



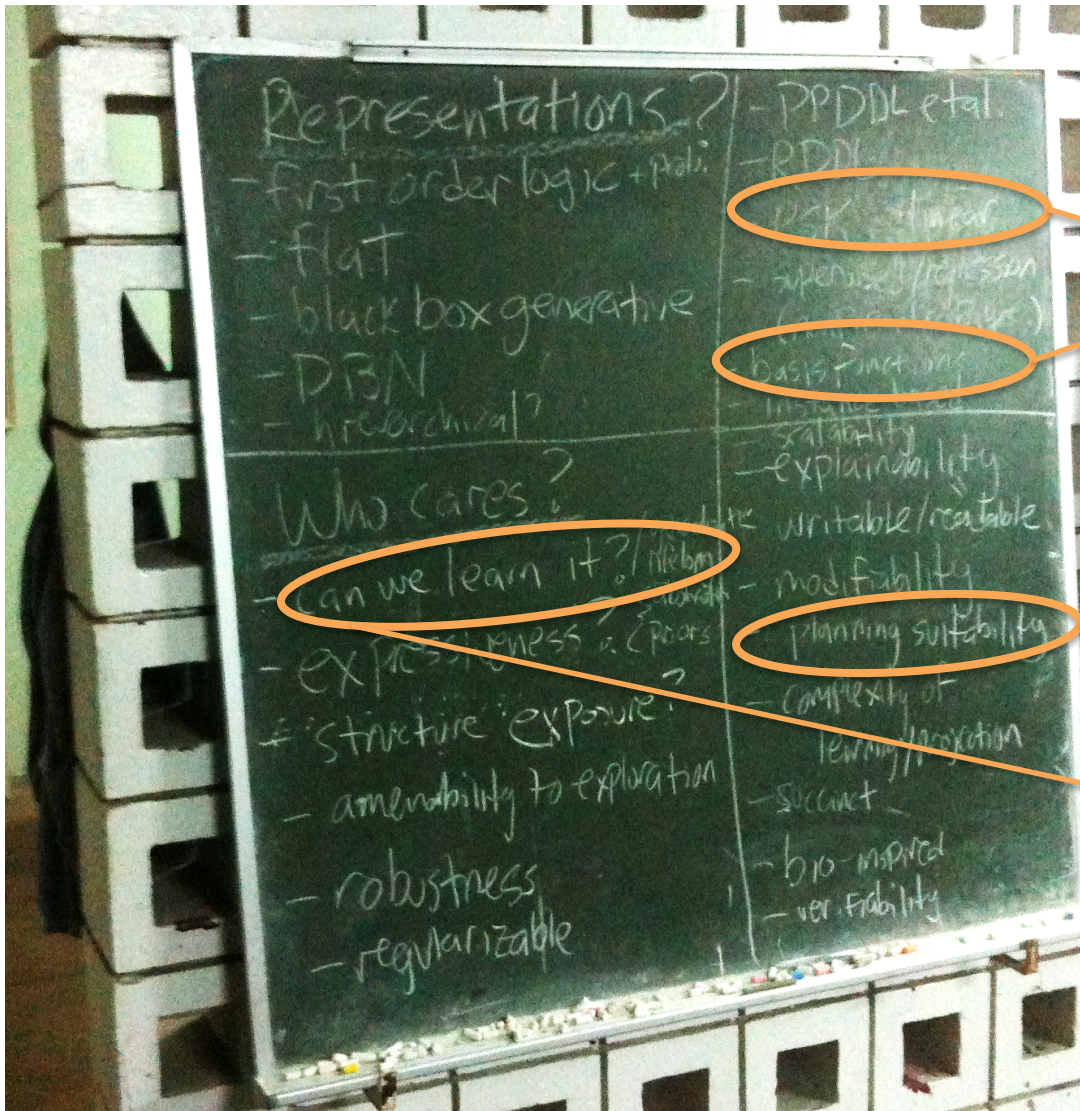
Better Generalization with Forecasts

Tom Schaul
Mark Ring





Which Representations?



