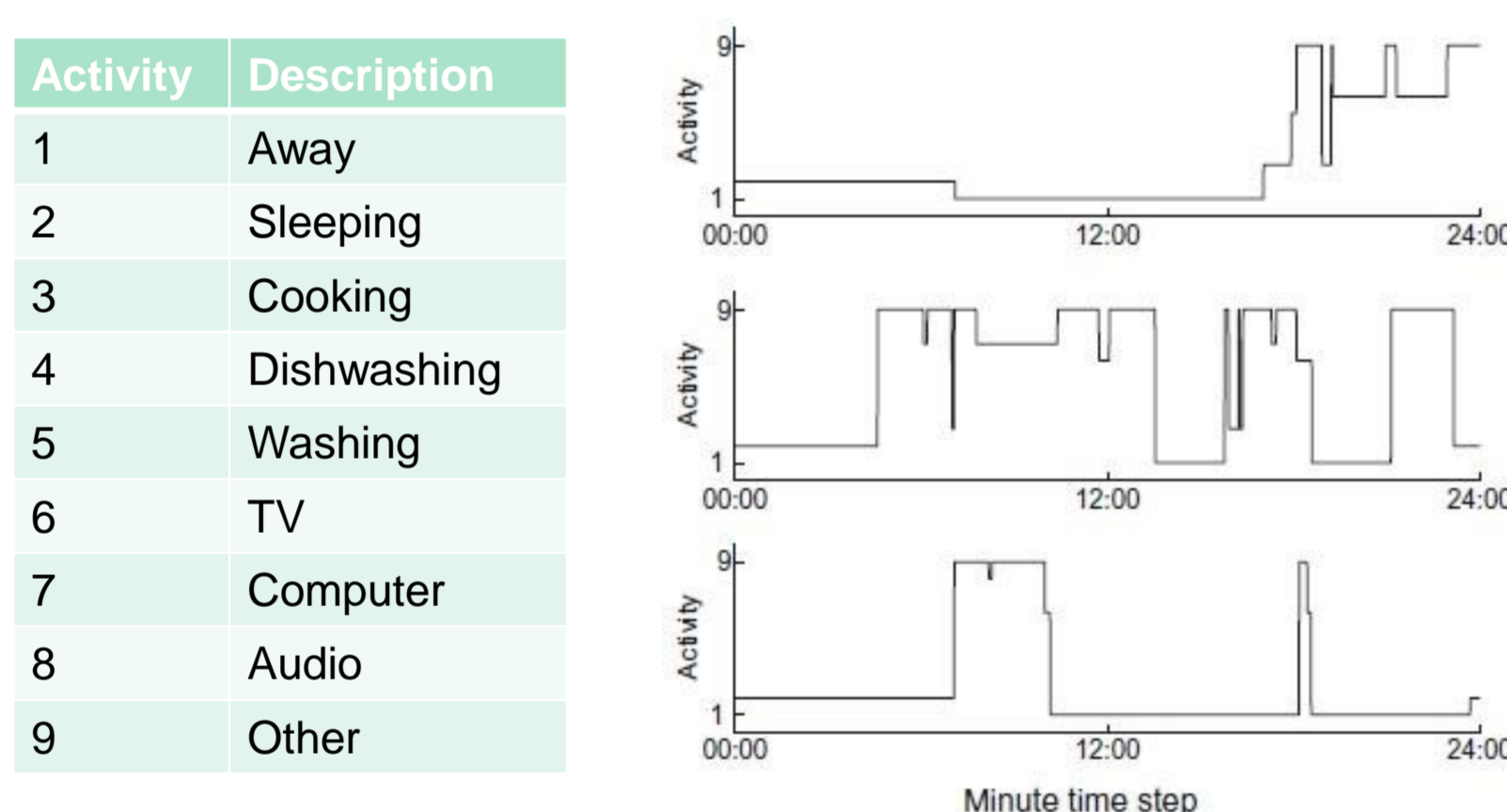
Energy saving through occupancy scheduling
Optimal usage of devices with occupancy constrains

