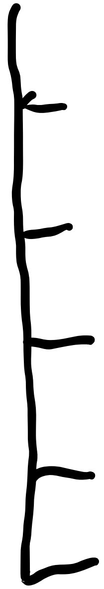
Recap

Recap

DMU



Recap

DMU

- Probabilistic Models

Recap

DMU
- Probabilistic Models
- MDPs
- Reinforcement Learning
-
-

Recap

DMU
- Probabilistic Models
- MDPs
- Reinforcement Learning
- POMDPs
- Games

Probabilistic Models

Probabilistic Models

3 Rules

$P(A)$

$P(A,B)$

$P(A|B)$

Probabilistic Models

$P(A)$

$P(A, B)$

$P(A \mid B)$

3 Rules

1. $0 \leq P(X \mid Y) \leq 1$

   $\sum_{x \in X} P(x \mid Y) = 1$

Probabilistic Models

P(A)
P(A,B)
P(A|B)

3 Rules

1. $0 \leq P(X \mid Y) \leq 1$
   $\sum_{x \in X} P(x \mid Y) = 1$

2. $P(X) = \sum_{y \in Y} P(X, y)$

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2. $P(X) = \sum_{y \in Y} P(X, y)$

3. $P(X \mid Y) = \frac{P(X,Y)}{P(Y)}$

Probabilistic Models

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Bayes Rule

$$P(A \mid B) = \frac{P(B \mid A) P(A)}{P(B)}$$

Probabilistic Models

P(A)
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Bayes Rule

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)}$$

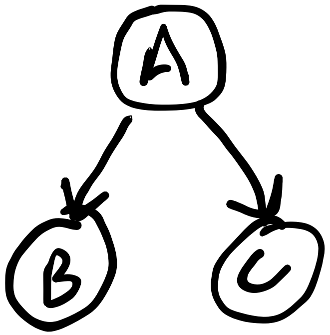
Independence

$$A \perp B \iff P(A, B) = P(A)P(B)$$

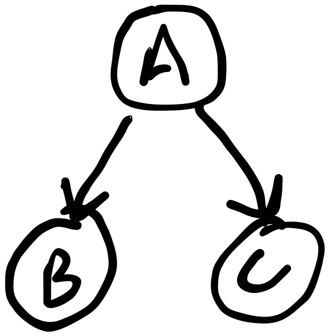
$$A \perp B \mid C \iff P(A, B \mid C) = P(A \mid C)P(B \mid C)$$

Bayesian Networks

Bayesian Networks



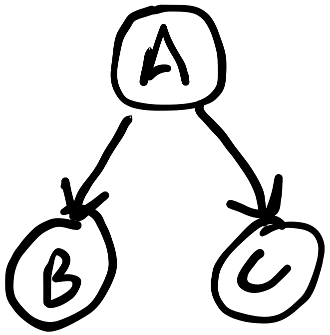
Bayesian Networks



Chain Rule

$$\underbrace{P(X_{1:n})} = \prod_i \underbrace{P(X_i \mid Pa(X_i))}$$

Bayesian Networks

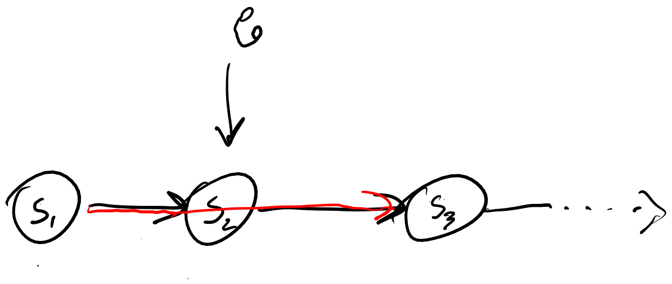


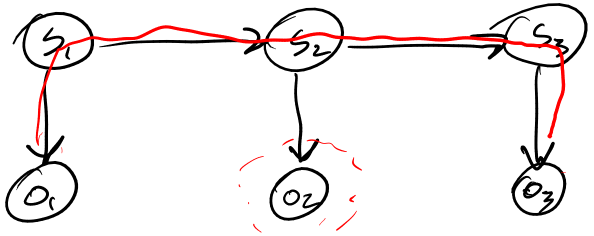
Chain Rule

$$P(X_{1:n}) = \prod_i P(X_i \mid Pa(X_i))$$

Conditional Independence

$X \perp Y \mid \mathcal{C}$ if all paths between X and Y are d-separated by $\mathcal{C}$





$o_1 \overset{?}{\perp} o_3 \mid o_2$

We cannot prove based on structure

Markov Decision Processes

Markov Decision Processes

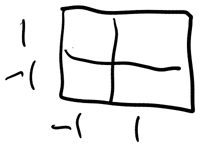
$$(S, A, R, T, \gamma)$$

Markov Decision Processes

$$(S, A, R, T, \gamma)$$

Examples: $S = \{1, 2, 3\}$ or $S = \mathbb{R}^2$

Markov Decision Processes



Cartesian Product of two sets

$\{-1,1\} \times \{-1,1\} = \{(-1,-1),(-1,1),(1,-1),(1,1)\}$

$$(S, A, R, T, \gamma)$$

Examples: $S = \underbrace{\{1,2,3\}}$ or $S = \mathbb{R}^2$

$$s = (x, \dot{x}) \in S = \mathbb{R}^2$$

$s = (x^1, y^1, x^2, y^2, b)$

$b \in \{1, 2\}$

$S = [-1,1]^4 \times \{1,2\}$

A state is usually represented as a vector or tuple of state variables

A state space is a set of all possible states

$s \in S$

$s = (x^1, y^1, x^2, y^2)$

Case 1
$x \in \{-1, 1\}$
$y \in \{-1, 1\}$

$S = \{-1,1\} \times \{-1,1\} \times \{-1,1\} \times \{-1,1\} = \{-1,1\}^4$

Case 2
$x \in [-1,1]$
$y \in [-1,1]$

$S = [-1,1] \times [-1,1] \times [-1,1] \times [-1,1] = [-1,1]^4$

Case 3
$x \in \{-10, -9, \dots, 9, 10\}$

$S = \{-10, \dots, 10\}^4$

Markov Decision Processes

$$(S, A, R, T, \gamma)$$

Examples: $S = \{1, 2, 3\}$ or $S = \mathbb{R}^2$

$$s = (x, \dot{x}) \in S = \mathbb{R}^2$$

$$\underset{\pi}{\text{maximize}} \; E\left[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t)\right]$$

Markov Decision Processes

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$$\underset{\pi}{\text{maximize}} \; E\left[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t)\right]$$

$$Q^{\pi}(s, a) = E\left[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t) \,\middle|\, \underline{s_0 = s}, \underline{a_0 = a}, \underline{a_t = \pi(s_t)}\right]$$

Markov Decision Processes

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$$V^\pi(s) = Q^\pi(s, \pi(s))$$

