Temporal Difference Reinforcement Learning in Time-Constrained Domains

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Thesis Proposal
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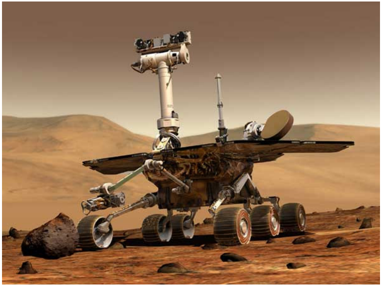
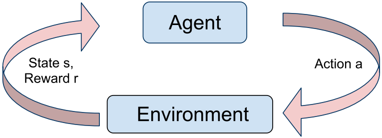
Robot Learning



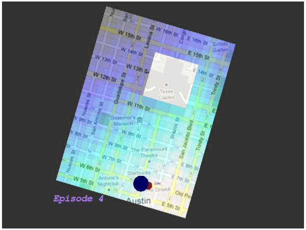
- Robots have the potential to solve many problems
- **But** they are held back by the need to hand-program them
- We need methods for them to learn and adapt to new situations

Reinforcement Learning



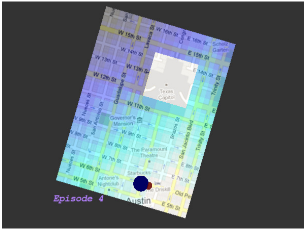
- Value function RL has string of positive theoretical results [Watkins 1989, Brafman and Tennenholtz 2001]
- Could be used for learning and adaptation on robots
- Typically take too many actions to be practical

Reinforcement Learning



Q-Learning

- Theoretically proven to converge
- Only updates VF when taking actions in the world



R-Max

- Learns a tabular model
- State-actions with fewer than m visits are given R_{max} transitions

Sample Complexity of Exploration

Definition: Number of sub-optimal actions the agent must take

- Lower bound is polynomial in N (# of states) and A (# of actions) [Kakade 2003]
- On a very large problem, NA actions is too many
- If actions are expensive, even a few thousand actions may be unacceptable
- What should we do when we do not have enough actions to guarantee convergence to an optimal policy?

Thesis Question

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How should an online reinforcement learning agent act in time-constrained domains?

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How should an online reinforcement learning agent act in time-constrained domains?

- Takes actions at specified frequency (not batch mode or policy search)
- Concerned with cumulative reward (not final policy)

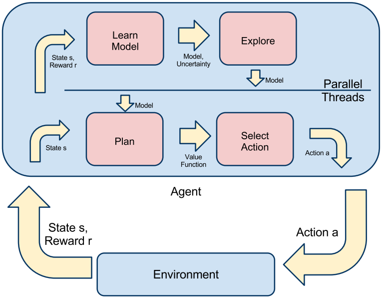
Thesis Question

Thesis Question

How should an online reinforcement learning agent act in time-constrained domains?

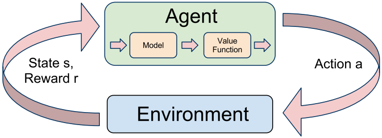
- Agent has a limited number of time steps
- Not enough time steps to learn optimal policy without some assumptions

Proposed Solution



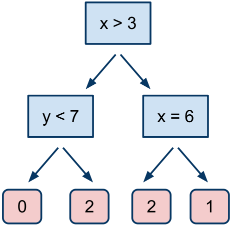
- Develop a model-based algorithm
- Incorporate generalization into the model learning
- Target exploration on specific states to improve model
- Novel architecture for real-time action

Model-Based RL



- Learn transition and reward dynamics, then update VF using model
- Typically more sample-efficient than model-free approaches
- Can update action-values without taking real actions in the world
- Algorithm is constrained by the number of actions it takes to learn an accurate model

Model Generalization

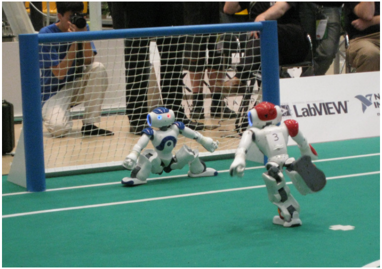


- Do **not** want a tabular model (must visit every state)
- Assume that transition and reward dynamics are similar across states
- Generalize these dynamics across states when learning model
- Can make predictions about states the agent has not visited

