Bayesian Nonparametric Approaches for Reinforcement Learning in Partially Observable Domains

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CSAIL Student Workshop 2010

Motivation

Specifying models is often difficult and tedious, yet is needed for lots of problems.

Remote Patient Monitoring

Need models of vital signs.

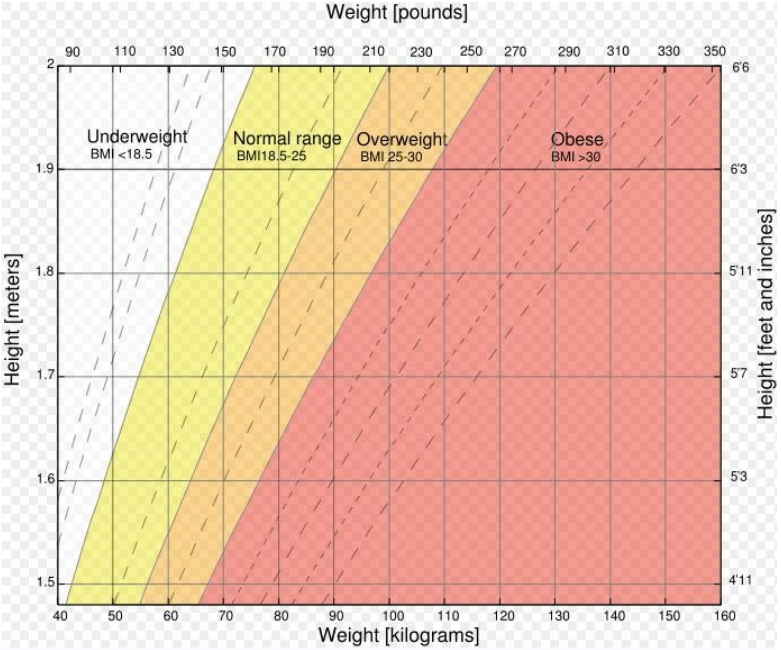
Assisted Living for the Elderly

Need models of resident behavior

Motivation

Learning as we go helps bias us toward parts of the model needed for good performance.

Remote Patient Monitoring



Common health regime of patient governs what vital sign deviations matter.

Assisted Living for the Elderly

Knowing what activities that a resident enjoys helps detect deviations.

Motivation

Different domains also usually come with various ways of gathering knowledge.

Remote Patient Monitoring

Nurses can suggest what vital signs are likely to be important.

Assisted Living for the Elderly

Caretakers are familiar with needs, personalities of residents.

Goal

Enable agents to learn how to act in partially observable environments without known models.

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Enable agents to learn how to act in partially observable environments without known models.

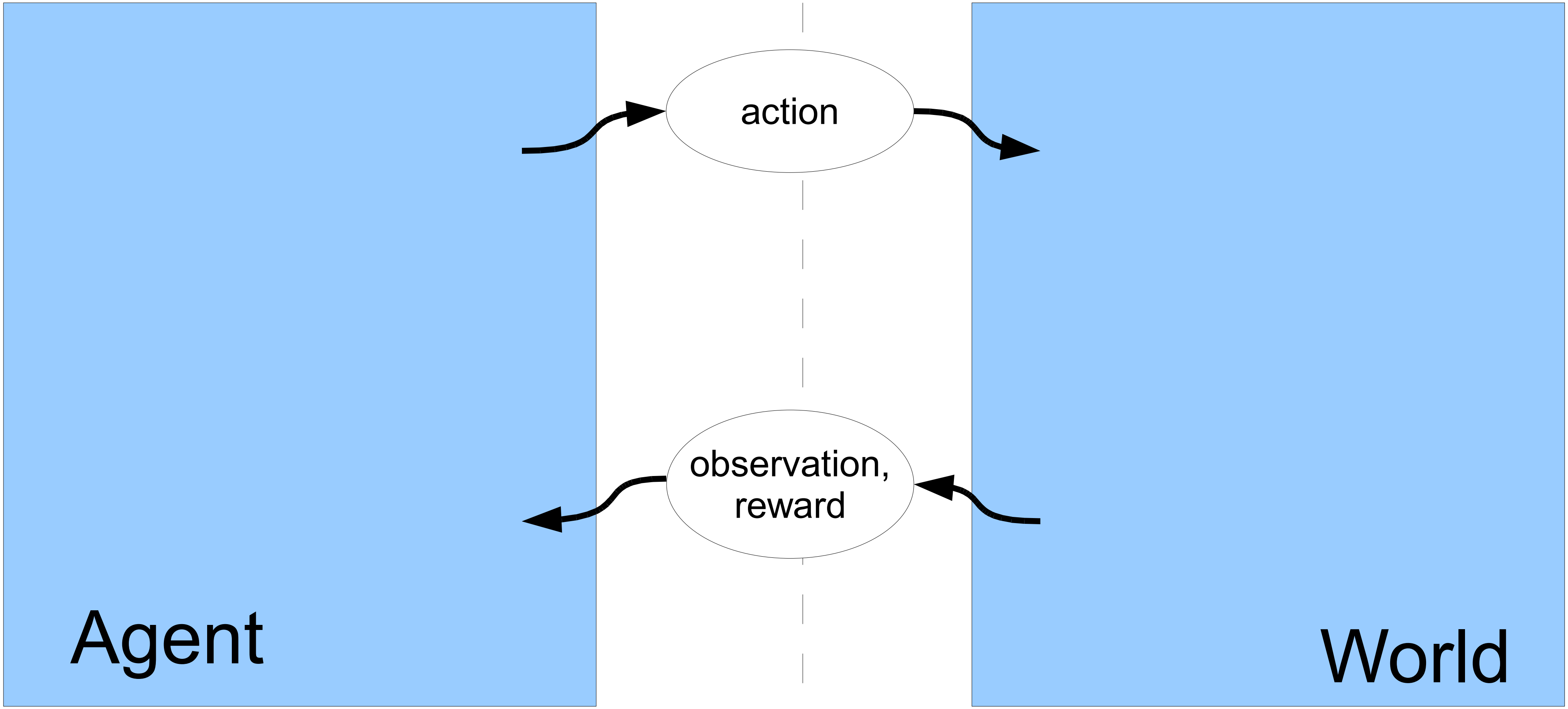
We also want to assume as little as possible about

the model (because specifying models is hard!); models should scale with sophistication of the data.

the kinds of information available; agents should be able to combine multiple sources of information.

