UT Austin Learning Agents Research Group

THE UNIVERSITY OF TEXAS AT AUSTIN

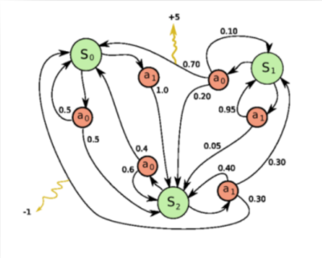
A Learning Agent for Heat-Pump Thermostat Control

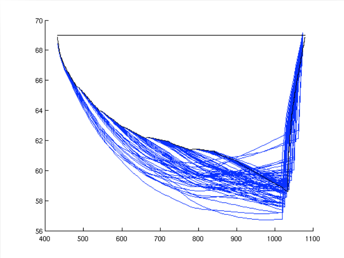
Daniel Urieli and Peter Stone

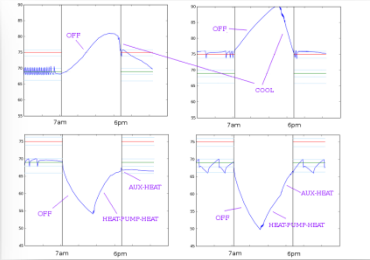
Department of Computer Science

The University of Texas at Austin

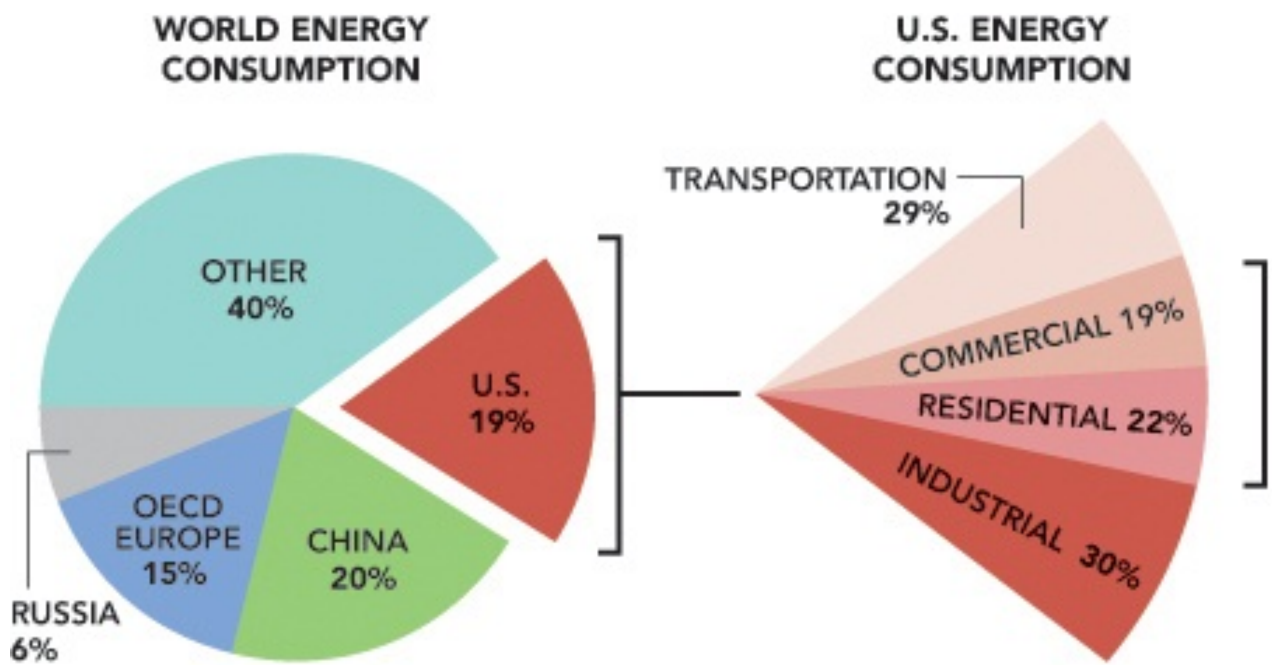
{urieli,pstone}@cs.utexas.edu







Chapter 1: Buildings Sector



BUILDINGS ENERGY DATA BOOK

U.S. DEPARTMENT OF ENERGY | Energy Efficiency & Renewable Energy

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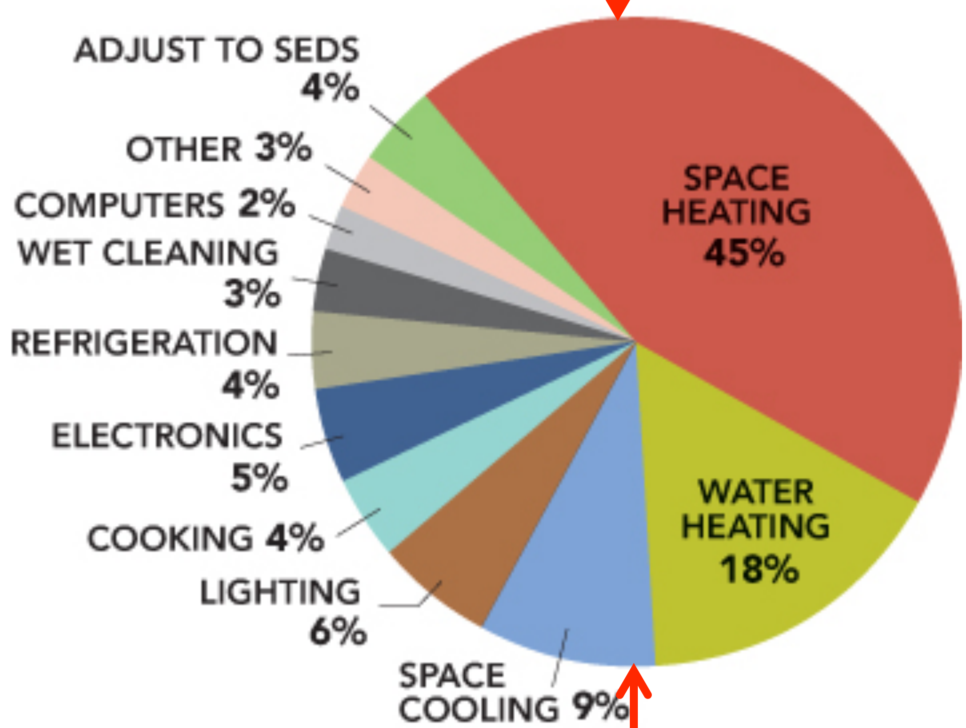
Chapter 2: Residential Sector

RESIDENTIAL SITE ENERGY CONSUMPTION BY END USE



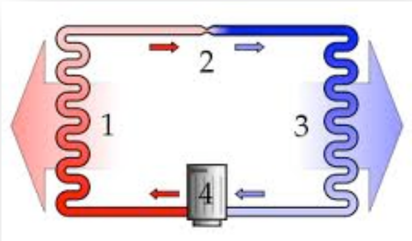
Heating, Ventilation, and Air-conditioning (HVAC) systems

Heat-Pump based HVAC System

- Heat-pump is widely used and highly efficient
  - Its heat output is up to 3x-4x the energy it consumes
  - Consumes electricity (rather than gas/oil based)
    ⇨ can use renewable resources
  - But: no longer effective in freezing outdoor temperatures

- Backed up by an auxiliary heater
  - Resistive heat coil
  - Unaffected by outdoor temperatures
  - But: consumes 2x the energy consumed by the heat-pump heater

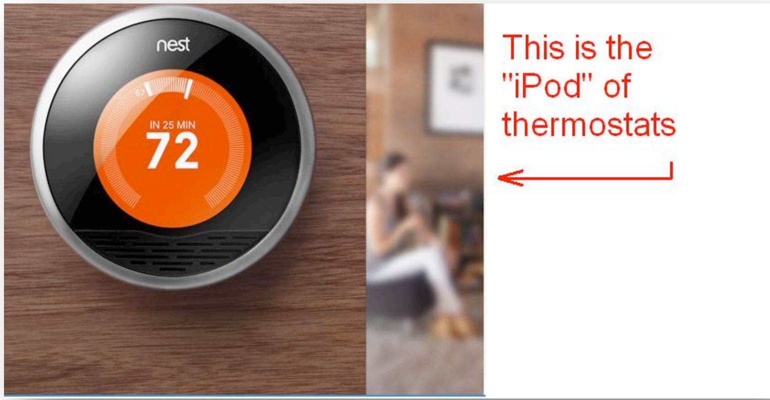
- Heat pump is also used for cooling



Thermostat – an HVAC System's Decision Maker

- The thermostat :
  - Controls Comfort
  - Significantly affects energy consumption

- Current interest evident from the appearance of startup companies like NEST, as well thermostats by more traditional companies like Honeywell



<u>Goal</u>:

Minimize energy consumption while satisfying comfort requirements

www.dot.gov

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Minimize energy consumption while satisfying comfort requirements

Contributions:

1. A complete reinforcement learning agent that learns and applies a new, adaptive control strategy for a heat-pump thermostat

2. Our agent achieves 7.0%-14.5% yearly energy savings, while maintaining the same comfort level, comparing to a deployed strategy

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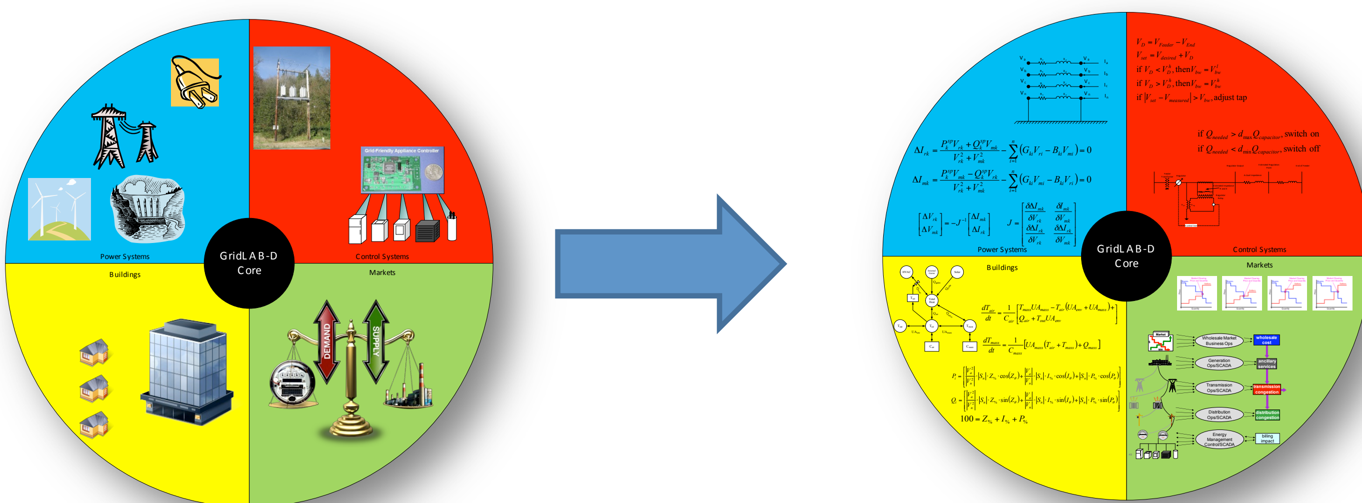
Simulation Environment

