TEXPLORE: Temporal Difference Reinforcement Learning for Robots and Time-Constrained Domains

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Thesis Defense
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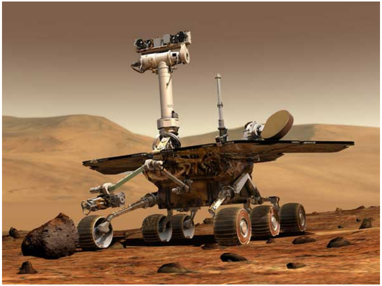
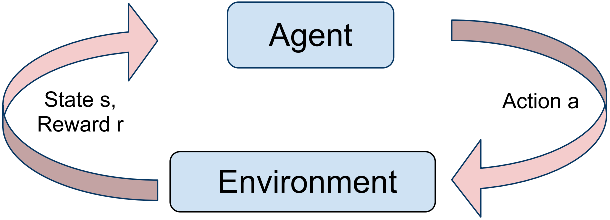
Robot Learning



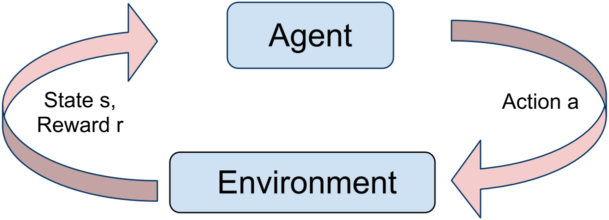
- Robots have the potential to solve many problems
- Moving from controlled to natural environments is difficult
- We need methods for them to learn and adapt to new situations

Reinforcement Learning



- Could be used for learning and adaptation on robots
- Value function RL has string of positive theoretical results [Watkins 1989, Brafman and Tennenholtz 2001]

Reinforcement Learning



- Could be used for learning and adaptation on robots
- Value function RL has string of positive theoretical results [Watkins 1989, Brafman and Tennenholtz 2001]
- However, learning on robots presents many challenges for RL

Velocity Control of an Autonomous Vehicle

- Upgraded to run **autonomously** by adding shift-by-wire, steering, and braking actuators.
- 10 second episodes (at 10 Hz: 100 samples / episode)

Velocity Control

- State:
  - Current Velocity
  - Desired Velocity
  - Accelerator Pedal Position
  - Brake Pedal Position
- Actions:
  - Do nothing
  - Increase/decrease brake position by 0.1
  - Increase/decrease accelerator position by 0.1
- Reward: -10.0 * velocity error (m/s)

Desiderata

1. Learning algorithm must learn in very few actions (be **sample efficient**)
2. Learning algorithm must handle **continuous** state
3. Learning algorithm must handle **delayed** actions
4. Learning algorithm must take actions **continually** in real-time (while learning)

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Common Approaches

Algorithm	Citation	Sample Efficient	Real Time	Continuous	Delay
R-MAX	Brafman and Tennenholtz, 2001	Yes	**No**	**No**	**No**
Q-LEARNING	Watkins, 1989	**No**	Yes	**No**	**No**
with F.A.	Sutton and Barto, 1998	**No**	Yes	Yes	**No**
SARSA	Rummery and Niranjan, 1994	**No**	Yes	**No**	**No**
PILCO	Deisenroth and Rasmussen, 2011	Yes	**No**	Yes	**No**
NAC	Peters and Schaal 2008	Yes	**No**	Yes	**No**
BOSS	Asmuth et al., 2009	Yes	**No**	**No**	**No**
Bayesian DP	Strens, 2000	Yes	**No**	**No**	**No**
MBBE	Dearden et al., 2009	Yes	**No**	**No**	**No**
SPITI	Degris et al., 2006	Yes	**No**	**No**	**No**
MBS	Walsh et al., 2009	Yes	**No**	**No**	Yes
U-TREE	McCallum, 1996	Yes	**No**	**No**	Yes
DYNA	Sutton, 1990	Yes	Yes	**No**	**No**
DYNA-2	Silver et al., 2008	Yes	Yes	Yes	**No**
KWIK-LR	Strehl and Littman, 2007	Yes	**No**	**Partial**	**No**
FITTED R-MAX	Jong and Stone, 2007	Yes	**No**	Yes	**No**
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TEXPLORE	This thesis	Yes	Yes	Yes	Yes

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, dangerous, or time-consuming, 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 continually at specified frequency (not batch mode)
- Concerned with reward during learning (not just 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

Solution

Model-Based Method

- Learn transition and reward dynamics, then update value function using model
- Typically more sample-efficient than model-free approaches
- Can update action-values without taking real actions in the world

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- **But,** can take significant computation time

Real-Time Architecture

- Parallelize model learning, planning, and acting onto 3 parallel threads
- Utilize an **anytime** sample-based planning algorithm

The TEXPLORE Algorithm

1. Model generalization for **sample efficiency**
2. Handles **continuous** state
3. Handles actuator **delays**
4. Selects actions continually in **real-time**

Available publicly as a ROS package:

www.ros.org/wiki/rl-texplore-ros-pkg

Time-Constrained Domains

- For many practical problems, agent cannot take thousands of actions
- Actions may be expensive, time-consuming, or dangerous
- Agent does not have enough actions to guarantee it can learn an optimal policy
- Define domains that have this property as **time-constrained domains**

Sample Complexity of Exploration

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

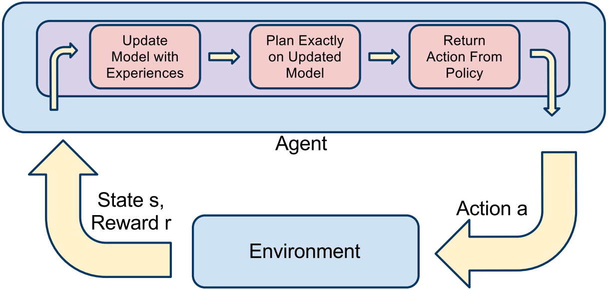
- Proven lower bound: $O(\frac{NA}{\epsilon(1-\gamma)} log(\frac{1}{\delta}))$
- For deterministic domains: $O(\frac{NA}{(1-\gamma)})$ [Kakade 2003]

Time-Constrained Domains

- Lifetime L bounds the number of actions agent 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
- **Assumption:** Transition and reward are **similar** across states

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
Two Rooms	51	4	204	20,400	72,400	408
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 Balancing	160,000	2	320,000	32,000,000	11,200,000	640,000