Overall approach



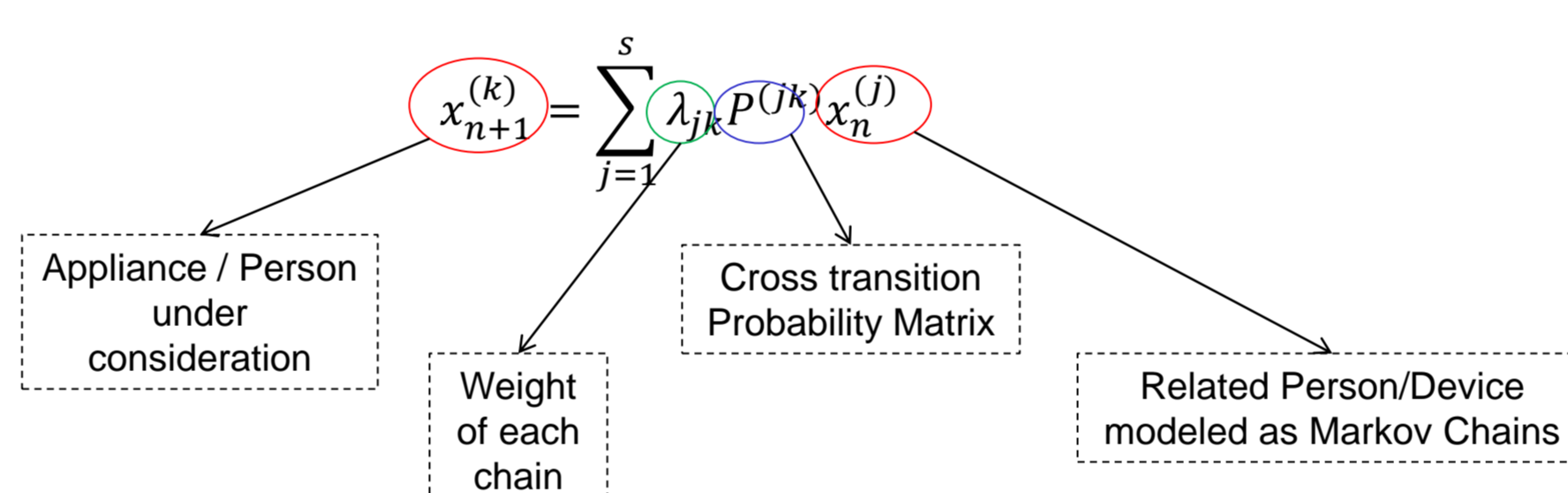
Occupancy activity Description

- High resolution discrete **Categorical** activity description
- Enable Non homogeneous Markov Chain to model the transition of activities for a single occupancy



A Mixed Markov Chain Model

- Consider **interaction** among occupancy and group dynamic
- Preliminary **estimation of relation** among occupancy and between occupancy and devices
- Naturally capture the **nonhomogeneous** character of the data by adding “**Dummy Chains**”
- Enable **prediction** from observation of related chains