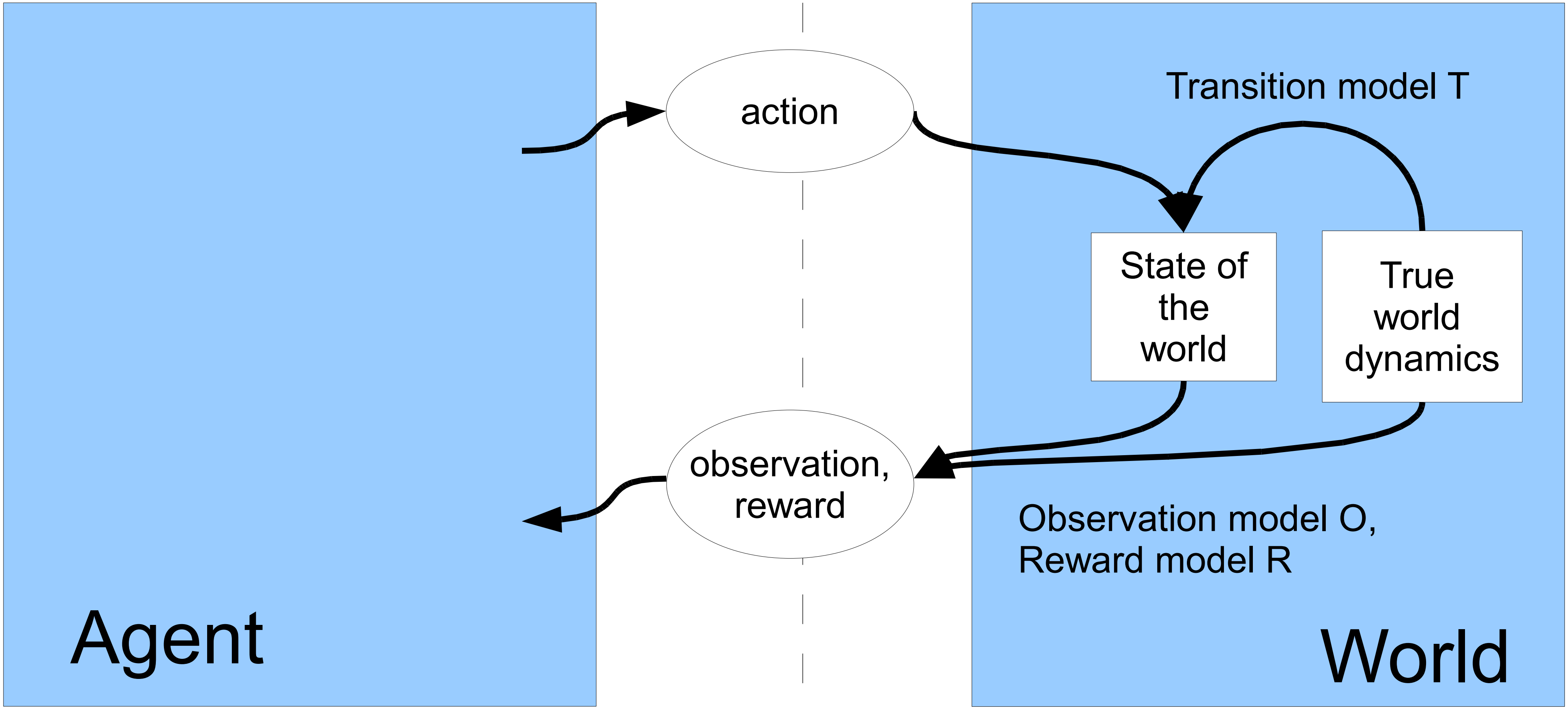
Formalizing the Problem

General Reinforcement Learning Framework



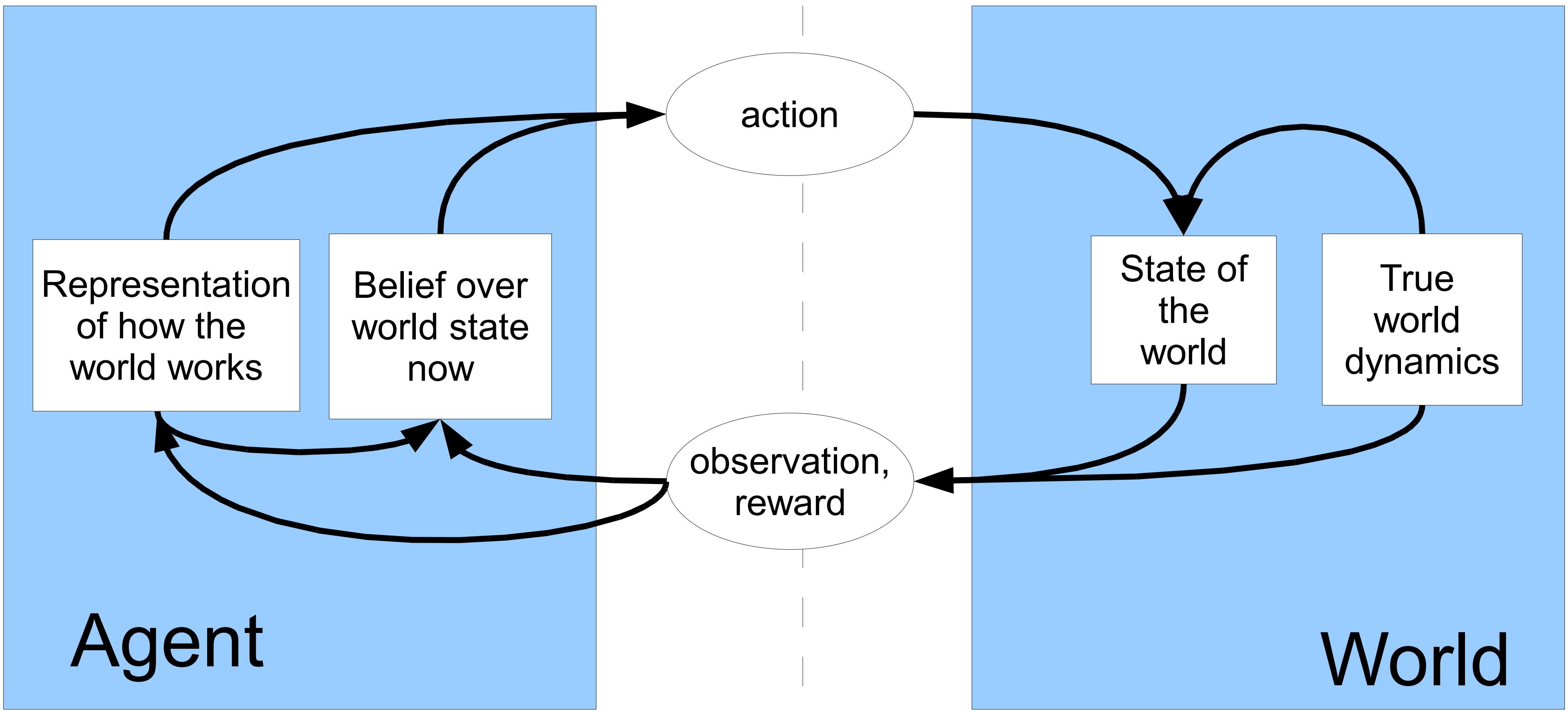
Defining the World

Assume that the world is a (discrete) partially observable Markov decision process (POMDP)



The Agent's Goal

Learn enough about how the world works to maximize expected discounted rewards



Challenges

Delayed rewards

Hidden world state

Noisy observations and transitions

Many unknowns to reason about

Many sources of information

Challenges

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Many unknowns to reason about

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Lots of previous work

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Our Focus

Challenges

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Our Focus

We address both these challenges with **Bayesian Nonparametric Techniques**

How Bayesian Nonparametrics Help

Let the agent reason about its uncertainty

Scale sophistication of the model with structure in the data

Incorporate multiple sources of information

How Bayesian Nonparametrics Help

Let the agent reason about its uncertainty

Scale sophistication of the model wi
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Incorporate multiple sources of info

Common to
all Bayesian
approaches

How Bayesian Nonparametrics Help

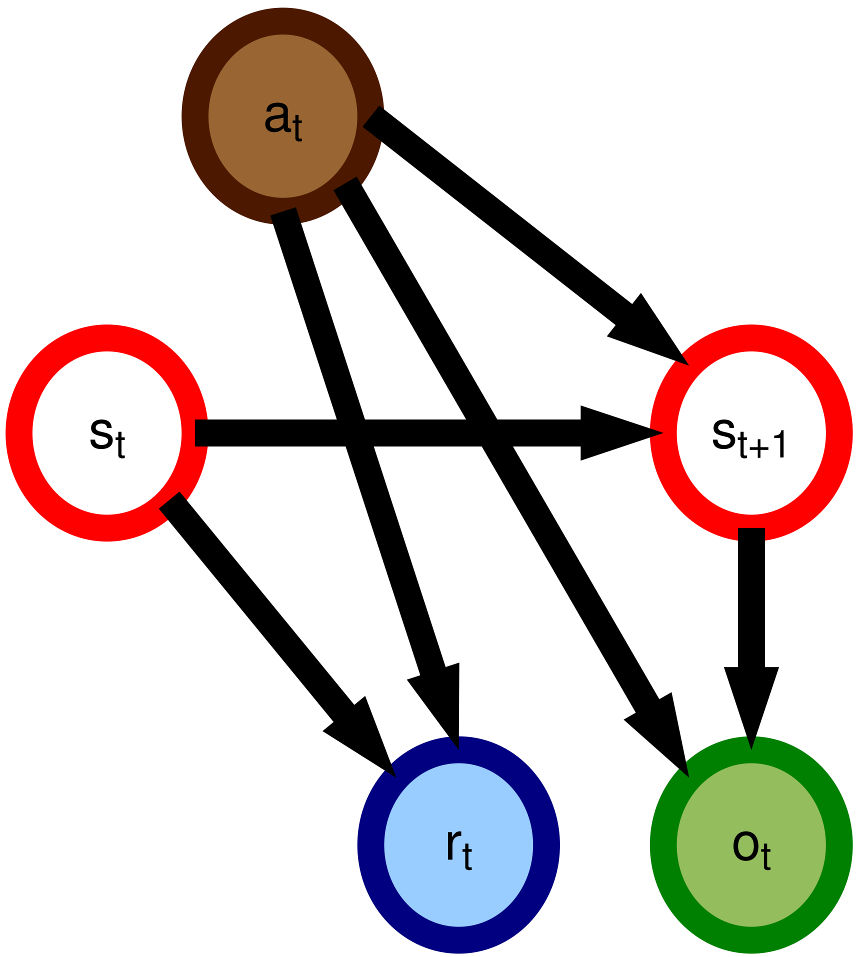
Let the agent reason about its uncertainty

Scale sophistication of the model with structure in the data

Incorporate multiple

Infinite-state POMDPs with many (infinite) states, but a strong bias to using only a few

Growing Representations: Infinite POMDP (built from iHMM)

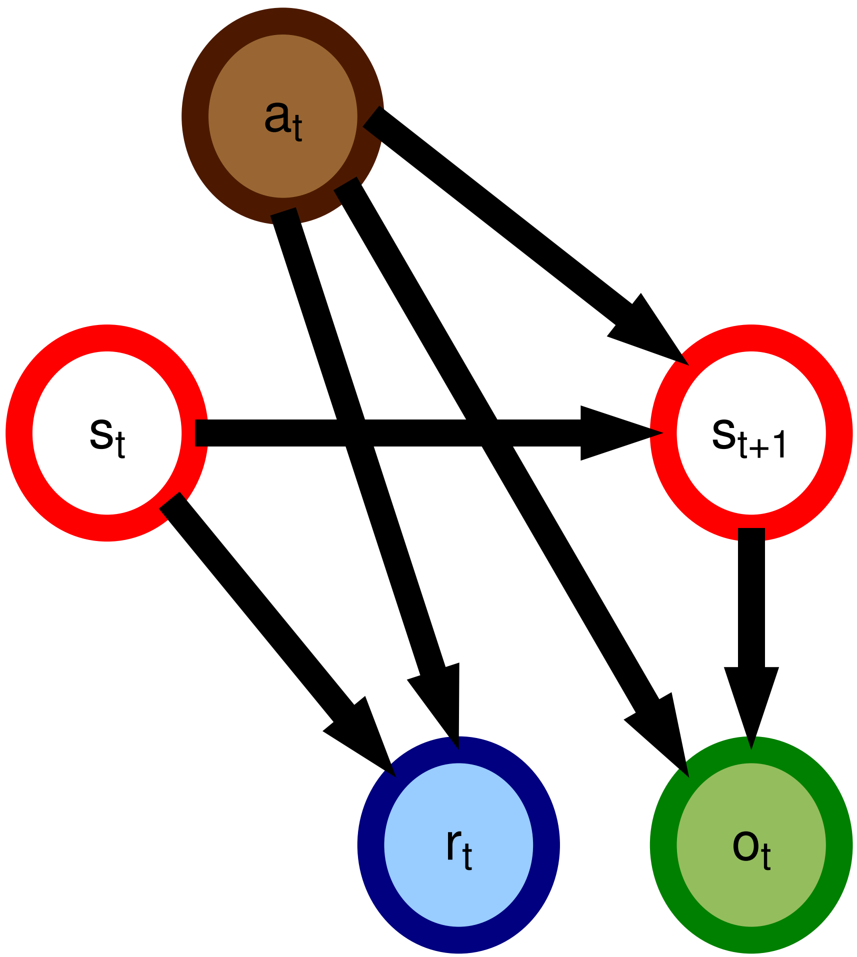


Input: actions
(observed, discrete)