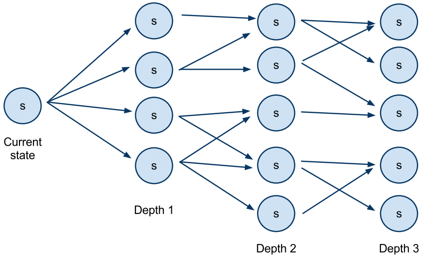
Real-Time Action Selection



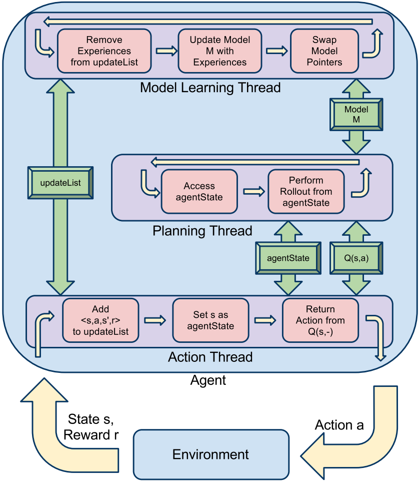
- Model update can take too long
- Planning can take too long

Monte Carlo Tree Search Planning

- **Simulate trajectory** from current state using model (rollout)
- Use upper confidence bounds to select actions (UCT [Kocsis and Szepesvári 2006])
- Focus computation on states the agent is most likely to visit
- **Anytime**—more rollouts, more accurate value estimates
- Update value function at each state in rollout

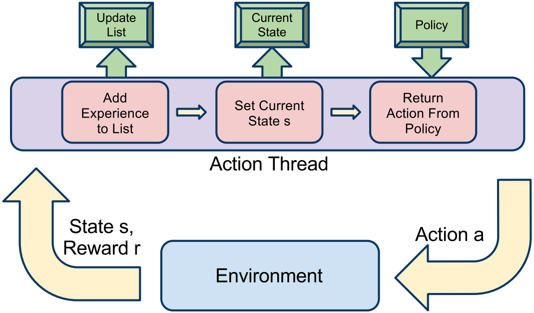


Real-Time Model Based Architecture (RTMBA)



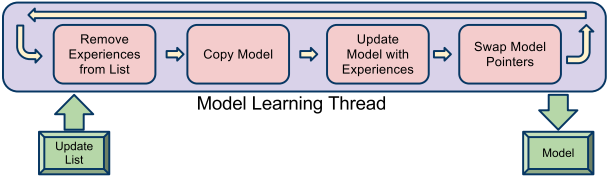
- Model learning and planning on parallel threads
- Action selection **is not restricted** by their computation time
- Use sample-based planning (anytime)
- Mutex locks on shared data

Action Thread



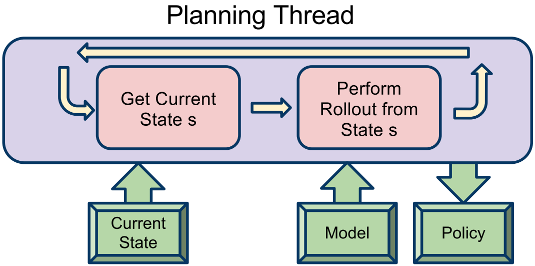
- Add experience, $\langle s, a, s', r \rangle$ to list of experiences to be added to model
- Set agent's current state for planning
- Return best action according to policy

Model Learning Thread



- Make a copy of current model
- Update model copy with new experiences from list (batch updates)
- Swap model pointers
- Repeat

Planning Thread



- Plan using a sample-based MCTS planner (i.e. UCT [Kocsis and Szepesvári 2006])
- Continually perform rollouts from agent's current state
- Rollouts from previous state can help

Sample Efficiency

Model Generalization

- Generalize that actions have similar effects across states
- Do not want to explore every state-action
- Speed model learning by making predictions about unseen state-actions

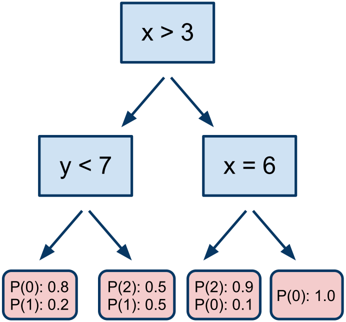
Exploration

- Model learning is dependent on acquiring useful experiences
- Balance exploration and exploitation to maximize rewards in time-constrained lifetime

Model Generalization

- Model learning is a supervised learning problem [Hester and Stone 2009]
- Input: State and Action
- Output: Distribution over next states and reward
- Factored state $s = \langle s_1, s_2, ..., s_n \rangle$
- Separate model for each state feature and reward

C4.5 Decision Trees [Quinlan 1986]

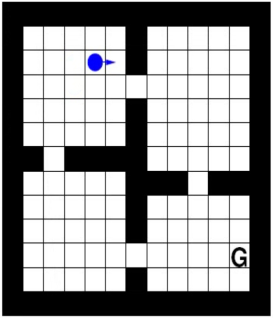


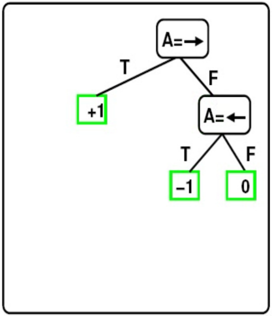
- Incremental and fast
- Generalize broadly at first, refine over time
- Split state space into regions with similar dynamics
- Good at selecting relevant state features to split on

Relative Effects

- Predict the **change in state**: $s^{rel} = s' - s$ 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

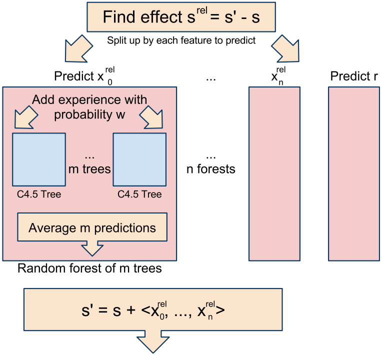




- Build one tree to predict each state feature and reward
- Combine their predictions: $P(s^{rel}|s,a) = \Pi_{i=0}^{n} P(s_i^{rel}|s,a)$
- Update trees on-line during learning

Random Forest Model [Hester and Stone 2010]

- Create a random forest of *m* different decision trees [Breiman 2001]
- Each tree is trained on a **random subset** of the agent's experiences
- Each tree represents a **hypothesis** of the true dynamics of the domain



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- Create a random forest of *m* different decision trees [Breiman 2001]
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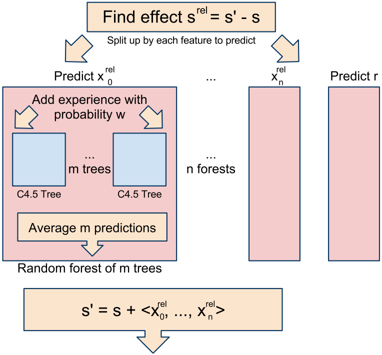
- Each tree represents a **hypothesis** of the true dynamics of the domain
- How best to use these different hypotheses?