Targeted Exploration

- The agent is not going to visit every state
- Which states to visit and which **not** to visit
- Target exploration on states that we are **uncertain** about
- And states that will be **relevant** to the final policy

Real-Time Action

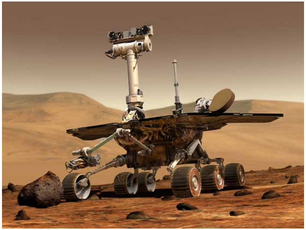


- In many problems, actions must be taken frequently
- Cannot stop and wait for model learning or planning to occur
- Must act in **real-time** at desired frequency

Sample Complexity of Exploration

- Proven lower bound: $O(\frac{NA}{\epsilon(1-\gamma)} log(\frac{1}{\delta}))$
- For deterministic domains: $O(\frac{NA}{(1-\gamma)})$ [Kakade 2003]
- Efficient RL algorithms require a number of actions polynomial in N, A, $\frac{1}{\epsilon}$, $\frac{1}{\delta}$, and $\frac{1}{1-\gamma}$.
- Even these algorithms must take at least this many actions to learn an optimal policy
- Look at cases where the agent does not have enough time steps for these algorithms to learn

Limited Time Steps



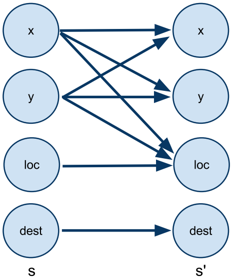
- For many practical problems, we do not have time to take thousands of actions
- Actions may be very time-consuming or expensive
- Need to learn on-line (rewards during learning are important)
- Cannot let the agent break/die during learning

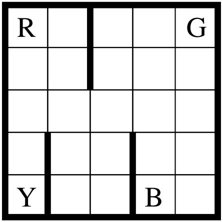
Time-Constrained Problems

- The agent has a lifetime L bounding the number of actions it can take
- Time-Constrained if $L < 2NA$
- Two orders of magnitude less than lower bound
- The agent does **not** have enough time steps to learn the optimal policy without some additional assumptions about the domain
- Evaluate agent on **cumulative** reward over L time steps

Domain	No. States	No. Actions	No. State-Actions	Min Bound Deterministic	Min Bound Stochastic	Maximum L
Taxi	500	6	3,000	300,000	1,050,000	6,000
Four Rooms	100	4	400	40,000	140,000	800
Fuel World	39,711	8	317,688	31,768,800	111,190,800	635,376
Mountain Car	10,000	3	30,000	300,000	10,500,000	60,000
Puddle World	400	4	1,600	160,000	560,000	3,200
Cart Pole	160,000	2	320,000	32,000,000	11,200,000	640,000

Factored Domains





- State is represented by n features: $s = < x_0, x_1, ..., x_n >$
- Transition represented by Dynamic Bayes Network (DBN)
- **Problem**: Learn the structure of the DBN
- Also need to learn the conditional probabilities

Expected Contributions

- Generalized Models (C)
- Model Uncertainty (C)
- Targeted Exploration (C)
- RL Method for Time-Constrained Domains (C)
- Model Learning with Dependent Feature Transitions (P)
- Extensions to Continuous Domains (P)
- Real-Time Architecture (P)
- Empirical Evaluation (P)
- Curious Agents (P)

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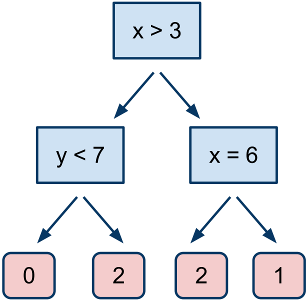
Why generalize the model?

- **Improve Sample efficiency**
- Want to learn a model of a large domain
- Do **not** want to explore every state-action
- Incorporate function approximation into the model learning
- Generalize the transition and reward effects in the model
- Not the same as generalizing Q-values in a model-free method

Make it a supervised learning problem

- Model learning is a supervised learning problem [AAMAS 2009]
- Input: State and Action
- Output: Next state and reward
- Separate model for each state feature and reward
- Compared Tabular, Decision Trees, Random Forests, SVMs, Neural Networks, and KNN [ICML ARL 2009]
- **Decision Tree** based models were the best

Why decision trees?