Infinitely many states
(hidden, discrete)

Output: observations,
rewards (observed)

Growing Representations: Infinite POMDP (built from iHMM)



Input: actions
(observed, discrete)

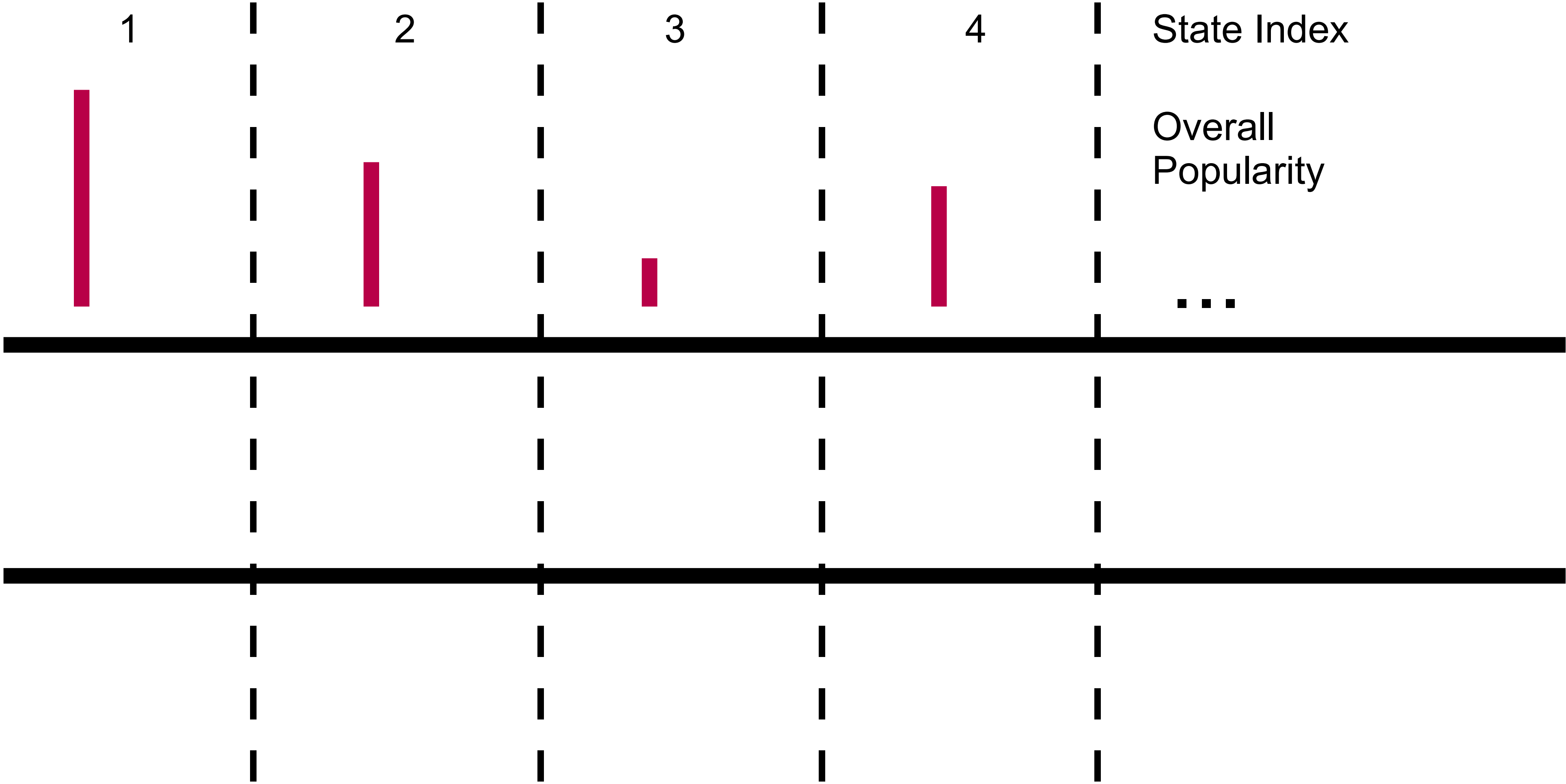
Infinitely many states
(hidden, discrete)

but a few popular states most likely to be visited

Output: observations,
rewards (observed)

Generative Process

First, sample overall popularities, observation and reward distributions for each state.



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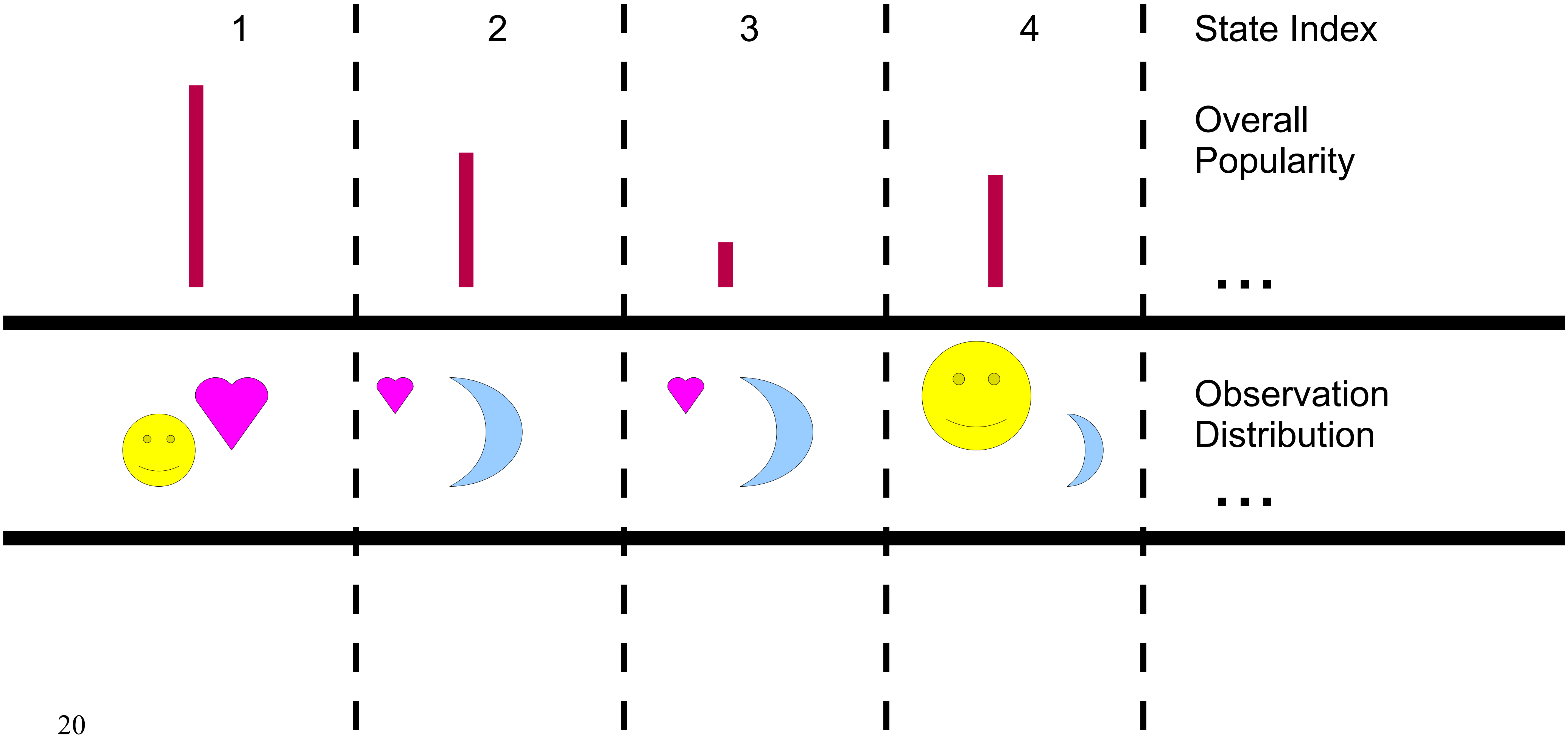