Type: Feature-based representations
(state = feature vector)

Quality 1:
Usefulness for linear policies

Quality 2:
Generalization



Outline

- ✓ Motivation
- Representation
 - Predictive State Representations
 - General Value Functions, aka “Forecasts”
 - Simplified subclass of Forecasts
- Evaluating Generalization
- Results



Predictive State Representations

- Question/test: “Will I hit the wall if I take a step left and then a step back?”
- Expected answer = feature ϕ
- Defined as a set of **testable predictions**
 - Observable quantities (wall sensor)
 - Conditional on action sequence (step left, step back)
 - Open-loop (ends at $t+2$)



General Value Functions

- ϕ = “After how many steps will I encounter a door if I head to the the wall in front of me, and follow it clockwise?”
- General Value Functions
 - More general questions
 - Closed-loop: arbitrary length sequences
- We call them “Forecasts”



Forecast Components

- Conditional on an **option**: following a policy (straight+clockwise) until termination (door)
 - I : states of interest
 - $\beta(s)$: termination probability
 - π : policy
- Target value (expectation): any function of the state, cumulative
 - $c(s)$: accumulated value before termination
 - $z(s)$: final value upon termination in s



Simplified Forecasts

- Constant components:
 - $c(s) = 0$
 - $I =$ all states
- Defined by only a **target set** of states \mathbf{T}
 - $z(s)$: 1 if s in \mathbf{T} , 0 elsewhere
 - $\beta(s)$: 1 if s in \mathbf{T} , $1-\gamma$ elsewhere
 - π : **implicitly** defined: maximizes the expected z

→ Only one free parameter: \mathbf{T}

→ Output: feature vector $\phi(s)$



Outline

- ✓ Motivation
- ✓ Representations
- Evaluating Generalization
 - Ideal vs. estimated forecast values
 - Canonical forecast ordering
 - Quality measures
- Results



Forecast Values

- Distinguish:
 - Forecast **definition** (“question”)
 - From target set T
 - Ideal forecast **value** (true “answer”)
 - Forecast value **estimate** (approximation)
 - can be learned
- Focus: quality of representation
 - Use ideal forecast values as features
 - We can ignore the learning issues (i.e., we can **cheat!**)
 - Namely: policy iteration with transition model



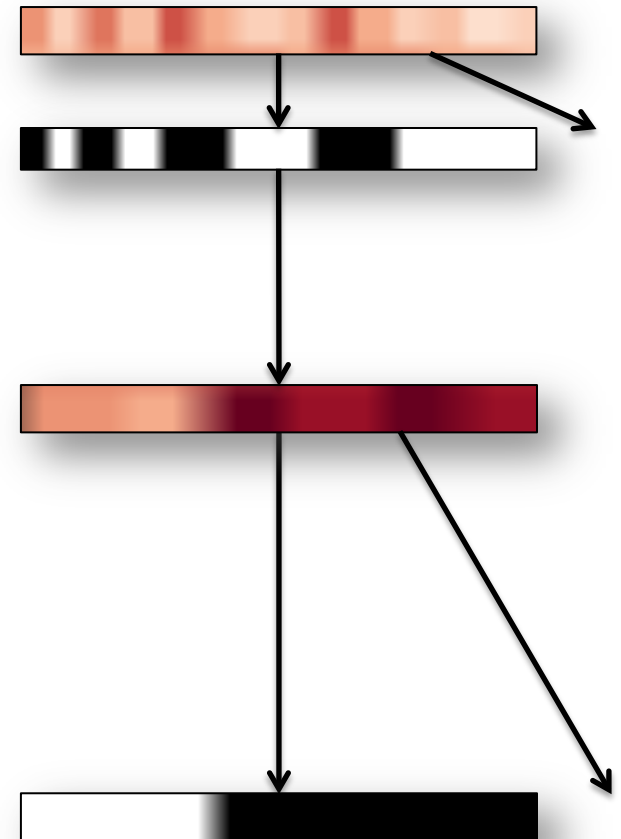
Forecast Generation (1)

- Canonical (breadth-first) exhaustive generation
 - First layer based on observations
 - Forecasts can build upon other forecasts
 - Unique ordering (lexicographic tie-breaking)



Forecast Generation (2)

1. Initially: observations define target sets \mathbf{T}
2. Compute ideal forecast values ϕ from \mathbf{T}
 - Cheat 1: transition model (infinite experience)
 - Cheat 2: knowledge of state
3. Threshold ϕ for new candidate \mathbf{T} sets
4. (Ignore redundant sets)
5. Go to step 2, until no \mathbf{T} is left





