Enabling Building Energy Auditing Using Adapted Occupancy Models

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BuildSys 2011

HVAC Systems

Heating, Ventilation and Air-Conditioning (HVAC) systems account for majority (≈50%) of building energy consumption (2008)*.

- Assumption: Condition based on maximum room occupancy
- Rooms are often unoccupied or partially occupied
- Leads to inefficient environmental conditioning
- Optimize energy usage using systems that actuate using occupancy models

Alternatively, ensure that buildings adhere to the strictest energy efficiency standards.

* **Source: Building Energy Data Book (http://buildingsdatabook.eren.doe.gov/docs/htm/1.1.4.htm)**

So where are all the green buildings?

Figure: South Hall - UC Berkeley (built 1873)

- Majority of existing buildings are older than 20 years.
- Do not meet current energy efficiency construction standards.
- Impact long-term energy consumption.
- Energy audits: energy savings through retrofitting.

Building Energy Auditing

- Involves inspection and analysis of the energy consumption from utility bills.
- Deploy sensors on-site to measure and verify energy use.
- Onsite work takes 1-2 days.
- Data is input to DOE-2, EnergyPlus, etc. to evaluate and recommend energy retrofits.

Further, maximize energy savings by including occupancy model information within energy audits.

Occupancy model caveats

- Large training datasets (weeks, months).
- Models are specific to the building.
- Therefore, for all other buildings, again collect large training dataset.

Problem Statement

How can we maximize energy savings by using occupancy models in building energy audits when collecting only 1-2 days of occupancy traces?

Occupancy Modeling

- Modern buildings have submetering systems, electronic locking systems, etc.
- Use of wireless sensor networks for other buildings:
  - PIR sensors - binary indicators.
  - Camera sensors - people counters.
- Data collection goal: collect data for 1-2 days.

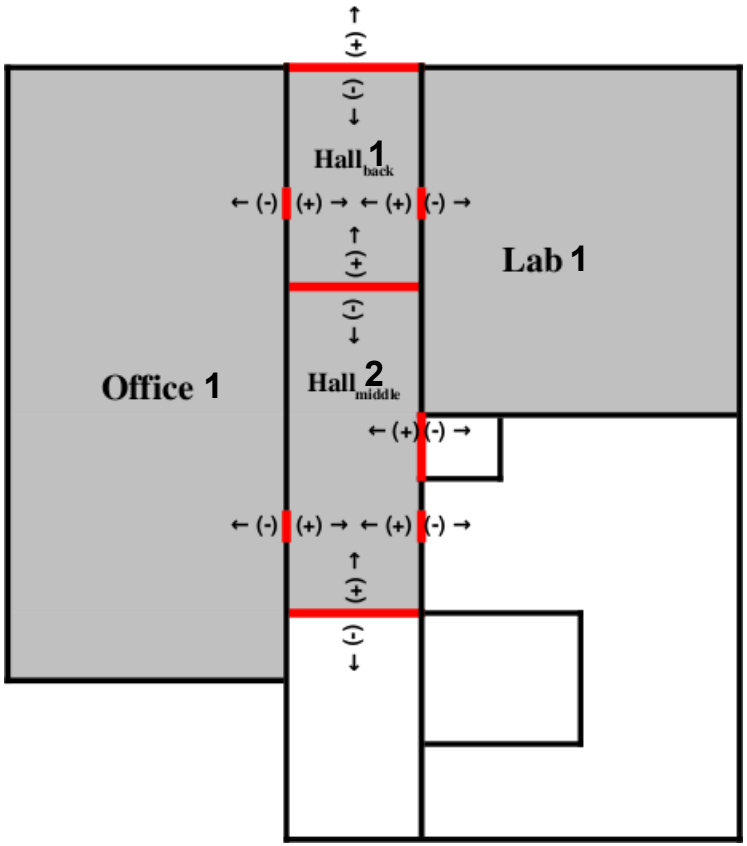
Proposed Approach

Use a **reference building occupancy model** that has been trained with extensive data and adapt it to the new building given a far **smaller occupancy data trace** than would be necessary to train a new model from scratch.