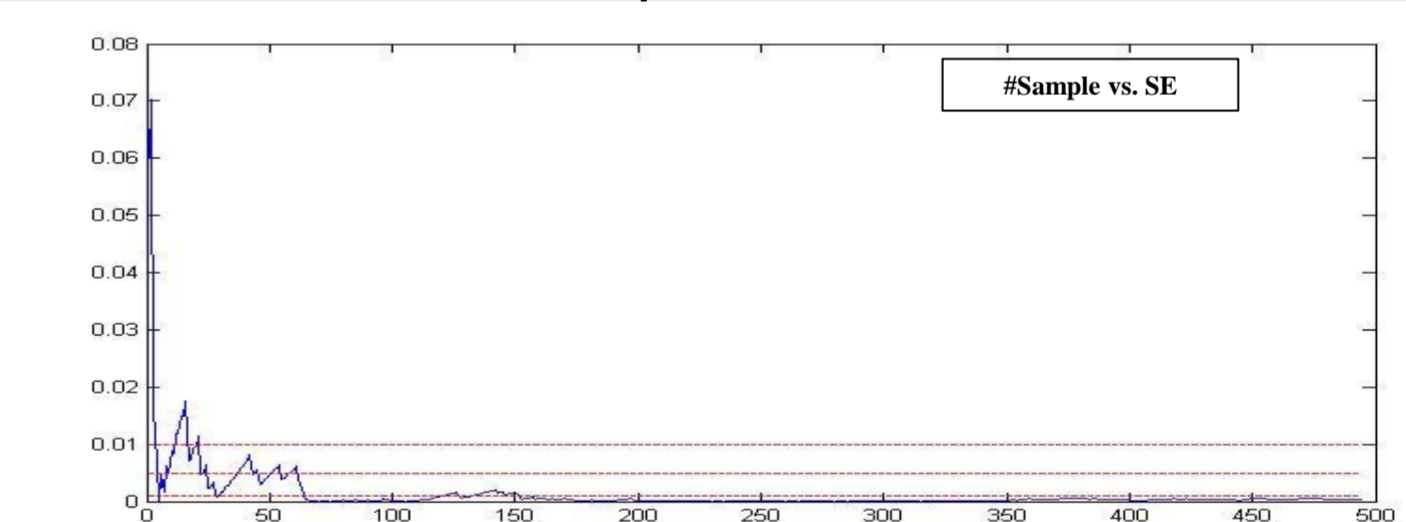
Parameter Estimation for MMC Model

Parameter estimation for p^{jk} : frequency; Parameter estimation for λ_{jk} : linear programming

$$P^{(k)} = \begin{pmatrix} f_{11}^{(k)} & \dots & f_{1m}^{(k)} \\ \vdots & \ddots & \vdots \\ f_{m1}^{(k)} & \dots & f_{mm}^{(k)} \end{pmatrix}, \quad \hat{P}^{(k)} = \begin{pmatrix} \hat{p}_{11}^{(k)} & \dots & \hat{p}_{1m}^{(k)} \\ \vdots & \ddots & \vdots \\ \hat{p}_{m1}^{(k)} & \dots & \hat{p}_{mm}^{(k)} \end{pmatrix}$$

subject to $\sum_{k=1}^m \lambda_{jk} = 1$, and $\lambda_{jk} \geq 0, \forall k$.

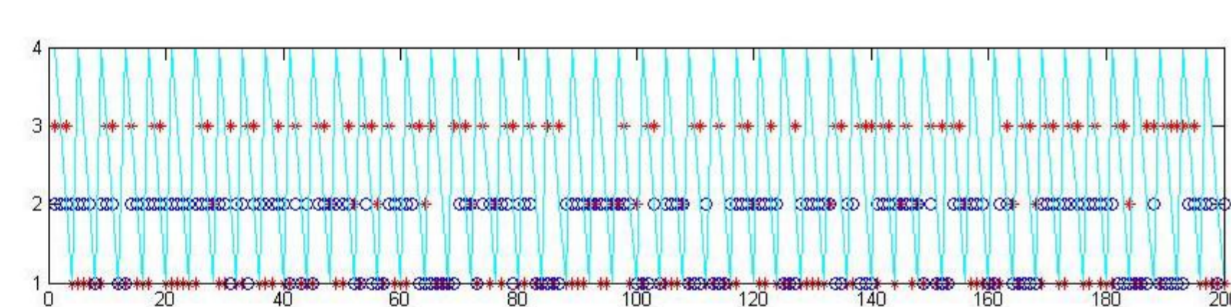
Estimation Convergence Result: sample size vs. total squared error



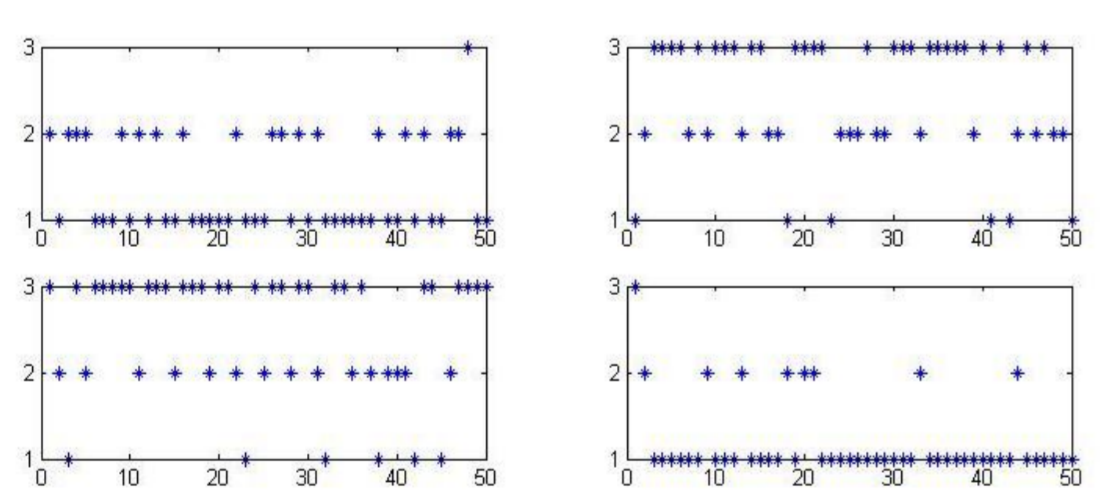
Dummy Chain to Capture Nonhomogeneous character