- GridLAB-D: A realistic smart-grid simulator, simulates power generation, loads and markets
- Open-source software, developed for the U.S. DOE, simulates seconds to years
- Realistically models a residential home
  - Heat gains and losses, thermal mass, solar radiation and weather effects, uses real weather data recorded by NREL (www.nrel.gov)

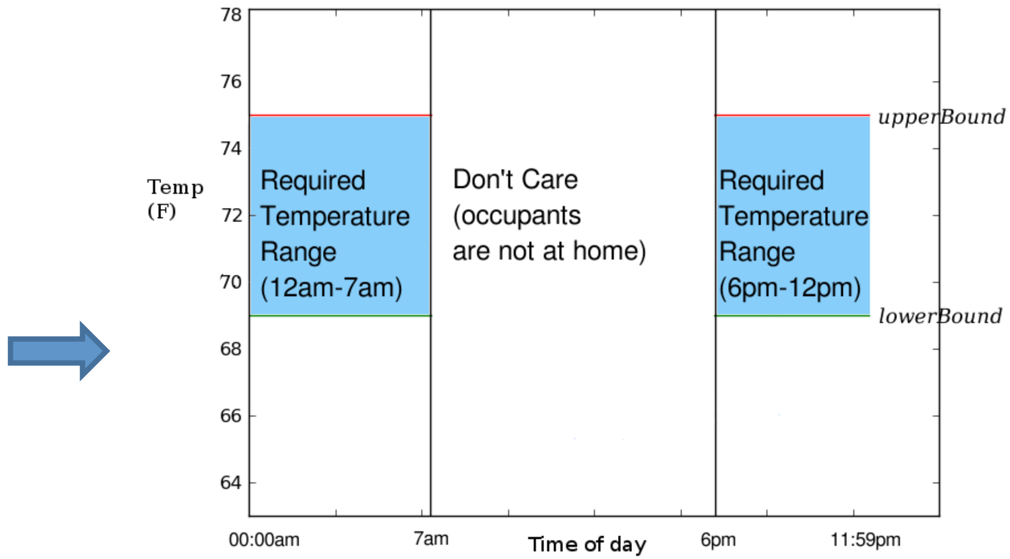


Problem Setup

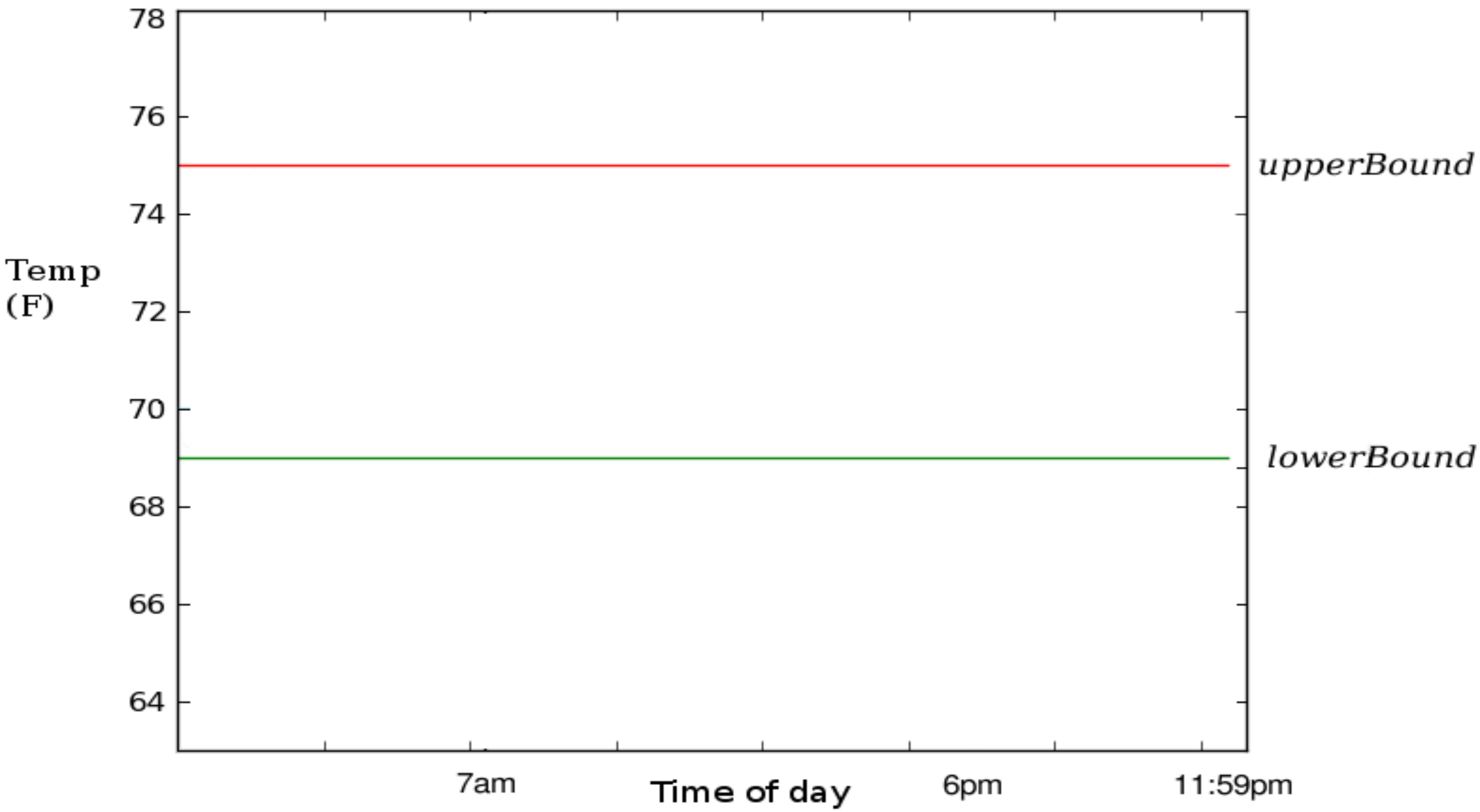
- Simulating a typical residential home

- **Goal:** minimize energy consumed by the heat-pump , while satisfying the following comfort spec:

Occupants are
- 12am-7am: **At home.**
- 7am-6pm: **Not at home.** (the ***"don't care"*** period)
- 6pm-12am: **At home.**



The Default Thermostat



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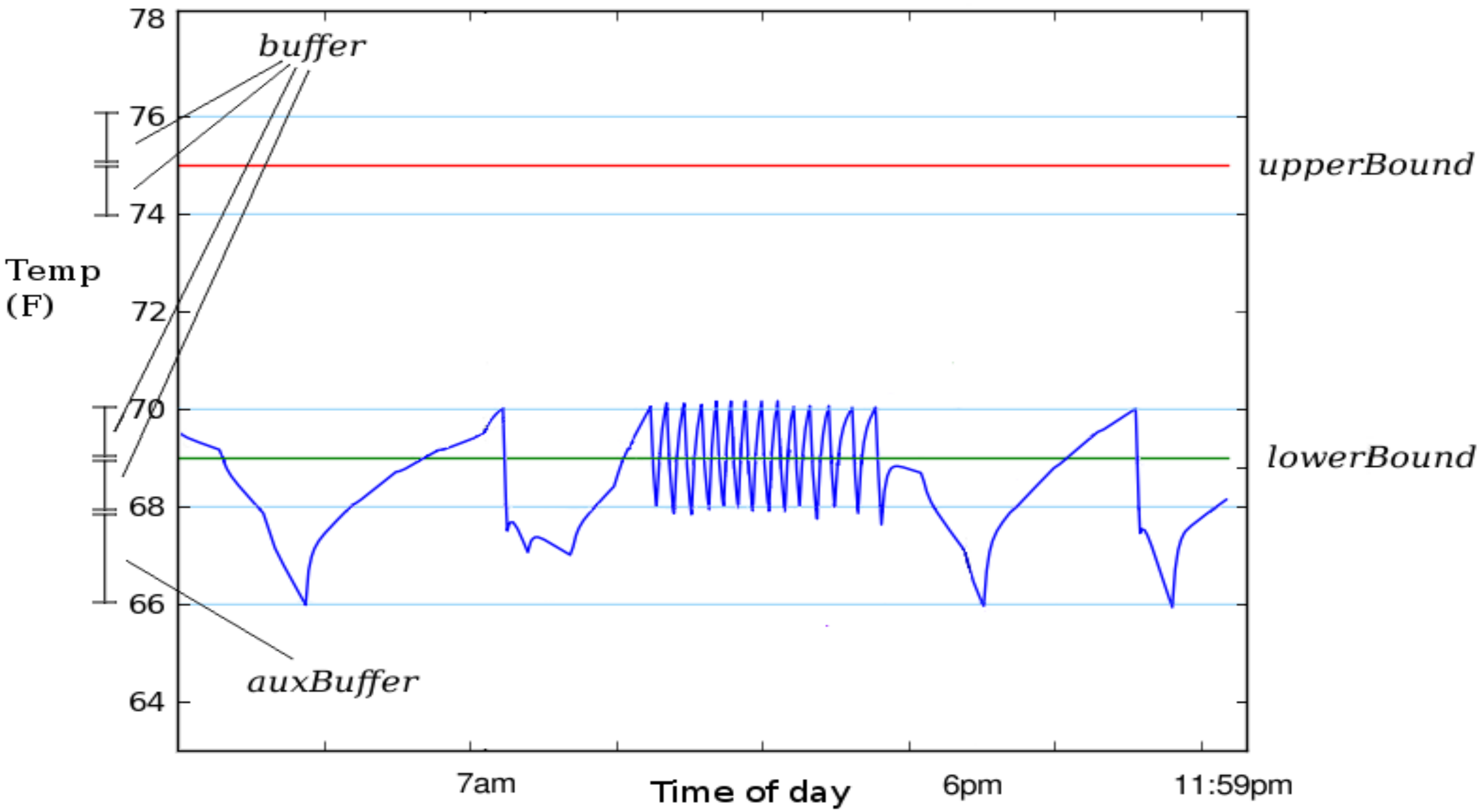