Markov Decision Processes

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$$V^\pi(s) = Q^\pi(s, \pi(s))$$

$$V^\pi(s) = R(s, a) + \gamma E[V^\pi(s')]$$

$$V^*(s) = \max_a \{R(s, a) + \gamma E[V^*(s')]\}$$

$$B[V](s) = \max_a \{R(s, a) + \gamma E[V(s')]\}$$

Markov Decision Processes

$$(S, A, R, T, \gamma)$$

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$$V^\pi(s) = Q^\pi(s, \pi(s))$$

$$V^\pi(s) = R(s,a) + \gamma E[V^\pi(s')]$$ Policy Evaluation

$$V^*(s) = \max_a \{R(s,a) + \gamma E[V^*(s')]\}$$ Bellman's Equation: Certificate of Optimality

$$B[V](s) = \max_a \{R(s,a) + \gamma E[V(s')]\}$$ Bellman's Operator

Offline MDP Algorithms

Offline MDP Algorithms

Policy Iteration

loop

    Evaluate Policy

    Improve Policy

Offline MDP Algorithms

Policy Iteration

loop

  Evaluate Policy

  Improve Policy

Value Iteration

loop

  $V \leftarrow B[V]$

Offline MDP Algorithms

Policy Iteration

loop

Evaluate Policy

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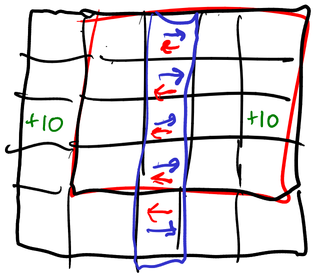
Converges because policy always improves and there are a finite number of policies

Value Iteration

loop

$V \leftarrow B[V]$

Offline MDP Algorithms



Policy Iteration

loop

Evaluate Policy

Improve Policy

Converges because policy always improves and there are a finite number of policies

Value Iteration

loop

$V \leftarrow B[V]$

Converges because B is a contraction mapping

Online MDP Planning

Online MDP Planning

Monte Carlo Tree Search

Online MDP Planning

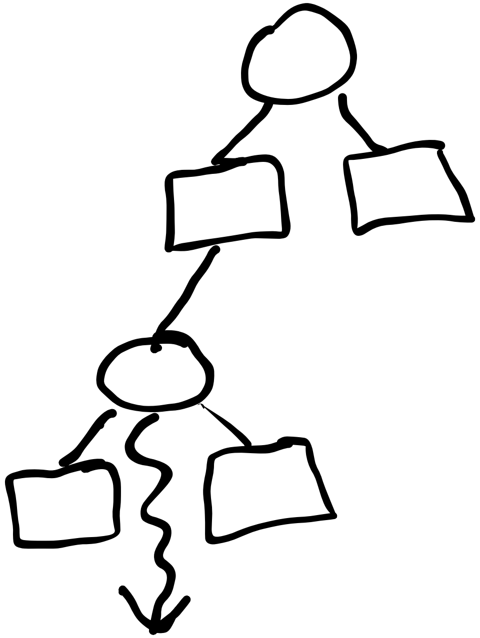
Monte Carlo Tree Search

Search

Expand

Rollout

Backup



Online MDP Planning

Monte Carlo Tree Search

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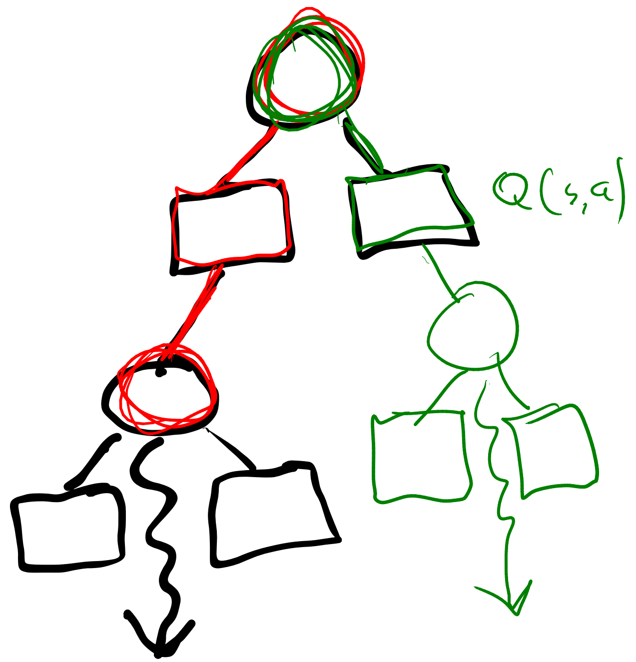
$$Q(s,a) + c\sqrt{\frac{\log N(s)}{N(s,a)}}$$



Online MDP Planning

Monte Carlo Tree Search

Sparse Sampling

Search

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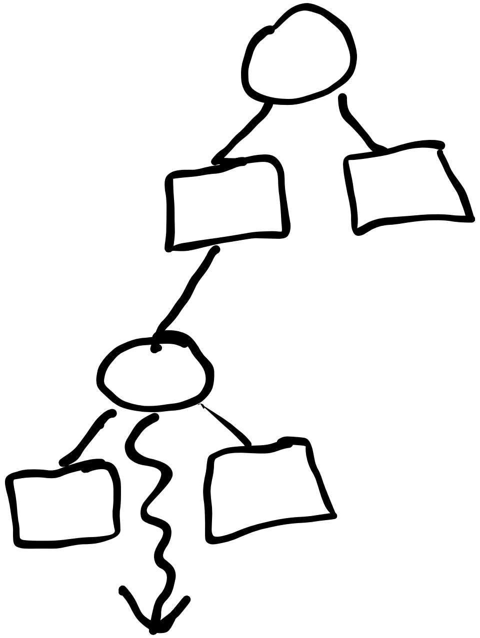

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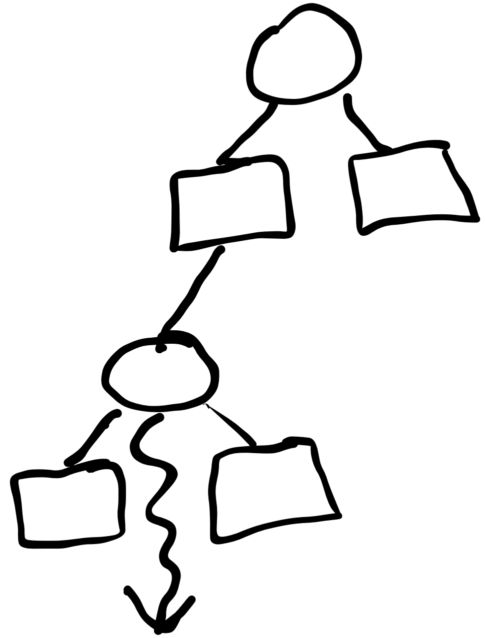
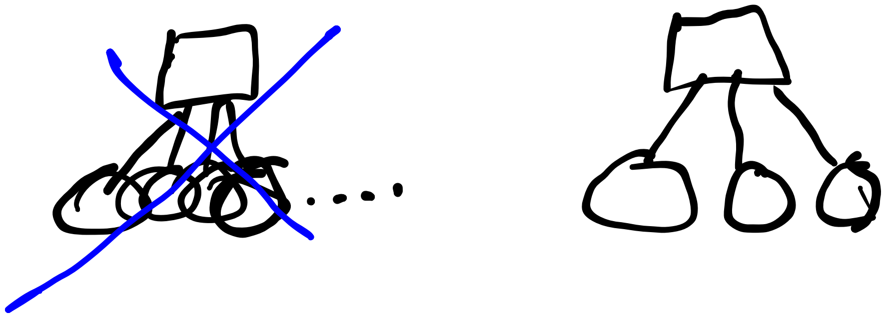