Model contributing factors and as “Dummy Markov Chains” and use mixed model to describe the chain of interest.

Case study: periodical laptop states simulated by MMC with time as “dummy” chain

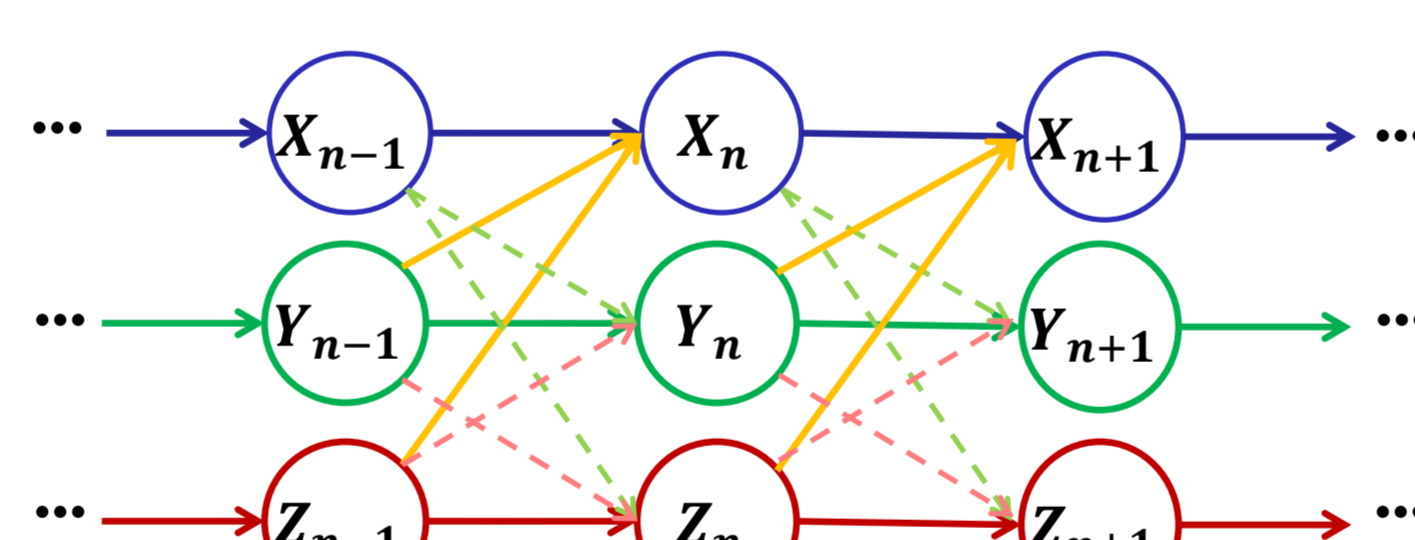


nonhomogeneous or seasonal variations can be easily captured and described in an unified model instead of specifying at each step a different transition probability matrix