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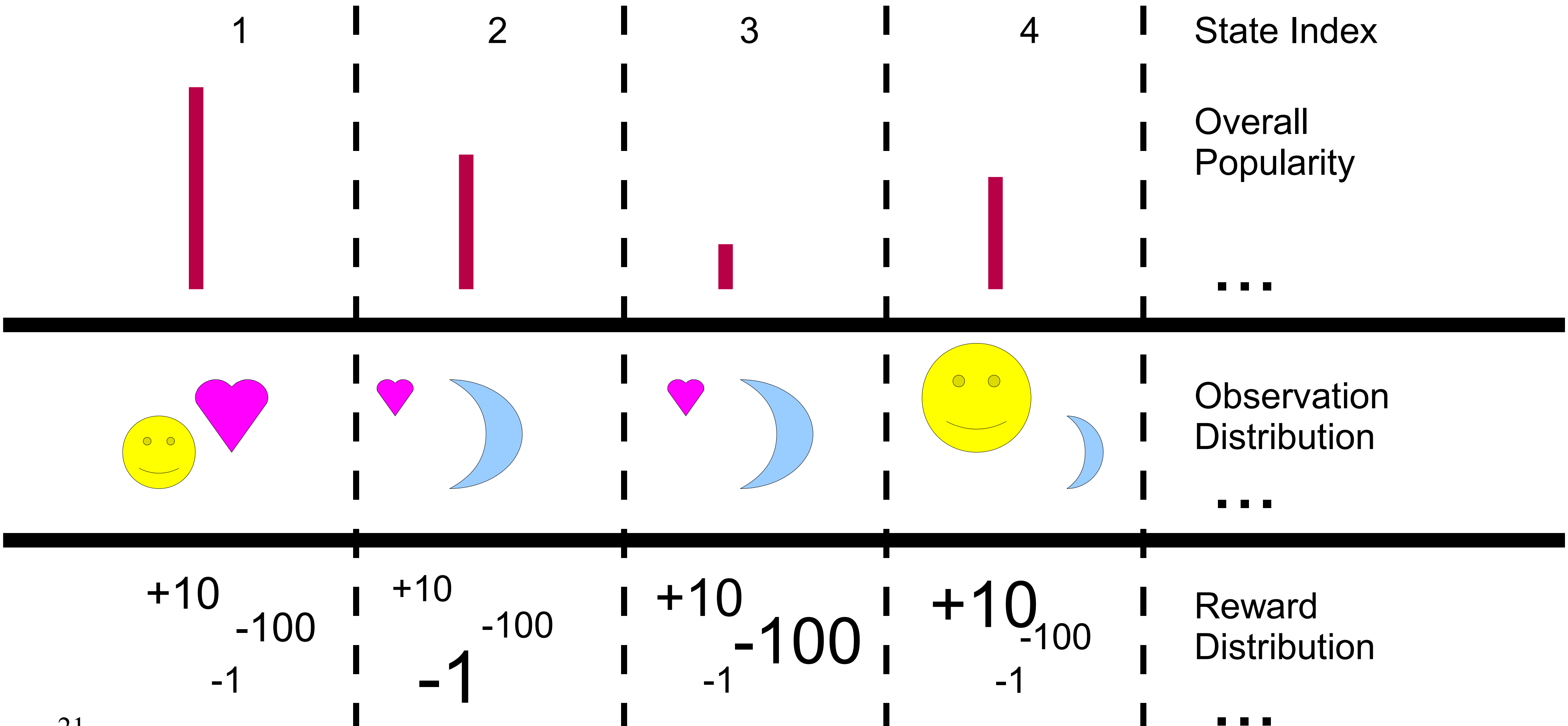
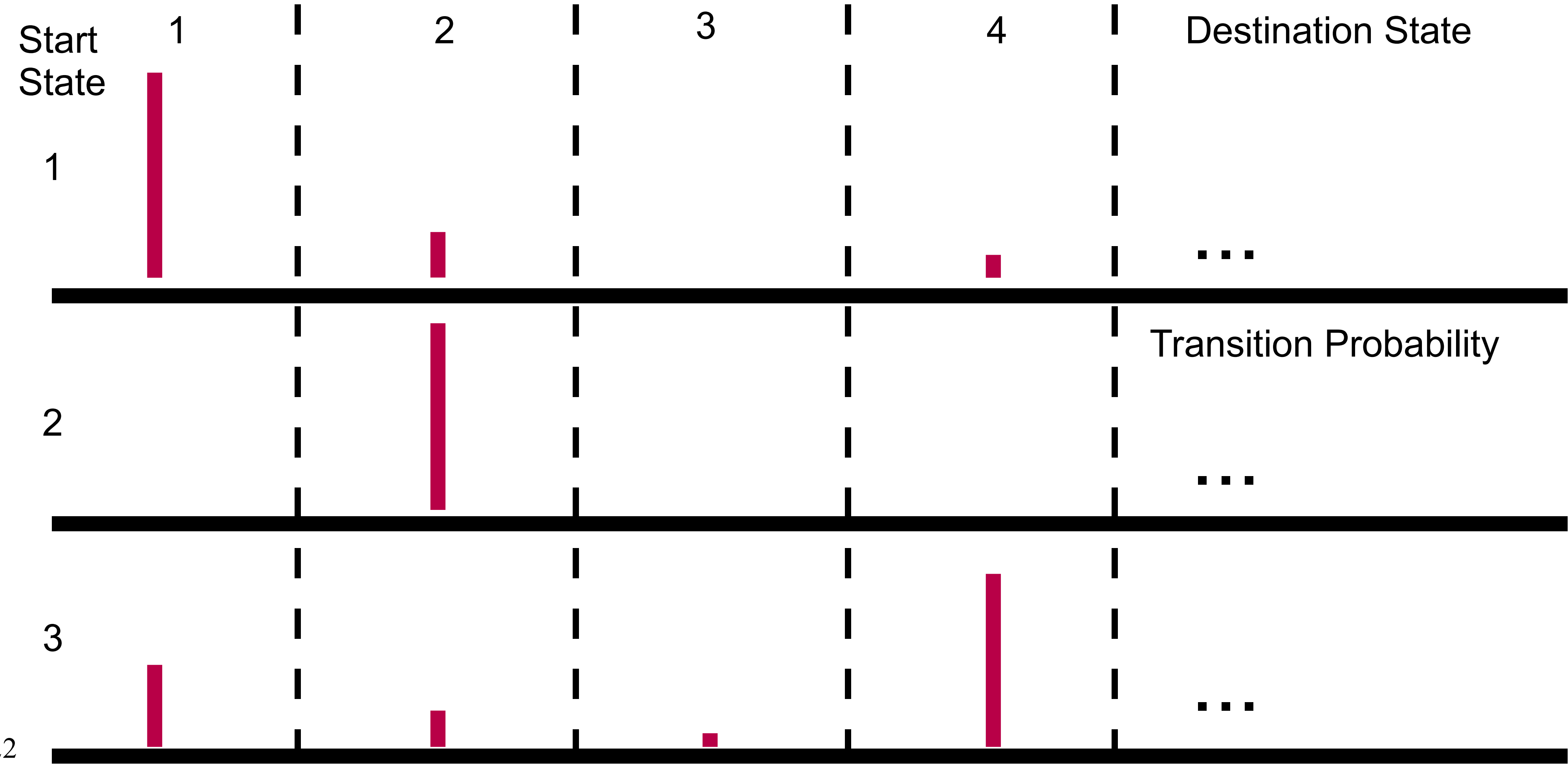


Generative Process

Next, sample transition matrix using the state popularities as a base distribution.



Inference

Key Idea: We only need to do inference over parameters of states that we've seen!

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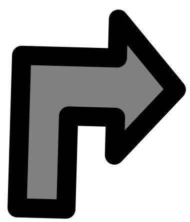
If you don't think you've visited a state

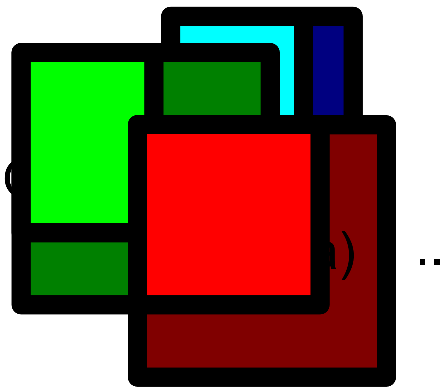
→ You have no data about that state!

→ Not point to doing inference about it!

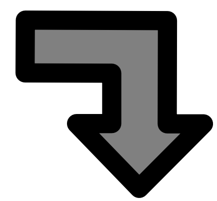
Inference

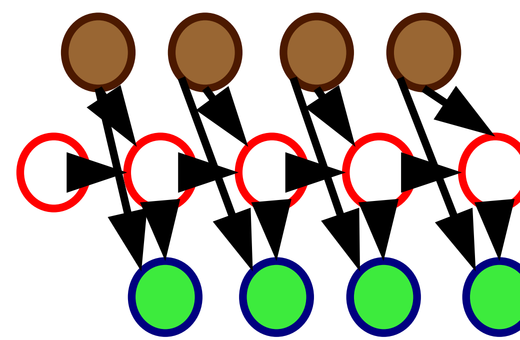
Use beam sampling to efficiently draw samples from our posterior belief over models.



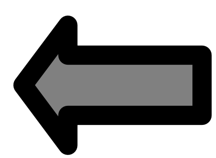


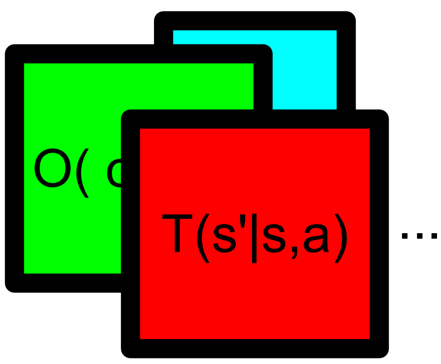
Slice “infinite” model to get a finite model.





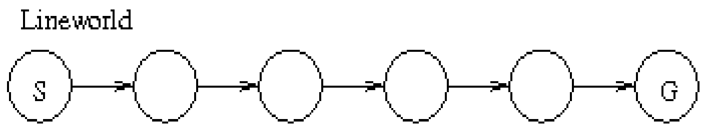
Run forward-filtering, backward sampling (not EM) on finite model to get visited states.