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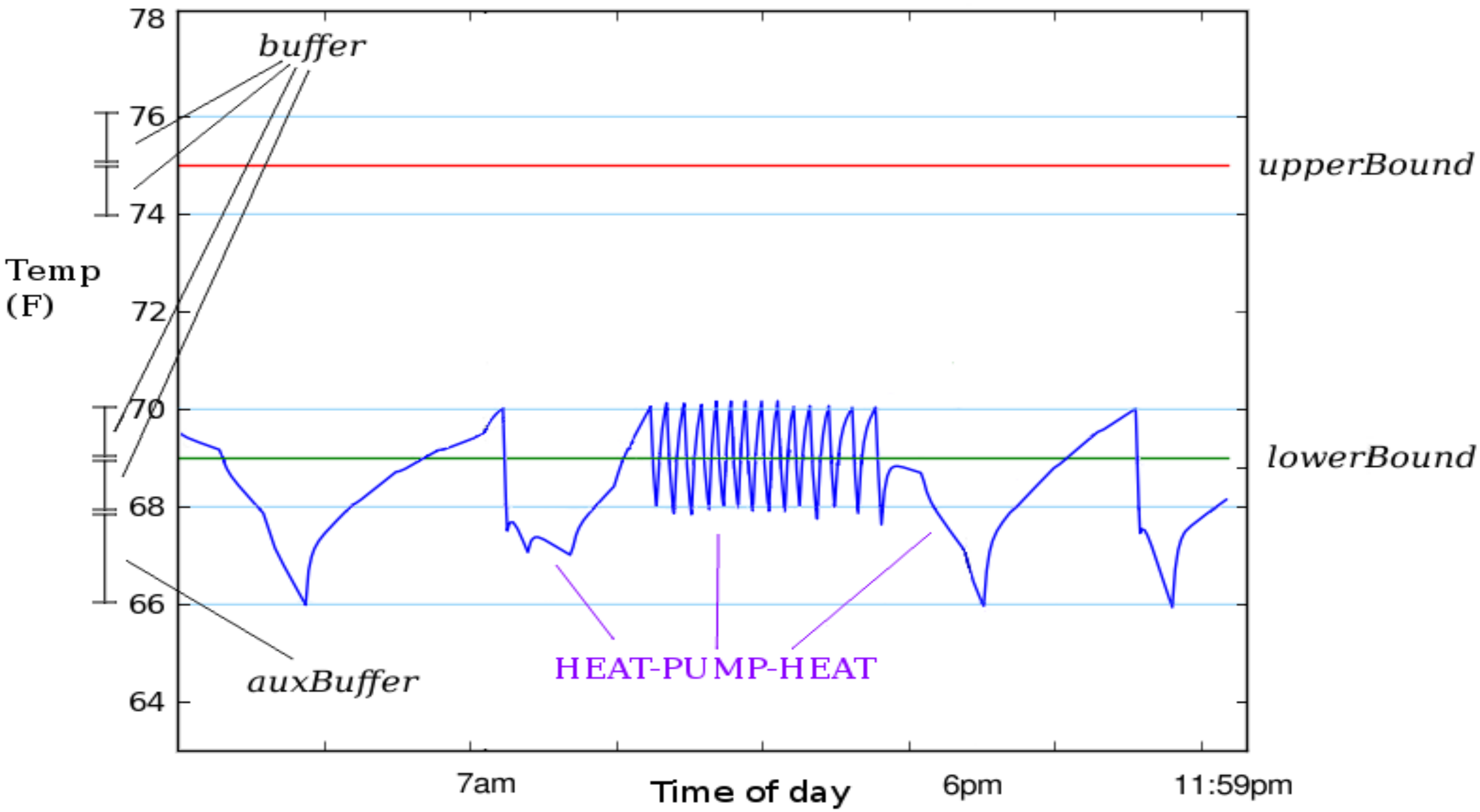

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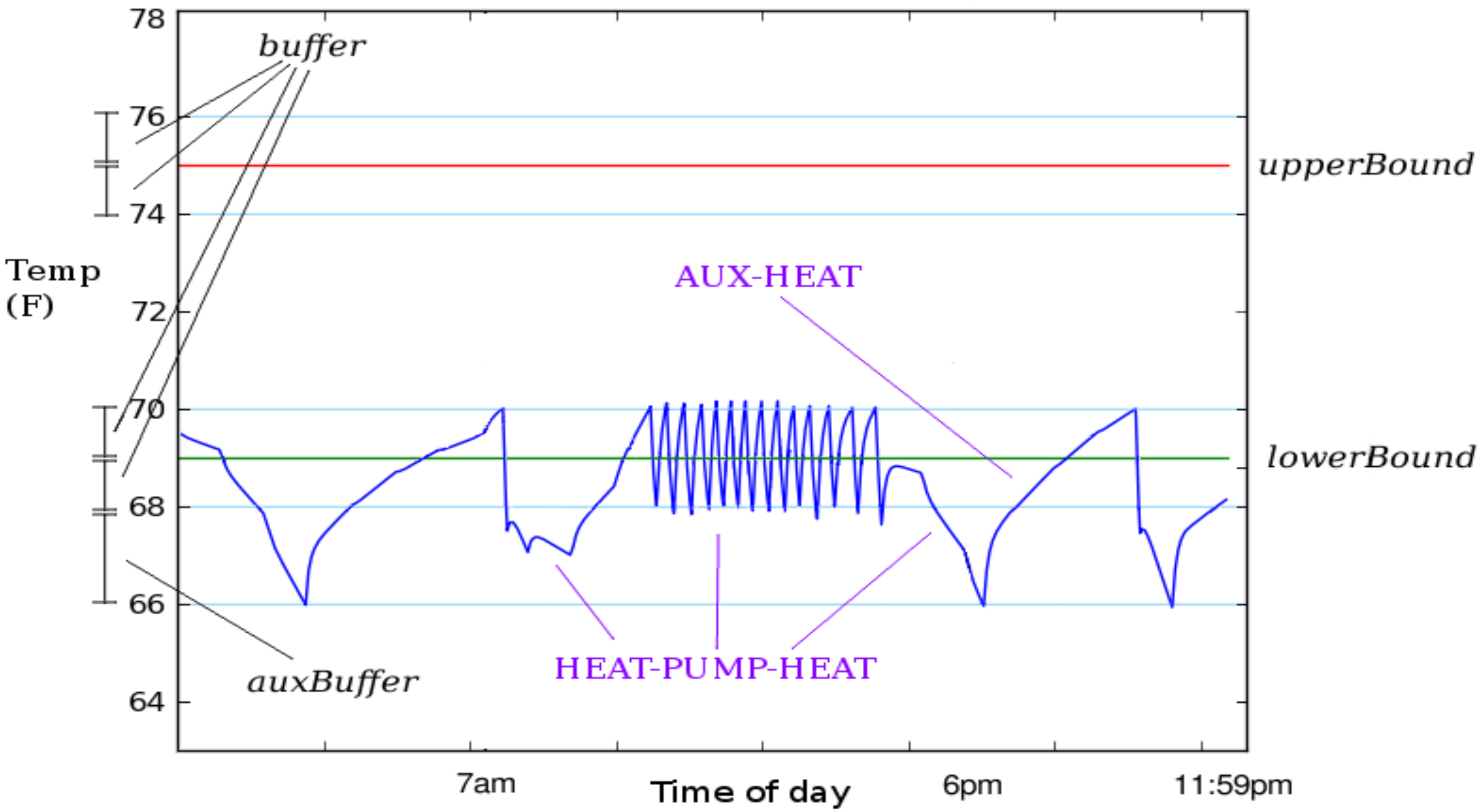
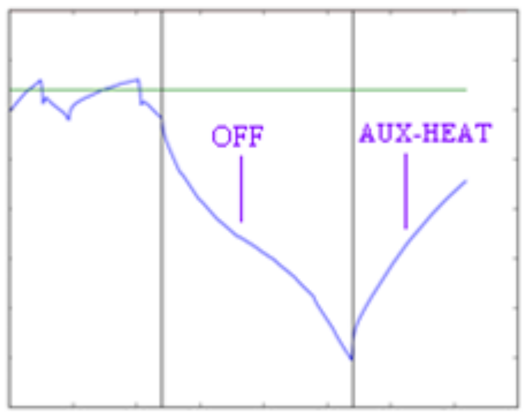


Can We Just Shut-Down The Thermostat During "don't-care" Period?

- Effective way to save energy
  - Indoor temp. closer to outdoor ⟹ heat dissipation slows down
- Simulating it…



- In this case, the result is:
  - Increased energy consumption
  - Failure to satisfy the comfort spec

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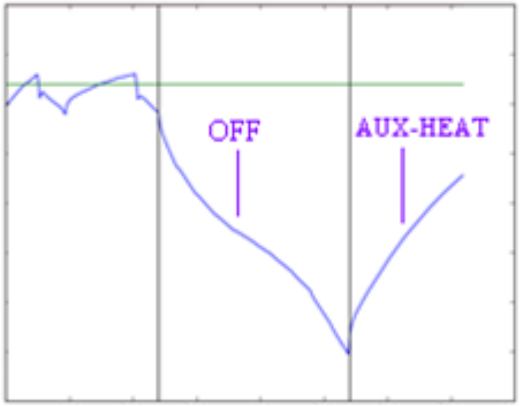

Therefore, people frequently prefer to leave the thermostat on all day

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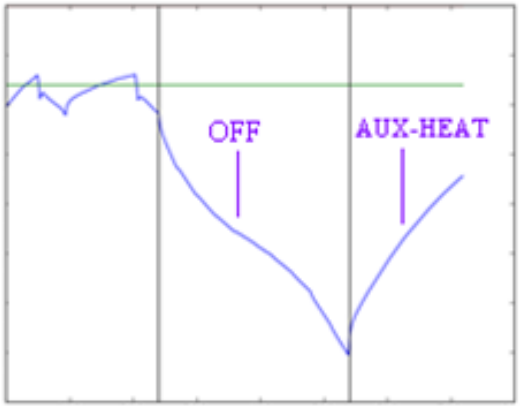

Therefore, people frequently prefer to leave the thermostat on all day

However, a smarter shut-down should still be able to save energy while maintaining comfort