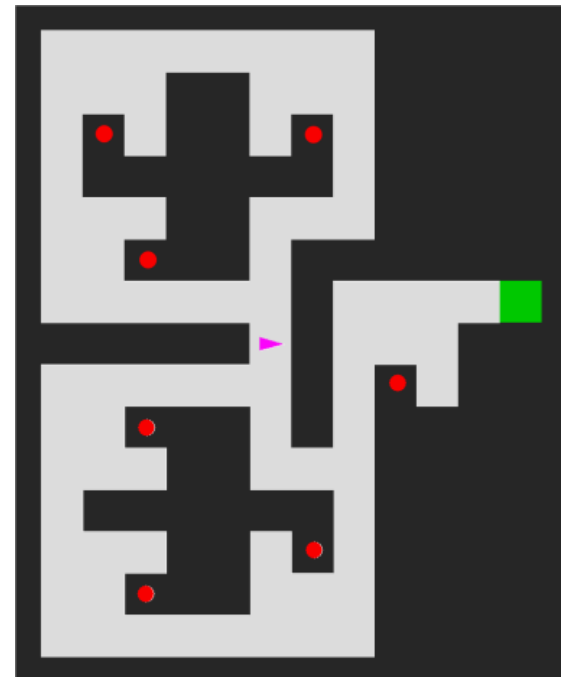
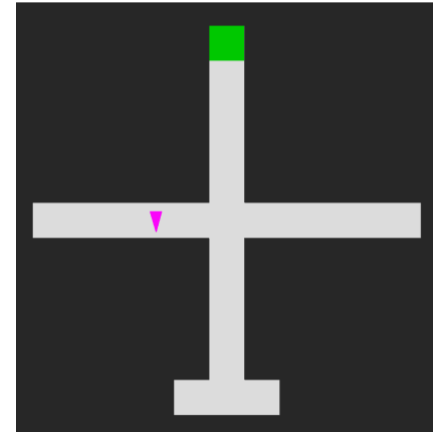
Evaluation of Feature Sets

- Quality measures:
 1. Optimal policy using linear function approximation (LFA) on features (LSTD+PI)
 2. Distance between estimated external value V' (using LFA on features) and true V^* (MSE)
- Generalization:
 - consider random subset of states (e.g. 50%)
 - train the LFA based on this limited experience
 - see how that V' generalizes to the remaining states



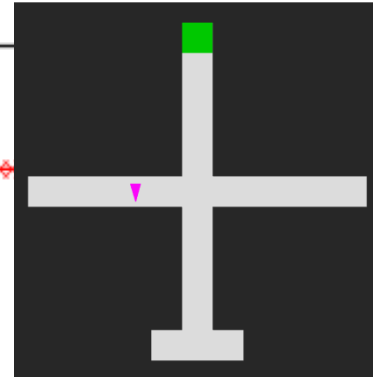
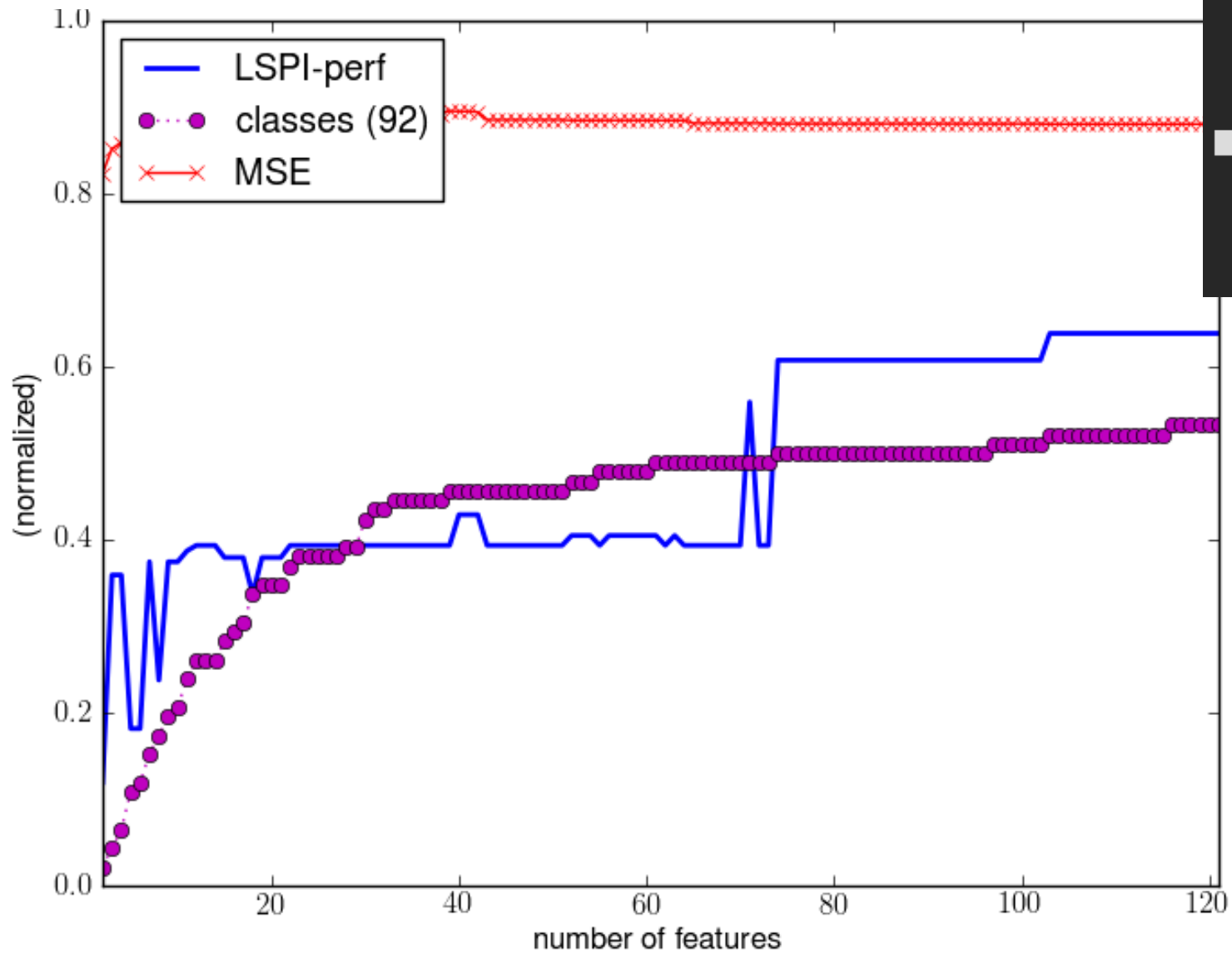
Outline