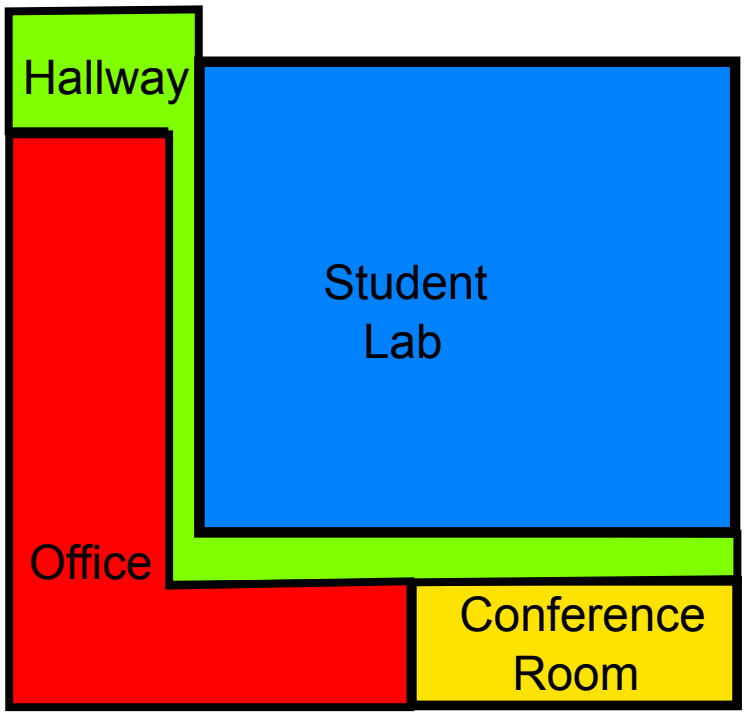
Reference Model

- Mixture of multivariate Gaussians (M) components in place of a single multivariate Gaussian for every hour.
- Parameters: means (μ) and covariance matrix (Σ) for each hour.
- $(D+1)M + D^2 - 1$ parameters for every hour ($D = \#rooms$).
- Use Expectation-Maximization (EM) algorithm for parameter estimation (**Retraining**).

Reference and Adaptation Model Datasets

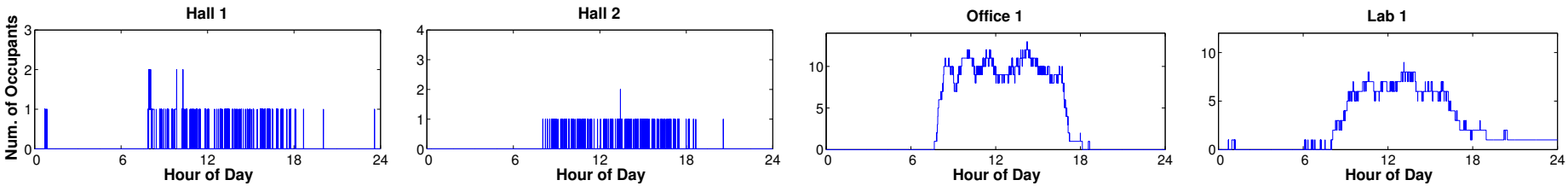


(a)
Reference

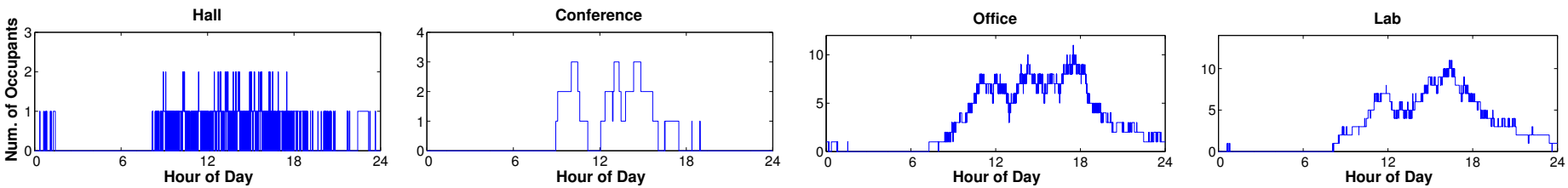


(b)
Adaptation

Reference and Adaptation Model Datasets



(a) Reference Dataset Room Occupancy



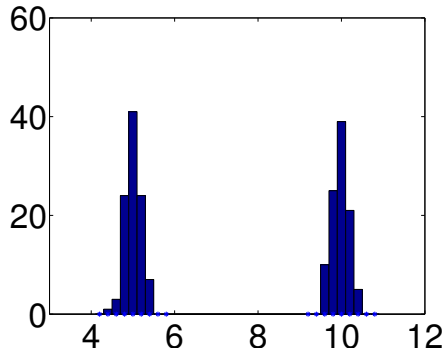
(b) Adaptation Dataset Room Occupancy

Figure: Room occupancy averaged over the length of dataset (5-days) for every hour for the reference model (a) and adaptation (and retrained) model (b), respectively.