How to use these hypotheses?

Bayesian Approaches

- BOSS: Plan over most optimistic model at each action
- MBBE: Solve each model and use distribution of q-values

How to use these hypotheses?

Bayesian Approaches

- BOSS: Plan over most optimistic model at each action
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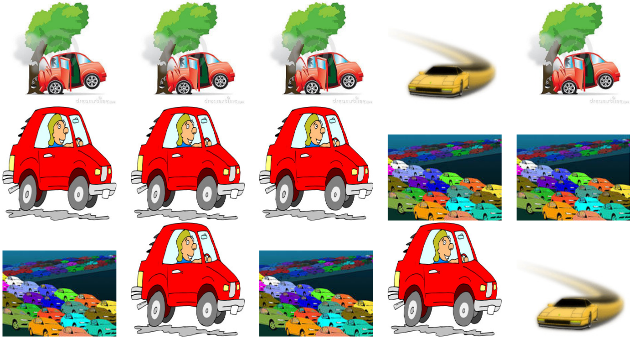
TEXPLORE

- Desiderata: Explore less, be greedier
- Plan on average of the predicted distributions
- Balance models that are optimistic with ones that are pessimistic

Exploration

- **Limits** exploration to state-actions that appear promising, **avoids** those which may have negative outcomes

A1:
A2:
A3:



5 models

Exploration

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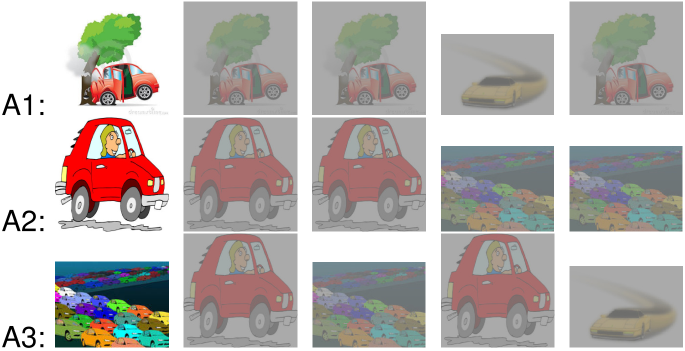

Model 1

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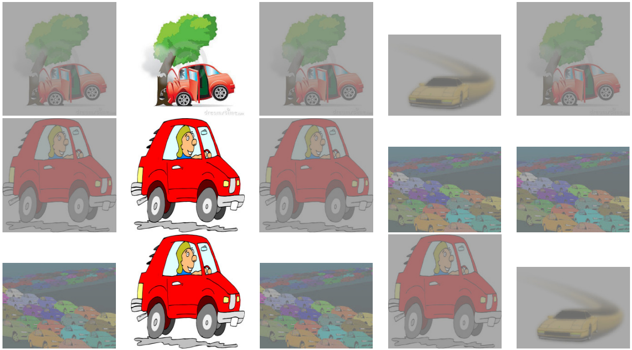

Model 2

Exploration

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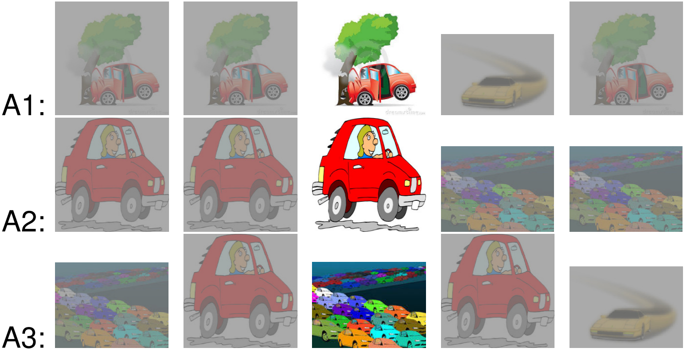

Model 3

Exploration

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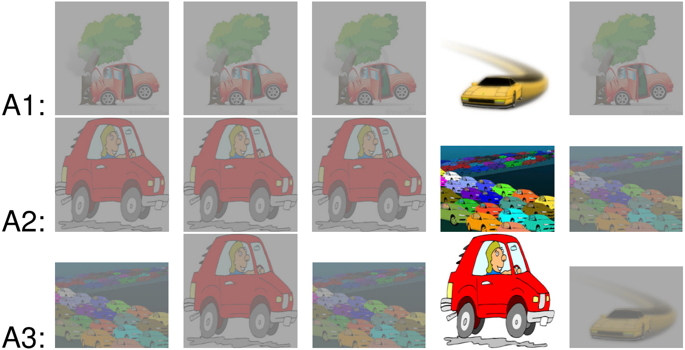


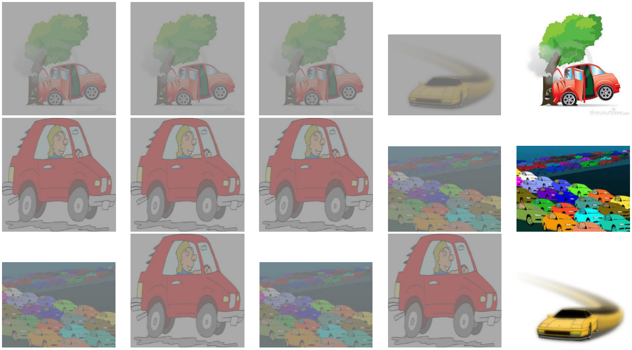
Model 4

- **Limits** exploration to state-actions that appear promising, **avoids** those which may have negative outcomes

A1:

A2:

A3:



Model 5

Exploration

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A2:

