

# Spectral learning for structured partially observable environments

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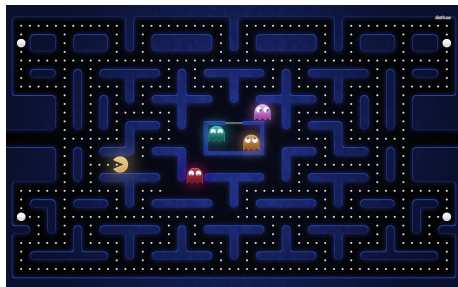
# Overview

- 1 Predictive state representations
- 2 The Base System
- 3 Experimental results
- 4 Learning the Base System

# Structure partially observable environments

## Structured Environments

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



# PSRs: The Timing Case

- Model environment with a Predictive state representation
- PSR defined by:  $\langle \alpha_0, \{A_\sigma\}, \alpha_\infty \rangle$ 
  - $\alpha_0$ : Initial weighting on states  $1 \times n$
  - $A_\sigma$  Transition matrix  $n \times n$
  - $\alpha_\infty$ : Normalizer  $n \times 1$
- PSRs compute probabilities of observations
  - Notation:  $\sigma$ : one time unit,  $\sigma^k$ : k time units
  - $f(\sigma^k) = \alpha_0 * A_\sigma^k * \alpha_\infty$
- Examples of a PSRs: HMMs, POMDPs

# Overview of Learning

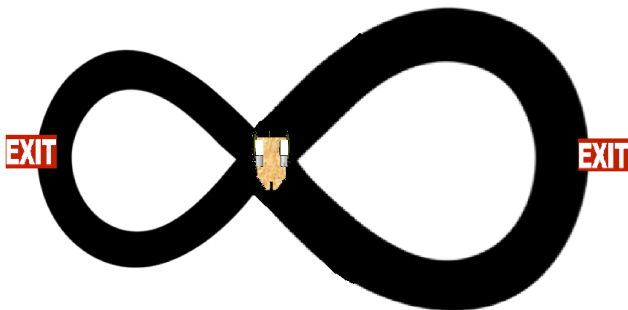
- Spectral algorithms can learn PSRs
- Flavour of learning algorithm:
  - Step 1: Represent data as a matrix
  - Step 2: Singular value decomposition
  - Step 3: Pick number of states for PSR
  - Step 4: Learn the PSR with matrix computations

# The Base System

- Idea: include  $\{A_a, A_{a^2}, A_{a^4}, \dots A_{a^N}\}$  as additional operators
- Timing queries  $f(a^{11}) = \alpha_0 * A_{a^8} * A_{a^2} * A_{a^1} * \alpha_\infty$
- Motivation:
  - 1) Express transitions directly to avoid error build up
  - 2) Faster queries. Discussion:  $M^k * v$

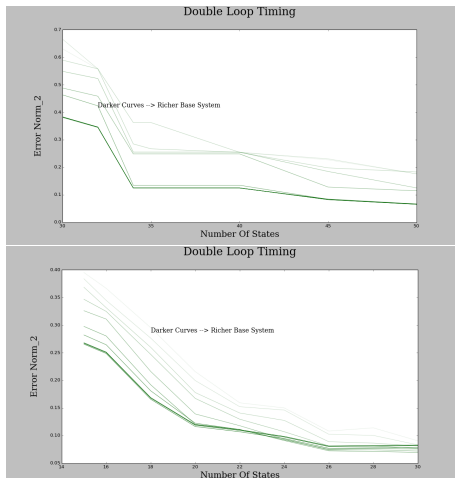
# Timing with the Base

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

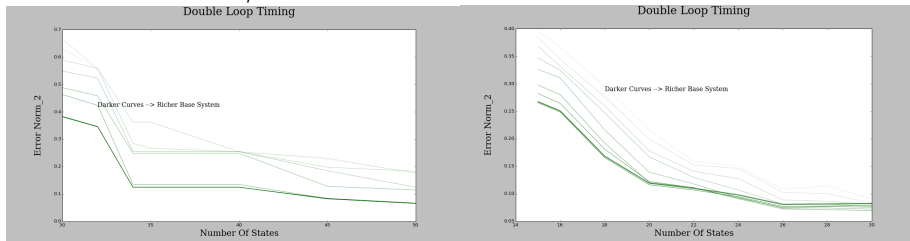
- Left Figure: No noise in durations
- Right Figure: Noise in loops
- Noise makes the loops more compressible





# Varying amount of data

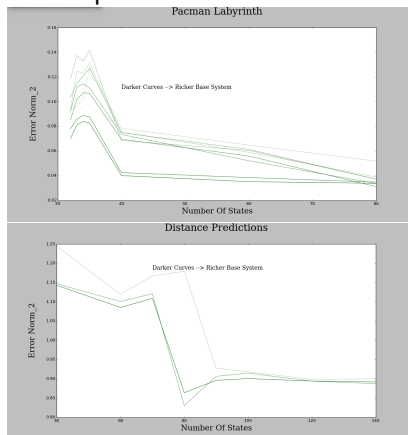
- The more data, the more effective the base



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

# Pacman Labyrinth

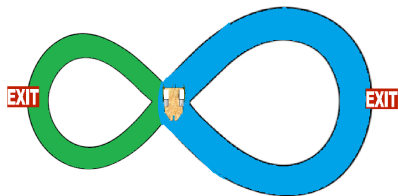
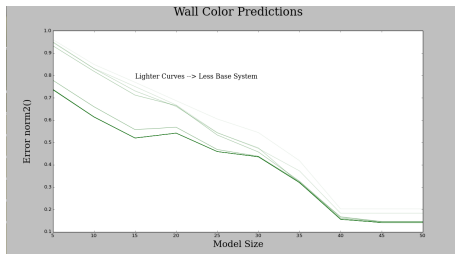
- Left figure: Timing predictions
- Right figure: Distance predictions



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

# Wall Color Predictions

We paint the first loop green and the second loop blue.



# Picking the Base System

- How do we pick transition operators?

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?