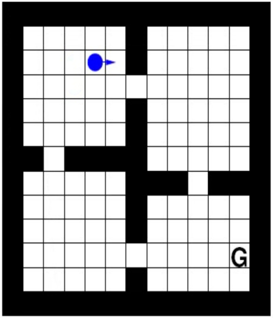


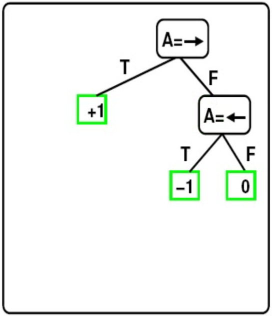
- Incremental and fast
- Generalize broadly at first, refine over time
- Can learn the structure of DBN

Relative Effects

- Predict the change in state: $s^r = s' - s$ rather than absolute next state s'
- Often actions have the same effect across states
- Previous work predicts relative effects [Jong and Stone 2007] [Leffler et al. 2007]

How the Decision Tree Model works





- Build one tree to predict each state feature and reward independently
- Combine their predictions: $P(s^r|s, a) = \Pi_{i=0}^{n} P(x_i^r|s, a)$
- Update trees on-line during learning

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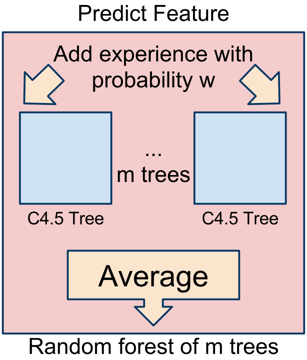
Model Uncertainty

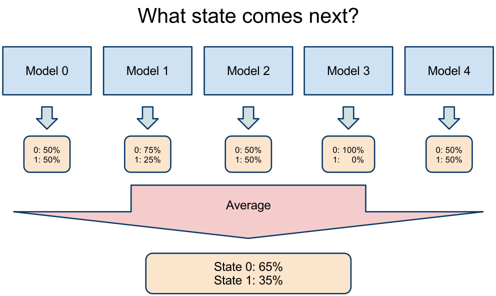
- **Improve Sample efficiency**
- Want some way to measure **uncertainty** of model
- Can use uncertainty to drive exploration and improve model
- Idea: Learn **multiple** possible models and compare them [ICDL 2010]

Random Forest Model



- Build *m* decision trees per forest
- Each tree gets each training experience with probability *w*
- When splitting, each feature is removed from potential split set with probability *f*

Random Forest Benefits



- Each tree represents a possible model of the domain
- Averaging the models inherently incorporates possibilities
- Can use the variance of model's predictions as an uncertainty measure

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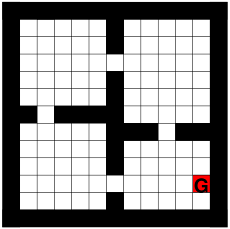
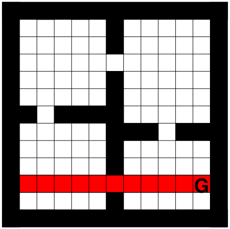
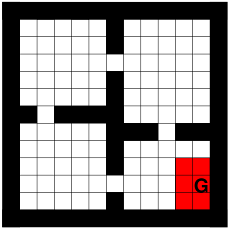
Targeted Exploration







- **Improve Sample efficiency**
- Want to **target** exploration on uncertain states that will be relevant to final policy
- Hypothesize that acting greedily with average model will work well

Use prediction variance

- Can add exploration bonus reward based on variance of model's predictions [ICDL 2010]
- $R(s,a) = R_o(s,a) + b\sigma^2(s,a)$
- $\sigma^2(s,a) = \frac{1}{n+1}[\sigma^2 R(s,a) + \sum_{i=1}^{n} \sigma^2 P(x_i^e|s,a)]$
- Use average variance from each random forest model (n features + reward)

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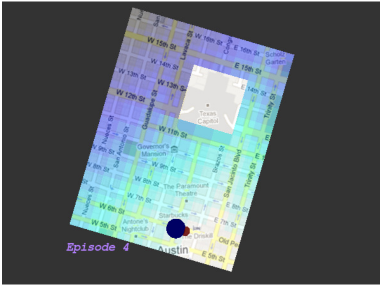
TEXPLORE algorithm [ICDL 2010]