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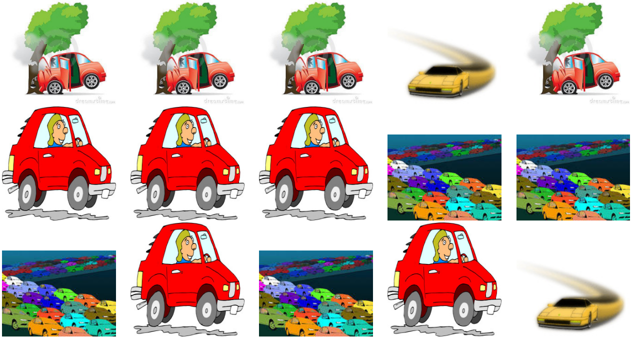

BOSS

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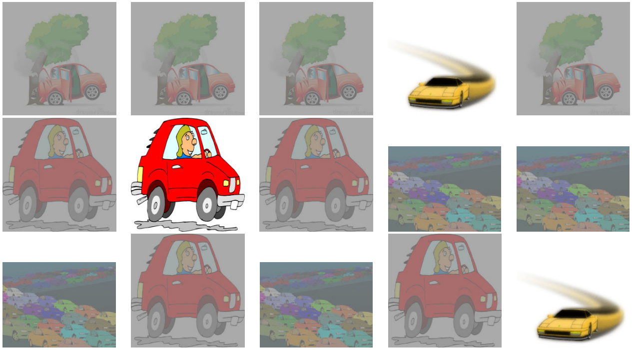

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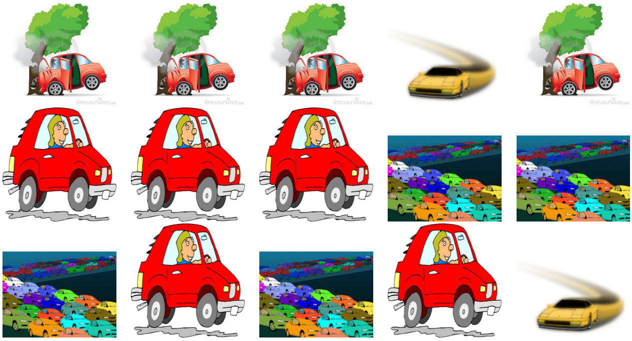

MBBE

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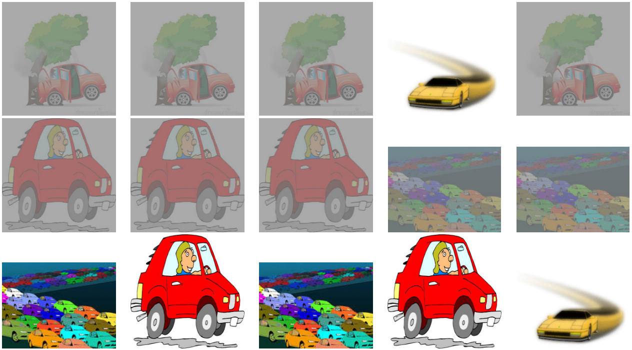

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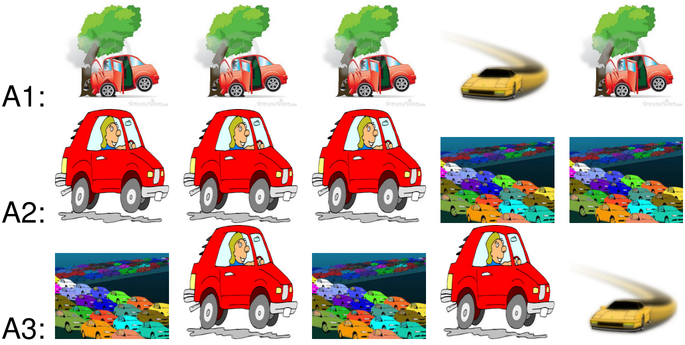

TEXPLORE

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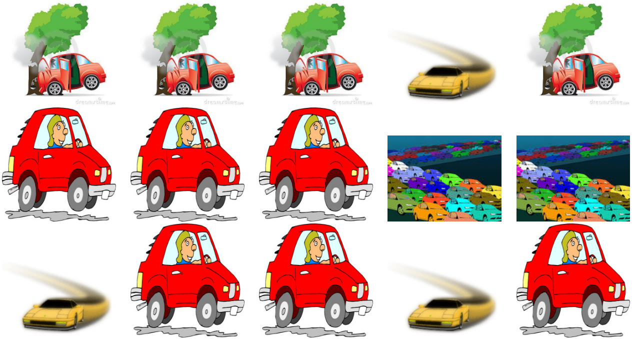


TEXPLORE

Seed experiences

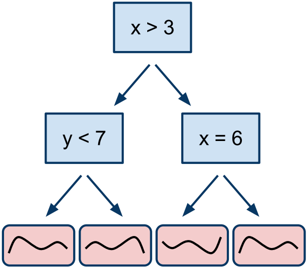
- Do not want to start from scratch learning on robots [Smart and Kaelbling 2002]
- Provide a few **example transitions** to initialize model
- Example transitions could come from human experience
- Avoid having the agent explore **every** state-action for unusual states

Continuous State

Problems

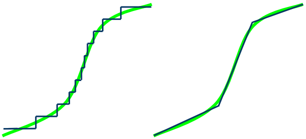
- Make continuous predictions
- Plan over continuous state space

Continuous Modeling



- Use M5 regression trees to model continuous state [Quinlan 1992]
- Each tree has a linear regression model at its leaves
- Piecewise linear prediction

Continuous Modeling



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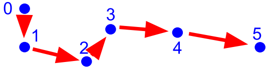
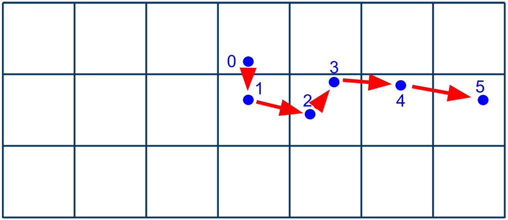
Continuous Planning



- Perform UCT rollouts over continuously valued states
- Discretize state space only for value backups