Sparse Sampling



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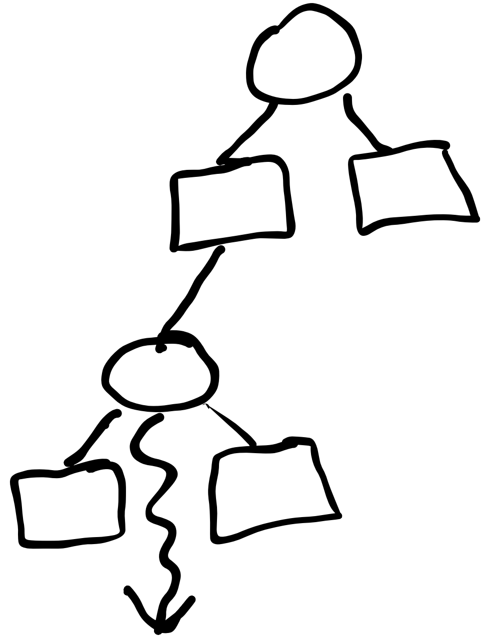

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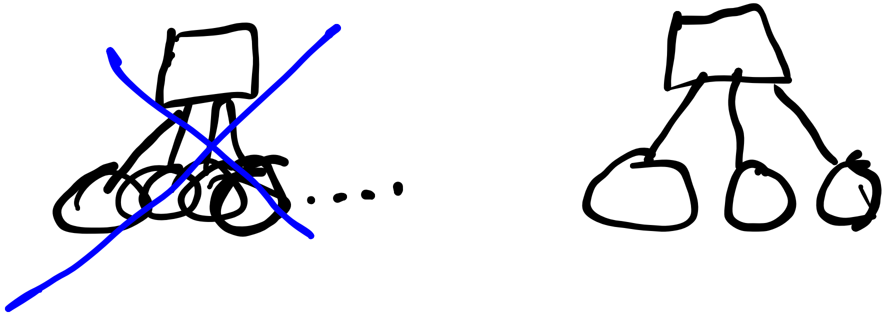


Guarantees *independent* of $|S|$!!

$s \in \mathbb{R}^n$ $\mathbb{R} \times \mathbb{R} \cdots$
$a \in \mathbb{R}^m$

LQR

Gaussian

$$\mathbf{s}' = \mathbf{T}_s \mathbf{s} + \mathbf{T}_a \mathbf{a} + \mathbf{w}$$

$$R(\mathbf{s}, \mathbf{a}) = \mathbf{s}^\top \mathbf{R}_s \mathbf{s} + \mathbf{a}^\top \mathbf{R}_a \mathbf{a}$$

$$\pi_h(\mathbf{s}) = \underbrace{-\left(\mathbf{T}_a^\top \mathbf{V}_{h-1} \mathbf{T}_a + \mathbf{R}_a\right)^{-1} \mathbf{T}_a^\top \mathbf{V}_{h-1} \mathbf{T}_s}_{K} \mathbf{s}$$

$V_h(s) = s^T V_h s + q_h$

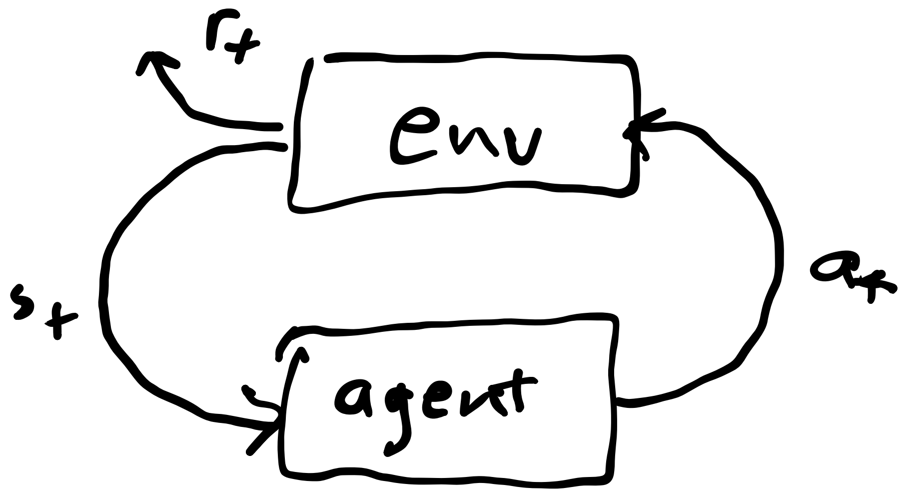
$$\mathbf{V}_{h+1} = \mathbf{R}_s + \mathbf{T}_s^\top \mathbf{V}_h^\top \mathbf{T}_s - \left(\mathbf{T}_a^\top \mathbf{V}_h \mathbf{T}_s\right)^\top \left(\mathbf{R}_a + \mathbf{T}_a^\top \mathbf{V}_h \mathbf{T}_a\right)^{-1} \left(\mathbf{T}_a^\top \mathbf{V}_h \mathbf{T}_s\right)$$

$V_1 = R_s$

Reinforcement Learning

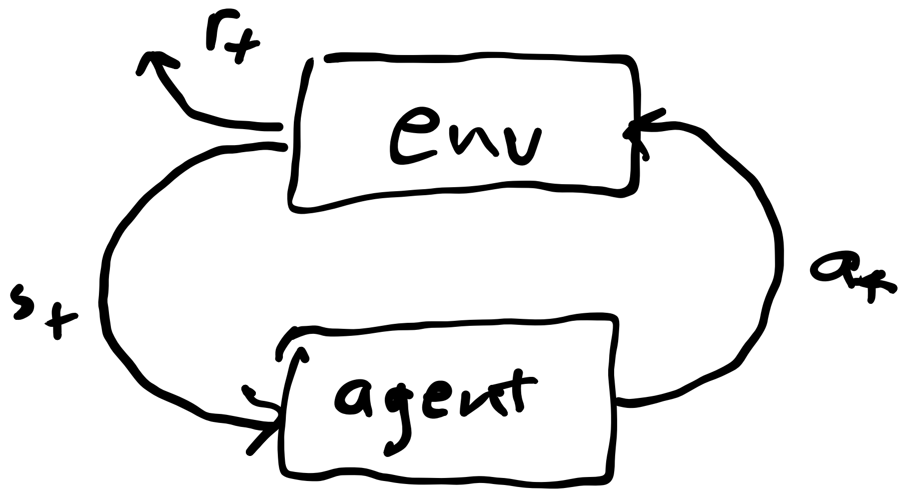
Challenges:

Reinforcement Learning



Challenges:

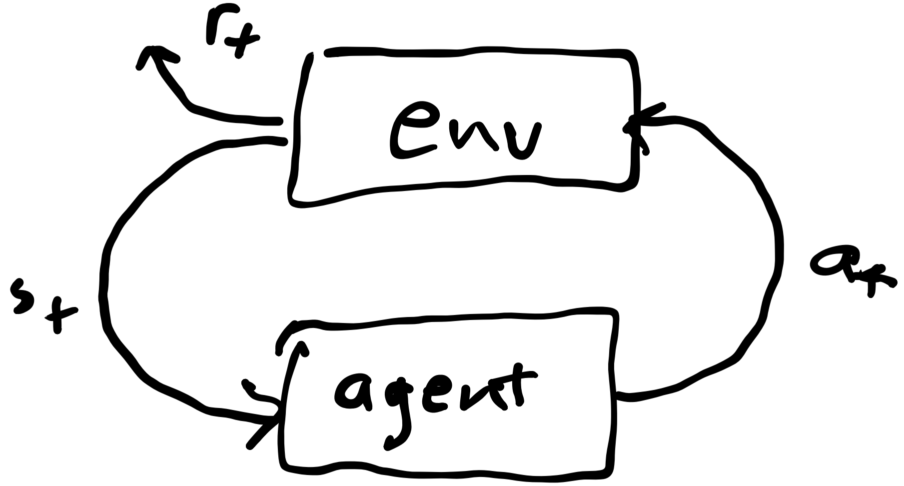
Reinforcement Learning



Challenges:

1. Exploration and Exploitation

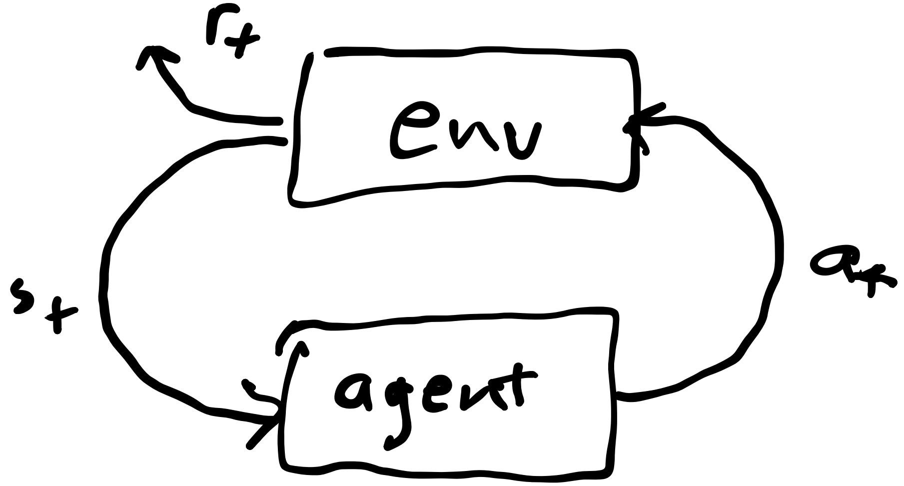
Reinforcement Learning



Challenges:

1. Exploration and Exploitation
2. Credit Assignment

Reinforcement Learning

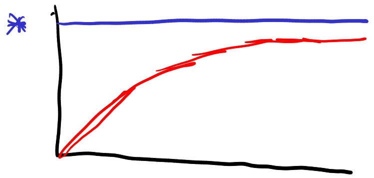


Challenges:

1. Exploration and Exploitation
2. Credit Assignment
3. Generalization

Exploration

Exploration



Bandits

- ϵ-greedy
- softmax
- UCB
- Thompson Sampling
- Optimal DP Solution (solving a POMDP!)

logarithmic regret

Exploration

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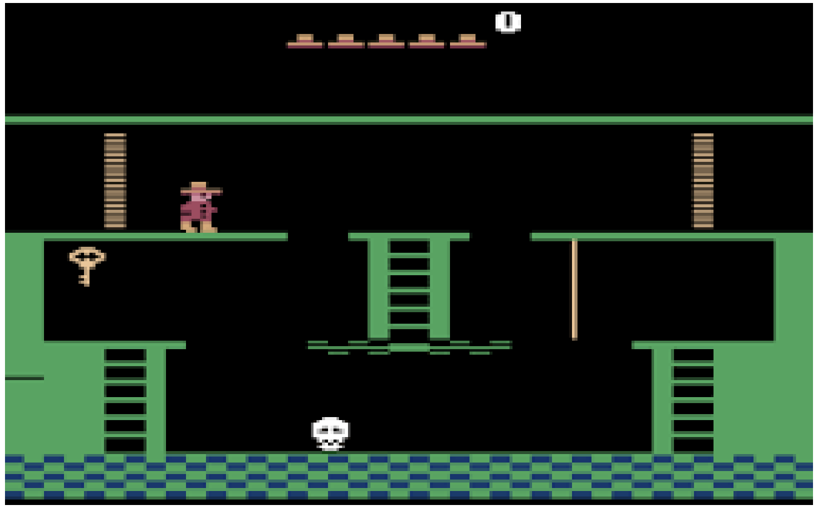

Montezuma's Revenge!

Exploration

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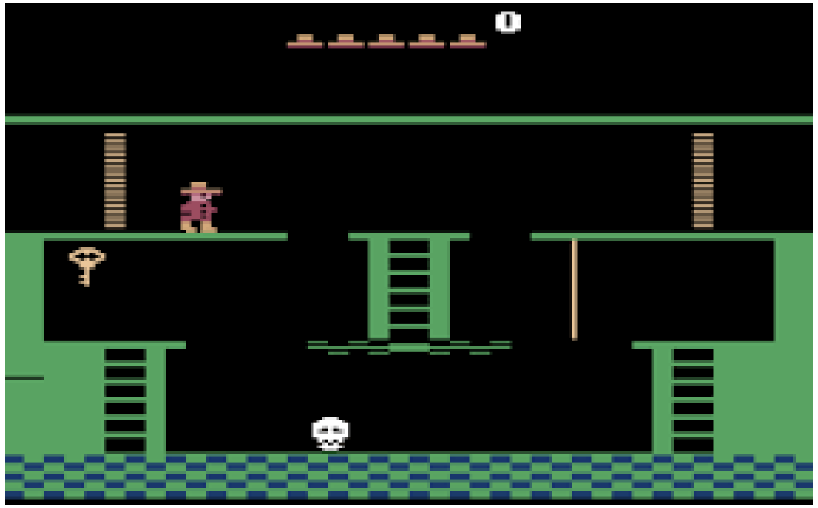
$Q(s,a) + B(s,a)$

- Pseudocounts



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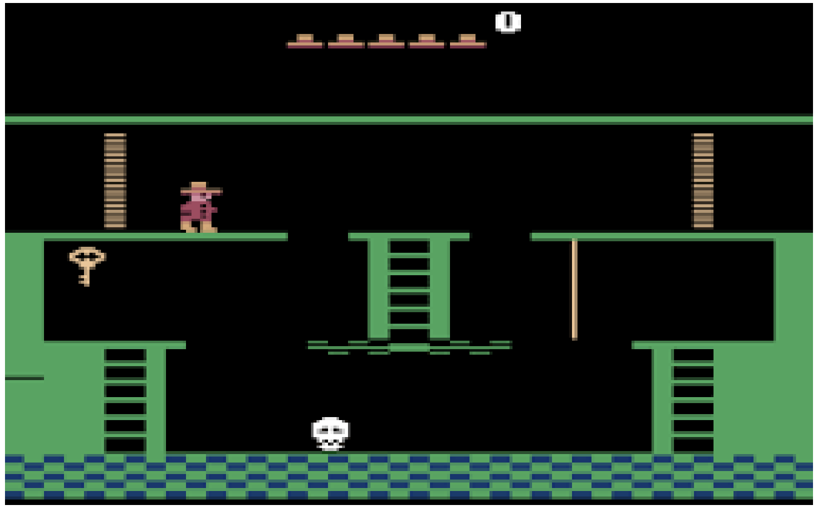

Montezuma's Revenge!

