

# Toward Visualization Methods for Interactive Improvement of MDP Specifications

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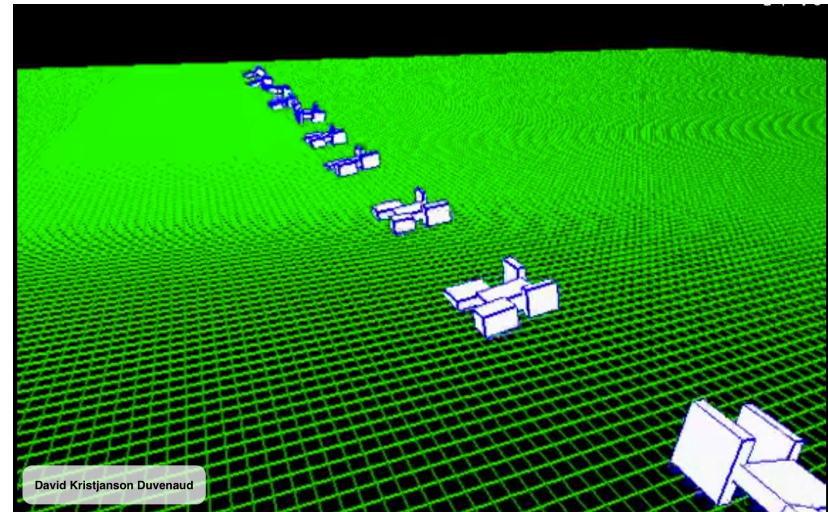
# Motivation

Large MDPs → “Complexity”

- Complex software systems are often buggy or misspecified.
  - Does the policy exploit **bugs** in the MDP definition?
  - Does the policy **balance disparate objectives** in an acceptable way?
- Stakeholders lack a means of interrogating the intersection of simulator, values, and policies.
  - How can **stakeholders believe** the policy recommendation?

# Examples of “Success”

- Debugging
  - Physics Bugs [0]
- Objectives
  - Vibrating Soccer Players [1]
  - Circling Bicycle [1]



## Specific Motivation of Wildfire

- **Immensely complex models** with numerous potential integration points: vegetative growth, numerous fires spreading spatially, wood products markets, city encroachment, climate change, etc.
- Given a natural wildfire, **SUPPRESS or LET-BURN**

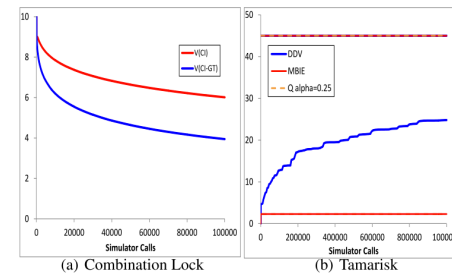


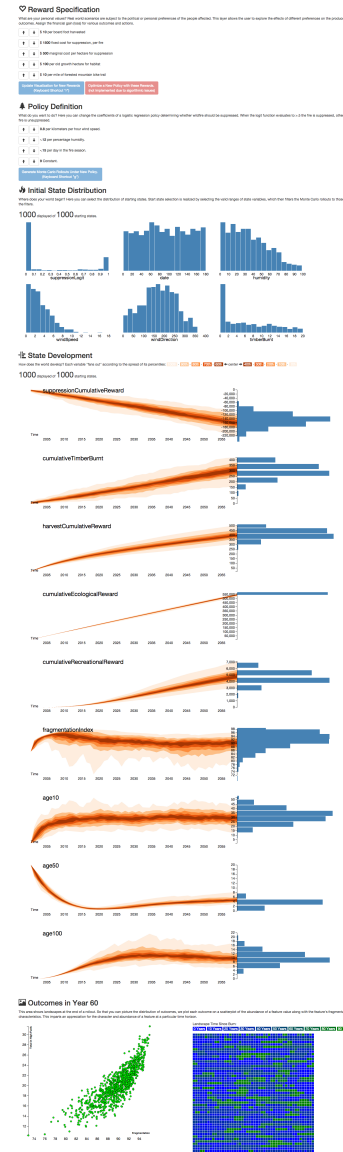
Figure 2: Left: Learning curve for DDV with and without incorporating Good-Turing confidence bounds. Right: Learning curves for MBIE, Q-learning, and DDV on a Tamarisk management MDP.