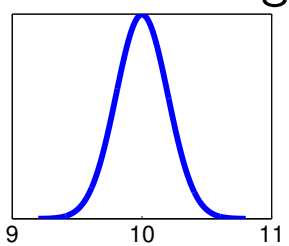
Adapted Model

- Assumptions: Well-trained reference model and occupancy data for target (audited) building.
- **Adaptation Approach: Tie the means of the reference model using a non-linear transformation**.

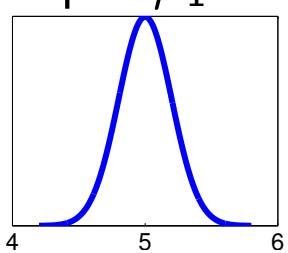
Adaptation Illustration with 2 Rooms



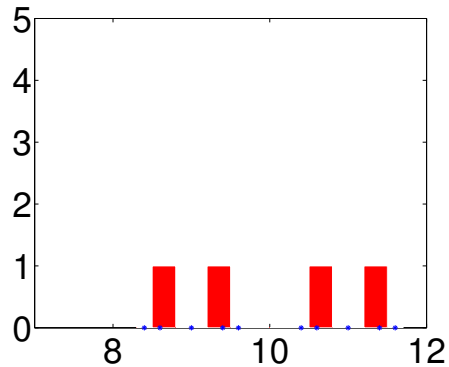
Ref Data Histogram



Comp 1 $\mu_1 = 10$

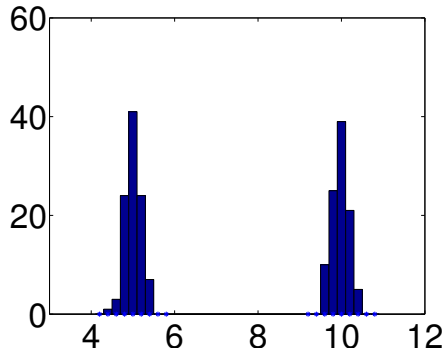


Comp 2 $\mu_2 = 5$

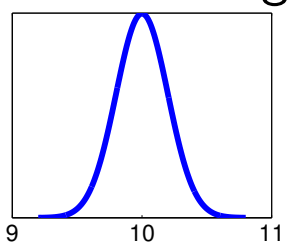


Adapt Data Histogram

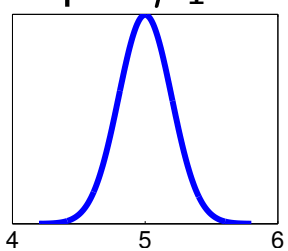
Adaptation Illustration with 2 Rooms



Ref Data Histogram



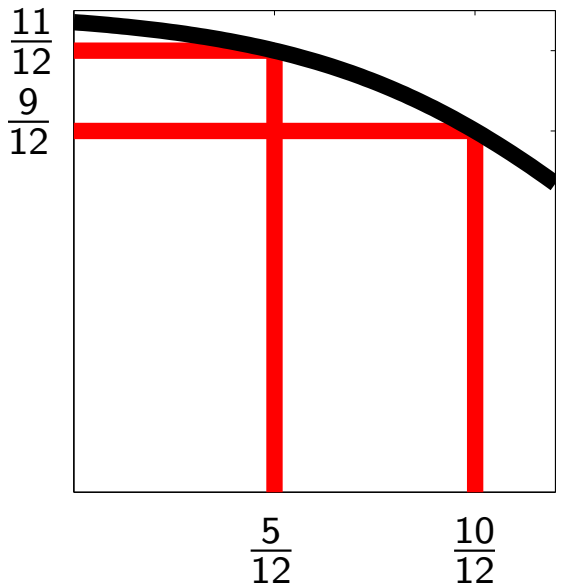
Comp 1 $\mu_1 = 10$



Comp 2 $\mu_2 = 5$

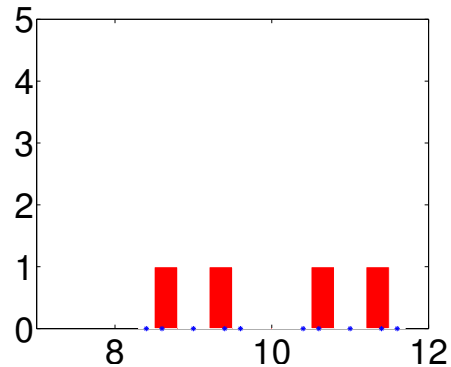
$$\widetilde{\mu_d} = \frac{O_m}{1+e^{-(a\mu_d/O_m+b)}}$$