24 hours laptop status with 1: off 2:sleep 3: on

Use MMC to estimate occupant impact on a specific device



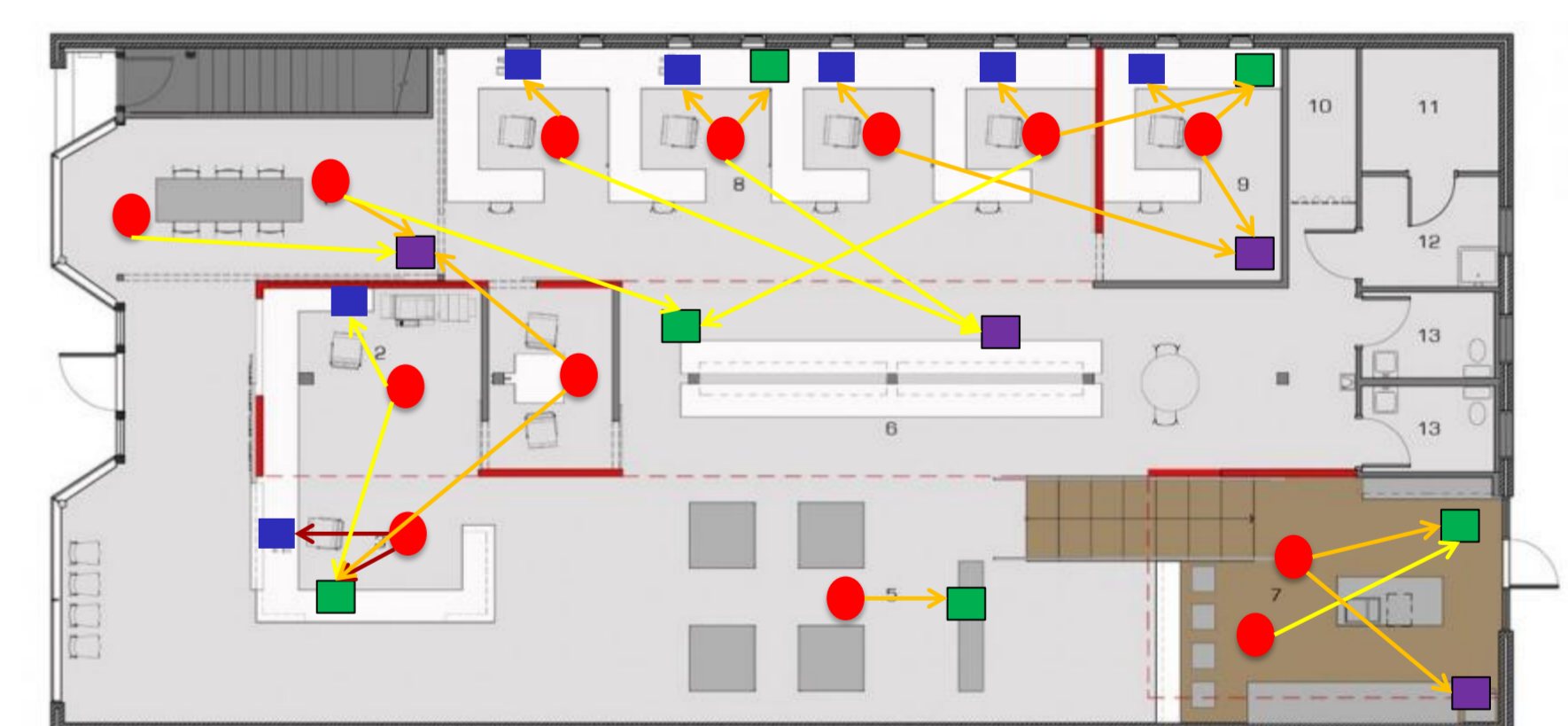
X_n : Device under consideration
 Y_n : Occupant activities
 Z_n : other contributing factors as dummy chains

OPTIMIZATION PROBLEM:	
OPTIMIZATION VARIABLES:	
0.4154	0.4343
0.3058	0.5230
0.0000	0.0000
0.2308	0.5435
0.0769	0.4545

Simple case: My activity determines the states of my laptop
 $y_{n+1} = p^{(1,1)}y_n$
 $x_{n+1} = p^{(1,2)}y_n$

Network causal relation estimation

- Establish the causal relation from occupancy to appliance usage/device energy consumption so we can:
- disaggregate and estimate energy consumption for each individual
 - Predict energy consumption based on occupant behavior data
 - Energy usage control based on occupant scheduling