# Solution: MDP Visualization

1. Control the rewards
2. Control the policy
3. Filter Initial State Distribution

## 4. View State Evolution

## 6. View Results



5. Filter Final States

# Large MDP Visualization Requirements

- Have a basis in the **MDP formulation**
- **Scale well**
- Provide for **real-time interaction + exploration**
- Explore **distribution of outcomes** rather than single realizations
- Interactively **explore the policy space – Challenge**
- For rapid debugging, **generate new policies** based on changing rewards – **Challenge**

## MDP Formulation of Visualization

Reward Definition:  $R(s,a)$

Policy Definition:  $\pi(s,a)$

Initial State Distribution:  $P_0$

State Development Distribution:  $P$

Final State Examination:  $S$

# MDP Formulation of Visualization

Reward Definition:  $R(s,a)$

## ♥ Reward Specification

- ↑ ↓ \$10 per board foot harvested
- ↑ ↓ \$1,500 fixed cost for suppression, per fire
- ↑ ↓ \$500 marginal cost per hectare for suppression
- ↑ ↓ \$100 per old growth hectare for habitat
- ↑ ↓ \$10 per mile of forested mountain bike trail

Update Visualization for New Rewards  
(Keyboard Shortcut "r")

Optimize a New Policy with these Rewards.  
(not implemented due to algorithmic issues)



# MDP Formulation of Visualization

Reward Definition:  $R(s,a)$

Policy Definition:  $\pi(s,a)$

Initial State  $E$

State Development

Final State  $E$



## Policy Definition



0.8 per kilometers per hour wind speed.



-.12 per percentage humidity.



-.15 per day in the fire season.



9 Constant.

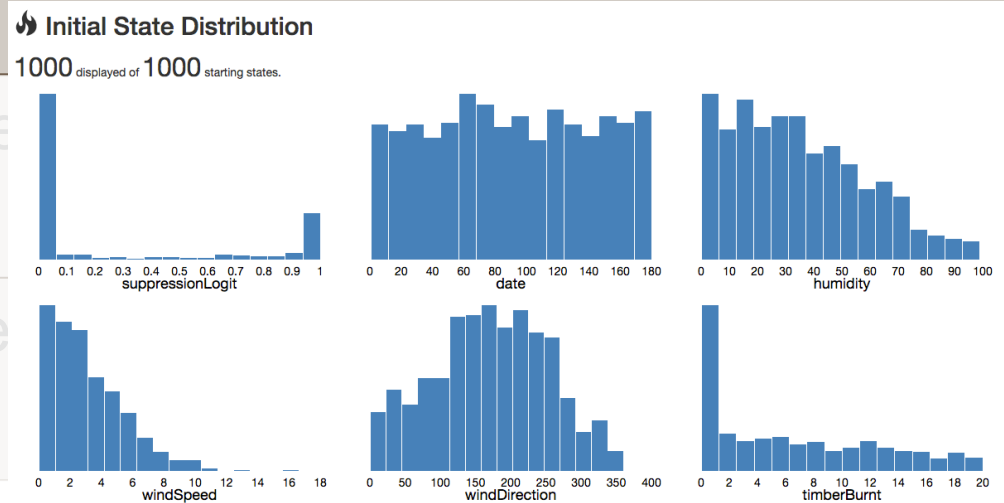
Generate Monte Carlo Rollouts Under New Policy.  
(Keyboard Shortcut "g")