- Combine this model learning method and exploration approach with a planner
- Use UCT as the planning algorithm
- **Seed** the model with a few experiences
- Seed experiences are a natural way to inject human knowledge into the agent

UCT algorithm [Kocsis and Szepesvári 2006]

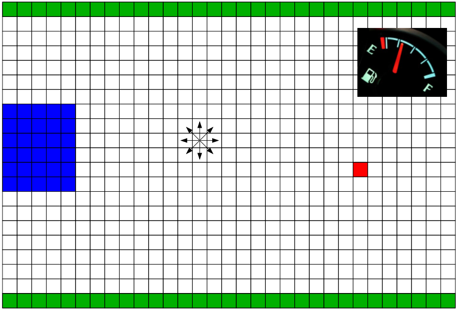
- Update value of a given state by sampling forward many times and updating towards the average return
- Choose actions at each state based on Upper Confidence Bounds
- $a = \mathrm{argmax}_a Q^d(s,a) + \sqrt{2\log(C(s,d))/C(s,a,d)}$
- Concentrates updates on parts of the state space agent is likely to visit soon
- Anytime algorithm

Results



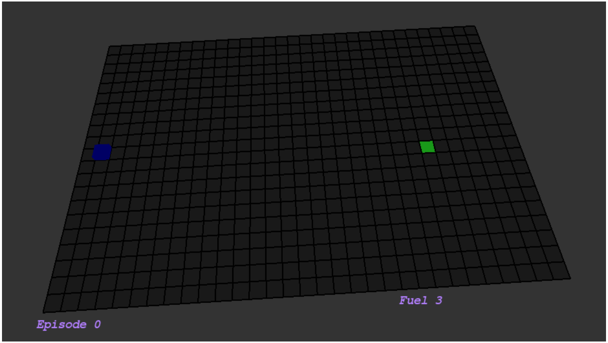
- Learns much faster than R-Max or Q-Learning

Fuel World



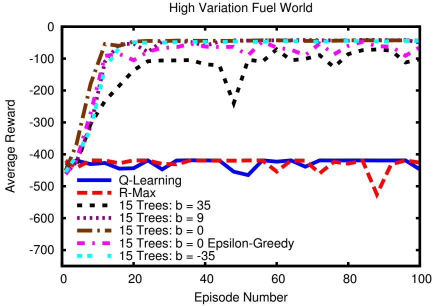
- Most of state space is very predictable
- But fuel stations have varying costs
- Want to explore mainly fuel stations, and particularly ones on short path to goal

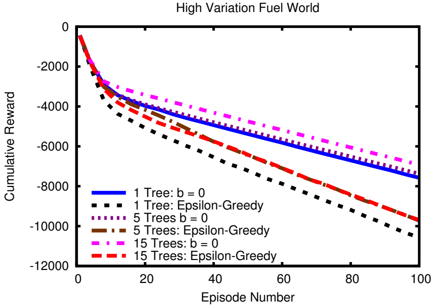
Fuel World Behavior



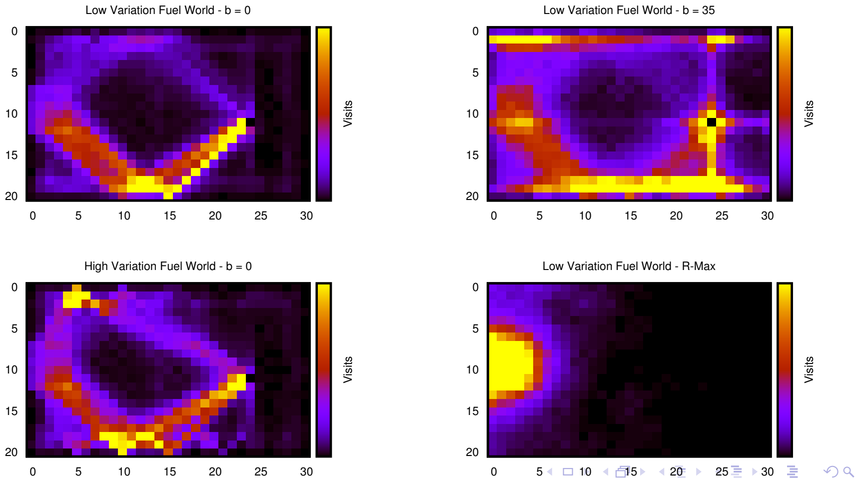
- Agent **focuses its exploration** on fuel stations near the shortest path to the goal.
- Agent **finds near-optimal policies**.