a = –3.1183 b = 3.6972

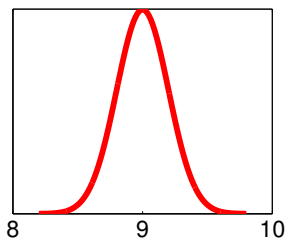


Sigmoid Transformation

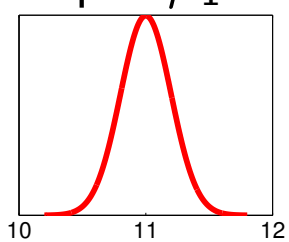
$O_m = 12$



Adapt Data Histogram



Comp 1 $\widetilde{\mu}_1 = 9$



Comp 2 $\widetilde{\mu}_2 = 11$

Adapted vs Retrained Model

- The objective function is the log-likelihood of the adaptation data given the constrained MVGM with $3M - 1$ free parameters:

$$L\left(\{\widetilde{\pi}_m, a_m, b_m\}_{m=1}^{M}\right) = \sum_{n=1}^{N} \log \sum_{m=1}^{M} \widetilde{\pi}_m p(\mathbf{x}_n; a_m, b_m)$$

- Adaptation: $3M - 1$ adaptation parameters.
- Retraining objective function

$$L\left(\{\widetilde{\pi}_m, \mu_{hm}, \Sigma_h\}_{m=1}^{M}\right) = \sum_{n=1}^{N} \log \sum_{m=1}^{M} \widetilde{\pi}_m p(\mathbf{x}_n; \mu_{hm}, \Sigma_h)$$

- Retraining: $(D+1)M + D^2 - 1$ parameters for every hour.