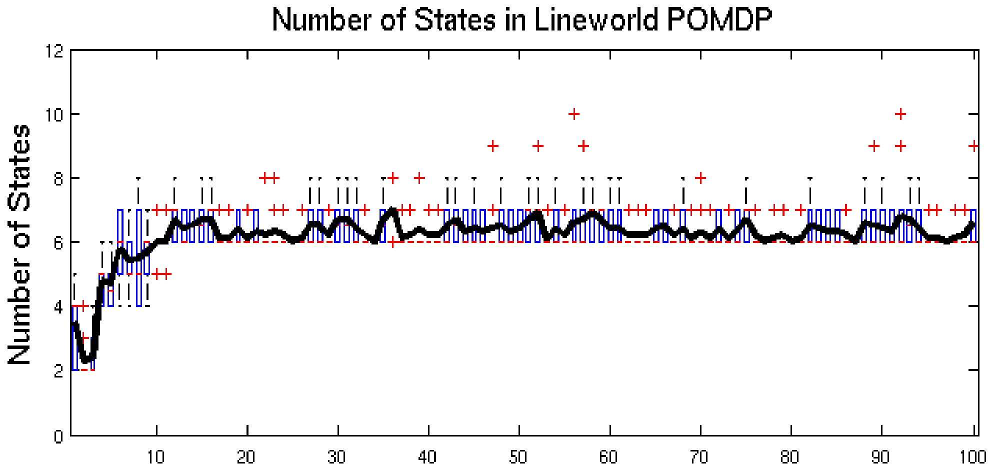


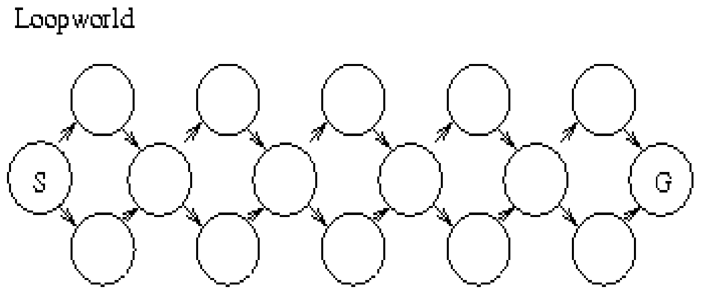


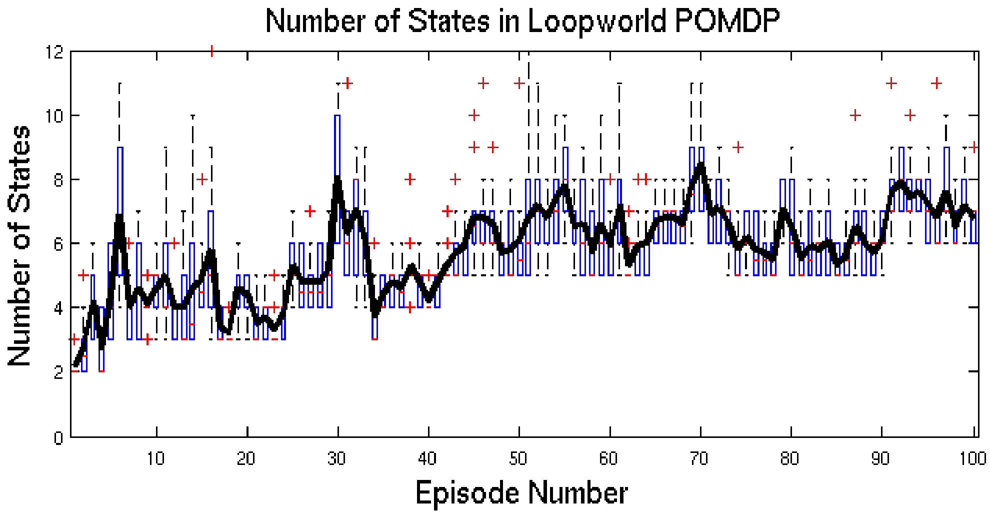
Construct “infinite” model; only visited states have parameters initialized.

Example Model Learned



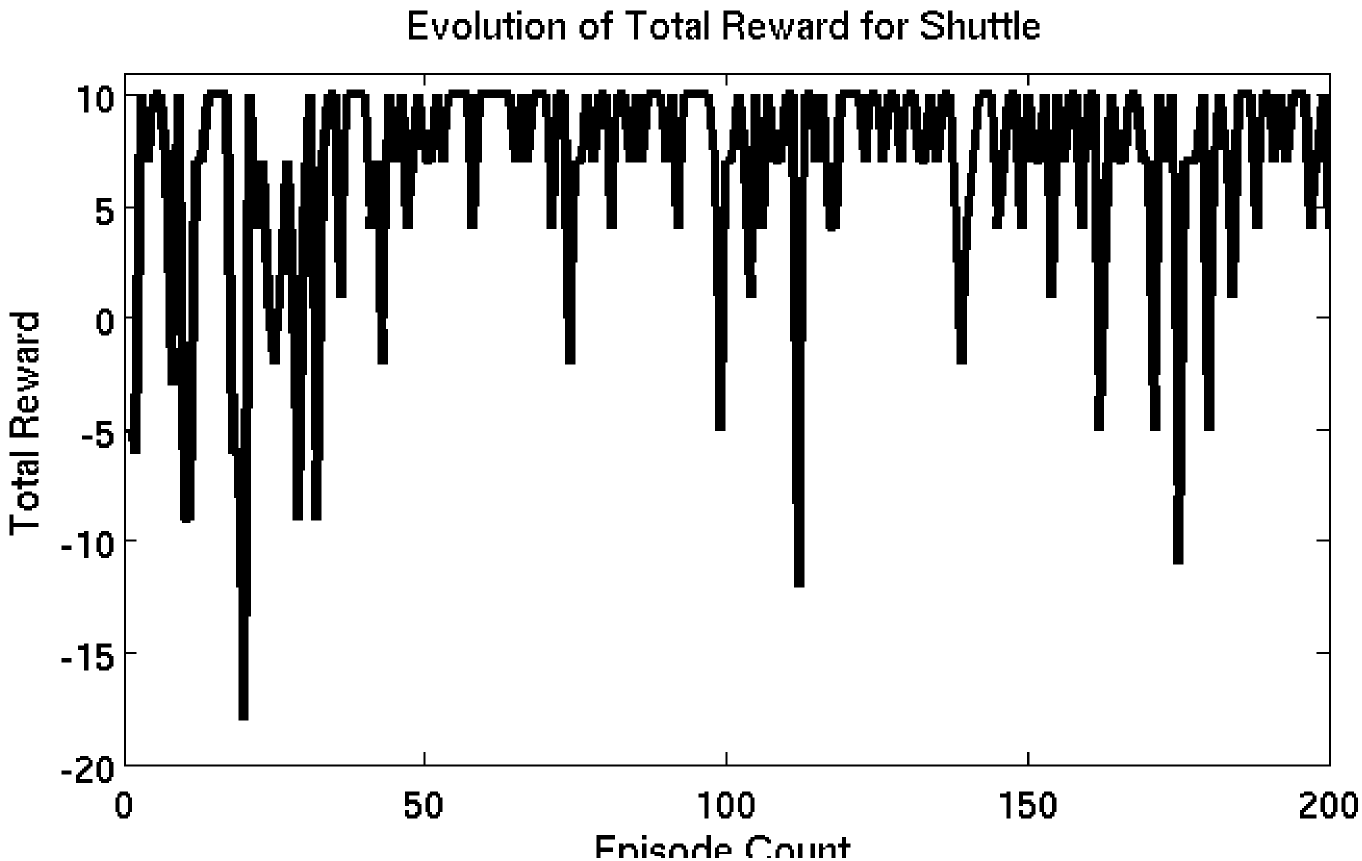


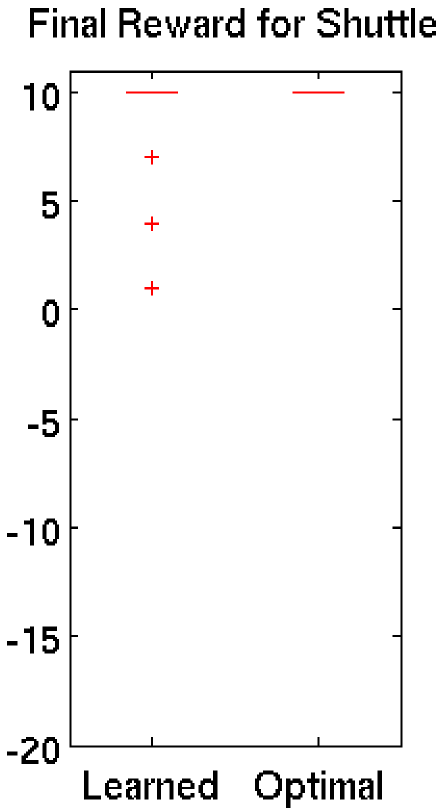




Another Example

Rewards while learning the POMDP Shuttle





How Bayesian Nonparametrics Help

Let the agent reason about its uncertainty

Scale sophistication of the model with structure in the data

Incorporate multiple sources of information

policy priors allow us to incorporate knowledge from self-exploration and expert knowledge

Leveraging Expert Trajectories

Often, an expert (could be another planning algorithm) can provide near-optimal trajectories.