- Pseudocounts
- Curiosity: extra reward for bad prediction

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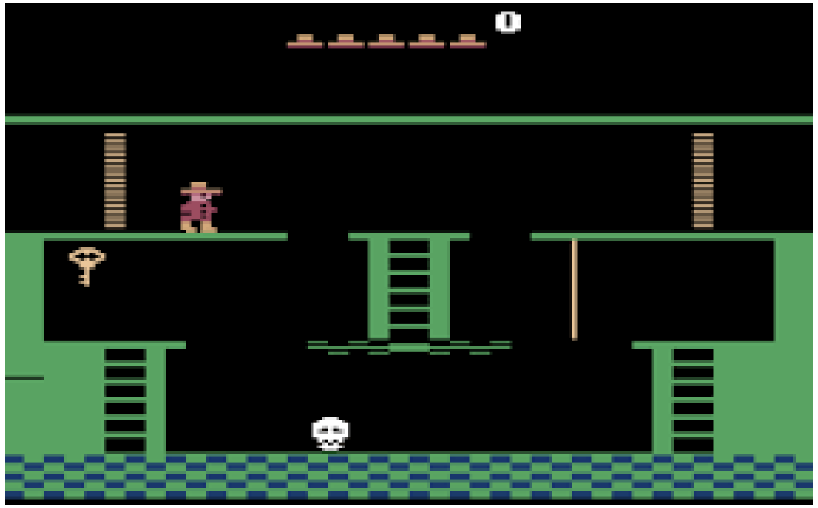
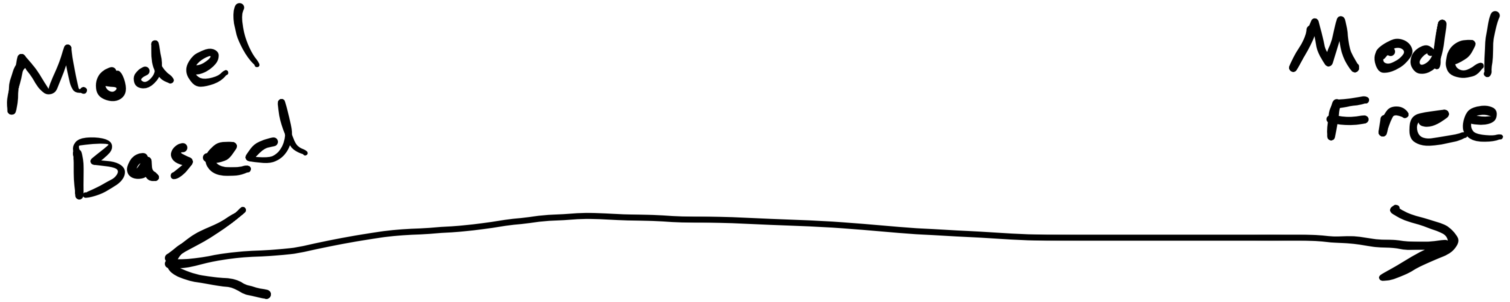


Montezuma's Revenge!

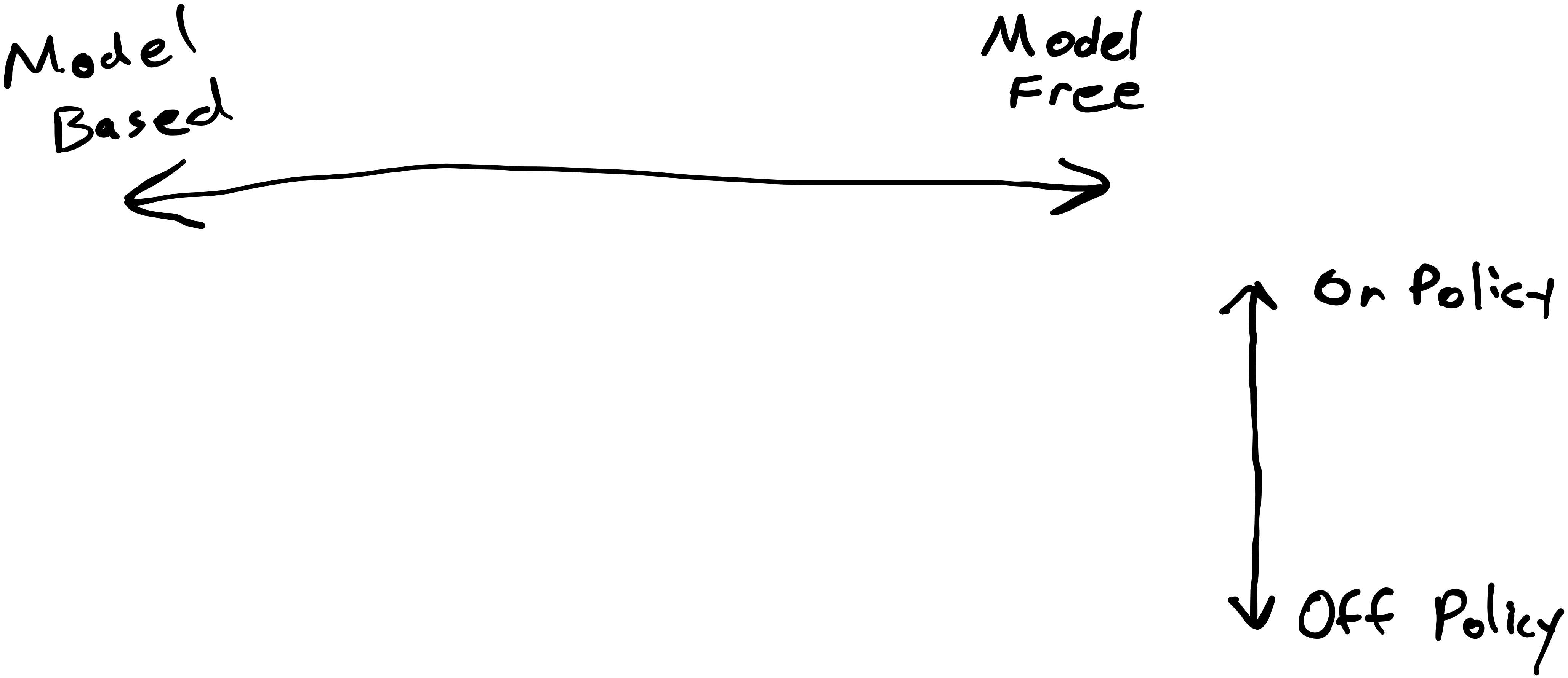
- Pseudocounts
- Curiosity: extra reward for bad prediction
- Random network distillation

RL Algorithms

RL Algorithms



RL Algorithms



RL Algorithms

Model Based

Model Free

On Policy

Off Policy

MLMBTRL
(learn T, R)

RL Algorithms

Model Based

Model Free

learn Q

learn π

On Policy

Off Policy

MLMBTRL
(learn T,R)

RL Algorithms

Model Based

Model Free

learn Q

learn π

Policy Gradient

On Policy

Off Policy

MLMBTRL

(learn T,R)

RL Algorithms

Model Based

Model Free

learn Q

SARSA

learn π

Policy Gradient

On Policy

Off Policy

MLMBTRL

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RL Algorithms

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learn π

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RL Algorithms

Model Based

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learn Q

learn π

On Policy

SARSA

Policy Gradient

MLMBTRL
(learn T, R)

Q-learning

Off Policy

BAMDP
(POMDP $\tilde{s} = (s, T, R)$)

Policy Gradient

Policy Gradient

- Likelihood ratio trick

$$\nabla_\theta p_\theta(\tau) = p_\theta(\tau) \nabla_\theta \log p_\theta(\tau)$$

Policy Gradient

- Likelihood ratio trick
- Causality

$$\nabla_\theta p_\theta(\tau) = p_\theta(\tau) \nabla_\theta \log p_\theta(\tau)$$

Policy Gradient

- Likelihood ratio trick
- Causality
- Baseline Subtraction

$$\nabla_\theta p_\theta(\tau) = p_\theta(\tau)\nabla_\theta \log p_\theta(\tau)$$

