Model-Selection for Non-Parametric Function Approximation: A Case Study in a Smart Energy System

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Motivation

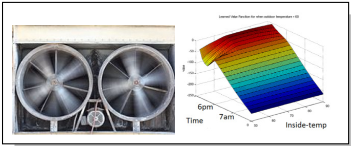
A smart energy problem:

Controlling a thermostat for reducing energy consumption in an HVAC[a] system while maintaining comfort requirements

[a] Heating, Ventilation and Air-Conditioning

General Motivation

Applying value-function based reinforcement learning (RL) to discrete-time, continuous-control problems



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Discrete-Time, Continuous Control Problems

- System's state-space is continuous
- Control actions are taken at discrete times
- Further assuming that action-set is small and discrete
- Examples:


Value-Function based RL

- In theory, value-function based RL can solve such problems optimally
- In practice, it is often unclear how to approximate the value function well enough
- Indeed, recent successes used direct policy search

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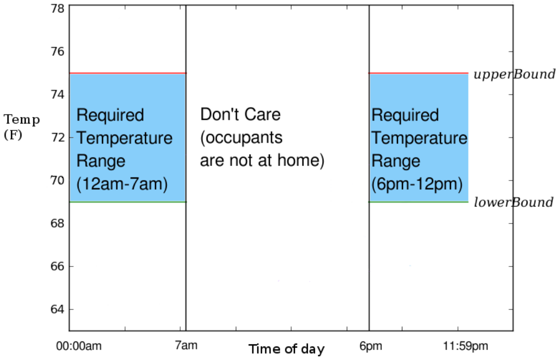
- Indeed, recent successes used direct policy search

Value-Function based RL

- Still, value-function based RL has desirable advantages:
  - Aiming for global optimum
  - Bootstrapping $\Longrightarrow$ less interactions with the real-world

Case Study: Smart Thermostat Control



- Minimize energy consumption while satisfying this comfort specification

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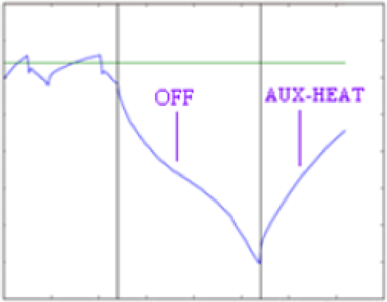


- Straightforward turn-off strategy fails to satisfy both requirements

Smart Thermostat Control as an MDP

We model the problem as an MDP:

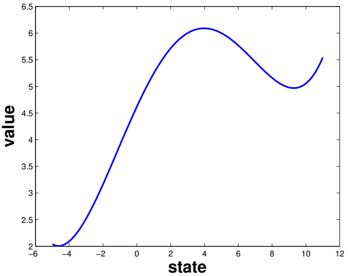
- **S**: $\{\langle T_{in}, T_{out}, Time\rangle\}$
- **A**: $\{\text{COOL}, \text{OFF}, \text{HEAT}, \text{AUX}\}$
- **P**: computed by the simulator, initially unknown
- **R**: $-energyConsumedByLastAction - C_{6pm}$
- **T**: $\{s \in S | s.time == \text{23:59pm}\}$

Plan

For the value-function (VF) approximation part, we need to:

1. Choose a function approximator
2. Choose an algorithm to compute the approximate VF
3. Tune the function approximator's parameters through model-selection

The Challenge of Value-Function Approximation



- Must differentiate optimal from suboptimal action
- Non-trivial with "small" action effects + smooth value function $\Longrightarrow$ losses accumulate over time

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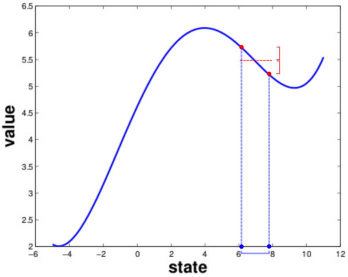

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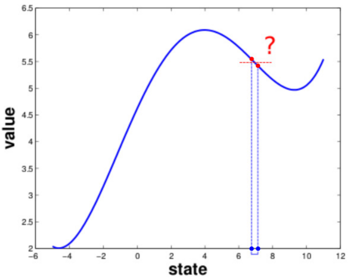