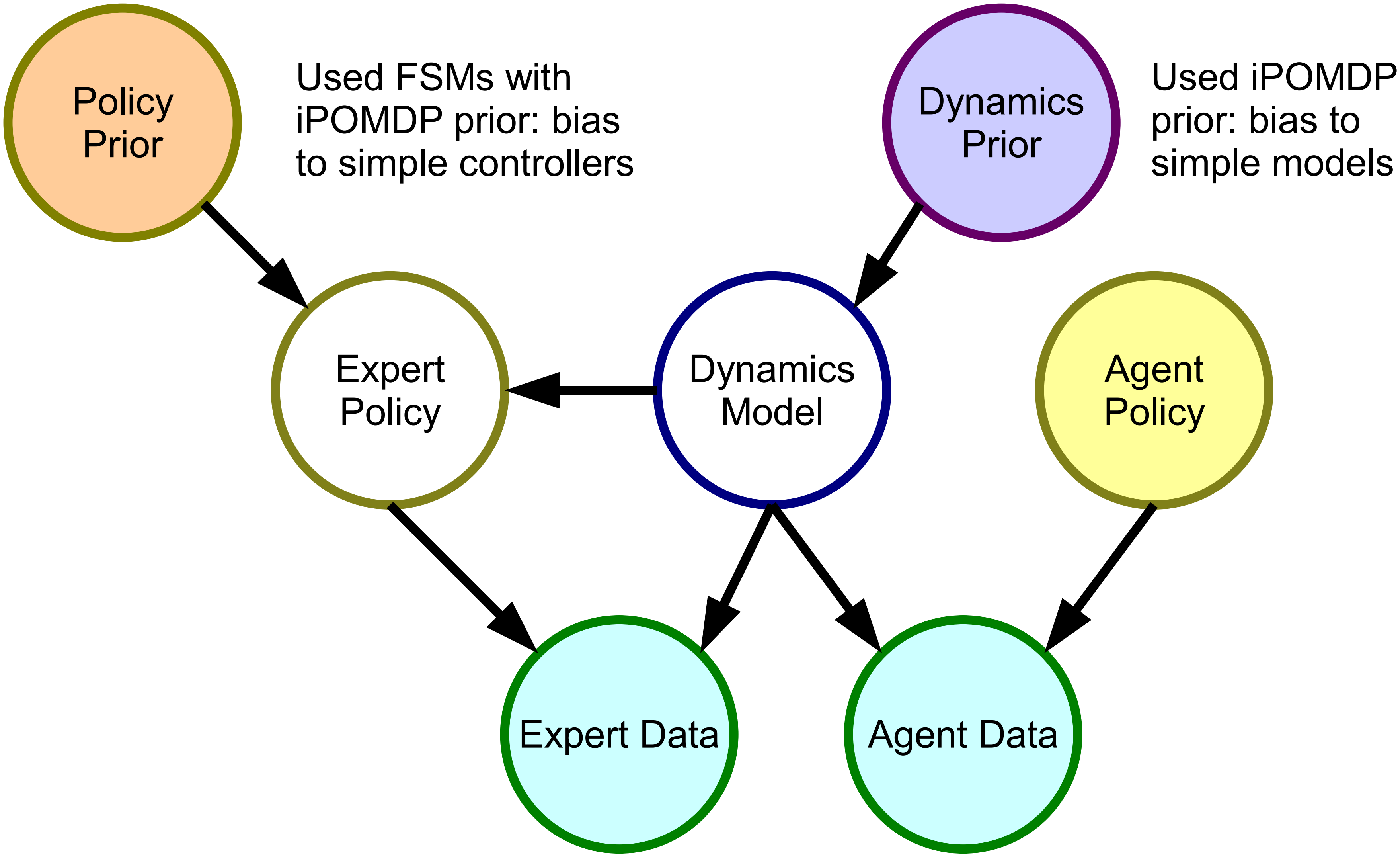
However, combining expert trajectories with data from self-exploration is challenging:

Experience provides direct information about the dynamics, which indirectly suggests a policy.

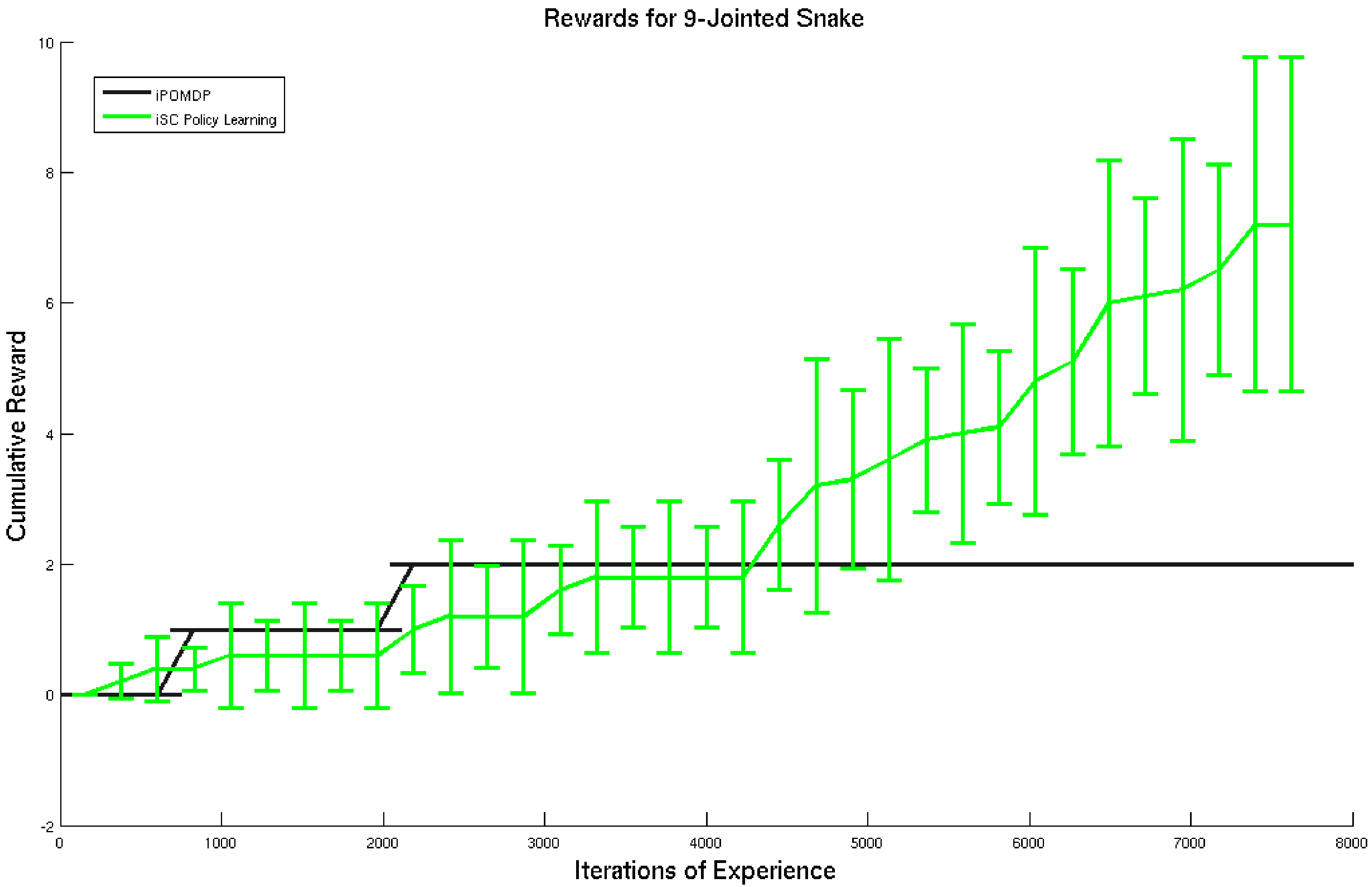
Experts provide direct information about the policy, which indirectly suggests dynamics.

Policy Prior Model

(joint work with David Wingate)



Example Result



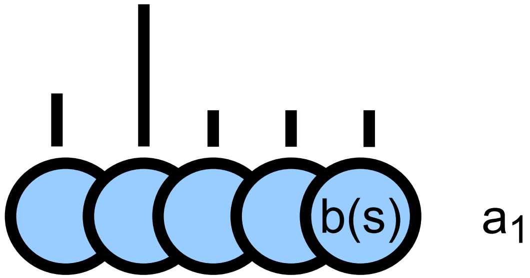
Vision for Future Work

More efficient planning and inference

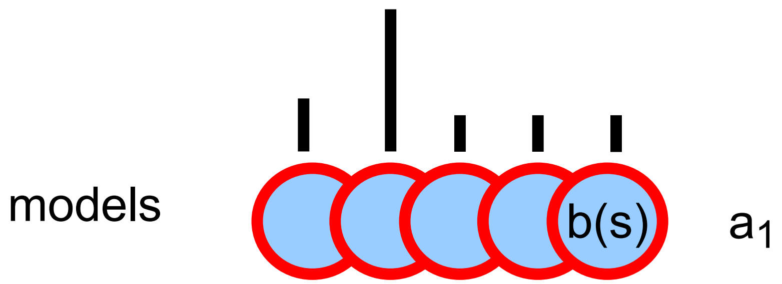
More structured nonparametric model priors

Applying models to healthcare domains

Planning with Sampled Models



Planning with Sampled Models



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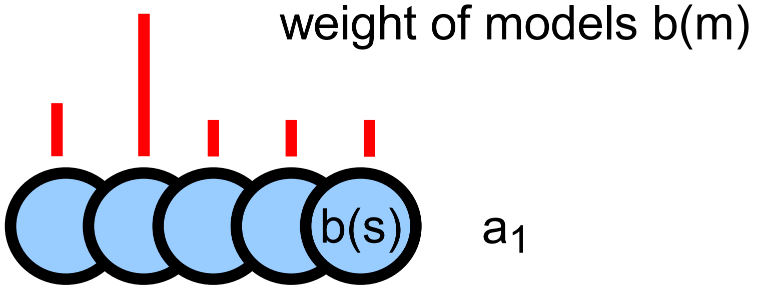