Modeling Performance

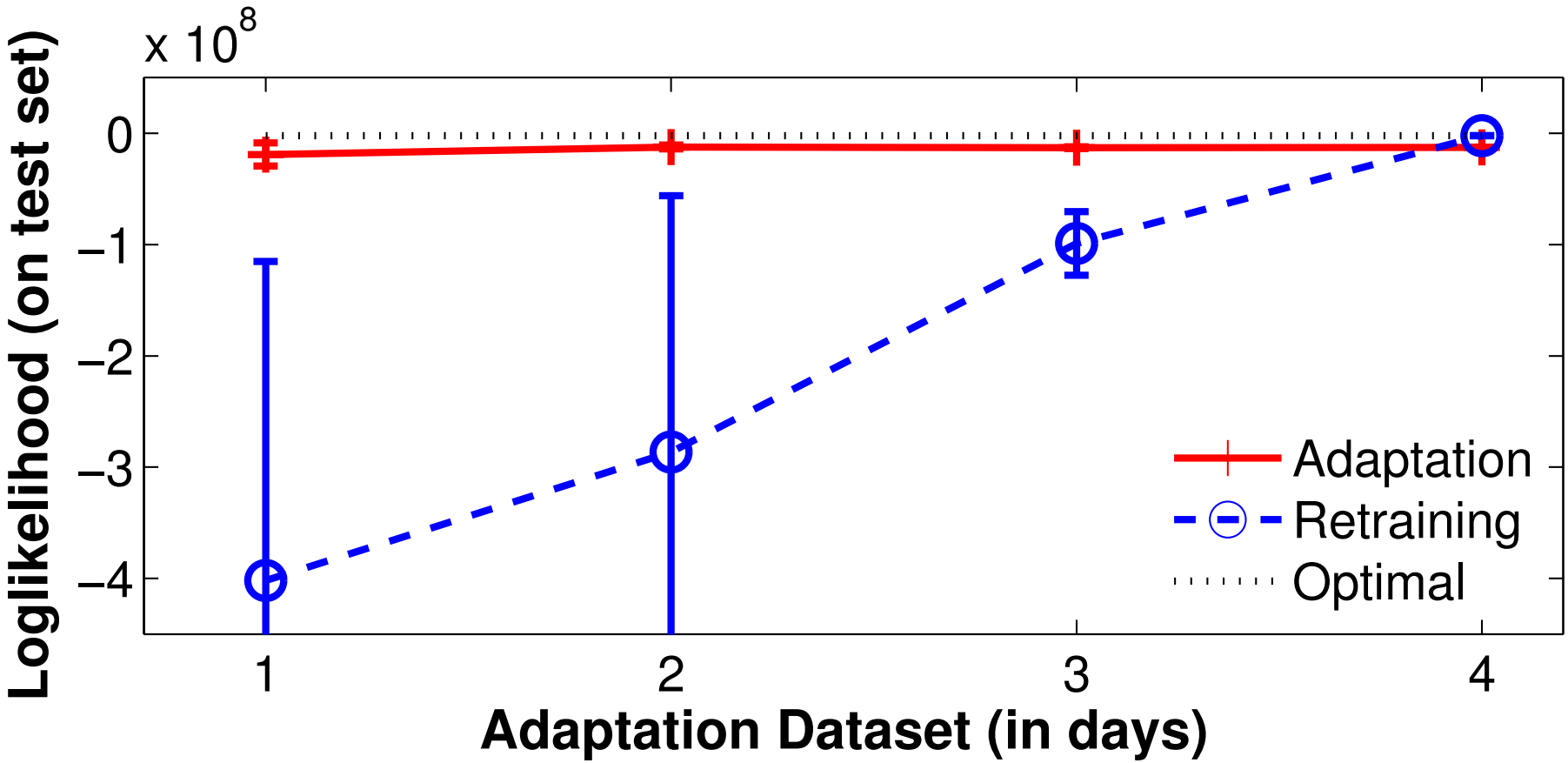