- ✓ Motivation
- ✓ Representations
- ✓ Evaluating Generalization
- Results
 - Two mazes
 - Simplistic agent
 - 1 binary observation (wall sensor)
 - 1 binary action (forward/rotate left)
 - Comparison to PSRs as baseline



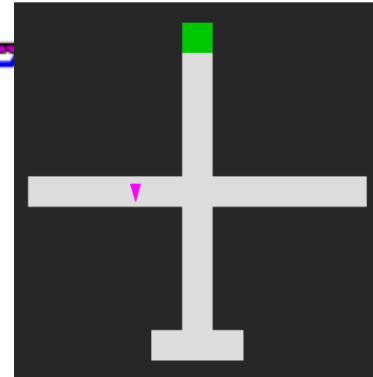
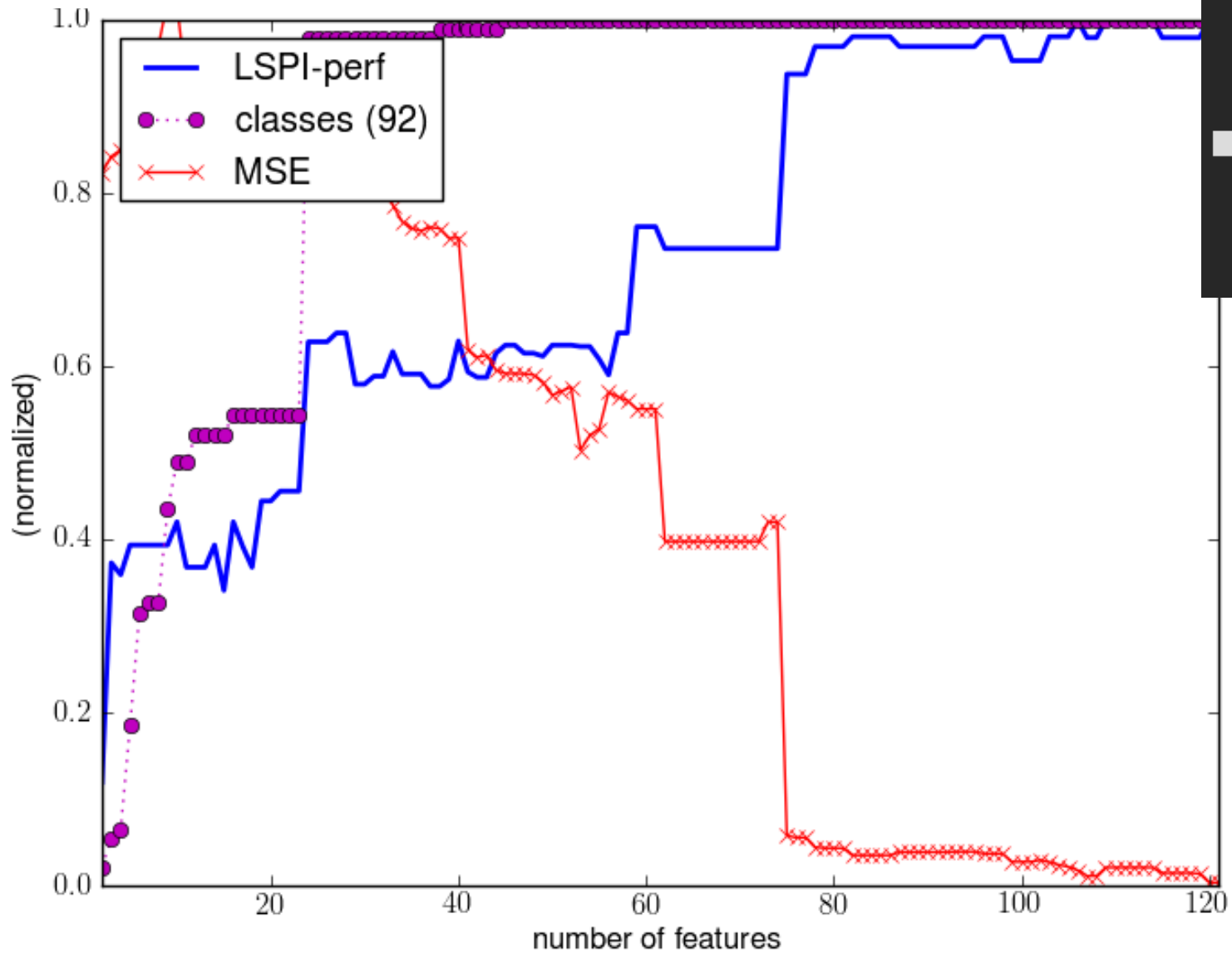