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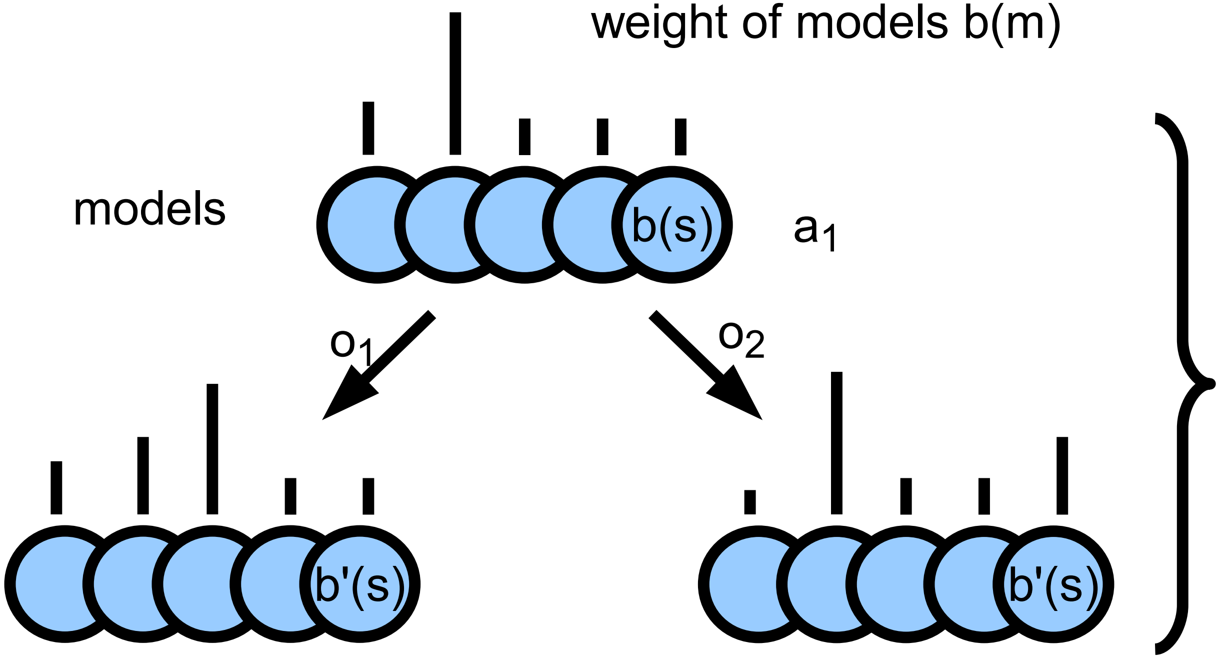
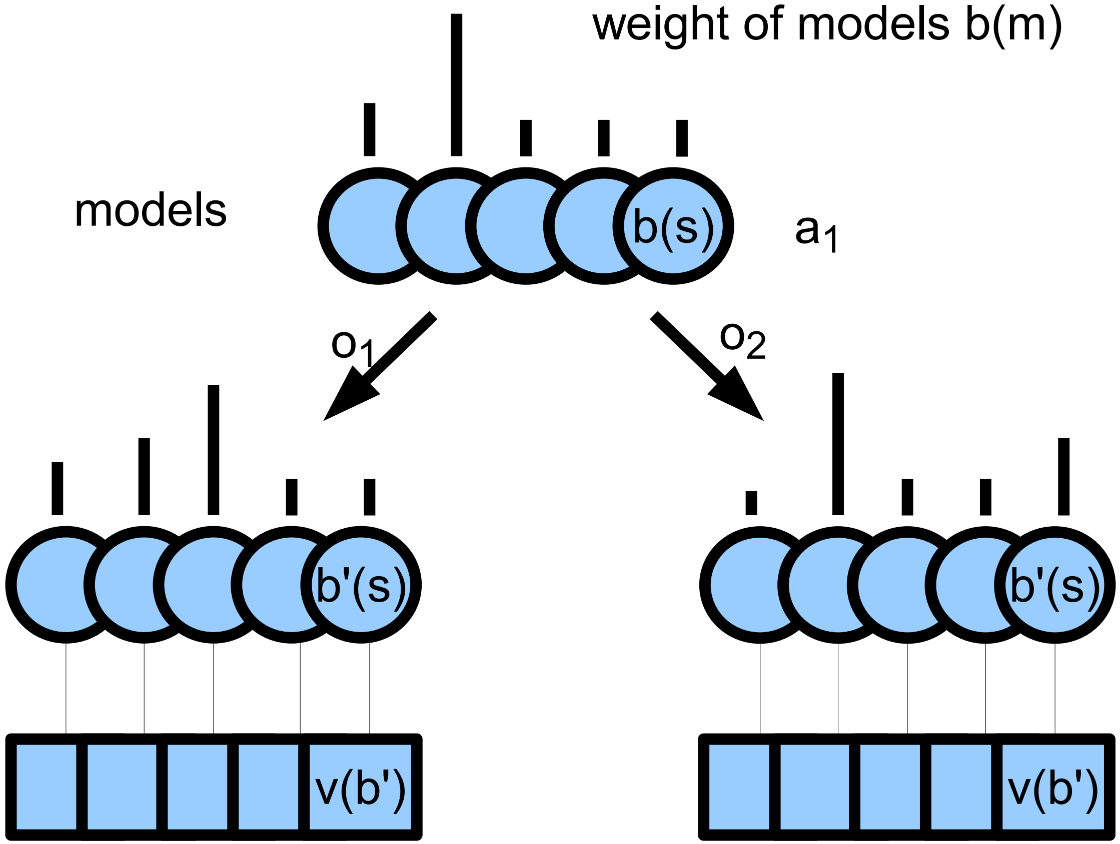


Plan in model-space using a basic forward search; each model updates its belief b(s).