Continuous Planning



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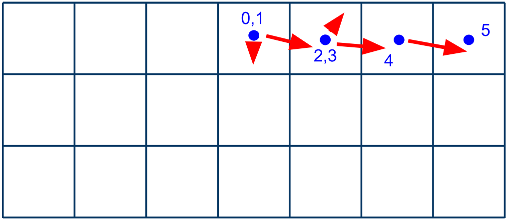
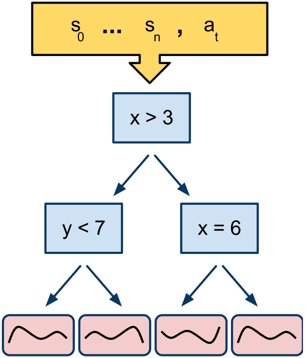


- Perform UCT rollouts over continuously valued states
- Discretize state space only for value backups
- Know where in discretized state you are

Delays

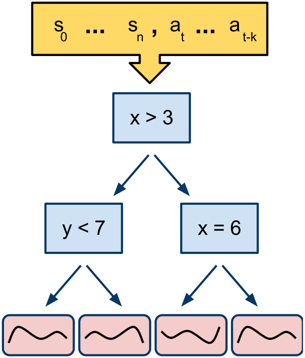
- Must know what state robot will be in when action is executed
- Delays make domain **non-Markov**, but **k-Markov**

Modeling Delay



- Provide model with previous *k* actions (Similar to U-Tree [McCallum 1996])
- Trees can learn which delayed actions are relevant
- Only requires **upper bound on *k***

Modeling Delay



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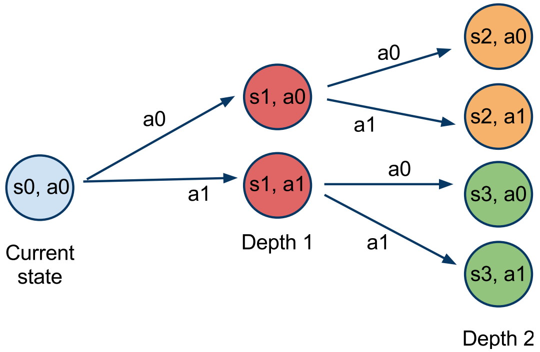
Planning with Delays



- UCT can plan over augmented state-action histories easily
- Would not be as easy with dynamic programming

The TEXPLORE Algorithm

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4. Selects actions continually in **real-time**

The TEXPLORE Algorithm

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2. Handles **continuous** state
3. Handles actuator **delays**
4. Selects actions continually in **real-time**
5. Models domains with **dependent feature transitions**

Autonomous Vehicle

- Upgraded to run **autonomously** by adding shift-by-wire, steering, and braking actuators.
- Vehicle runs at 10 Hz.
- Agent **must** provide commands at this frequency.

Velocity Control Task

- State:
  - Current Velocity
  - Desired Velocity
  - Accelerator Pedal Position
  - Brake Pedal Position
- Actions:
  - Do nothing
  - Increase/decrease brake position by 0.1
  - Increase/decrease accelerator position by 0.1
- Reward: -10.0 * velocity error (m/s)

Simulated Velocity Control Task

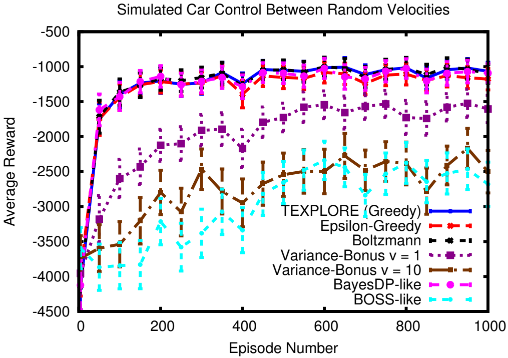
- Experiments performed **in simulation**
- 10 second episodes (100 samples)
- **Random starting and target velocity** chosen each episode
- Time-Constrained Lifetime is $436,150$ actions ($4,361$ episodes)
- **No seed experiences**
- Brake is controlled by a **PID** controller

Exploration Comparisons using TEXPLORE's model

1. TEXPLORE
2. ϵ-greedy exploration ($\epsilon = 0.1$)
3. Boltzmann exploration ($\tau = 0.2$)
4. VARIANCE-BONUS Approach $v = 1$ [Deisenroth & Rasmussen 2011]
5. VARIANCE-BONUS Approach $v = 10$
6. Bayesian DP-like Approach (use sampled model for 1 episode) [Strens 2000]
7. BOSS-like Approach (use optimistic model) [Asmuth et al. 2009]

First five approaches use **TEXPLORE's model**

Sample Efficiency Results

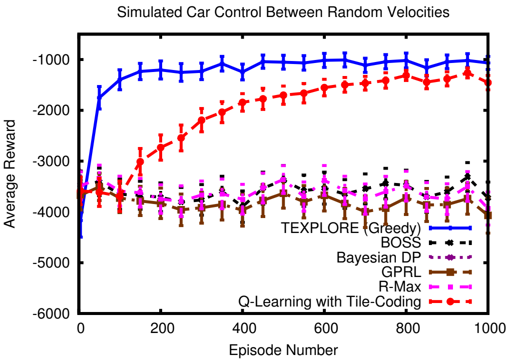


- Adding ϵ-greedy, Boltzmann, or Bayesian DP-like exploration **does not** improve performance

Comparing with other models

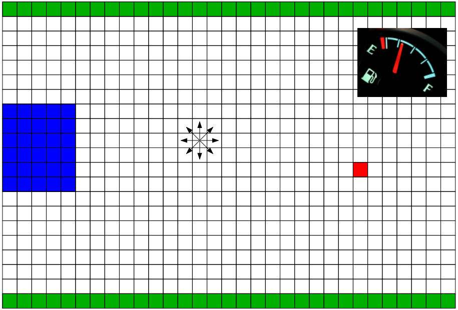
1. BOSS (Sparse Dirichlet prior) [Asmuth et al. 2009]
2. Bayesian DP (Sparse Dirichlet prior) [Strens 2000]
3. PILCO (Gaussian Process Regression model) [Deisenroth & Rasmussen 2011]
4. R-MAX (Tabular model) [Brafman & Tennenholtz 2001]
5. Q-LEARNING using tile-coding [Watkins 1989]

Sample Efficiency Results



- TEXPLORE accrues **significantly more rewards** than all the other methods after episode 24 ($p < 0.01$).