4-Arm-Maze: PSRs



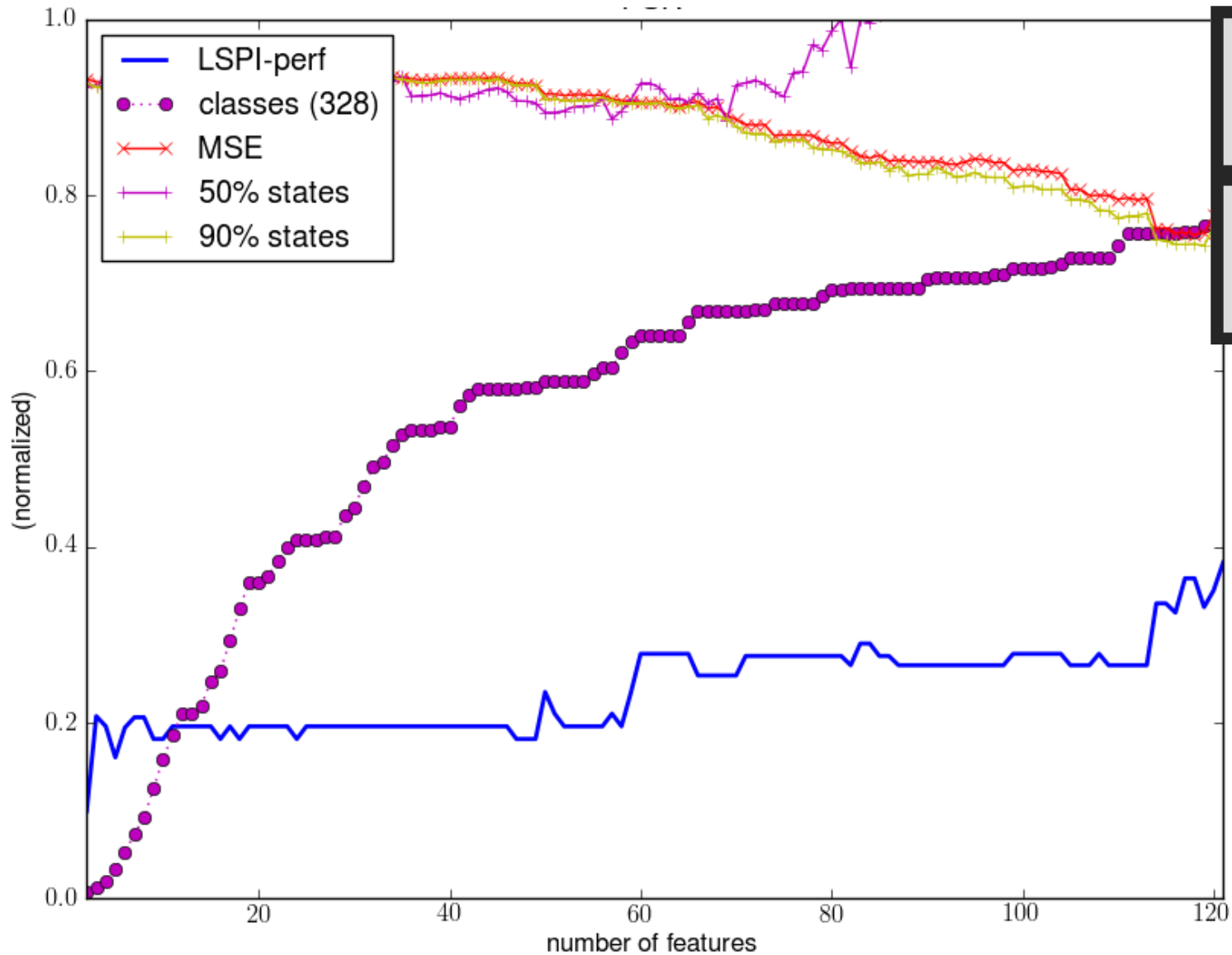


4-Arm-Maze: Forecasts