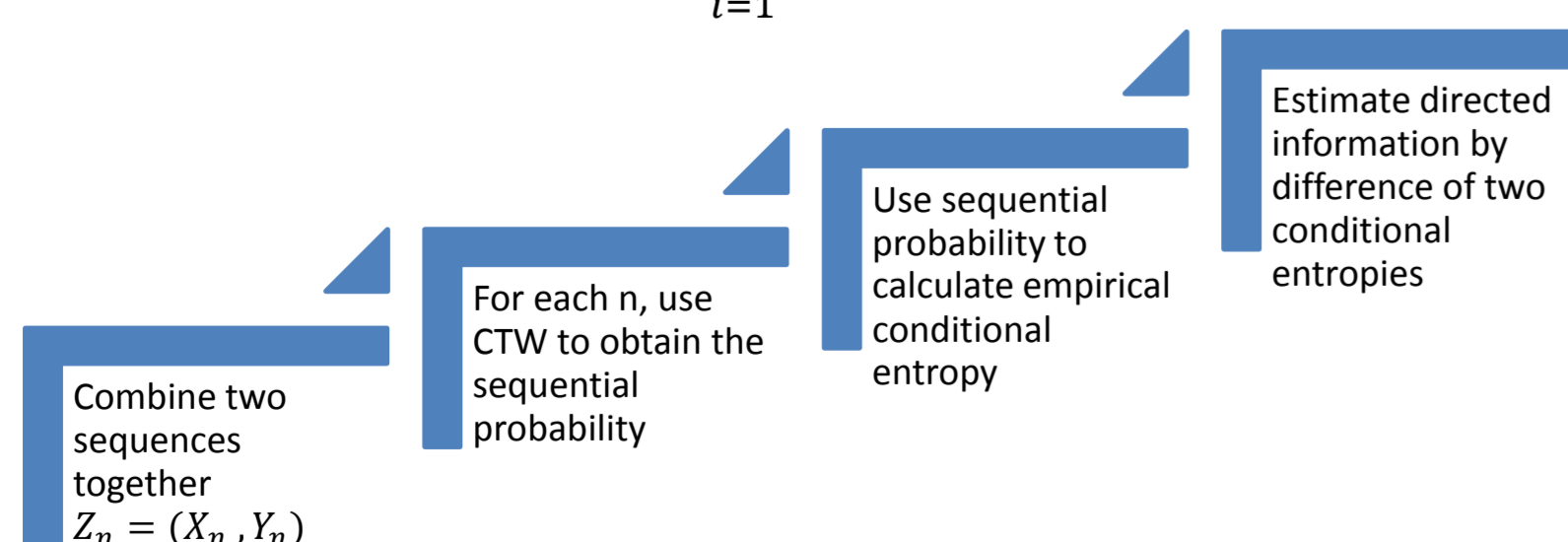
Causal relation estimation: Directed Information

In order to measure the causal influence from sequence X to sequence Y , define directed information as

$$I(X^n \rightarrow Y^n) = H(Y^n) - H(Y^n | X^n)$$

With conditional entropy defined as

$$H(Y^n | X^n) = \sum_{i=1}^n H(y_i | y^{i-1}, x^i)$$



Conclusion and References

- Proposed a mixed Markov formulation to model nonhomogeneous occupancy activities. Established a optimization based method to estimate model parameters
- Use mixed Markov model to analyze occupant impact on energy consumption of certain devices. Preliminary relationship model can be abstracted along the way.
- For multi-dimensional causal relation estimation, we proposed a framework using directed information estimation.

References:
1) Joakim Widen, Ewa Wachelgard, “A high-resolution stochastic model of domestic activity patterns and electricity demand.” Applied Energy 87 (2010) 1880-1892.
2) Wai-Ki Ching, Eric S. Fung, Michael K. Ng, “A multivariate Markov chain model for categorical data sequences and its applications in demand predictions.” IMA Journal of Management Mathematics (2002) 13, 187-199
3) J. Massey, “Causality, feedback and directed information.” Proc. Int. Symp. Inf. Theory Applic. (ISITA-90)
4) F. Williams, “The Context-Tree Weighting Method: Extensions”, IEEE Trans. On Inf. Th. Vol44, No.2, Mar. 1998, pp 792-798

Future Goals

- Data acquisition and further validation of the proposed method
- Propose a prediction framework for energy consumption based on occupancy modeling
- Establish a quantified measure for the causal network, variations of directed information
- Examine the efficiency of parameter estimation involved in our framework
- Consider control strategies with the knowledge of occupant activity and response model