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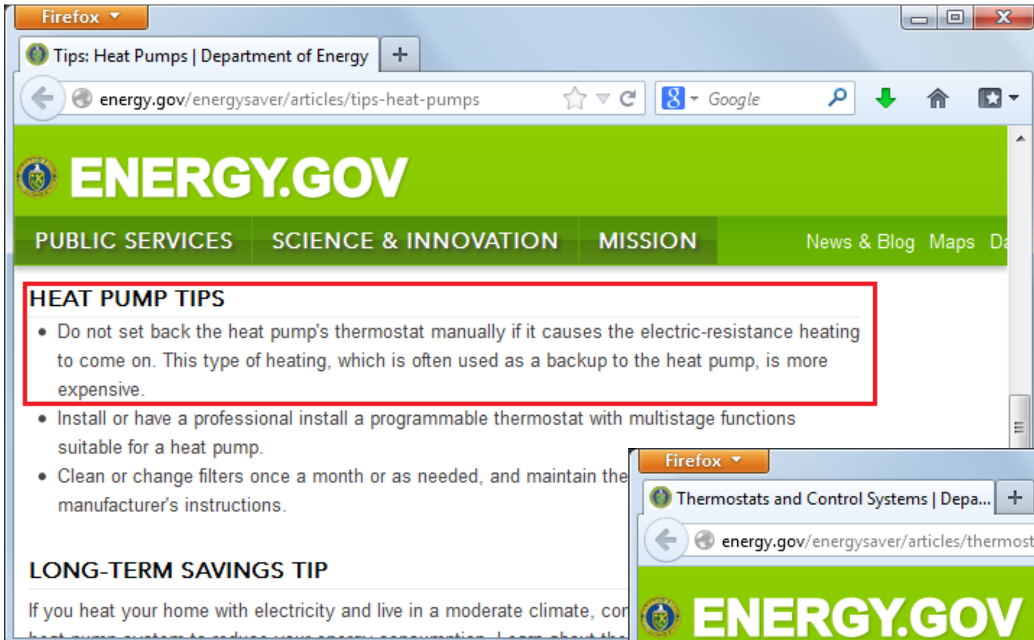
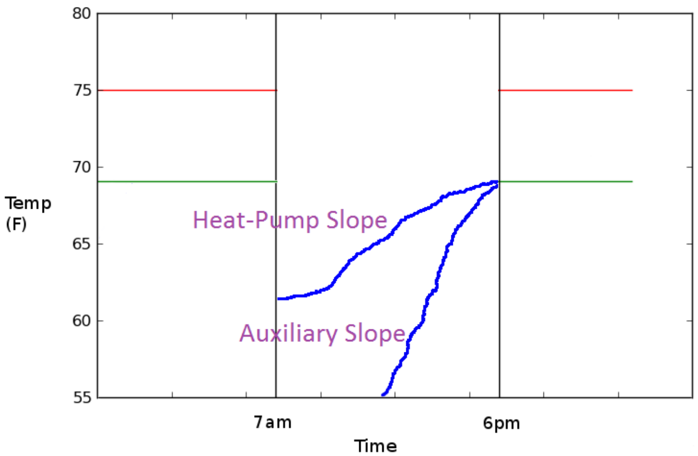
From the US Dept. of Energy’s website



Challenges

Desired behavior:

- Maximize shut-down time while staying above the heat-pump slope
- Similarly for cooling (no AUX)

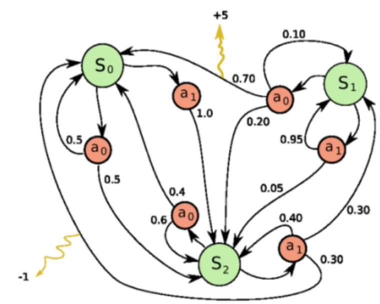


Challenges:

- The heat-pump slope:
  - Is unknown in advance
  - Changes every day
  - Depends on future weather
  - Depends on specific house characteristics
- Action effects are:
  - Drifting rather than constant: since heat is being moved rather than generated, heat output strongly depends on the temperatures indoors, outdoors and along the heat path
  - Noisy due to hidden physical conditions
  - Delayed due to heat capacitors like walls and furniture
- Also, in a realistic deployment:
  - Exploration cannot be too long or too aggressive
  - Customer acceptance will probably depend on worst-case behavior
- Making decisions in continuous, high dimensional space

Our Problem as a Markov Decision Process (MDP)

- **States:**
- **Actions:**



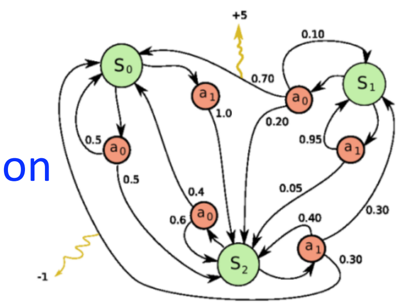
- **Transition:**
- **Reward:**
- **Terminal States:**

- Action is taken every 6 minutes
  - Modeling a realistic lockout of the system

Our Problem as a Markov Decision Process (MDP)

- **States:**
- **Actions:** {COOL, OFF, HEAT, AUX}

  1 : 0 : 2 : 4 ⟸ consumption (e_a) proportion



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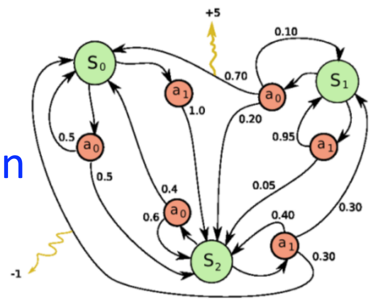

- **Transition:**
- **Reward:** $-e_a - 100000\,\Delta^2_{6pm}$ *where:*
  Δ^2_{6pm} := (indoor_temp_at_6pm – required_indoor_temp_at_6pm)
- **Terminal States:**

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Our Problem as a Markov Decision Process (MDP)

- **States:** **???**

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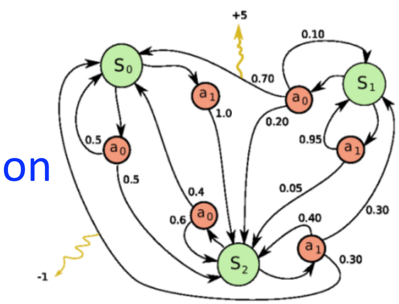

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- **Terminal States:**

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How Should We Model State?

- Choosing a state representation is an important design decision. A state variable:
  - captures what we need to know about the system at a given moment
  - is the variable around which we construct value function approximations
    [Powell 2011]

- Definition 5.4.1 from [Powell 2011]:
  - ***A state variable** is the minimally dimensioned function of history that is necessary and sufficient to compute the decision function, the transition function, and the contribution function.*

Our Problem as a Markov Decision Process (MDP)

- **States:** <T_{in}, Time, e_a>
- **Actions:** {COOL, OFF, HEAT, AUX}

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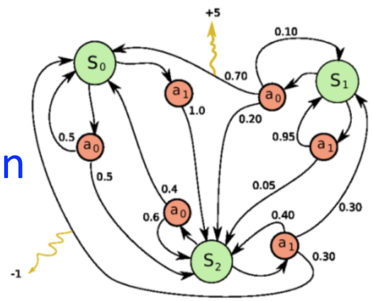

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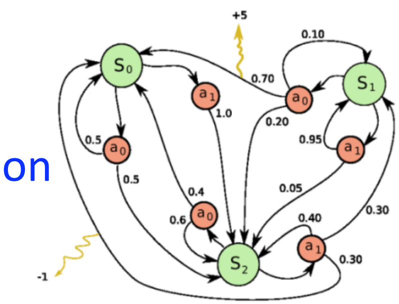

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- **Terminal States:**

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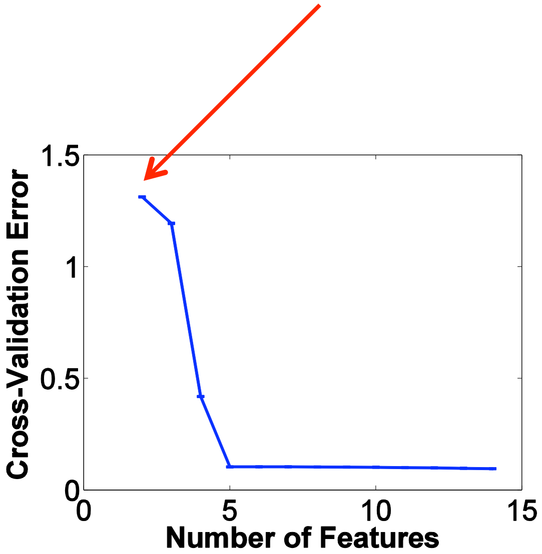
Expanding State to Compute the Transition Function

- Can we predict action effects for each of the state variables?
- Current state representation: $\langle T_{in}, Time, e_a \rangle$
- Need to be able to predict T_{in} and e_a
- Method: generate simulated data, use cross-validation to test for regression prediction accuracy

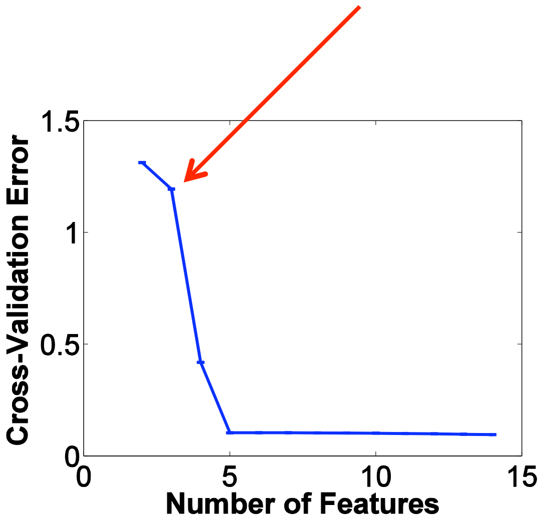
Predicting T_{in}

- Prediction error is unacceptably high – state <T_{in}, Time, e_a> doesn't capture enough information



Predicting T_{in}

- Prediction error is unacceptably high – state <T_{in}, Time, e_a> doesn't capture enough information
- Add T_{out} – directly affects T_{in} . Prediction error still unacceptably high



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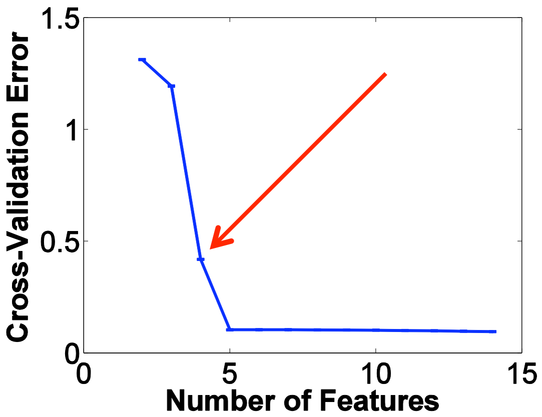
  - Previous action