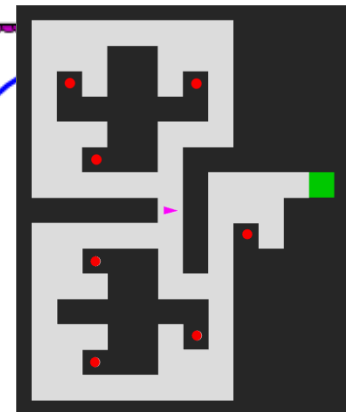
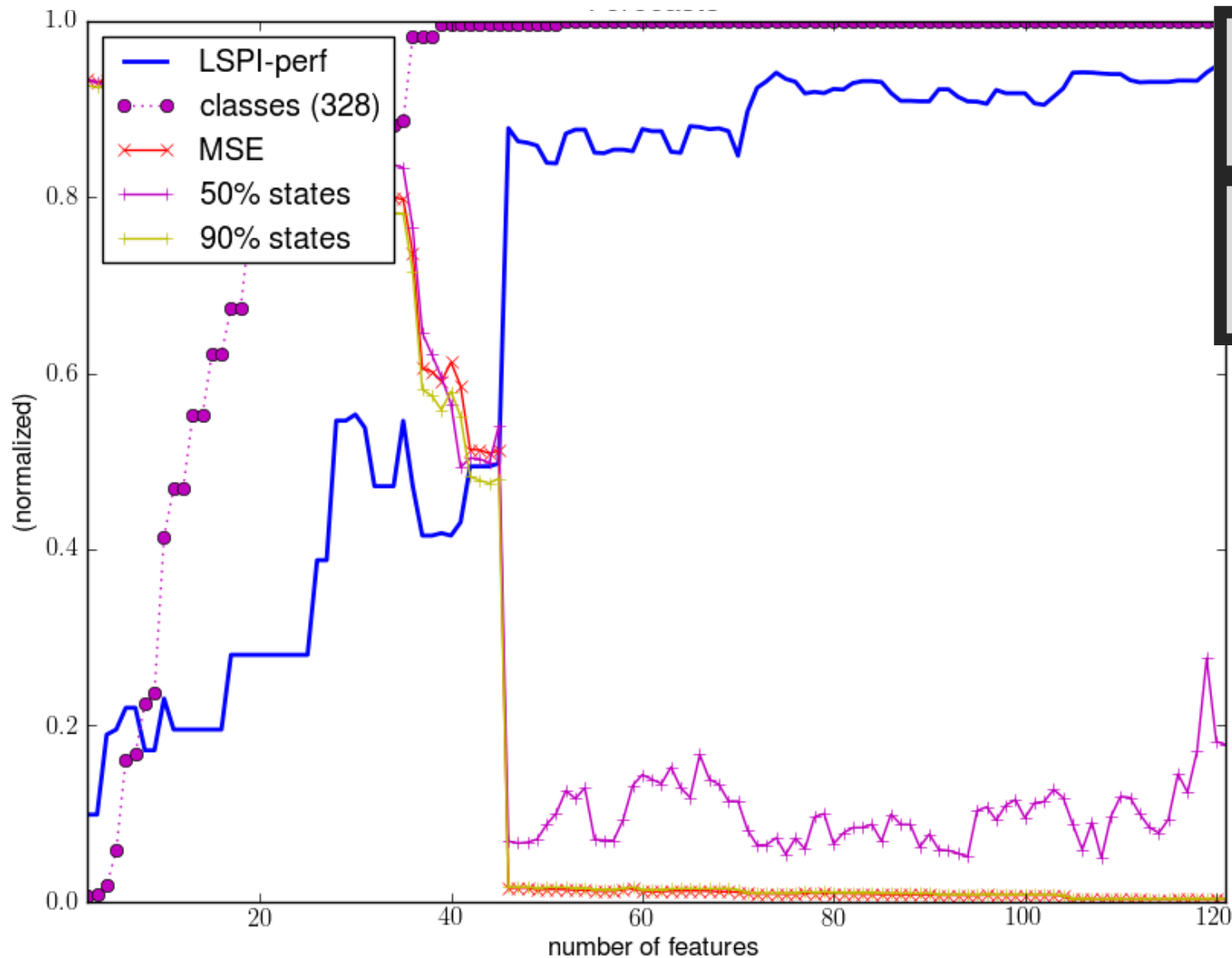