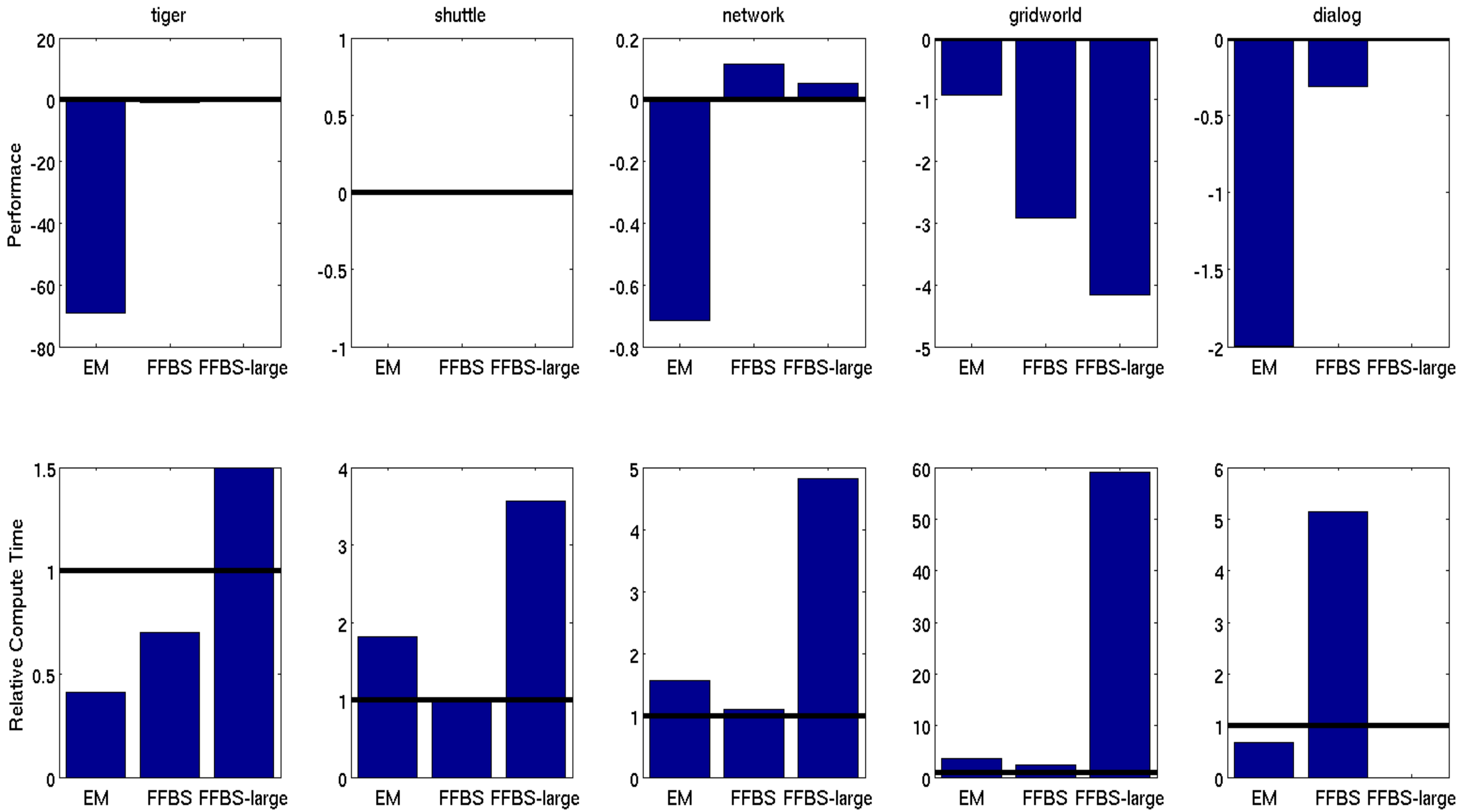
Planning with Sampled Models



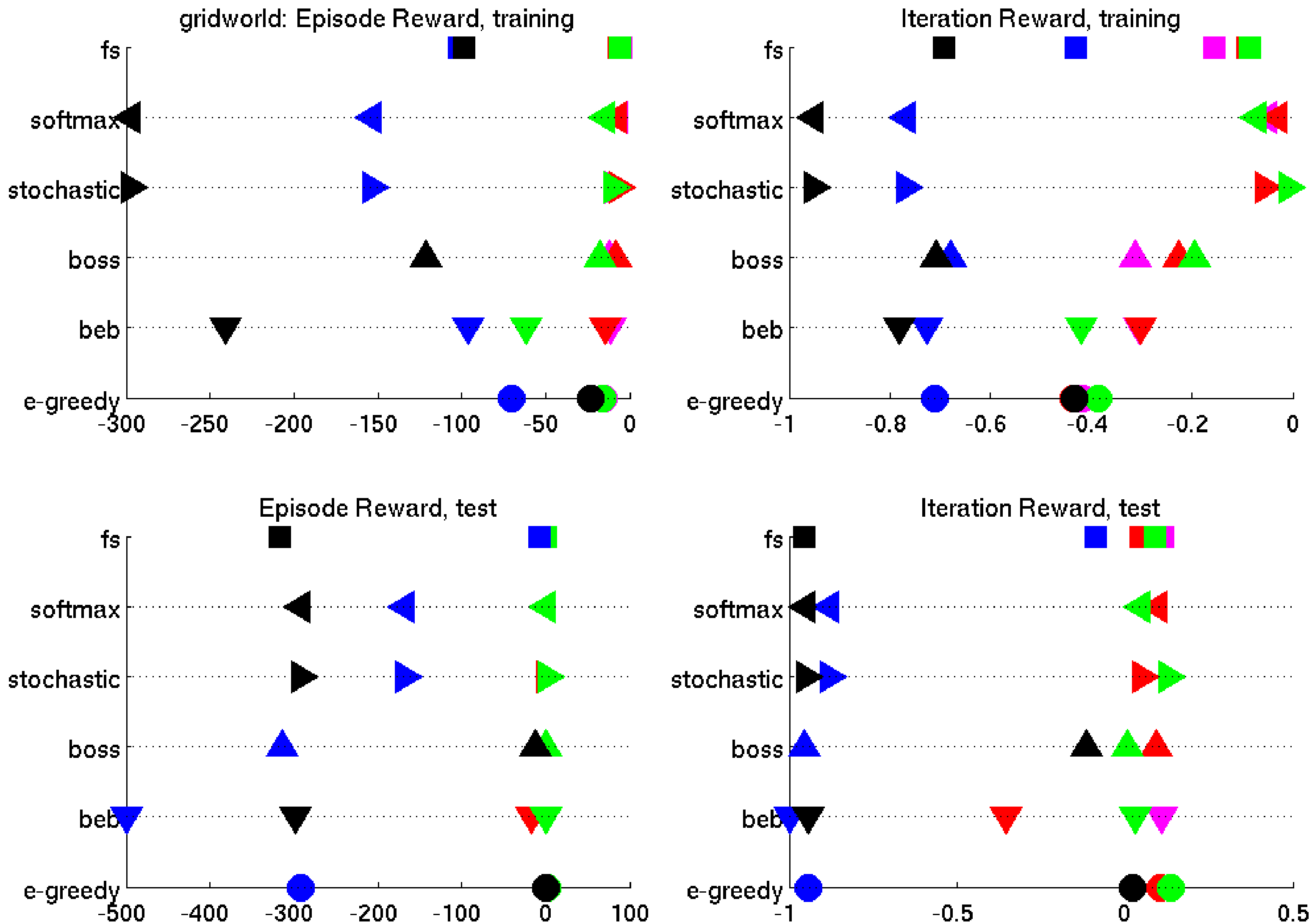
Plan in model-space using a basic forward search; each model updates its belief b(s).

Leaves use values of beliefs for each model; sampled models are **small, quick to solve.**

Results on Standard Problems

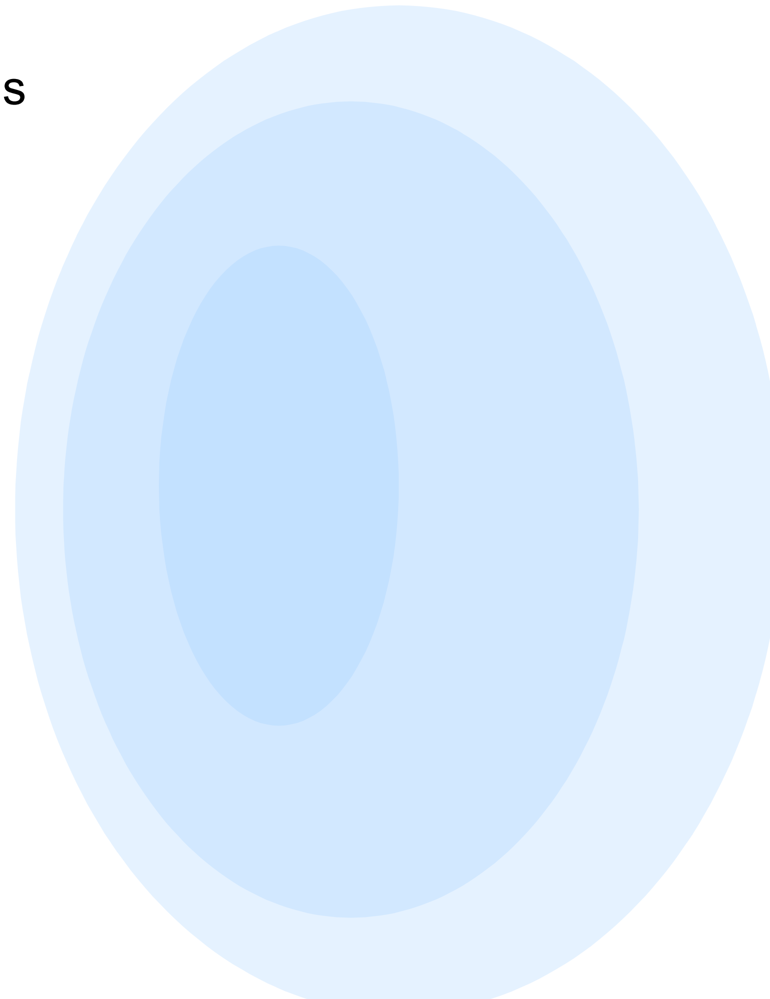


IPOMDP: Different Planning Approaches



Policy Prior: What it means

Mass of models
with simple
dynamics



Model Space

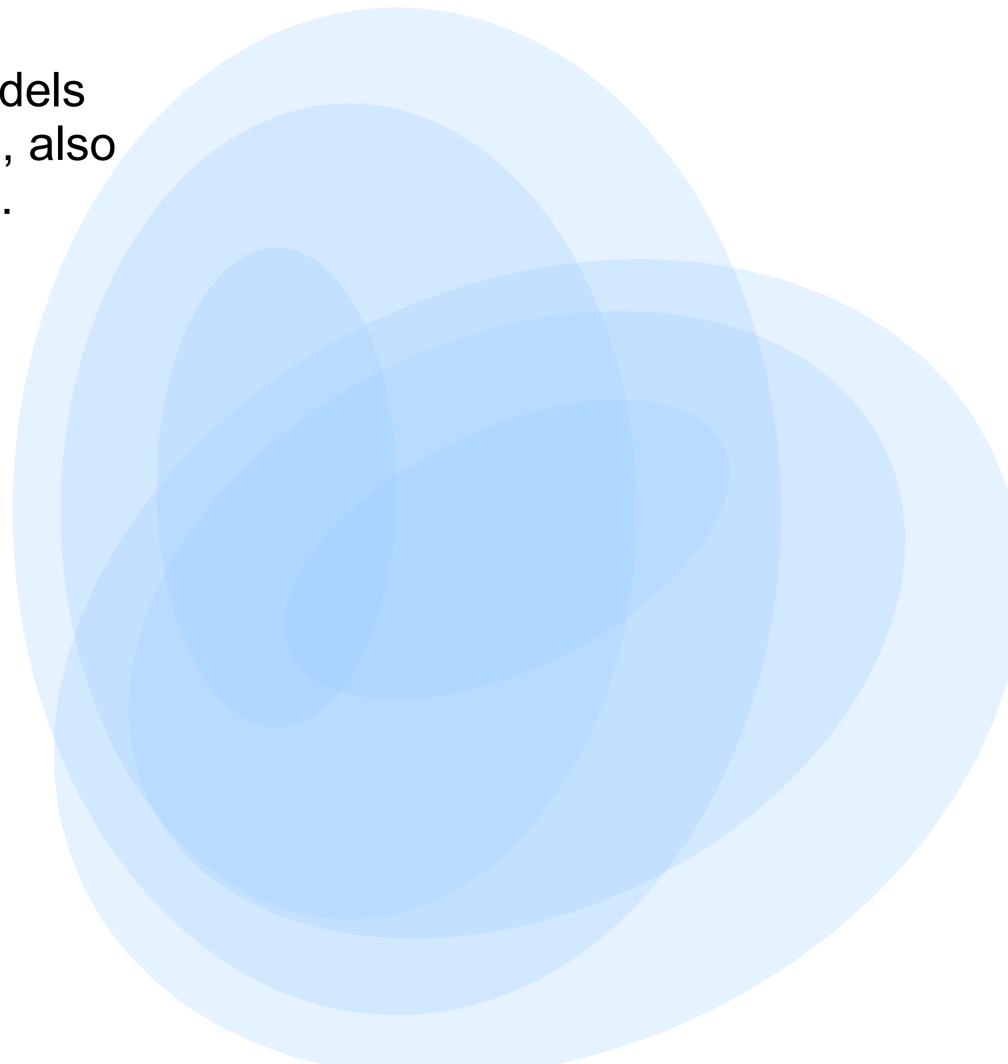
Policy Prior: What it means

Model Space

Mass of models with simple control policies.

Policy Prior: What it means

Joint Prior: models with few states, also easy to control.



Model Space