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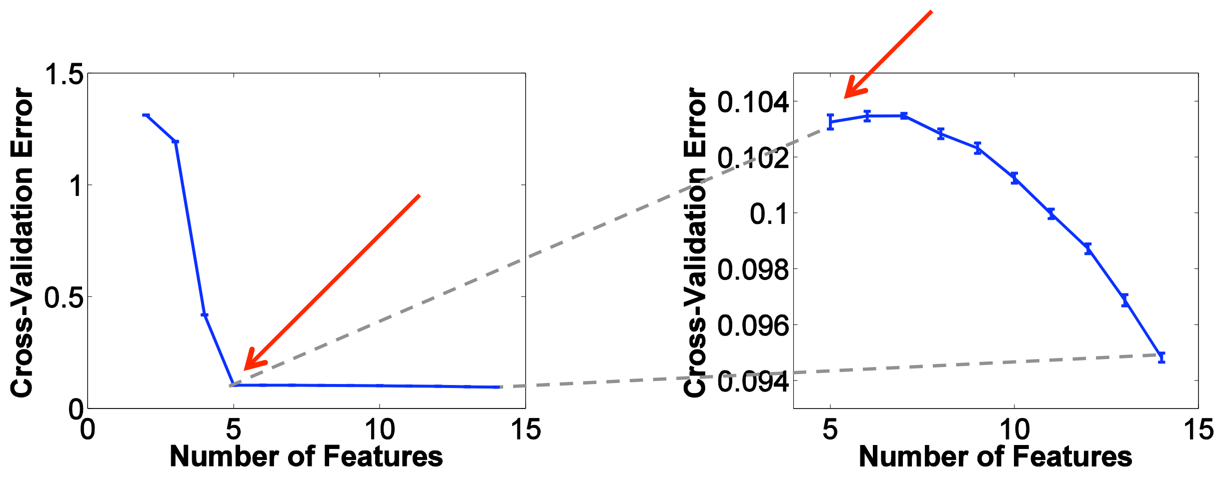
  - Measured T_{in} history of 10 temperatures: <t_0>



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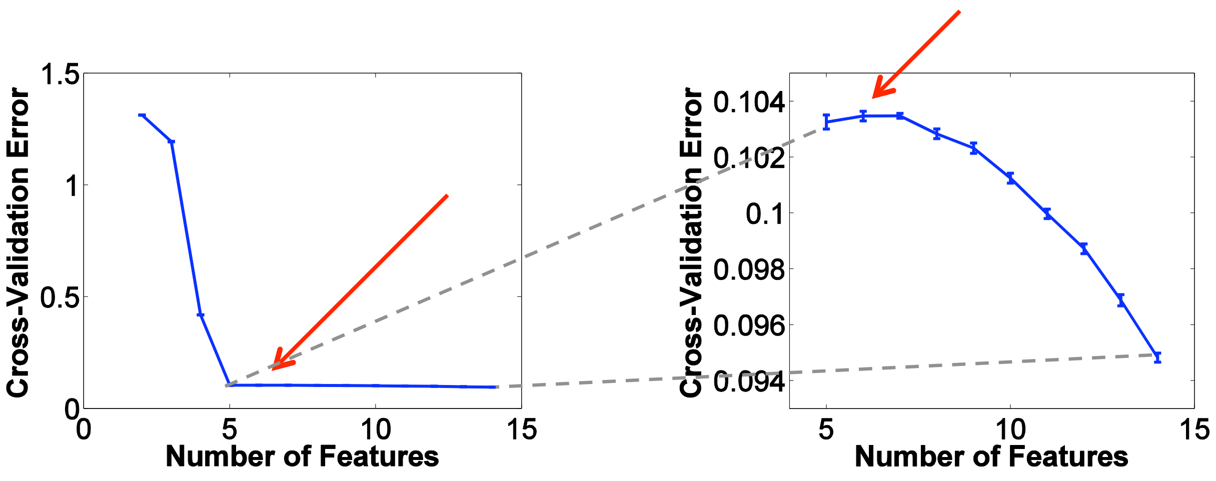
  - Measured T_{in} history of 10 temperatures: $\langle t_0, t_1 \rangle$



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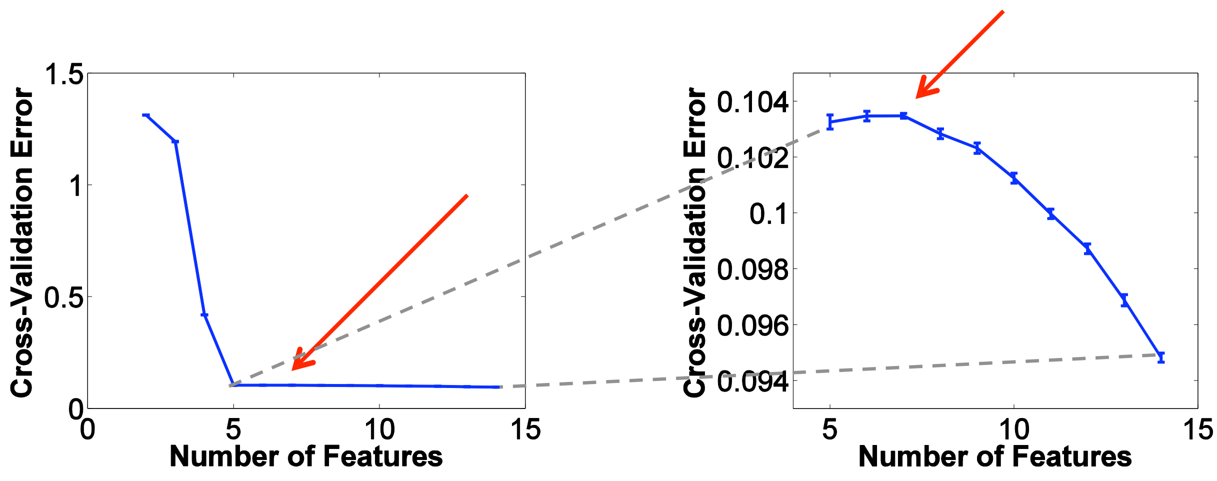

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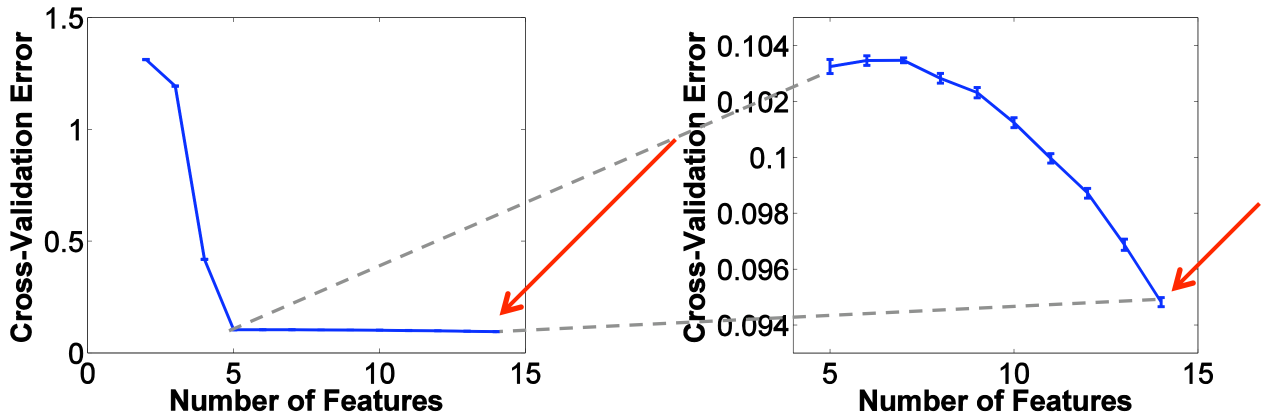

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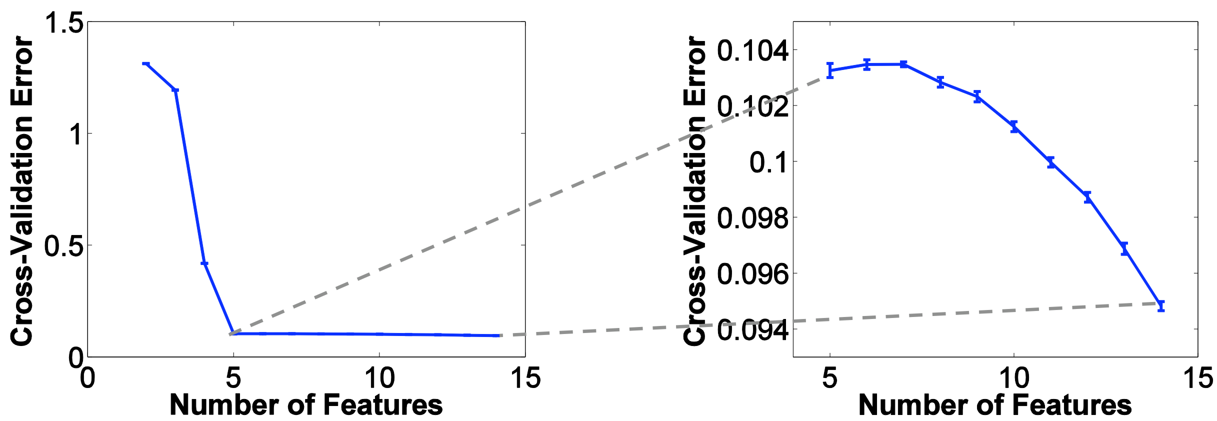
  - Previous action
  - Measured T_{in} history of 10 temperatures: <t_0, t_1, t_2, …, t_9>
  - Resulting state: <T_{in}, T_{out}, Time, e_a, prevAction, t_0, …,t_9>



Completing the state definition

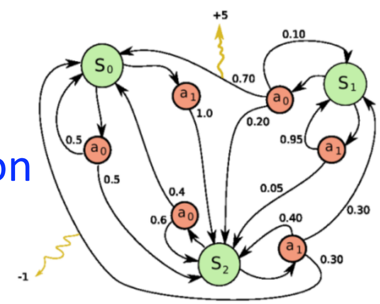
- Resulting state: <T_{in}, T_{out}, Time, e_a, prevAction, t_0, …,t_9 >
- Can we predict the newly added variables?
- Trivially, except for T_{out}
- Therefore, add weatherForecast to state
- weatherForecast doesn't need to be predicted in our transition function
- This completes our state definition
- The final resulting state is:

  <T_{in}, T_{out}, Time, e_a, prevAction, t_0, …,$t_{9,}$ weatherForecast>

Our Problem as a Markov Decision Process (MDP)

- **States:** <T_{in}, T_{out}, Time, e_a, prevAction, t_0, …,t_9, weatherForecast>
- **Actions:** {COOL, OFF, HEAT, AUX}

  1 : 0 : 2 : 4 ⟸ consumption (e_a) proportion



- **Transition:** unknown in advance ⟹ learned
- **Reward:** $-\, e_a \,-\, 100000\, \Delta^2_{6pm}$ *where:*