7-Rooms-Maze: PSRs



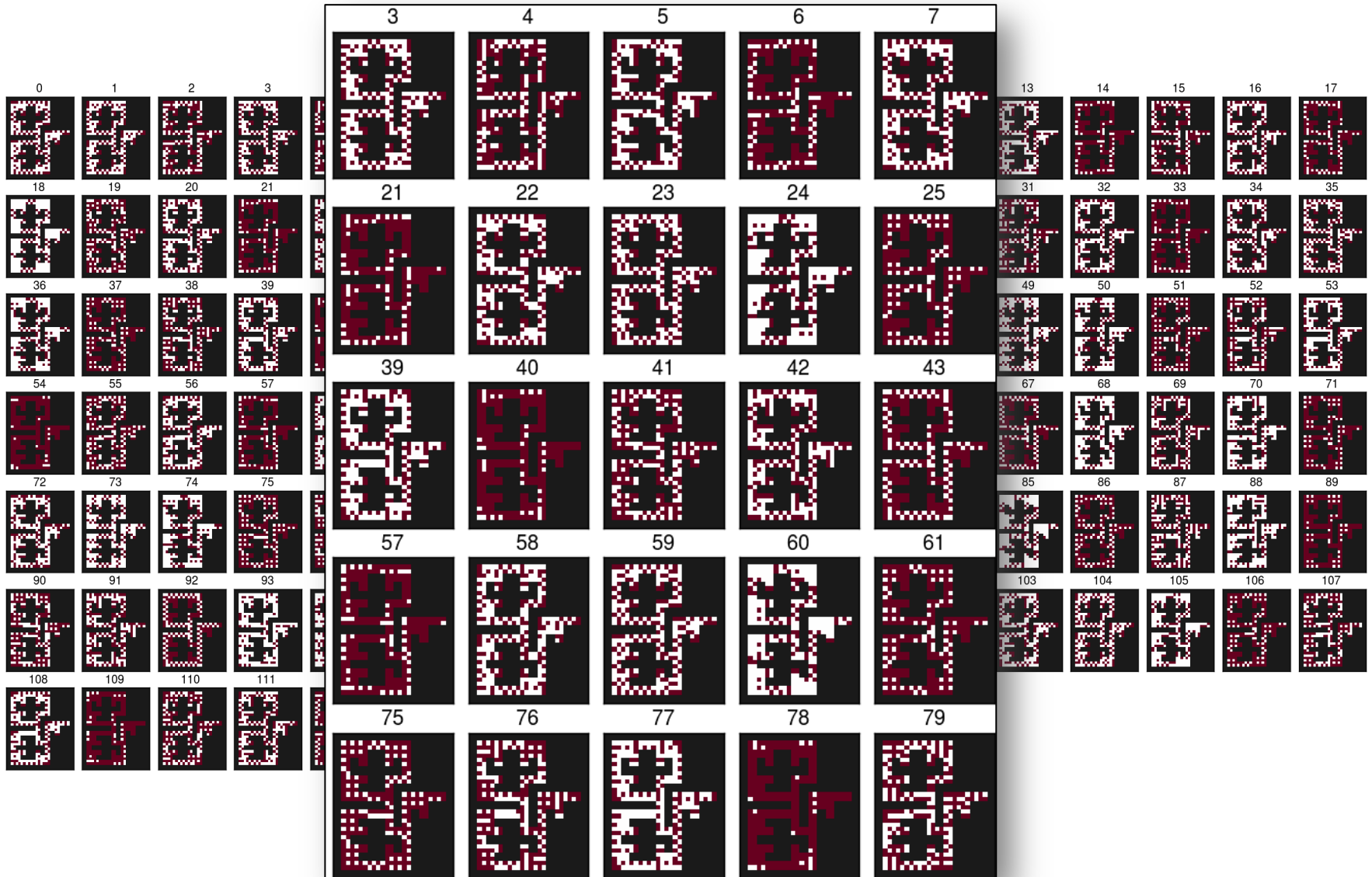


7-Room-Maze: Forecasts



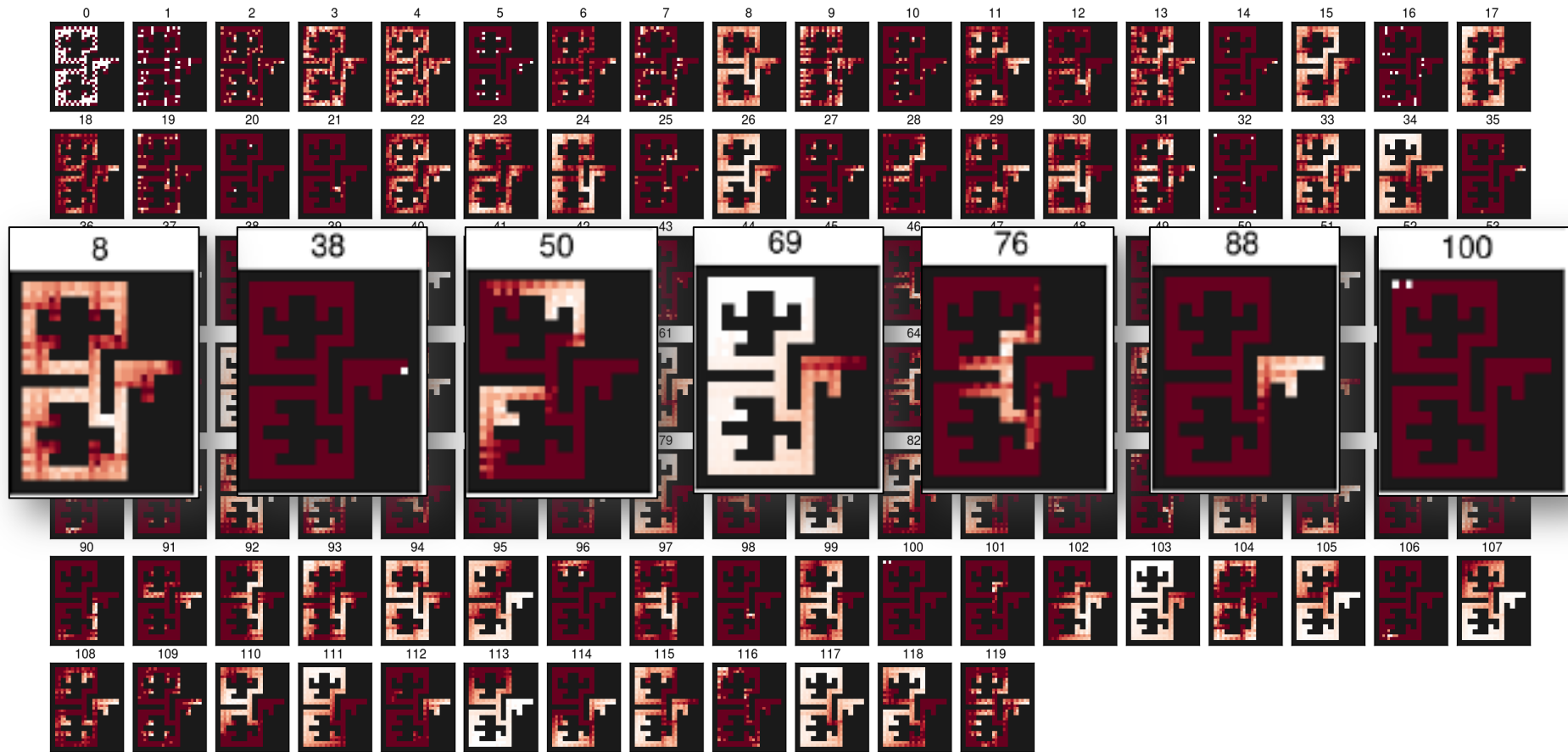


PSR Features





Forecast Features





Summary

Forecasts as representations:

- Temporal abstraction (closed-loop)
- Simple structure
- Useful features for linear evaluation and control
- Good generalization with linear FA

Future work

1. Removing the cheats: using learned estimates instead of ideal forecast values
2. Smarter forecast generation than exhaustive