Policy Gradient

- Likelihood ratio trick
- Causality
- Baseline Subtraction

$\nabla_\theta p_\theta(\tau) = p_\theta(\tau) \nabla_\theta \log p_\theta(\tau)$

$$\nabla U(\theta) = \mathbb{E}_\tau \left[\sum_{k=1}^{d} \nabla_\theta \log \pi_\theta(a^{(k)} \mid s^{(k)}) \gamma^{k-1} \left(r_{\text{to-go}}^{(k)} - r_{\text{base}}(s^{(k)}) \right) \right]$$

Policy Gradient

- Likelihood ratio trick
- Causality
- Baseline Subtraction

$$\nabla_\theta p_\theta(\tau) = p_\theta(\tau) \nabla_\theta \log p_\theta(\tau)$$

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- Natural Gradient

Policy Gradient

- Likelihood ratio trick
- Causality
- Baseline Subtraction

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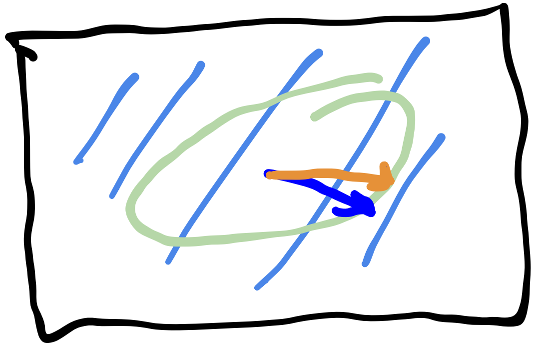
- Natural Gradient



KL div.
Bound

Q-Learning

Q-Learning

SARSA

$$Q(s,a) \leftarrow Q(s,a) + \alpha(r_t + \gamma Q(s', a') - Q(s,a))$$

Q-Learning

SARSA

$$Q(s,a) \leftarrow Q(s,a) + \alpha(r_t + \gamma Q(s',a') - Q(s,a))$$

Eligibility Traces

Q-Learning

SARSA

$$Q(s,a) \leftarrow Q(s,a) + \alpha(r_t + \gamma Q(s',a') - Q(s,a))$$

Eligibility Traces

Q-learning

$$Q(s,a) \leftarrow Q(s,a) + \alpha(r_t + \gamma \underbrace{\max_{a'} Q(s',a')} - Q(s,a))$$

Q-Learning

SARSA

$$Q(s,a) \leftarrow Q(s,a) + \alpha(r_t + \gamma Q(s',a') - Q(s,a))$$

Eligibility Traces

Q-learning

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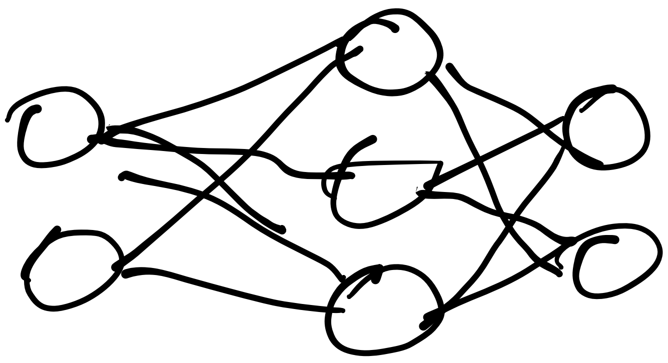
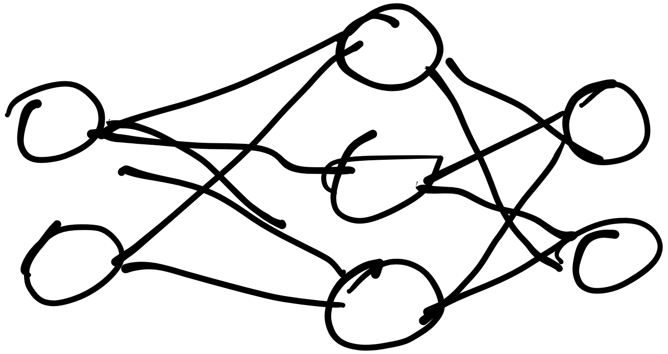
Double Q Learning

Neural Networks and DQN

Neural Networks and DQN



Neural Networks and DQN



$$f_\theta(x) = \sigma(W_2\sigma(W_1 x + b_1) + b_2)$$

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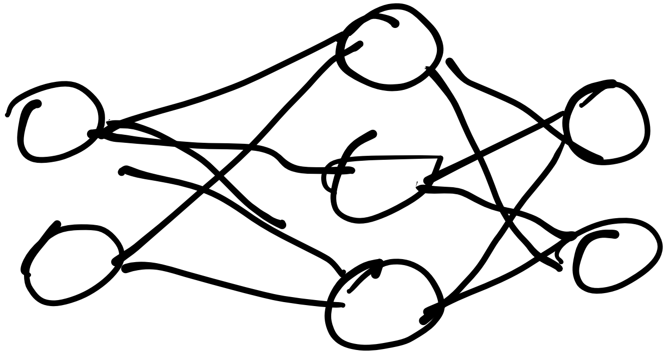

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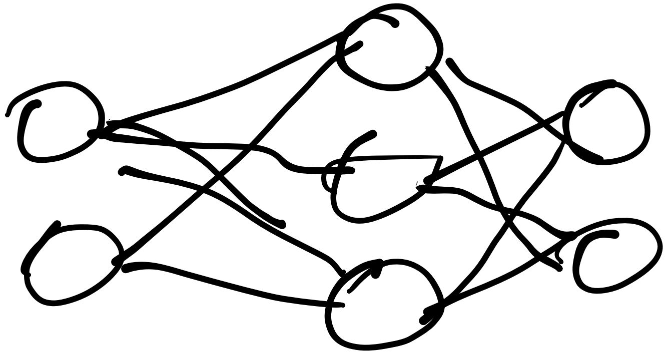
Backprop

Neural Networks and DQN



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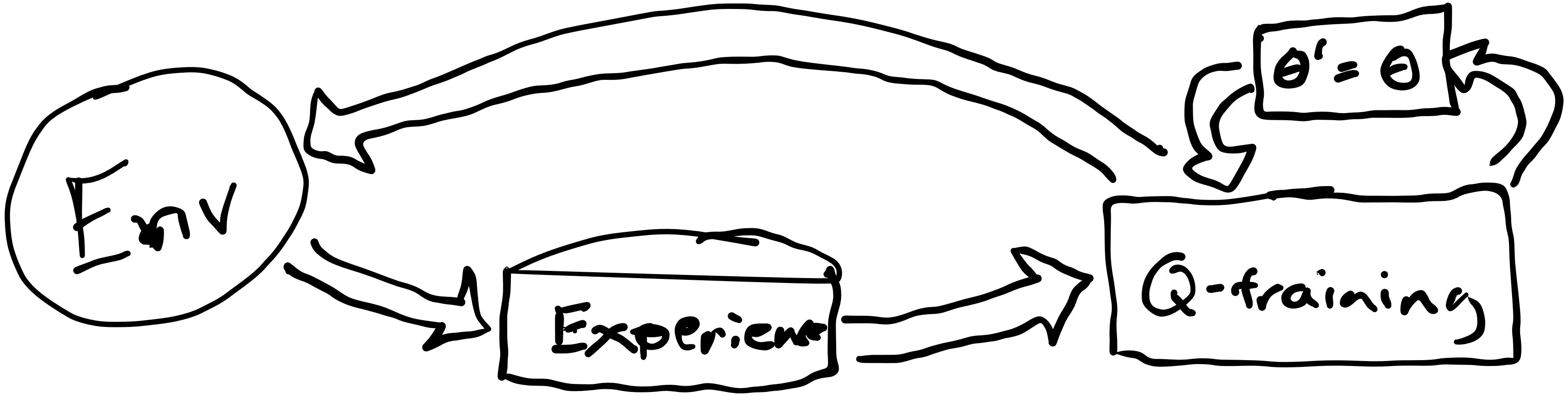