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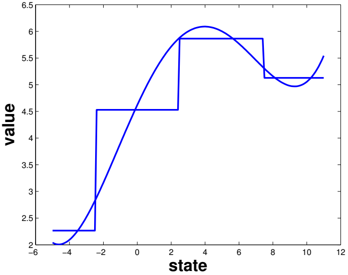
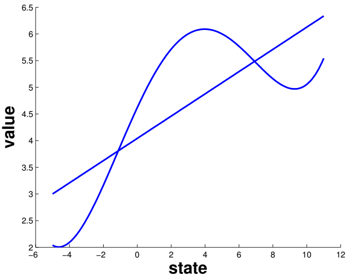
Function Approximation Methods



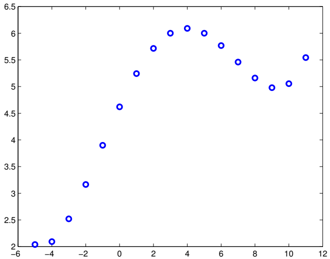
- Discretization
- Suffers from the curse of dimensionality at the required resolution levels

Function Approximation Methods



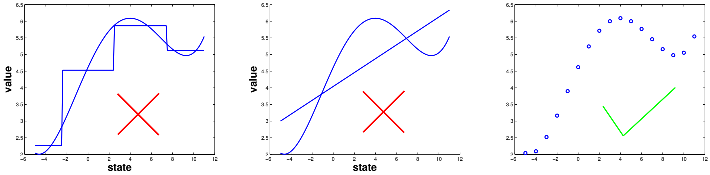
- Linear Function Approximation
- Depends on choosing good features
- Frequently not clear how to do that

Function Approximation Methods



- Non-Parametric: can represent any function
- Using lots of data...

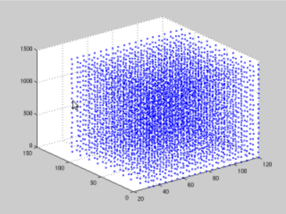
Non-Parametric Value Function Approximation



- To minimize the assumptions about the VF representation we use a smooth, non-parametric function approximator: Locally Weighted Linear Regression (LWR)

Compute an Approximate VF Using FVI

- To compute the approximate VF, we use Fitted Value Iteration (FVI):



S_FVI $:= \{s^{(1)}, s^{(2)}, \ldots, s^{(m)}\}$

$$
\begin{aligned}
&RepeatUntilConvergence\{\\
&\quad \forall i \in 1, \ldots, m\\
&\quad y^{(i)} := max_a \left(R(s^{(i)}, a) + \gamma E_{[s' \mid s^{(i)} a]} [\hat{V}^{\pi^*}(s')] \right)\\
&\quad \hat{V}^{\pi^*}(s) := LWR \left(\{ \langle s^{(i)}, y^{(i)} \rangle \mid i \in 1, \ldots, m \} \right)\\
&\}
\end{aligned}
$$

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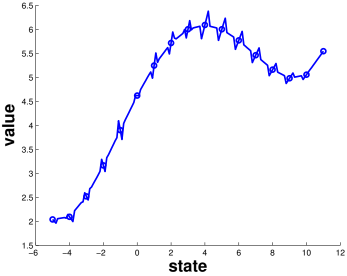
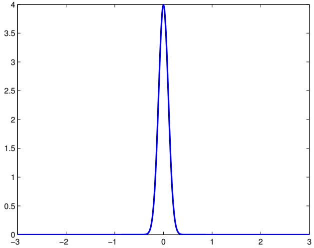
Model-Selection for LWR

- LWR needs tuning, for instance the kernel bandwidth in 1-d:





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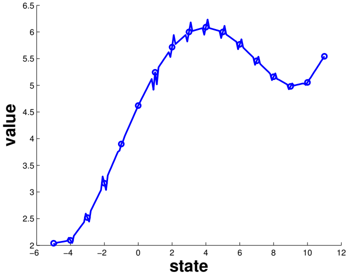