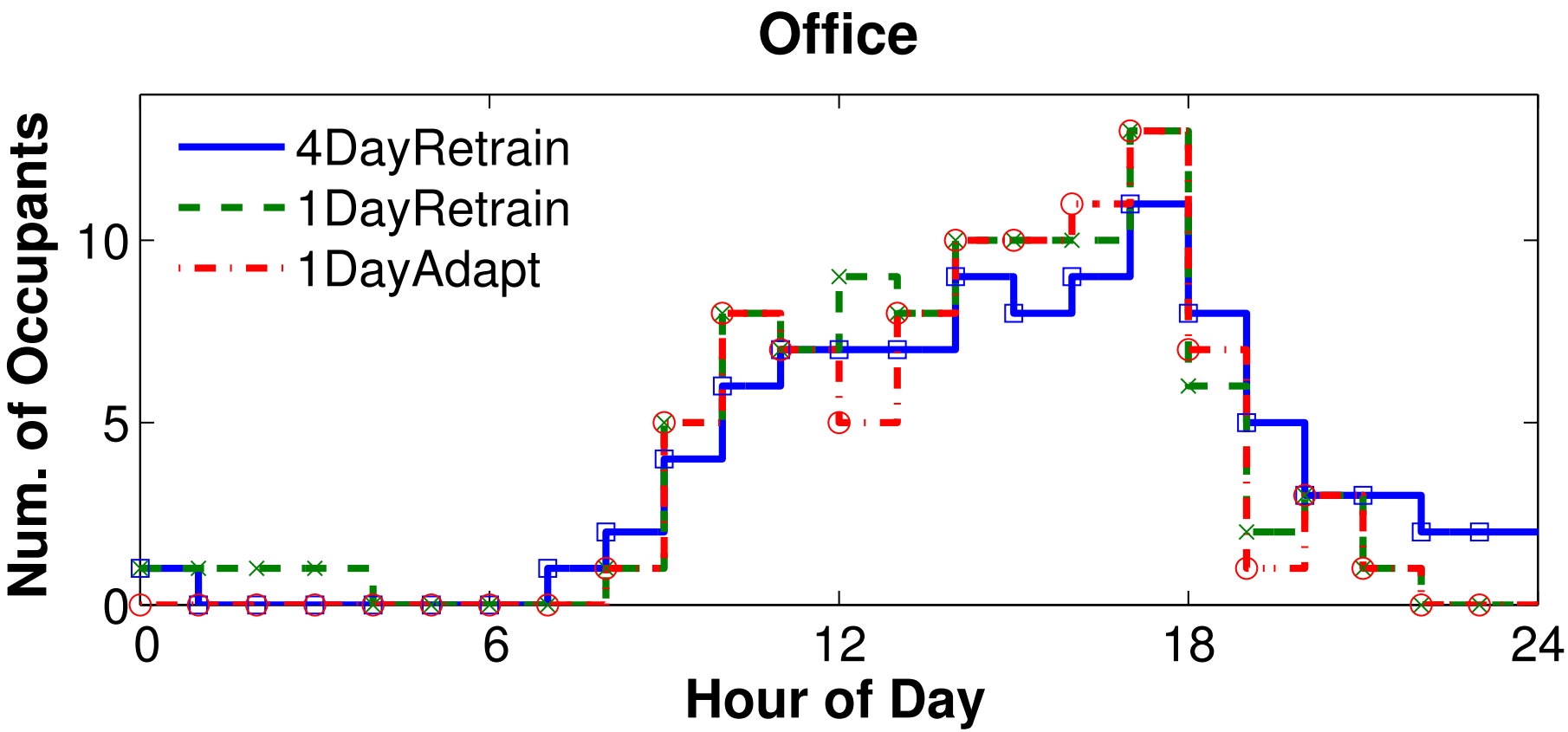
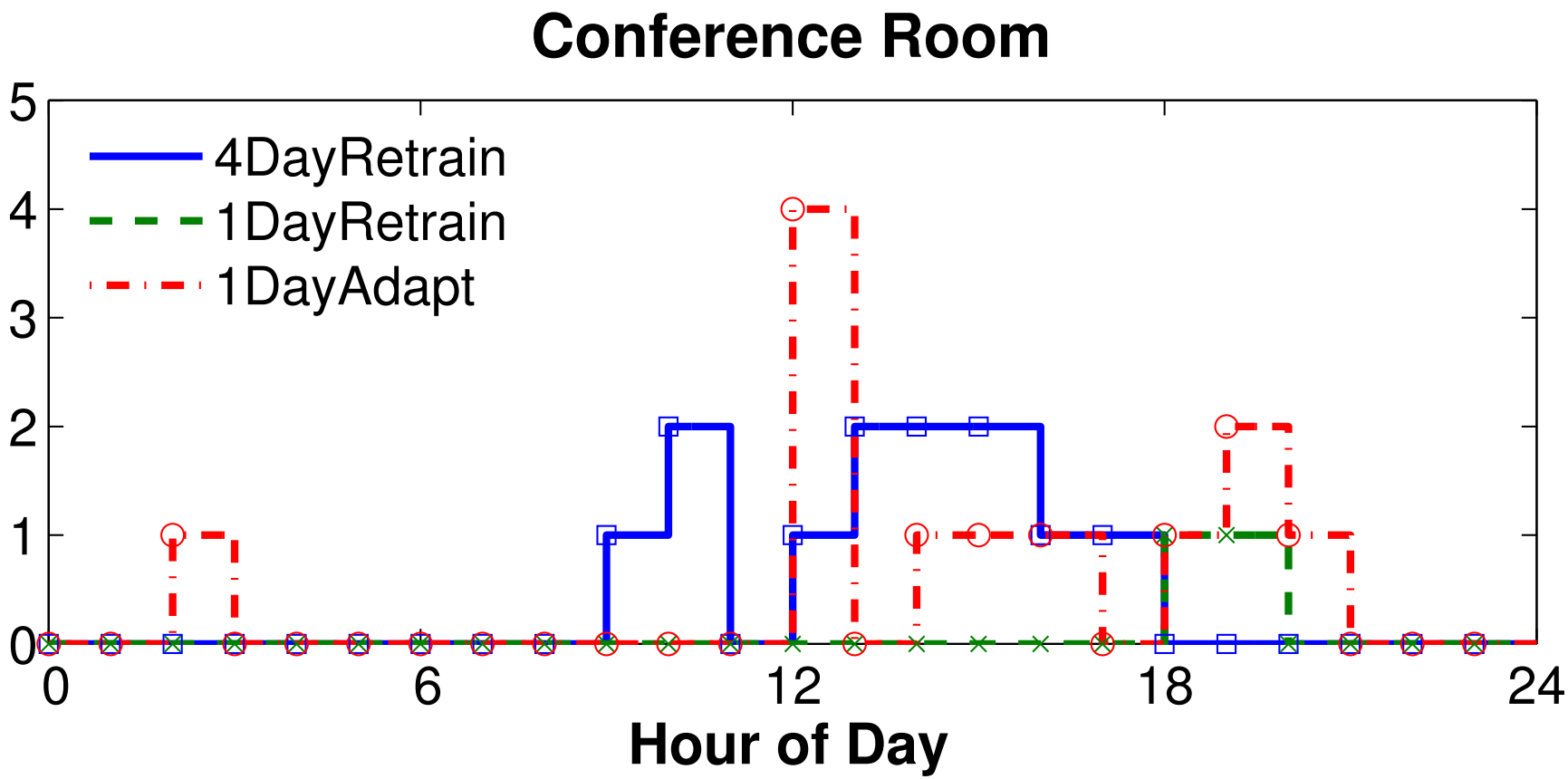