# MDP Formulation of Visualization

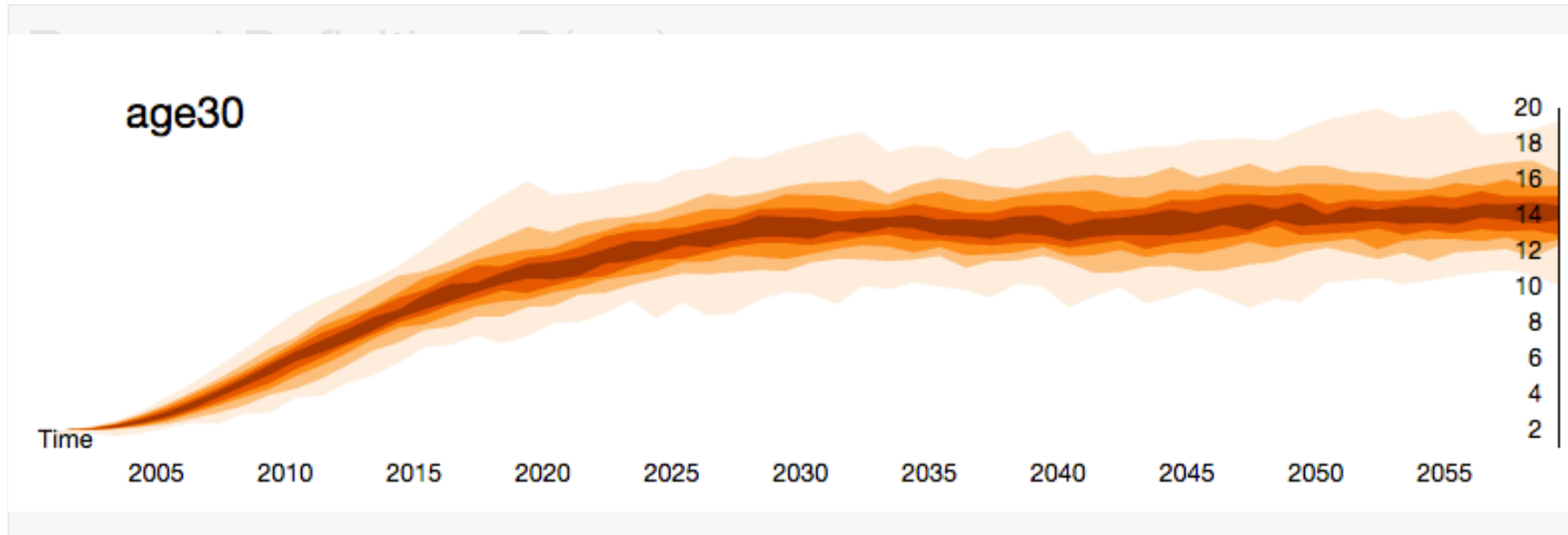
Reward Definition:  $R(s,a)$

Policy Definition:  $\pi(s,a)$

Initial State Distribution:  $P_0$



# MDP Formulation of Visualization



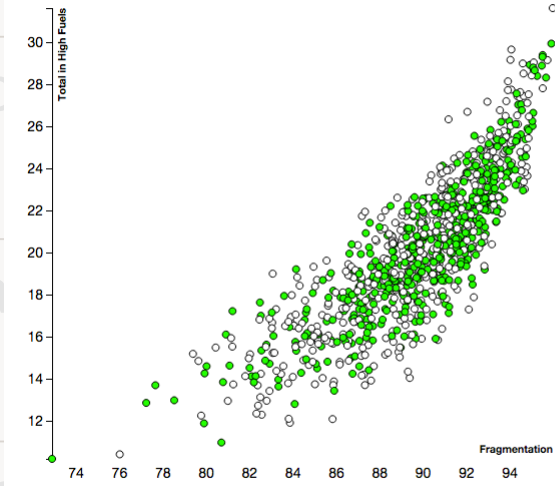
State Development Distribution: P

Final State Examination: S

# MDP Formulation of Visualization

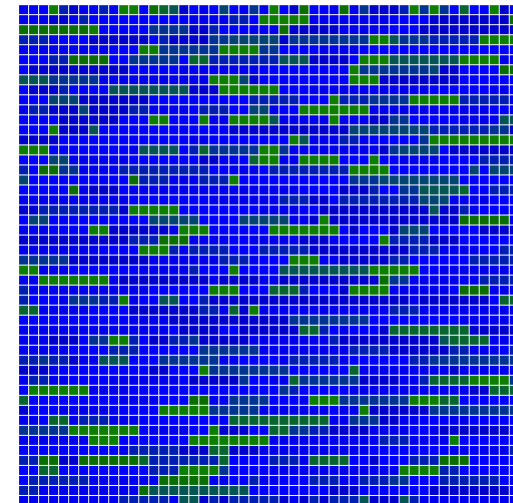
Reward Definition:  $R(s,a)$

🖼️ Outcomes in Year 60



Landscape Time Since Burn:

0 Years | 10 Years | 20 Years | 30 Years | 40 Years | 50 Years | 60 Years | 70 Years | 80 Years | 90 Years



Final State Examination:  $S$

## ♥ Reward Specification

What are your personal values? Real world scenarios are subject to the political or personal preferences of the people affected. This layer allows the user to explore the effects of different preferences on the produced outcomes. Assign the financial gain (loss) for various outcomes and actions.

- ↑ ↓ \$ 10 per board foot harvested
- ↑ ↓ \$ 1500 fixed cost for suppression, per fire
- ↑ ↓ \$ 500 marginal cost per hectare for suppression
- ↑ ↓ \$ 100 per old growth hectare for habitat
- ↑ ↓ \$ 10 per mile of forested mountain bike trail

Update Visualization for New Rewards  
(Keyboard Shortcut "r")

Optimize a New Policy with these Rewards.  
(not implemented due to algorithmic issues)

## 🌲 Policy Definition

What do you want to do? Here you can change the coefficients of a logistic regression policy determining whether wildfire should be suppressed. When the logit function evaluates to  $>.5$  the fire is suppressed, otherwise the fire is unsuppressed.