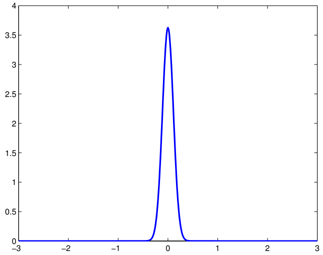

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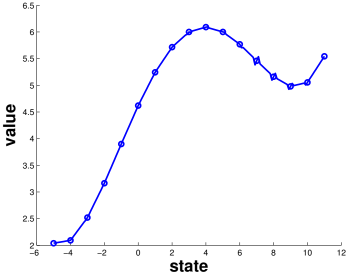

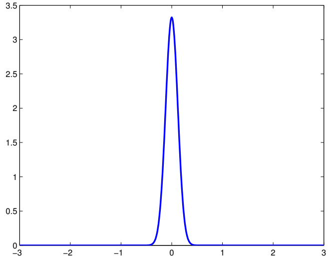

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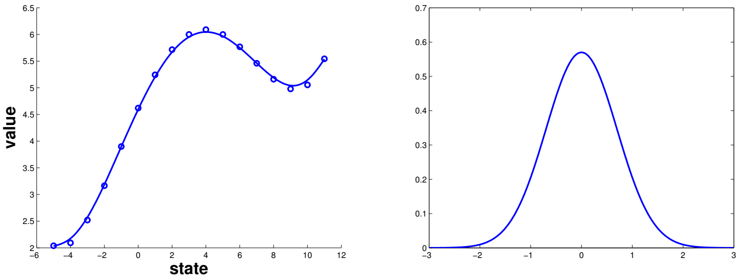

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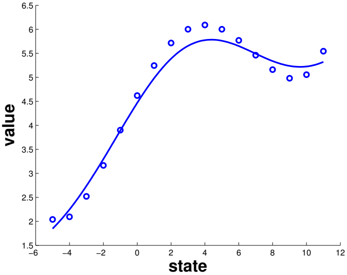

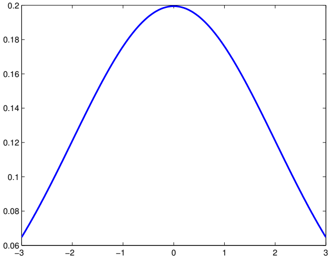

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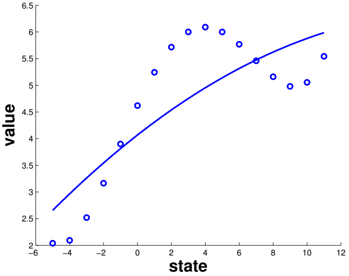

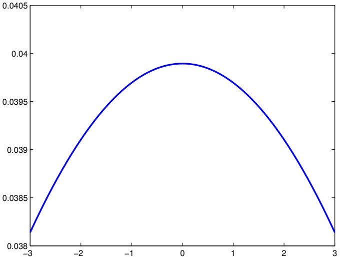

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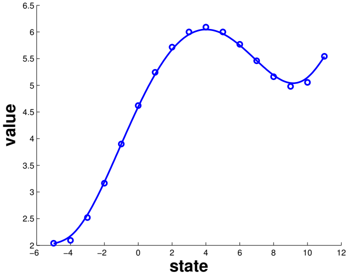
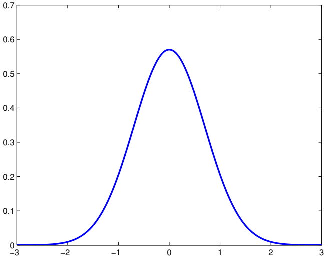
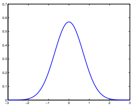
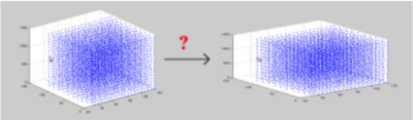




Model-Selection for LWR in N-dimensions

- In N dimensions, it is common to tune N+1 parameters:
  - 1 bandwidth parameter: τ
  - N attribute-scaling parameters: $c_1, \ldots, c_n$



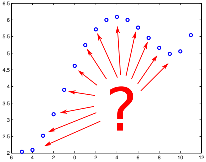


- Tuning these parameters is a form of model-selection

Model Selection - How to Evaluate A Model?