Figure: Log-likelihood of the different models as a function of the days in the adaptation dataset.

Estimated occupancy models



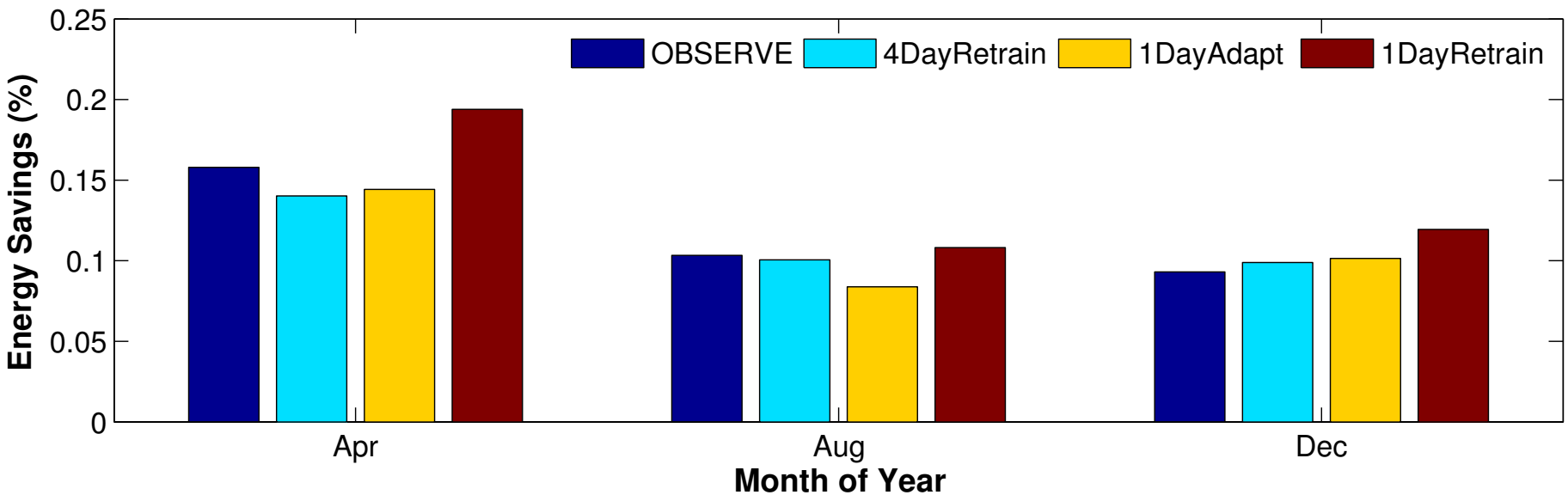
Estimated occupancy models



Building Energy Simulation Results

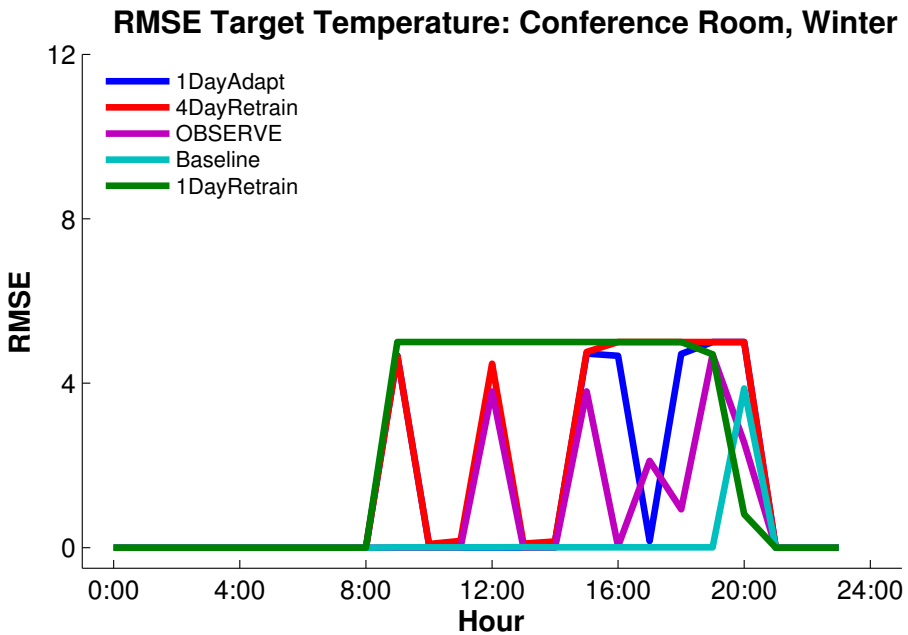
- Construct occupancy schedule using models 4DayRetrain (MVGM-R4), 1DayRetrain (MVGM-R1) and 1DayAdapt (MVGM-A1).
- EnergyPlus model of the building floorplan (total 32,000 sq.ft.) from which we have adaptation data for a Hall, Office, Lab and Conference room (approx. 12,000 sq.ft.)
- Compare to:
  - Baseline: maximum room occupancy between 7a.m.-10p.m. and is off at other times.
  - OBSERVE: Markov chain approach to model the temporal changes in occupancy of a building. Close to optimal conditioning.