Actor-Critic

Actor-Critic

- Actor: π_θ

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- Critic: Q_ϕ

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Soft Actor Critic

Actor-Critic

- Actor: π_θ
- Critic: Q_ϕ

Soft Actor Critic

$$J(\pi) = E\left[\sum_{t=0}^{\infty} \gamma^t \left(r_t + \alpha \mathcal{H}(\pi(\cdot \mid s_t))\right)\right]$$

POMDPs

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$$(S, A, T, R, O, Z, \gamma)$$

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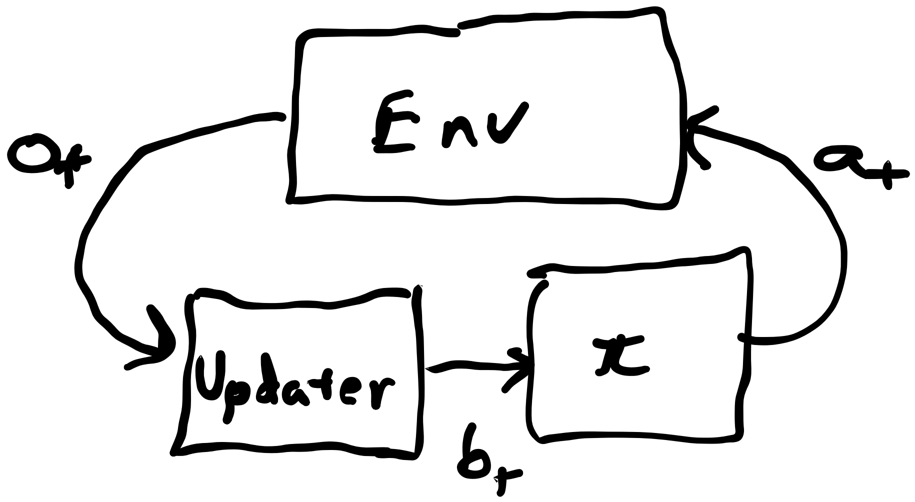

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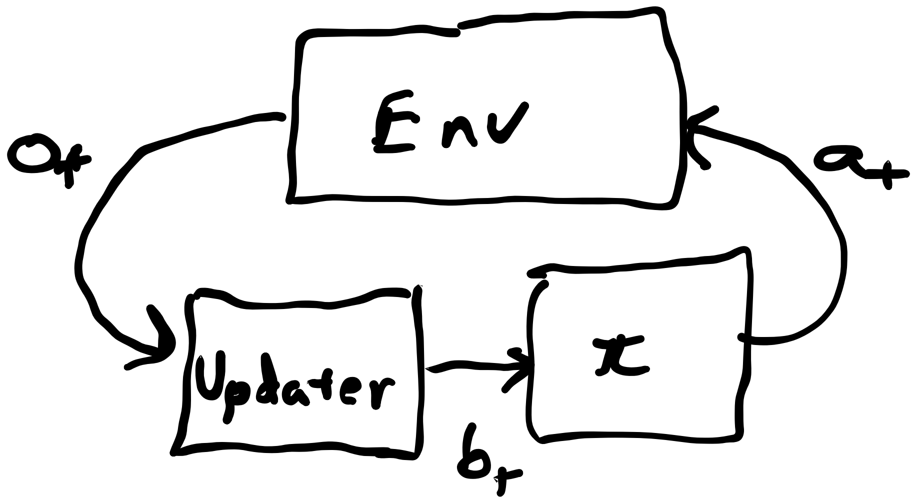

Belief Updates

- Discrete Bayesian Filter
- Particle Filter

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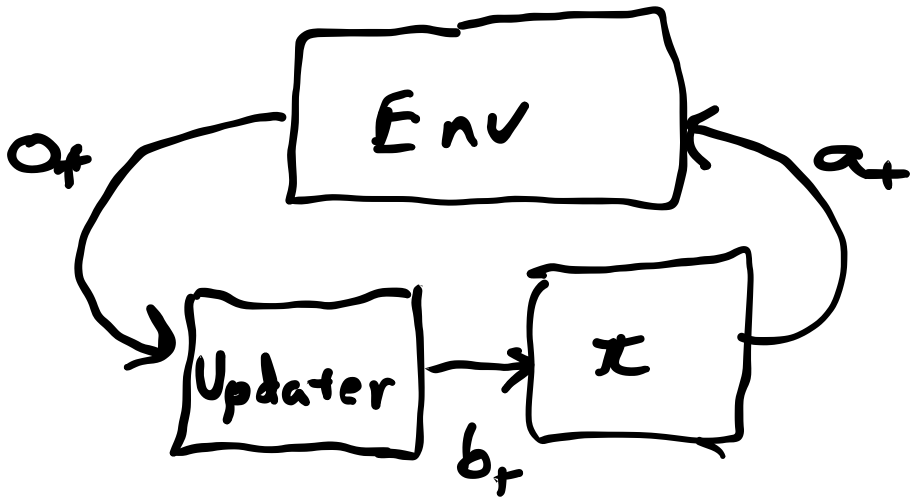

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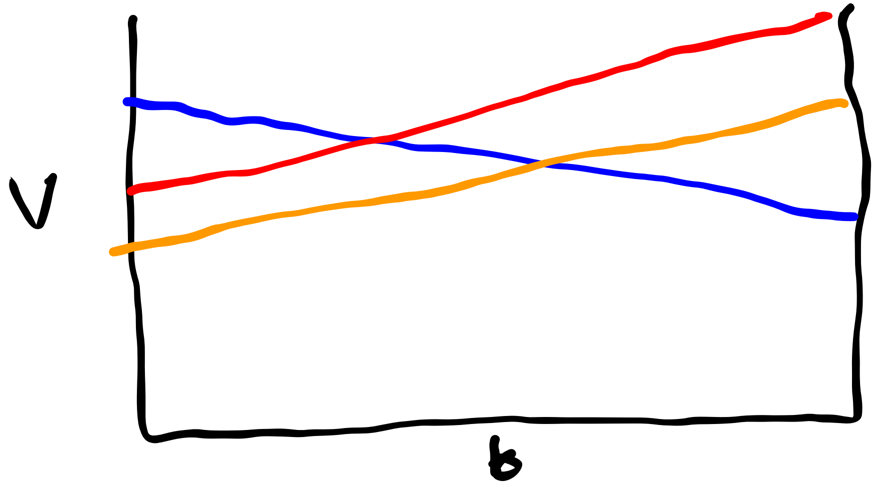
Alpha Vectors



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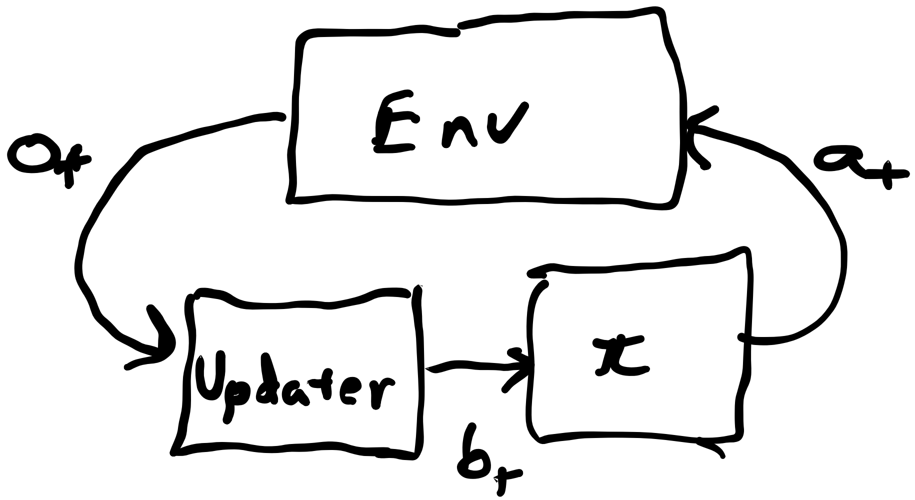