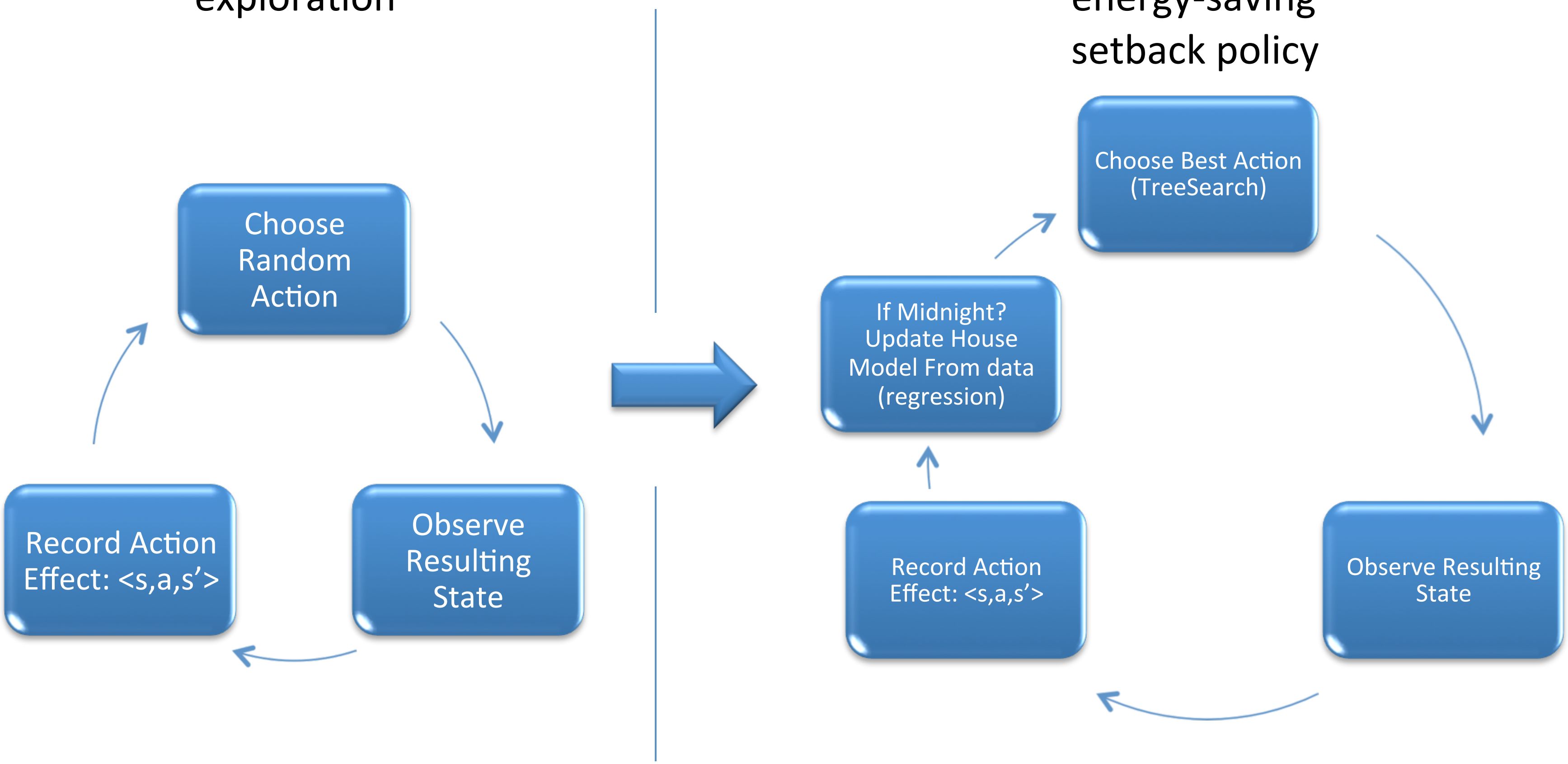
  Δ^2_{6pm} := (indoor_temp_at_6pm – required_indoor_temp_at_6pm)
- **Terminal States:** {s | s.time = 11:59pm}

- Action taken every 6 minutes
  - Modeling a realistic lockout of the system
- State space is continuous and high dimensional

Agent Operation

First 3 days:
exploration

Starting day 4:
energy-saving
setback policy



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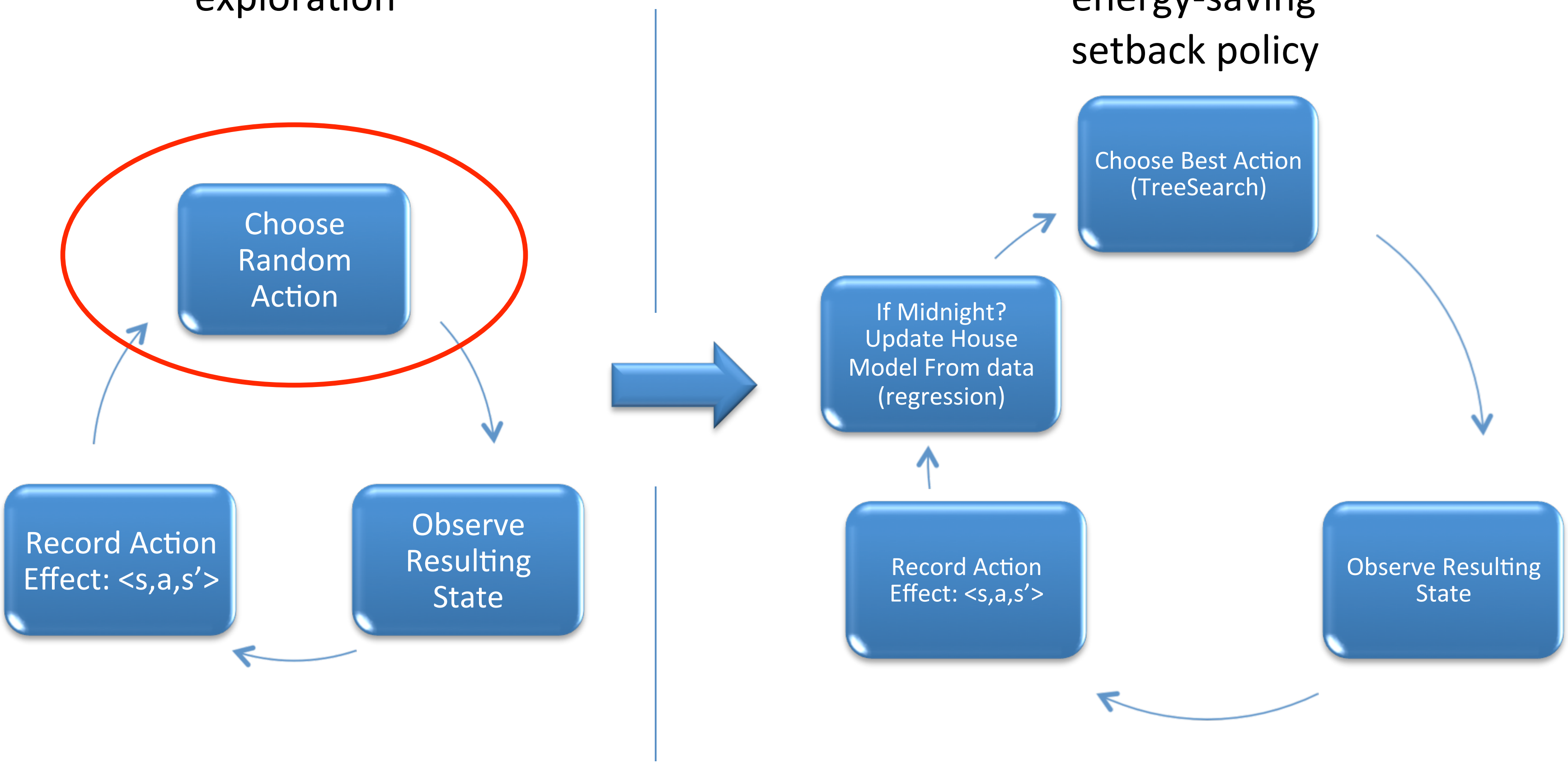

Exploration

- Random actions for 3 days
- Could use more advanced exploration policy
- However, this is still a realistic setup

Exploration

- Random actions for 3 days
- Could use more advanced exploration policy
- However, this is still a realistic setup
  - For instance when occupants are traveling during the weekend