Fuel World

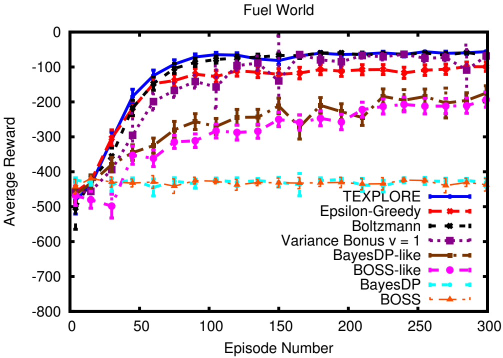


- Most of state space is very **predictable**
- But fuel stations have **varying costs**
- 317, 688 State-Actions, Time-Constrained Lifetime: 635, 376 actions
- Seed experiences of goal, fuel station, and running out of fuel

Comparison methods

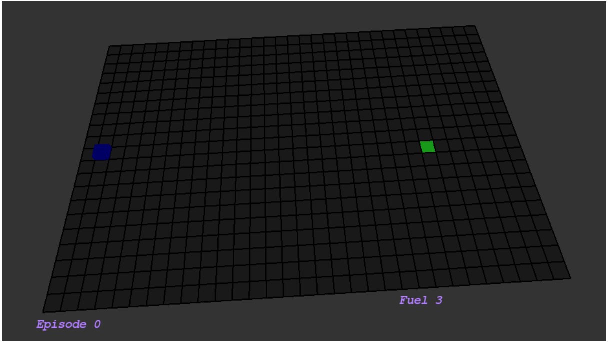
1. TEXPLORE (Greedy w.r.t. aggregate model)
2. ϵ-greedy exploration ($\epsilon = 0.1$)
3. Boltzmann exploration ($\tau = 0.2$)
4. VARIANCE-BONUS Approach $v = 10$ [Deisenroth & Rasmussen 2011]
5. Bayesian DP-like Approach (use sampled model for 1 episode) [Strens 2000]
6. BOSS-like Approach (use optimistic model) [Asmuth et al. 2009]
7. BOSS (Sparse Dirichlet prior) [Asmuth et al. 2009]
8. Bayesian DP (Sparse Dirichlet prior) [Strens 2000]

Fuel World Results



- TEXPLORE learns the **fastest** and **accrues the most cumulative reward** of any of the methods.
- TEXPLORE learns the task **within the time-constrained lifetime** of 635, 376 steps.

Fuel World Behavior

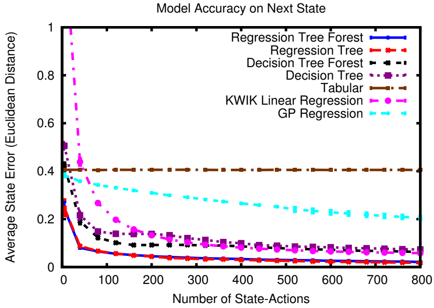


- Agent **focuses its exploration** on fuel stations near the shortest path to the goal.
- Agent **finds near-optimal policies**.

Continuous Models

1. Regression Tree Forest (TEXPLORE Default)
2. Single Regression Tree
3. Decision Tree Forest
4. Single Decision Tree
5. Tabular Model
6. KWIK Linear Regression [Strehl and Littman 2007]
7. Gaussian Process Regression (PILCO model) [Deisenroth & Rasmussen 2011]

Continuous Model Accuracy



- **Regression tree forest and single regression tree** have significantly less error than all the other models in predicting the next state ($p < 0.001$).
- For reward, regression tree is significantly better than all models but GP regression after 205 state-actions ($p < 0.001$).

Methods for Delays

Model-Based Simulated (MBS) [Walsh et al. 2009]

- Input **exact value** of delay k
- Use model to simulate forward k steps
- Use policy at that state to select action

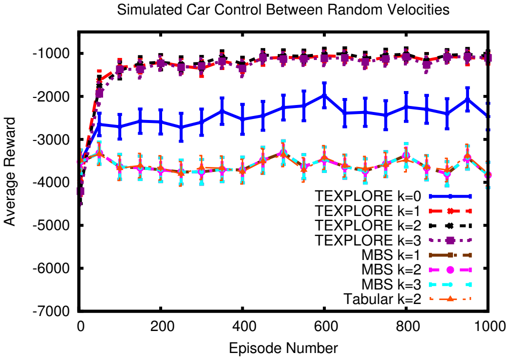
Tabular model

- Separate table entry for each state-action-history tuple

Car brake delay

- Brake pedal is physically actuated, controlled with PID
- Delay is **not** a number of discrete steps
- **Delay varies** based on how far brake is from target position

Handling Action Delays



- TEXPLORE with $k = 1, 2$, or 3 all perform **significantly better** than than using no delay ($k = 0$) ($p < 0.005$).
- These approaches are **significantly better** than using another approach to handling delay ($p < 0.005$).

Real-Time Action Selection Methods

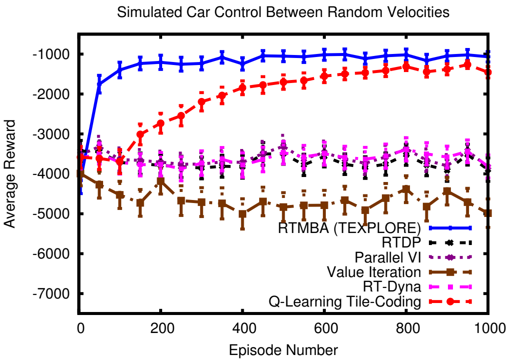
Using TEXPLORE's model

1. RTMBA (TEXPLORE)
2. Real Time Dynamic Programming (RTDP) [Barto et al. 1995]
3. Parallel Value Iteration
4. Value Iteration

Other methods

1. Dyna [Sutton 1990]
2. Q-Learning with tile-coding [Watkins 1989]

Real-Time Action Selection Results



- TEXPLORE receives **significantly more average rewards** per episode than the other methods after episode 29 ($p < 0.01$)

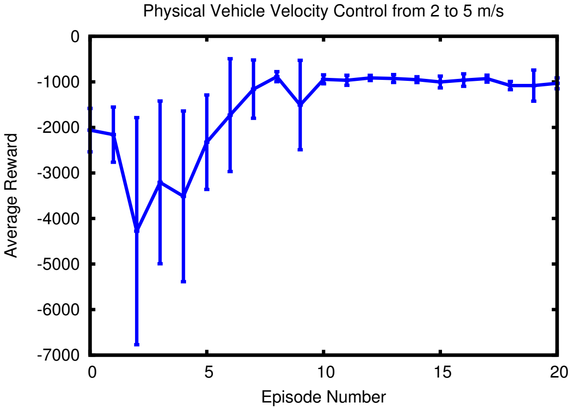
On the physical vehicle

- But, does it work on the actual vehicle?