Model-evaluation measure?

- In supervised learning: prediction performance on held-out sets
- In reinforcement learning?



- We don't have the true values (labels) of states

```
for i = 1 → numModels do
    run agent for 1 year with model?
    Record Total Reward
end for
choose best model
```

- Performance is accumulated reward - often too expensive to evaluate

Model Selection - How to Evaluate A Model?

- We use the fact that the optimal value function must satisfy Bellman's optimality equation:

$$\hat{V} \equiv V^{\pi^*} \iff \forall s \in S : BE_{\hat{V}(s)} = 0$$

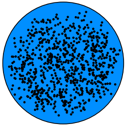
where

$$BE_{\hat{V}}(s) := |\hat{V}(s) - max_a(R(s,a) + \gamma E_{[s'|sa]}[\hat{V}(s')])|$$

- It already holds for $s \in S_{FVI}$ (FVI's convergence condition).
- But not necessarily for $s \notin S_{FVI}$

The Resulting Model Evaluation Measure

- Therefore, to evaluate a model, we:
  1. Sample random states $\mathcal{T} := \{t^{(1)}, ..., t^{(m')}\}$, $t_i \notin S_{FVI}$, $|\mathcal{T}| >> |S_{FVI}|$



  2. Use $||BE_{\hat{V}}(\mathcal{T})||_\infty$ as model evaluation measure
- Model-Selection becomes minimizing

$$F : \mathbb{R}^{n+1} \rightarrow \mathbb{R}$$

where

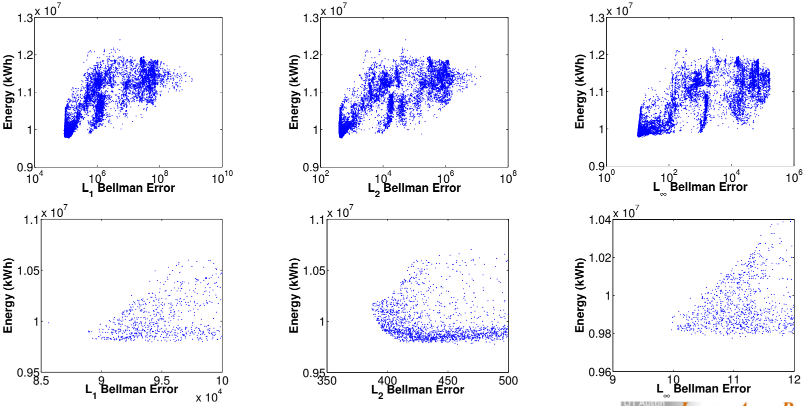
$$(c_1, \ldots, c_n, \tau) \mapsto ||BE_{\hat{V}}(\mathcal{T})||_\infty$$

- No need to evaluate an agent in the environment

Practical Model-Selection: 2 conditions

- To have a practical model-selection algorithm we need to show that:
  1. Bellman Error is correlated with actual performance
  2. Finding the minimum can be done efficiently

Correlation Between the Bellman Errors and Performance



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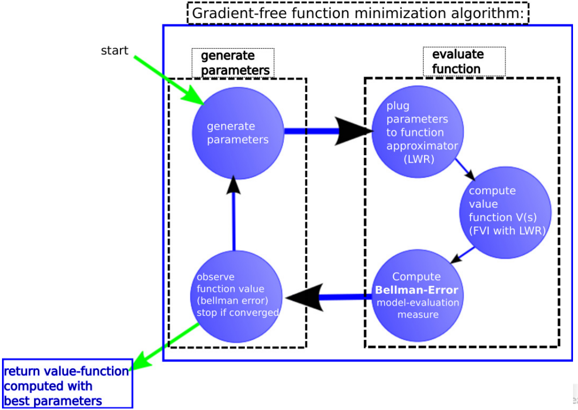
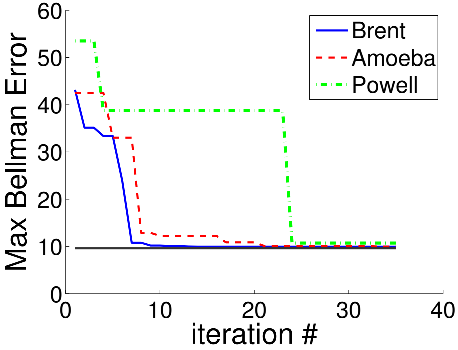
The MSNP Algorithm