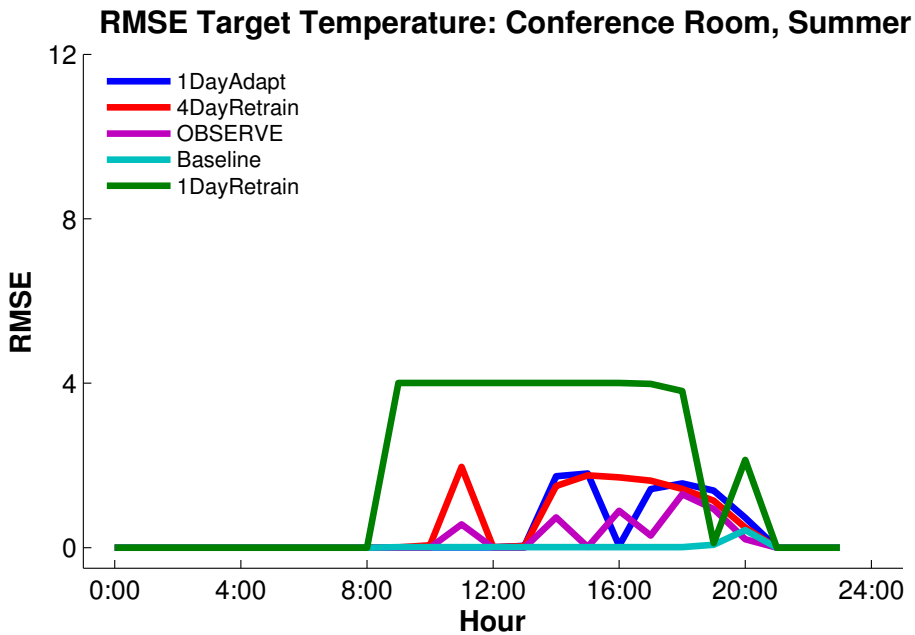
Energy Savings



1DayAdapt (10.9%) < OBSERVE (11.2%) < 1DayAdapt (11.4%) < 1DayRetrain (12.9%)

Conditioning Effectiveness





Summer:
4DayRetrain, OBSERVE, 1DayAdapt (< 0.5°F) $<$ 1DayRetrain (1.8°F)

Winter:
4DayRetrain, OBSERVE, 1DayAdapt (< 1.4°F) $<$ 1DayRetrain (2.4°F)

Lessons Learned

- Retraining with little data leads to poor models.
- Adapted model generalizes well ..... if the reference model is close enough to the new adaptation occupancy data.

Summary

- Use model adaptation for construction of good-quality occupancy models with 1-day of occupancy data.
- Conditioning effectiveness on par with other models that require 4 times as much training data.
- Energy auditing improvements using adapted occupancy models.

Thank You ....
Questions?