Fuel World Rewards

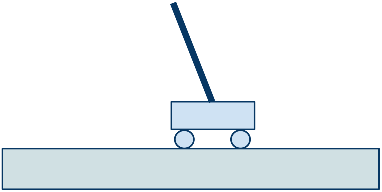




Where did the agent explore?

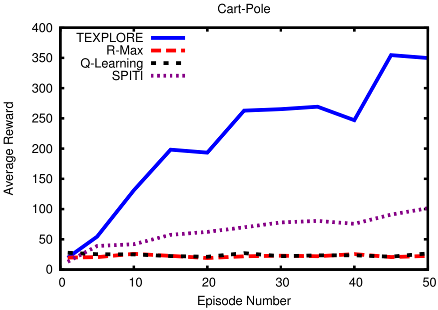


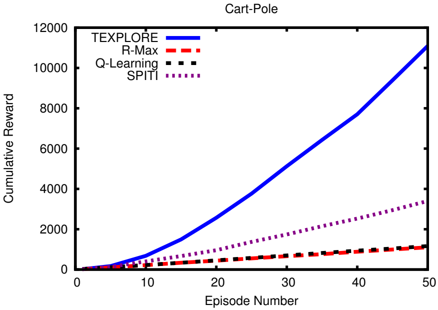
Results: Cart-Pole



- State Features: Pole Angle, Pole Vel, Cart Pos, Cart Vel
- Two Actions: -Force, +Force
- Reward +1 until pole falls or cart moves too far
- Discretized each dimension into 20 values

Cart-Pole Rewards

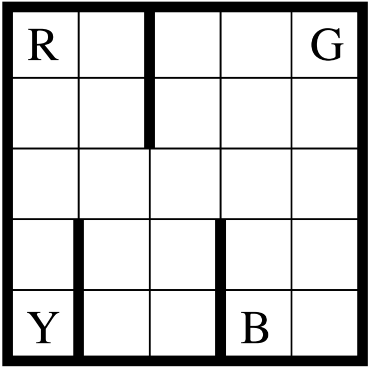




Additional Results

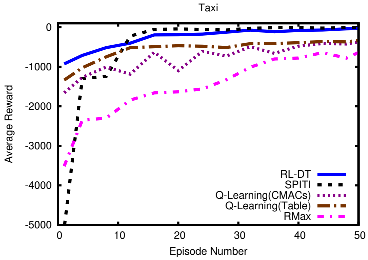
- From Previous Algorithm: RL-DT [AAMAS 2009]
- Used single decision tree model rather than random forest
- No measure of model uncertainty, so no targeted exploration
- Exploration heuristic: Until agent sees reward near R_{max}, it explores unvisited states

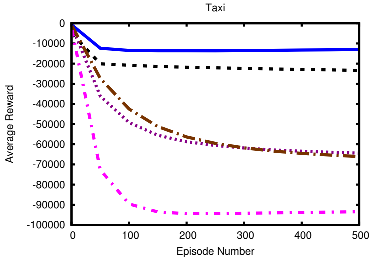
Results: Taxi [Dietterich 1998]



- State Features: x, y, passenger, destination
- Six Actions: East, West, North, South, PickUp, PutDown
- Stochastic: Move in intended direction 80% of time

