

Spectral learning for structured partially observable environments

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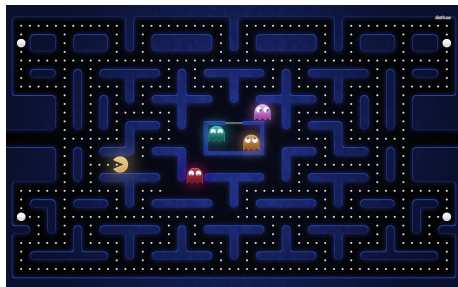
Overview

- 1 Predictive state representation (PSR)
- 2 The Base System: extending PSRs
- 3 Experimental results
- 4 Learning the Base System

Structured partially observable environments

Structured Environments

- ① Goal: Predictions
- ② Plan: Exploit structure
- ③ Example: Pacman



PSR: The Timing Case

- Model environment with a Predictive state representation
- For timing we have one observation symbol: σ
- PSR defined by: $\langle \alpha_0, \{A_\sigma\}, \alpha_\infty \rangle$

α_0 : Initial weighting on states $1 \times n$

A_σ : Transition matrix $n \times n$

α_∞ : Normalizer $n \times 1$

- PSRs compute probabilities of observations

Notation: σ : one time unit, σ^k : k time units

$$f(\sigma^k) = \alpha_0 * A_\sigma^k * \alpha_\infty$$

- Examples of a PSRs: HMMs, POMDPs

Spectral Learning of PSRs

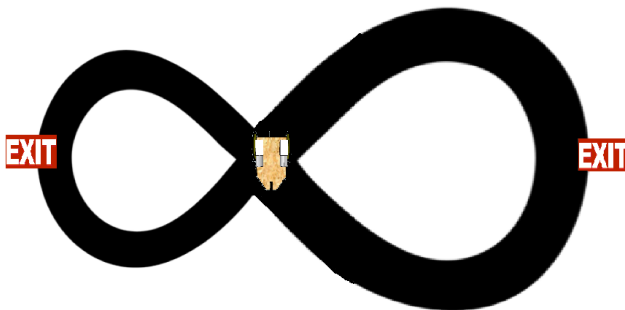
- Step 1: Represent data as a matrix
- Step 2: Singular value decomposition
- Step 3: Pick number of states for PSR
- Step 4: Learn the PSR with matrix computations

The Base System

- Idea: Add $\{A_\sigma, A_{\sigma^2}, A_{\sigma^4}, A_{\sigma^8}, \dots A_{\sigma^N}\}$ as extra transition operators
- Timing queries: $f(\sigma^{11}) = \alpha_0 * A_{\sigma^8} * A_{\sigma^2} * A_{\sigma^1} * \alpha_\infty$
- Motivation:
 - 1) Express transitions directly to avoid error build up
 - 2) Faster queries

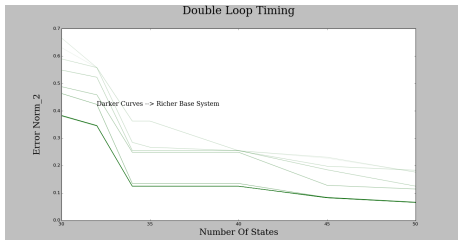
Timing with the Base

Agent goes through loops until leaving through an exit state. Exit states have transition probabilities of 0.4 and 0.6. Loop lengths are 64 and 16.

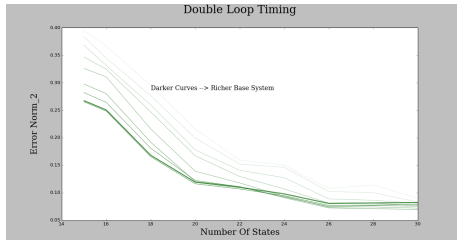


Varying noise in loops

No noise in durations



Noise in durations

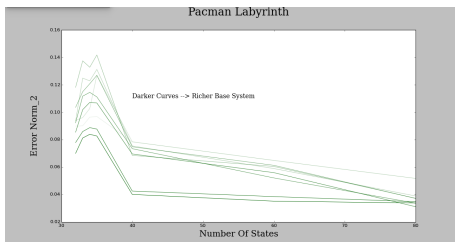


- Noise allows for smaller models

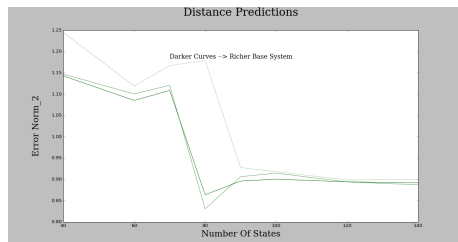
- $$\|f - \hat{f}\| = \sqrt{\sum_{x \in \text{observations}} (f(x) - \hat{f}(x))^2}$$

Pacman Labyrinth

Timing Predictions



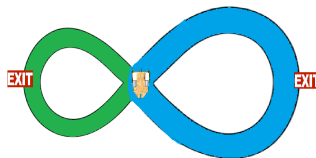
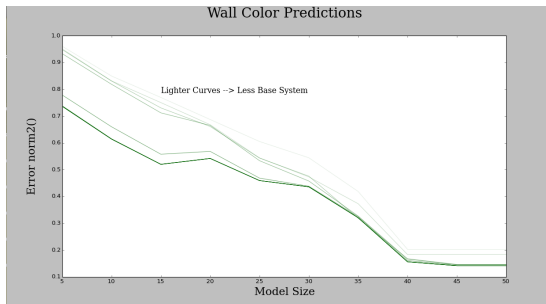
Distance Predictions



$$\bullet \quad \|f - \hat{f}\| = \sqrt{\sum_{x \in \text{observations}} (f(x) - \hat{f}(x))^2}$$

Wall Color Predictions

We paint the first loop green and the second loop blue



- $$\|f - \hat{f}\| = \sqrt{\sum_{x \in \text{observations}} (f(x) - \hat{f}(x))^2}$$

Picking the Base System

- Picking operators to exploit structure

Observations: $\{ "a^{30}":10, "a^{60}":5, "b^{18}":15 \}$

Desired Base System: $A_{a^{30}}, A_{b^{18}}, A_a, A_b$

- Substring properties: **long, frequent, diverse**
- Solution: iterative greedy heuristic

Computing with the Base System

- Using the Base System well involves requires good **string partitions**

Query string: "abcacb", Base System = $\{A_{ab}, A_{bca}, A_{cb}, A_a, A_b\}$

Desired partition: "a—bca—cb""

- Goal: minimize matrices used
- Solution: dynamic programming

Conclusion and Future Work

- What's left for the Base System?
 - 1) Theoretical analysis
 - 2) Test heuristics on labyrinths
 - 3) Further optimize heuristics

Questions? Comments?