We use these two assumptions to define the following model-selection algorithm, named MSNP:

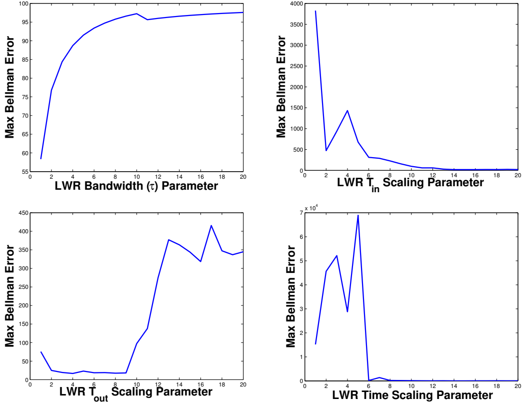


Efficiently Optimizing the Bellman Errors

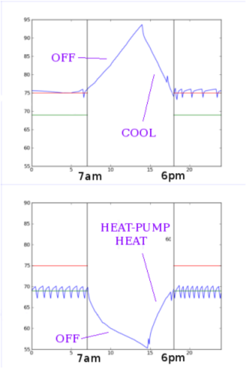


Basins of Convergence of the Max Bellman Error

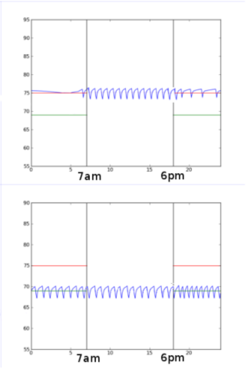
Plotting $p_i \mapsto ||BE_{\hat{V}}(\mathcal{T})||_\infty$, for each $p_i \in \{c_1, c_2, c_3, \tau\}$ (for $j \neq i$, p_j are held fixed at default values)



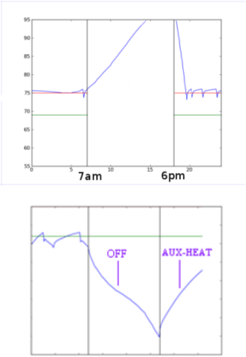
Temperature Graphs



- MSNP



- Default



- Turn-off

Performance of MSNP

- Comparing Yearly energy consumption (lower is better)
- **Default**: default strategy that is deployed in practice
- **MSNP**: our model-selection algorithm is
  1. better than **LargeSample**
  2. close to **CMA-ES**

City	Default (kWh)	LargeSample (kWh)	MSNP **(kWh)**	CMA-ES (kWh)	% Energy-Savings
New York City	11084.8	10923.5	**9859.3**	9816.3	**11.0**%
Boston	12277.1	12480.7	**11433.6**	11052.8	**6.9**%
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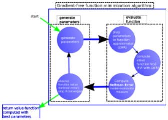
Related Work

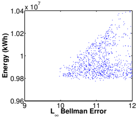
- Bellman error for generalized policy iteration (Antos et al 2008, Lagoudakis and Parr 2003)
- Bellman error for tuning basis functions in linear architectures (Keller et al 2006, Menache et al 2005, Parr et al 2007)
- LWR Model selection for learning a transition-function (Ng et al 2004)
- Abstract model-selection algorithm for RL (Farahmand and Szepesvari 2011)

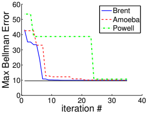
Summary

- Introduced MSNP - practical model selection algorithm for RL



- MSNP is based on two main ideas:





- Value-function based RL for thermostat control
- Outlook
  - Theoretical analysis, Bellman Error's basin of convergence
  - High-dimensional problems