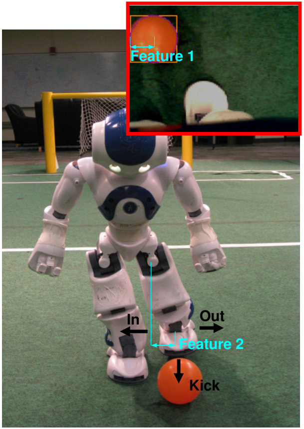
Results: Taxi



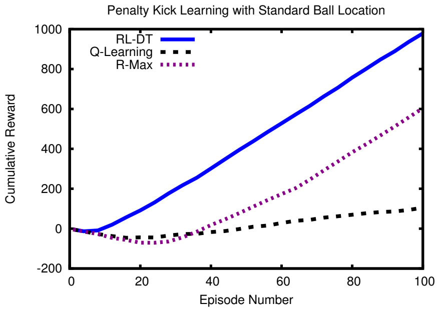


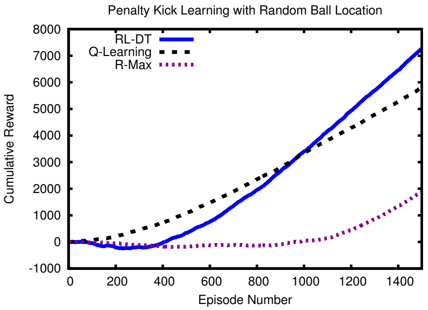
- Performs better on first episode
- Converged in fewer steps (more episodes) than SPITI
- Greater cumulative rewards

Robot Experiments [ICRA 2010]

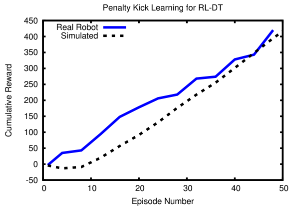


Simulated Results





Physical Robot Results



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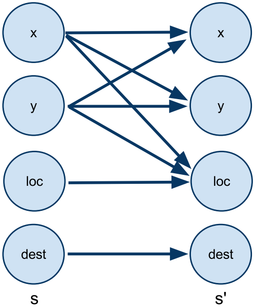
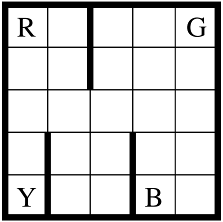
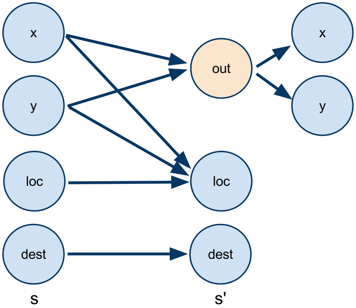
Dependent Feature Transitions

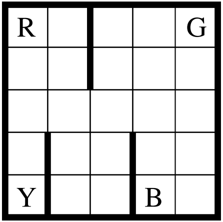




- Make model more accurate and robust
- Algorithm applies to more domains
- Features sometimes transition together

Dependent Feature Transitions





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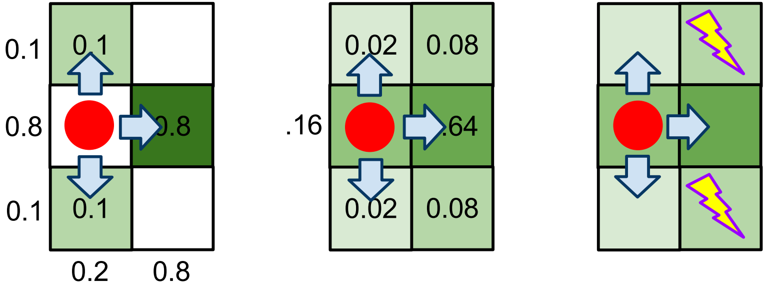
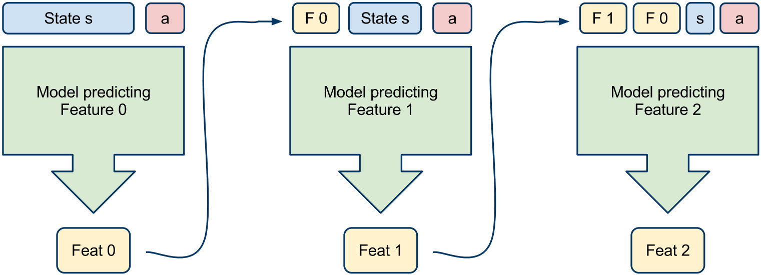


Proposed Dependent Feature Modeling



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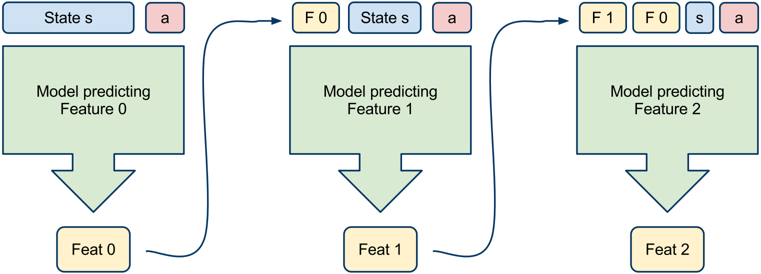

- What if predicting one feature is harder than predicting the other?
- What if its easier to predict x_1 from x_0 rather than x_0 from x_1?