- ↑ ↓ 0.8 per kilometers per hour wind speed.
- ↑ ↓ -.12 per percentage humidity.
- ↑ ↓ -.15 per day in the fire season.
- ↑ ↓ 9 Constant.

Generate Monte Carlo Rollouts Under New Policy.  
(Keyboard Shortcut "g")

## 🔥 Initial State Distribution

Where does your world begin? Here you can select the distribution of starting states. Start state selection is realized by selecting the valid ranges of state variables, which then filters the Monte Carlo rollouts to those matching the filters.

1000 displayed of 1000 starting states.



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## Summary

- As **RL matures** it needs **new tools**.
- Powerful tools require **solving algorithmic challenges**.

## Algorithmic Challenges

Intelligent Caching of High Dimensional State Transitions →

Generate Monte Carlo Rollouts Under New Policy.  
(Keyboard Shortcut "g")

Quickly optimizing new policies →

Optimize a New Policy with these Rewards.  
(not implemented due to algorithmic issues)

## Interactive Demo

# AtlasOfLife.com/mdp



# Thanks

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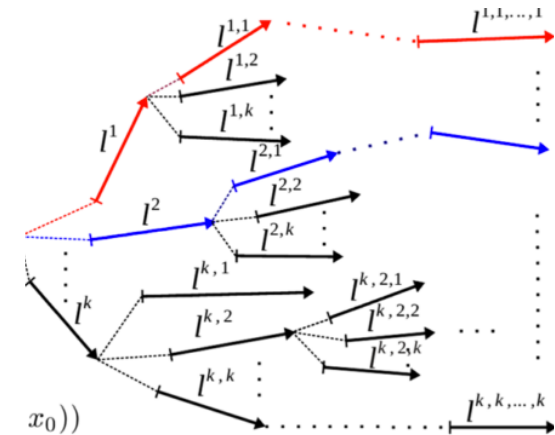
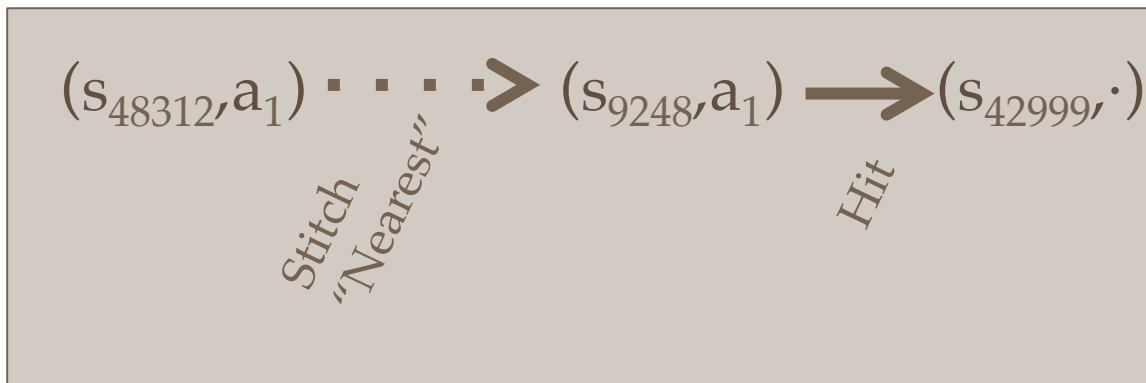
# Generating New Monte Carlo Rollouts

- Problem: Slow simulator prevents changing policies.
- Proposed Solution: pre-compute a database of transitions.

Database "Hit" on  $(s_0, a_0)$



Database "Miss" on  $(s_{48312}, a_1)$



Fonteneau, R., Murphy, S. a, Wehenkel, L., & Ernst, D. (2013). Batch Mode Reinforcement Learning based on the Synthesis of Artificial Trajectories. *Annals of Operations Research*, 208(1), 383–416.

## Updating Policy for New Rewards

- Simulator is still slow
- Optimizing in large MDPs is slow.

“It is important that the physical simulation be reasonably accurate... errors, will inevitably be discovered and exploited... Although this can be a lazy and often amusing approach for debugging a physical modeling system, it is **not necessarily the most practical.**” – Karl Sims

## Make it practical in non-physical systems!