On the physical vehicle

- 5 trials, starting at 2 m/s, target of 5 m/s.
- Time-constrained lifetime: 33, 550 steps, or 335 episodes.
- No seed experiences

On the physical vehicle



- **Yes!** It learns the task in **2 minutes** (< 11 episodes)

Characterization of Domains

Haystack Domains

- Some state-action with unusual transition or reward function image (doorway, goal, etc.)
- Best exploration: try each state-action

Informative Domains

- Some state features predict the locations of unusual states (robot with distance sensors, camera)
- Can use these features to explore more intelligently

Prior Information Domains

- Agent is given information about location of unusual states (given a map for navigating)

Exploration for Different Domain Types

- Haystack Domains
  - **TEXPLORE with Explicit Exploration** (TEXPLORE-EE)
- Informative Domains
  - **TEXPLORE with Variance and Novelty Intrinsic Rewards** (TEXPLORE-VANIR)
- **Unknown** Domain Type
  - **TEXPLORE with Learning Exploration Online** (TEXPLORE-LEO)

Exploration for Different Domain Types

- Haystack Domains
  - **TEXPLORE with Explicit Exploration** (TEXPLORE-EE)
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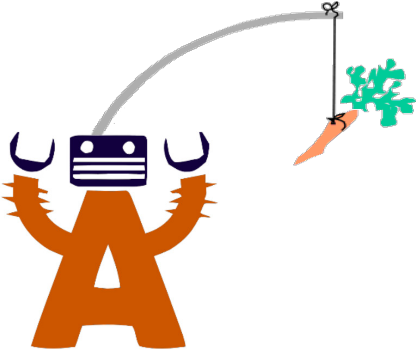
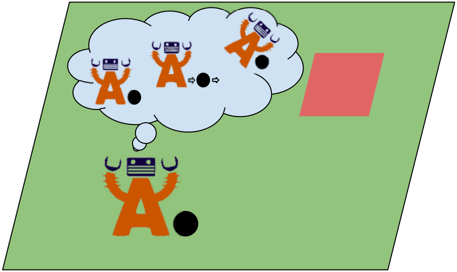
TEXPLORE-VANIR for Informative Domains



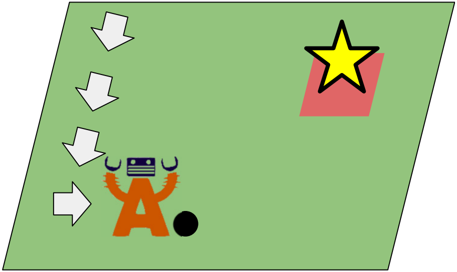
- Use **intrinsic rewards** to drive exploration
- Combine TEXPLORE model with **two** intrinsic rewards:
  1. Drives agent to where model is uncertain
  2. Drives agent to transitions different from what the model was trained on

Variance Intrinsic Reward



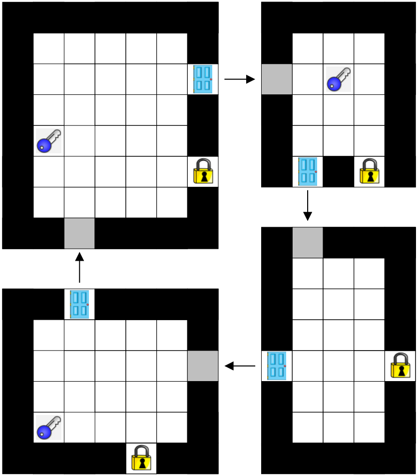
- Reward where model is **uncertain**
- Calculate a **measure of variance**:
  $D(s,a) = \sum_{i=1}^{n} \sum_{j=1}^{m} \sum_{k=1}^{m} D_{KL}(P_j(x_i^{rel}|s,a) || P_k(x_i^{rel}|s,a))$
- Add intrinsic reward proportional to variance measure:
  $R(s,a) = \mathbf{v} D(s,a)$

Novelty Intrinsic Reward



- Reward transitions that are **most different** from what was seen
- Calculate L_1 **distance in feature space** to nearest state where this action was taken:
  $\delta(s,a) = \min_{s_x \in X_a} ||s - s_x||_1$
- Add intrinsic reward proportional to novelty measure:
  $R(s,a) = \mathbf{n}\delta(s,a)$
- Given enough time, will drive agent to explore **all** state-actions.

LightWorld Domain [Konidaris and Barto 2007]



- Six actions: N, S, E, W, PICKUP, PRESS
- Agent must PICKUP key, use it to PRESS lock, and then can leave through door
- Keys, locks, and unlocked doors **emit** different colors of light
- 17 state features: ROOM, X, Y, KEY, LOCKED, and RED, GREEN, and BLUE light sensors in each of the four directions
- Reward: $+10$ for exiting door, 0 otherwise

Comparison Methods

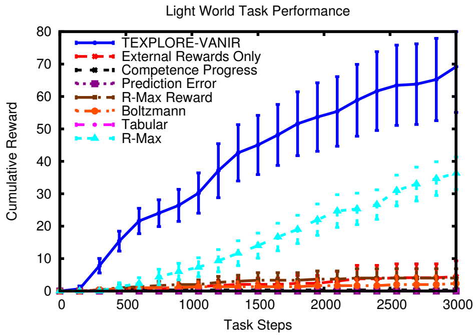
TEXPLORE Model

1. TEXPLORE-VANIR with v = 1, n = 3
2. External Rewards Only (TEXPLORE)
3. Bonus for regions with more competence progress (similar to IAC [Baranes and Oudeyer 2009])
4. Bonus for regions with higher prediction errors
5. Explore state-actions with fewer than m visits (R-MAX [Brafman and Tennenholtz 2001])

Tabular Model

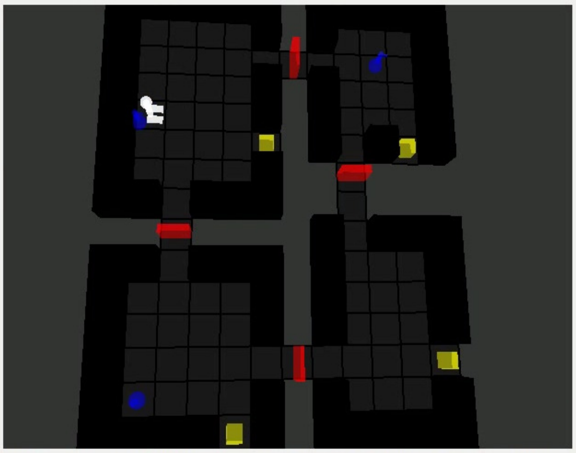
1. External Rewards Only
2. R-MAX (explore state-actions with fewer than m visits)

Task Performance



- TEXPLORE-VANIR receives **significantly more** cumulative rewards ($p < 0.001$).