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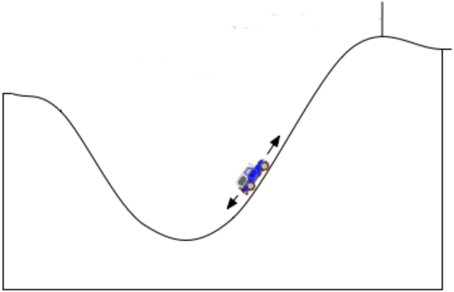
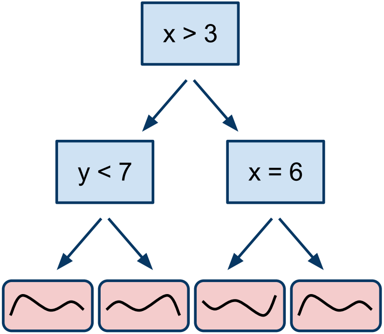
- **Extensions to Continuous Domains** (P)
- Real-Time Architecture (P)
- Empirical Evaluation (P)
- Curious Agents (P)

Continuous Problems



- Most real-world problems are continuous
- First step: Quantize state space

Continuous Models



- Regression trees: More computation?
- Gaussian Process Regression

Continuous Planning

- Fitted Value Iteration [Gordon 1995]
  - Update values for sampled set of states
  - Use function approximator to fit value function
  - Probably computationally slow like VI
- Fitted UCT
  - Can we fit a value function here?
  - Also must maintain visit counts

Expected Contributions

- Generalized Models (C)
- Model Uncertainty (C)
- Targeted Exploration (C)
- RL Method for Time-Constrained Domains (C)
- Model Learning with Dependent Feature Transitions (P)
- Extensions to Continuous Domains (P)
- **Real-Time Architecture** (P)
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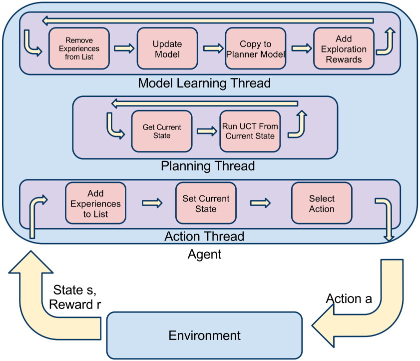
Real-Time Need

- Sometimes planning takes too long
- Sometimes model learning takes too long

Proposed Real-Time Architecture



- Model learning and planning on background threads
- Threads interact through mutex locked data structures
- Can operate at specified action frequency

Expected Contributions

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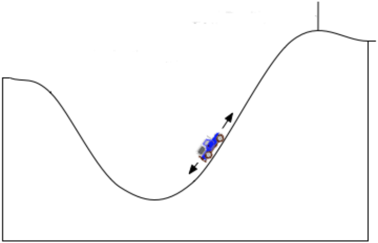
Empirical Evaluation

Evaluation Criteria

- Compare **cumulative** rewards because we are interested in **online** learning
- Look at sum of rewards over the L time steps given to the agent
- Evaluate on tasks that require real-time actions (robots)

Empirical Evaluation



- Typical RL Benchmarks (Mountain Car, Cart Pole, Acrobot)
- Robot Tasks: Nao robot, Autonomous vehicle
- Compare with PAC MDP efficient algorithms (MET-RMAX)
- Try to compare with Bayesian RL on **small** problem

Expected Contributions

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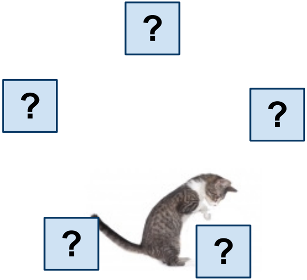
Curious Agents

Alternate Evaluation Criteria

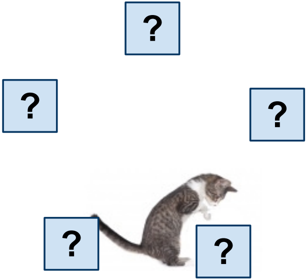
- What does the agent do without external rewards?
- How does the agent explore given a distribution of possible future tasks?