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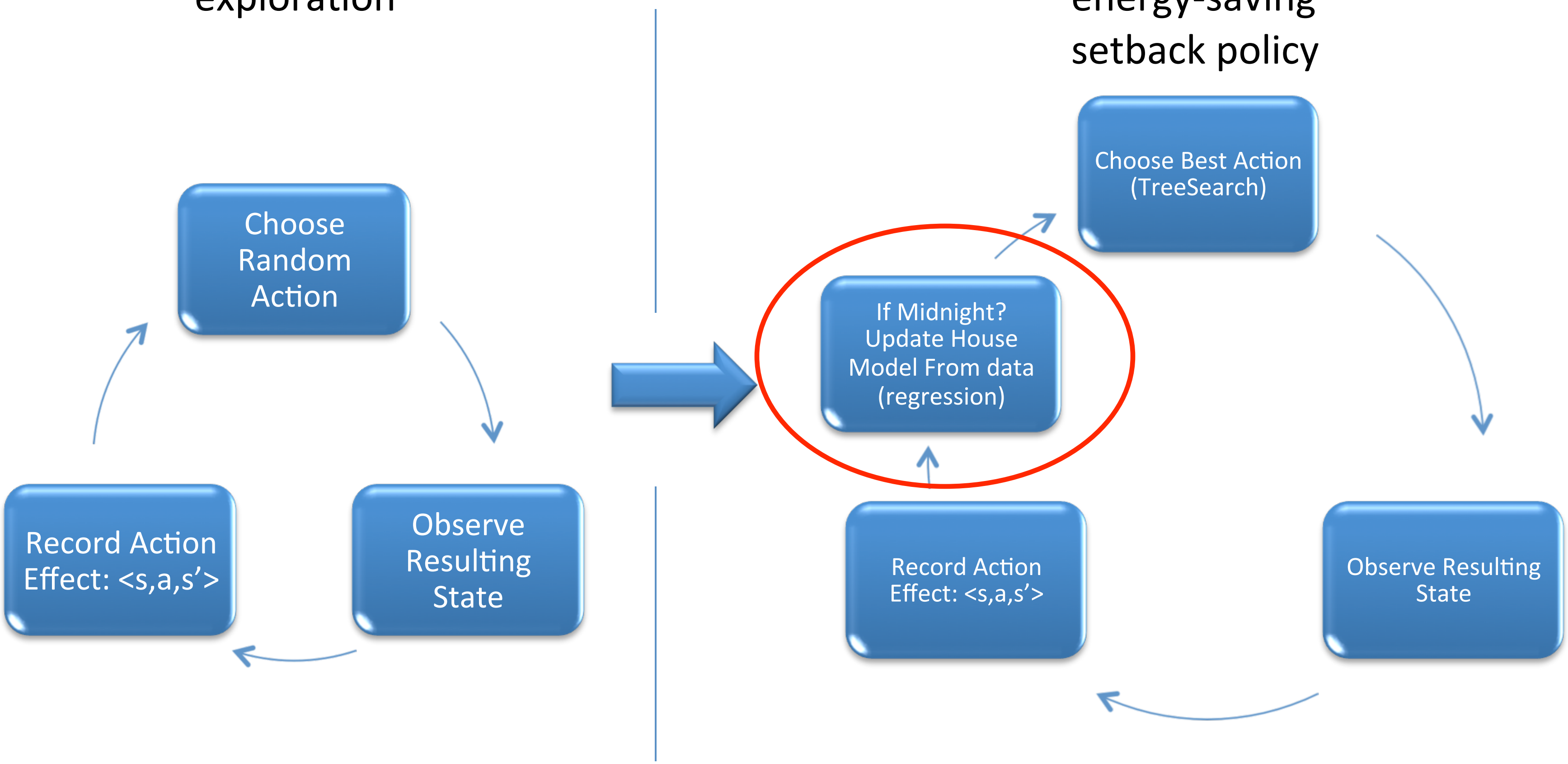
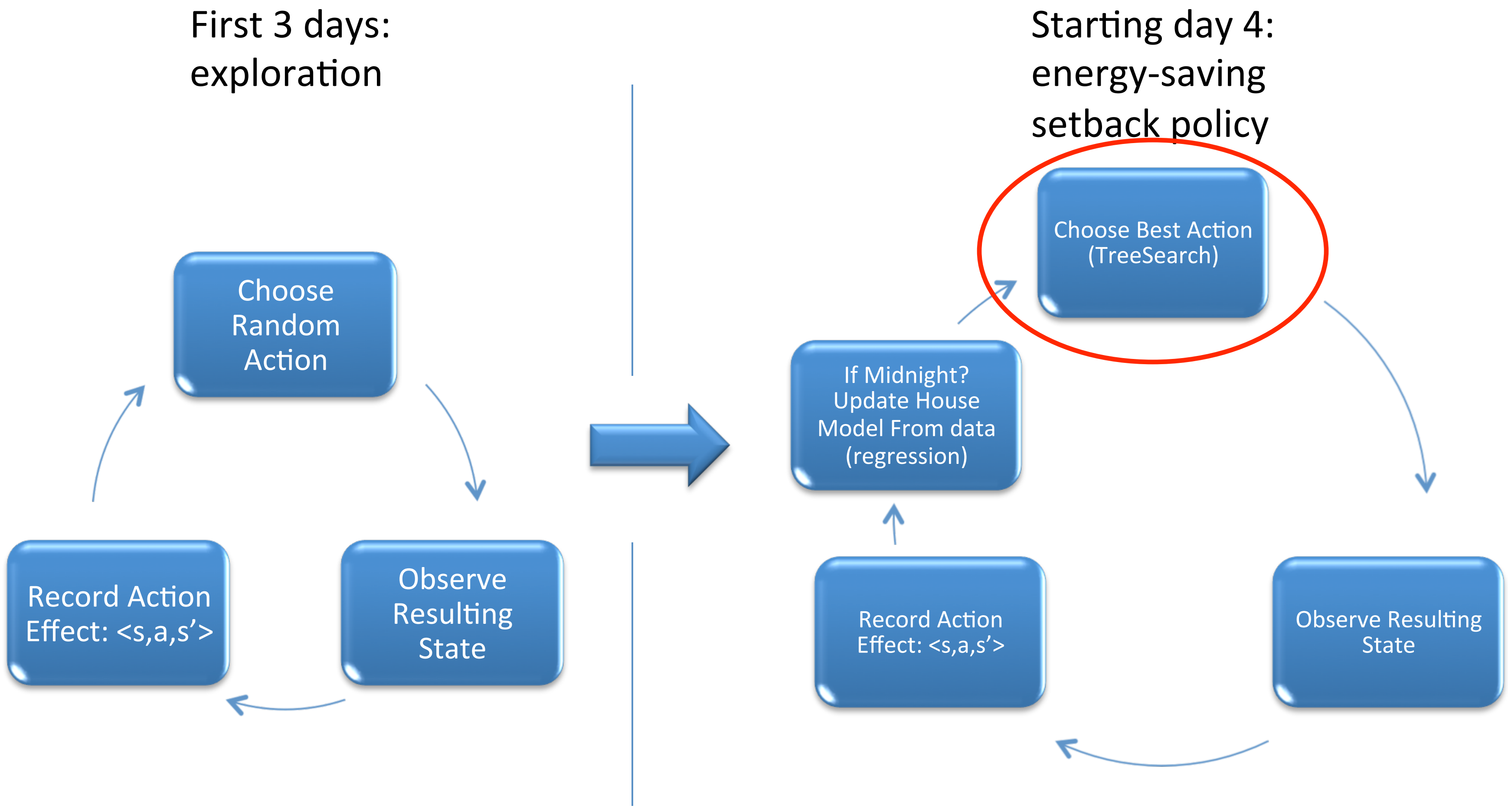


Update House Model from Data

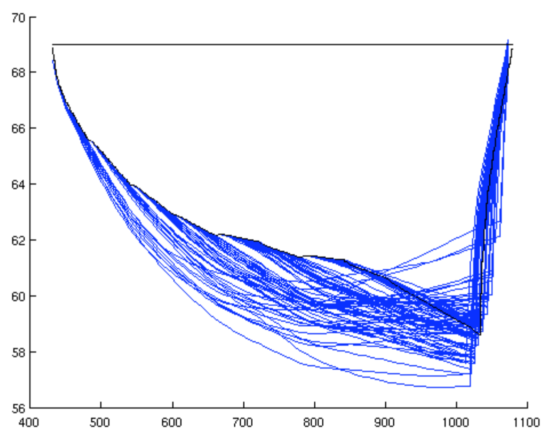
- Every midnight, use all the recorded data *<s, a, s'>* to estimate the house's transition function
- Linear Regression to estimate *<s,a>* → *s'*

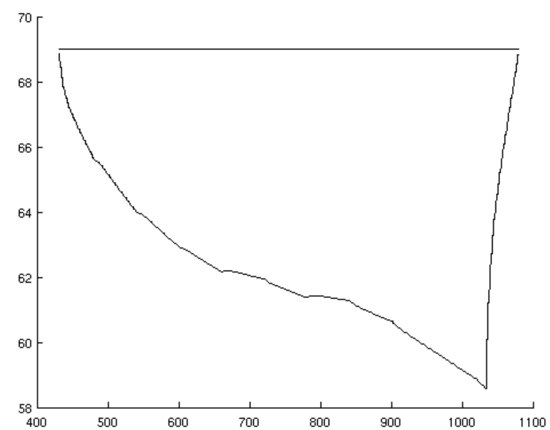
Agent Operation



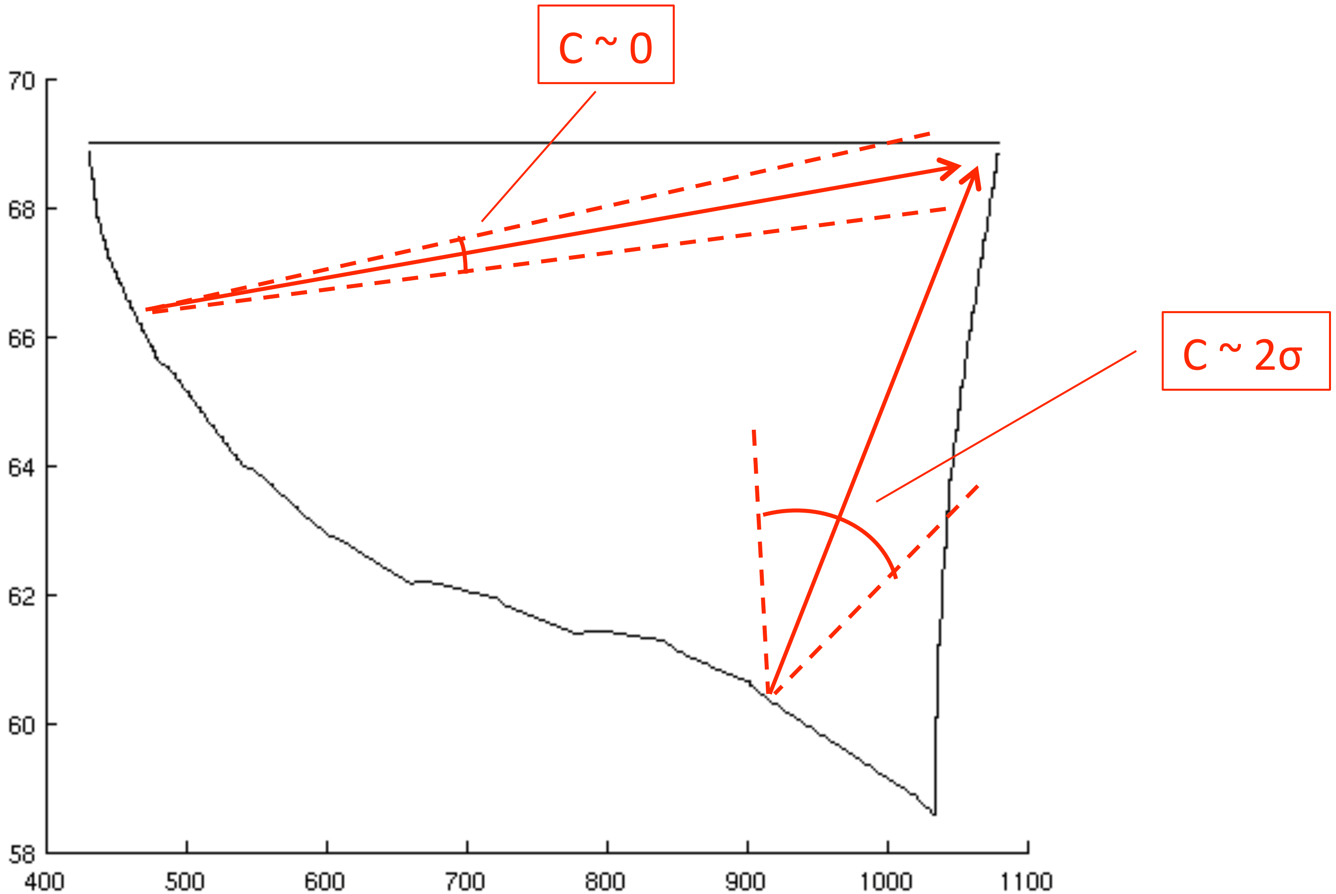
Choosing the Best Action

- Dealing with continuous high-dimensional state space
- Impractical to compute a value function
- Run a tree search at every step
- Choose the first action of the best search as the next action





Safety Buffer in a Tree Search



Results

- Simulate 1 year under different weather conditions
- 21 residential homes of sizes 1000-4000 ft^2
- Using real weather data recorded in