TEXPLORE-VANIR Exploration



- **Novelty** rewards draw agent to objects and corners.
- **Variance** rewards make it explore using objects.

Related Work: Sample Efficient Model Learning

- **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
- **PILCO** [Deisenroth and Rasmussen 2011]
  - Use Gaussian Process regression to model dynamics
  - Exploration based on variance of GP predictions
  - Batch mode, agent is provided reward model

Related Work: 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]

Related Work: Continuous State

- **KWIK Linear Regression** [Strehl and Littman 2007]
  - Linear regression model with prediction confidence
  - Only for linearly parametrized domains
- **FITTED-R-MAX** [Jong and Stone 2007]
  - R-MAX style algorithm in continuous state
  - Use fitted value iteration [Gordon 1995]

Related Work: Sensor and Actuator Delay

- **Model Based Simulation** (MBS) [Walsh et al. 2009]
  - Provide domain's delay, k
  - Simulate k steps ahead in model, take best action for this state
- **U-TREE** [McCallum 1996]
  - Build decision trees for representing value function
  - Split on previous actions to handle delays

Related Work: Real-Time Architecture

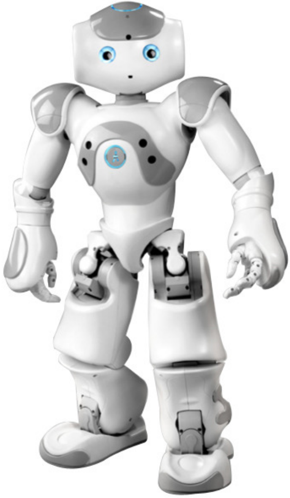
- **Dyna** Framework [Sutton 1990, 1991]
  - Do Bellman updates on random states using model when not action
  - Still uses tabular model, assumes model update takes insignificant time
- Combining sample-based planning with model-based method
  - With UCT [Silver et al. 2008], With FSSS [Walsh et al. 2010]
  - Neither places a time restriction on model update or planning
- **Real-Time Dynamic Programming** RTDP [Barto et al. 1995]
  - Similar to UCT, but full backups at each state

Related Work: Robot Learning

- **Helicopter Control** [Ng et al. 2003]
  - Learn helicopter model from experiences acquired from human expert
  - Computation performed off-line
- **PILCO** [Deisenroth and Rasmussen 2011]
  - Use Gaussian Process regression for model learning and planning
  - Very sample efficient in learning to control cart-pole
  - Takes 10 minutes of computation for every 2.5 seconds of experience
- **POWER** [Kober and Peters 2008]
  - Policy search for parameterized motor primitives
  - Only for episodic tasks

Future Work: Continuous Actions

- Many robots could utilize **continuous actions** (angles, velocities)
- Regression tree model can make predictions on the basis of continuous actions
- Could utilize work on UCT-like planning in continuous actions spaces (HOOT) using continuous bandit algorithms [Bubeck et al. 2011; Mansley et al. 2011; Weinstein and Littman 2012]



Future Work: Opponent Modeling

- Initialize each tree in forest with **possible opponent strategy**
- Could be from experience with past opponents
- Explore to determine which type of opponent you are playing

Future Work: Lifelong Robot Learning

- **Goal:** Act and learn in environment over lifetime, performing many tasks
- Handle large and complex state space: **Make algorithm more parallel**
- Generalize knowledge to new tasks: **Find best state representation**

Contributions

- The TEXPLORE algorithm
- MDP Models that generalize action effects
- Targeted Exploration
- Real-Time Architecture
- ROS RL Interface
- Empirical Evaluation

Contributions

- The TEXPLORE algorithm
  - Limits exploration to be **sample efficient**
  - Handles **continuous** state
  - Handles actuator **delays**
  - Selects actions continually in **real-time**
  - Models domains with **dependent feature transitions**
- MDP Models that generalize action effects
- Targeted Exploration
- Real-Time Architecture
- ROS RL Interface
- Empirical Evaluation

Contributions

- The TEXPLORE algorithm
- MDP Models that generalize action effects
  - Random forests of regression trees
- Targeted Exploration
- Real-Time Architecture
- ROS RL Interface
- Empirical Evaluation

Contributions

- The TEXPLORE algorithm
- MDP Models that generalize action effects
- Targeted Exploration
  - Average predictions of each tree in random forest
  - Use intrinsic rewards for **informative** domains
- Real-Time Architecture
- ROS RL Interface
- Empirical Evaluation

Contributions

- The TEXPLORE algorithm
- MDP Models that generalize action effects
- Targeted Exploration
- Real-Time Architecture
  - Maintain **sample efficiency** of model-based methods
  - While acting in **real-time**
- ROS RL Interface
- Empirical Evaluation

Contributions

- The TEXPLORE algorithm
- MDP Models that generalize action effects
- Targeted Exploration
- Real-Time Architecture
- ROS RL Interface
  - Enables **easy integration** of RL on robots using ROS
- Empirical Evaluation

Contributions

- The TEXPLORE algorithm
- MDP Models that generalize action effects
- Targeted Exploration
- Real-Time Architecture
- ROS RL Interface
- Empirical Evaluation
  - Real-time learning while running on-board **physical robot**

Conclusion

- TEXPLORE:
  1. Learns in few **samples**
  2. Acts continually in **real-time**
  3. Learns in **continuous** domains
  4. Handles sensor and actuator **delays**
- TEXPLORE has been released as a ROS package: www.ros.org/wiki/rl-texplore-ros-pkg