InfoMax [Fasel et al. 2010]



- Partially observable state space
- Agent receives internal rewards proportional to negative entropy of agent's belief distribution
- Learns to take actions to maximize the information it knows about the world

Curious Agents



- Does $b > 0$ with no external rewards compare with InfoMax?
- Can we learn to explore for a distribution of possible future tasks?
- Our agent should focus exploration on parts that are relevant to future tasks, rather than exploring fully

Related Work

- Bayesian RL
- PAC MDP Efficient algorithms
- Intrinsic Motivation
- Generalized Models
- Real Time Architectures

Bayesian RL

- Offers optimal solution to exploration problem [Duff 2003]
- Computationally intractable
- Many approximate solutions:
  - Tie model parameters together [Poupart et al. 2006]
  - Sample from model distributions [Strens 2000, Asmuth et al. 2009]
  - Learn Bayesian optimal policy over time [Kolter and Ng 2009]

Value of Information Approaches

- Model-Based Bayesian Exploration [Dearden et al. 1999]
  - Maintain belief over models
  - Sample and plan on k models
  - Utilize distribution over q-values to calculate VPI: improvement in policy value · probability
  - Add this onto average value from value functions

PAC MDP Efficient Algorithms

- MET-RMAX [Diuk et al. 2009]
  - Assume Transition dynamics are represented by DBN with n binary factors and in-degree D
  - Consider all possible parent combinations $\binom{n}{D}$
  - Separate meteorologist predicts based on each possible parent
  - If any meteorologist does not know the answer, use R_{max}
  - If meteorologists disagree, use R_{max}
  - Remove meteorologists with significantly more error
  - $\binom{n}{D}$ can be very large, D provided

Intrinsic Motivation

- Simsek and Barto [2006]
  - Model-free approach
  - Intrinsic rewards for where value function improves the most
- Intelligent Adaptive Curiosity [Oudeyer et al. 2007]
  - Learn separate dynamics models for different regions of statespace
  - Provide intrinsic rewards based on slope of error curve in each region
  - Only one-step planning, does not use RL/MDP framework

Supervised Learning of Models

- SPITI [Degris et al. 2006]
  - Learn decision tree models for each feature
  - Used ϵ-greedy exploration
- AMBI [Jong and Stone 2007]
  - Instance-based model with relative effects
  - R_{max} bonus for state regions with few visits
- GPRL [Deisenroth and Rasmussen 2009]
  - Use Gaussian Process regression to model dynamics
  - Exploration based on variance of GP predictions
  - Batch mode, agent is provided reward model

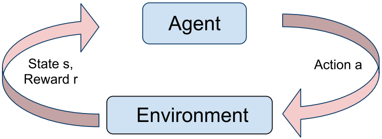
Real-Time Methods

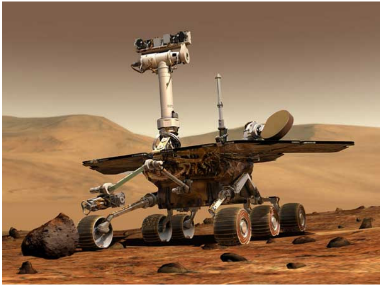
- Dyna Framework [Sutton 1990, 1991]
  - Do Bellman updates on random states using model when not action
  - Still uses tabular model, assumes model update takes insignificant time
- Combining sample-based planning with model-based method
  - With UCT [Silver et al. 2008]
  - With new FSSS [Walsh et al. 2010]
  - Neither places a time restriction on model update or planning

Where will this apply?

- Assumes domains have similar transition and reward effects across states
- Requires factored domains
- Can run in real-time at specified frequency
- Can learn in a limited number of time steps in domain
- Applicable to robots and other real-world problems

Robot Learning





- Real-time sample-efficient reinforcement learning on domains with a limited number of time-steps

Thank You

- Generalized Models (C) [AAMAS, ICML ARL 2009]
- Model Uncertainty (C) [ICDL 2010]
- Targeted Exploration (C) [ICDL 2010]
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