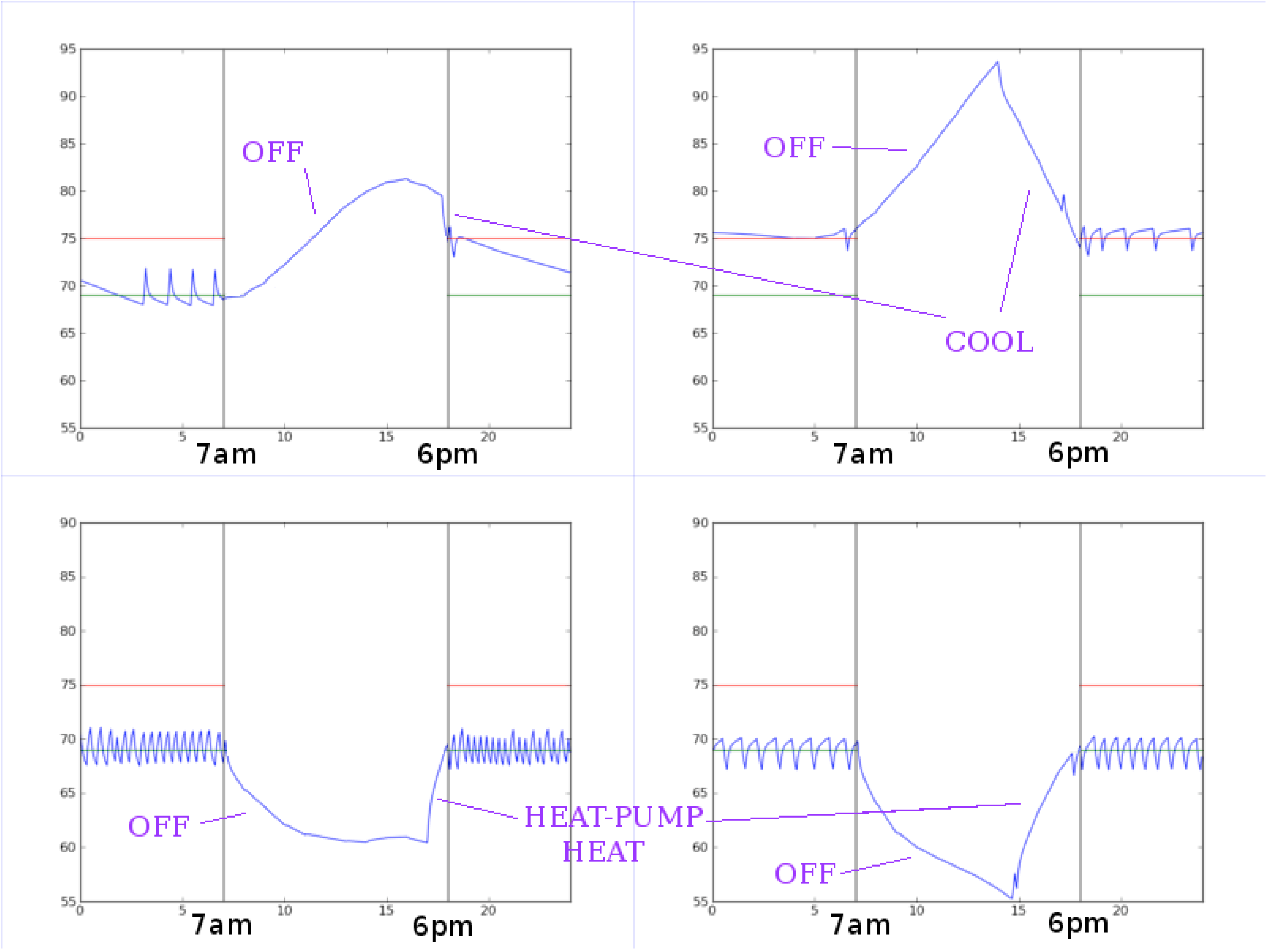
NYC

Boston

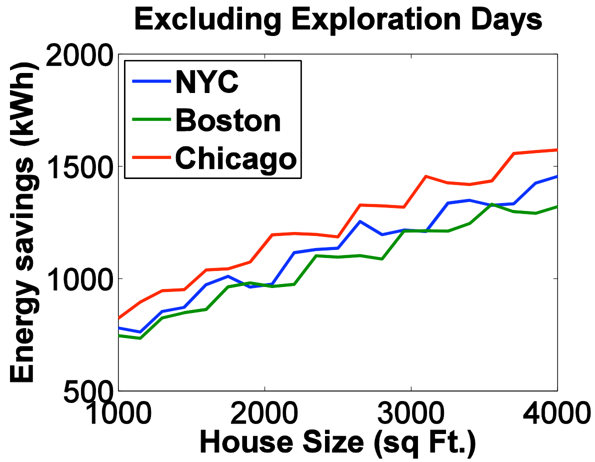
Chicago

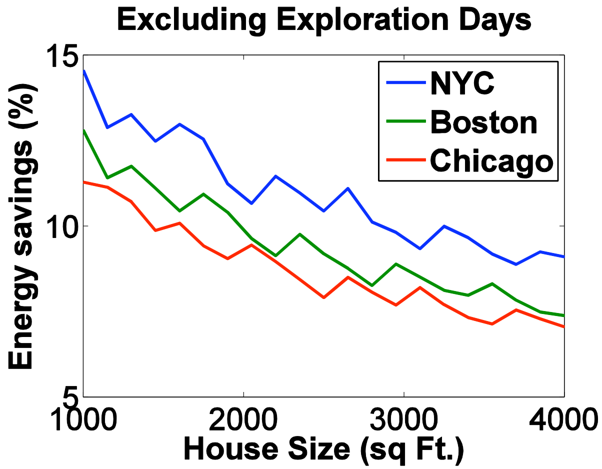
- Why cold cities? Since heating consumes 2x-4x more energy

Temperature Graphs – Learned Setback Policy



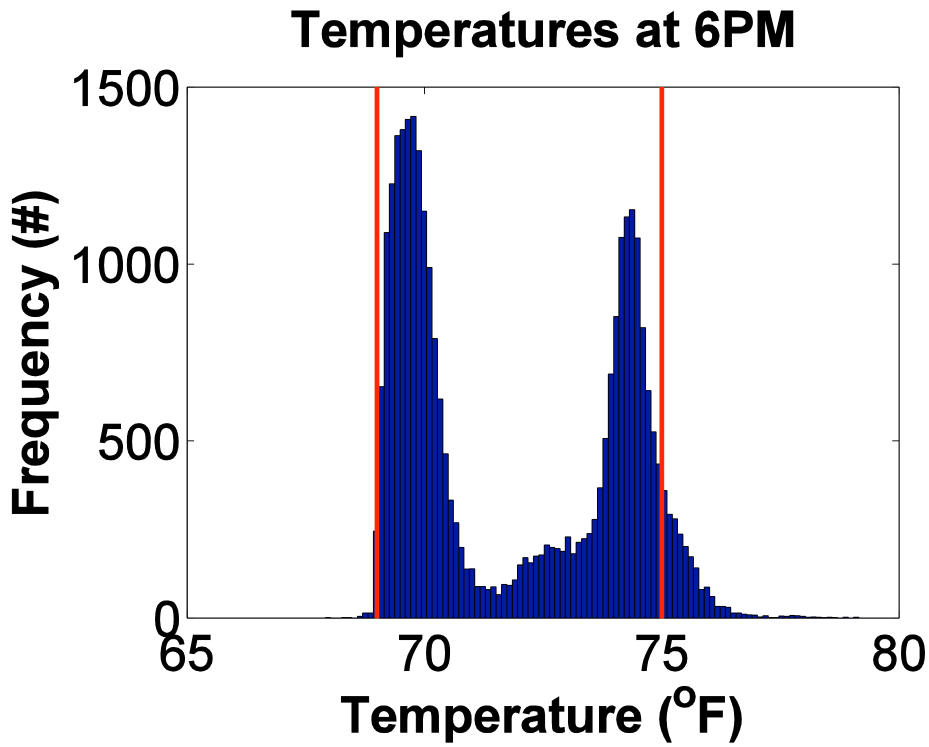
Energy Savings





Comfort Performance

- In more than 22,000 simulated days



Related Work

- [Rogers et al. 2011] – adaptive thermostat that tries to minimize price & peak demand rather than the total amount of energy.

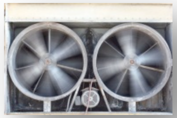
- [Hafner and Riedmiller 2011; Kretchmar 2000] – use RL to tune an HVAC system.

- [T. Peffer et al. 2011] – How people use thermostats in homes

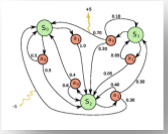
- Learning thermostats in commercial companies
  - NEST, Honeywell…
  - Technical details and actual performance are not published

Summary

- A complete, adaptive, RL agent for controlling a heat-pump thermostat



- Techniques:
  - Carefully defined the problem as an MDP
  - Carefully chose a state representation
  - Using an efficient, specialized tree-search



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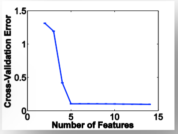

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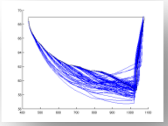
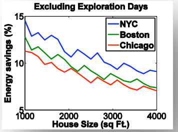


- Experiments run on a range of homes and weather conditions

- Achieves 7%-14.5% yearly energy savings in simulation, while satisfying comfort requirements, comparing to the deployed strategy



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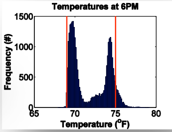

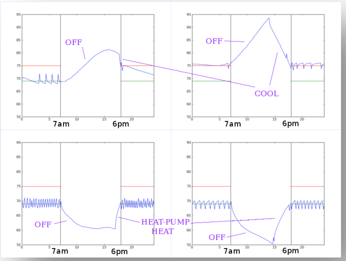

Thank you!

BACKUP

Ablation Analysis

Table 1: Ablation Analysis

Analysis Type		Energy Consumption (kWh)	Comfort Violations (#)	Range of 6pm Temp.
Removed Feature	prevAct+hist+ conf	1112(+9.5%)	232	60.1-84.4
	prevAct+hist	1070(+5.4%)	193	60.8-80.9
	conf	1024(+0.8%)	138	67.5-78.3
	hist	1016(+0.0%)	133	67.1-77.7
	prevAct	1015(+0.0%)	65	67.8-76.5
Other conf. bounds	2σ	1090(+7.3%)	29	69.0-78.5
	$c = 2$	1039(+2.3%)	27	69.0-77.8
Final Agent		**1015**	**23**	**68.8-76.6**

- Removing features and their combinations
  - State features:
    - prevAct: previousAction
    - Hist: temperature history t_0, …, t_9
  - conf: confidence buffer
- Setting other values to the confidence bound