- Each alpha vector corresponds to a conditional plan

Belief Updates

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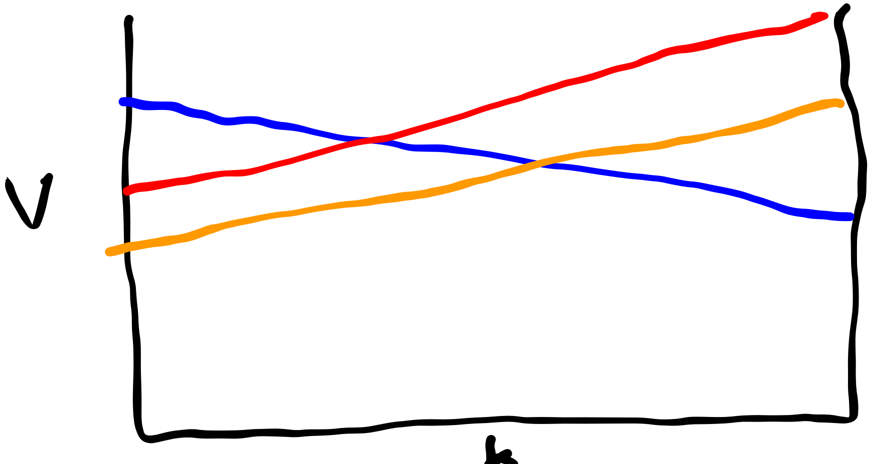
Alpha Vectors



POMDPs

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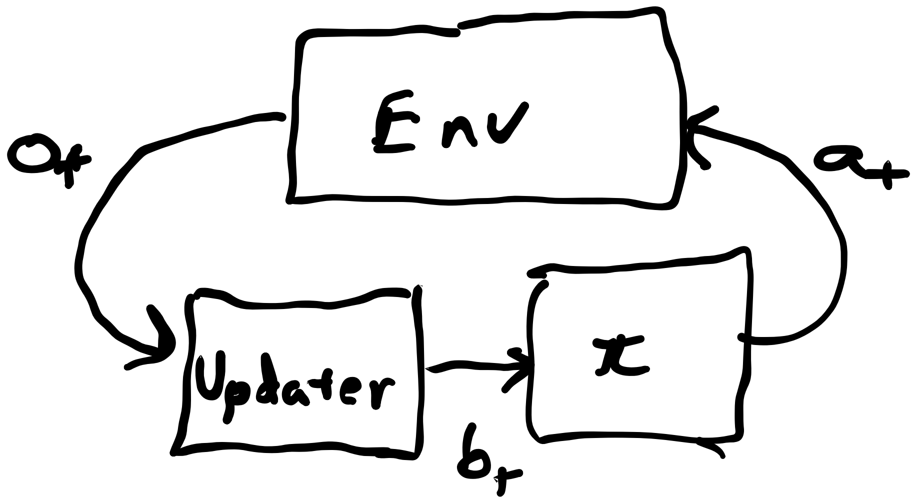

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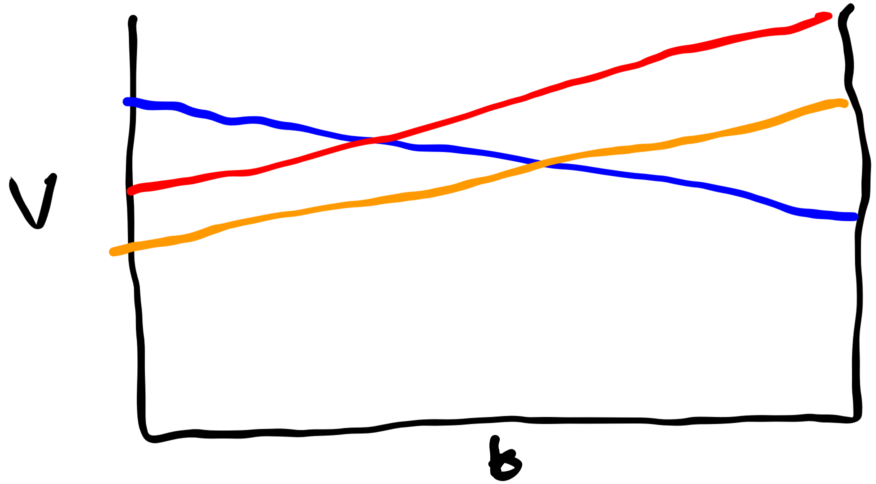

- Each alpha vector corresponds to a conditional plan
- You can prune alpha vectors by solving an LP

POMDP Approximations

POMDP Approximations

Formulation

Optimal for LQG

- Certainty Equivalence
- QMDP

$\pi_{QMDP}(s) = \underset{a}{\operatorname{argmax}} \underset{s \sim b}{E}\left[Q_{MDP}(s,a)\right]$

POMDP Approximations

Formulation

- Certainty Equivalence
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Numerical

POMDP Approximations

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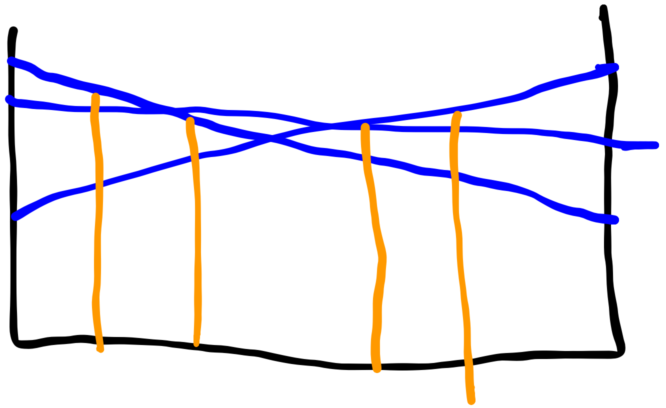
Numerical

Offline

- Point-Based Value Iteration
- SARSOP



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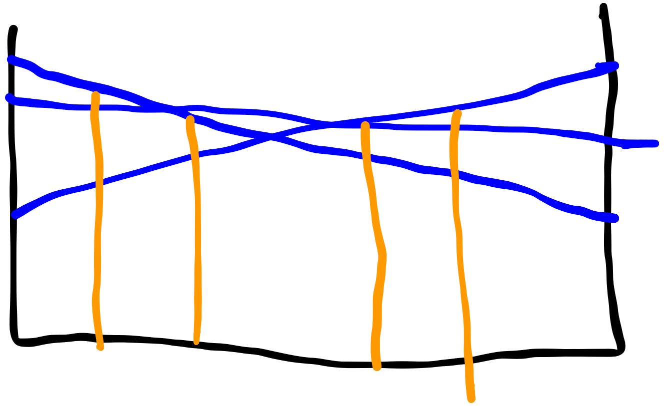

Online

- POMCP
- DESPOT

POMDP Approximations

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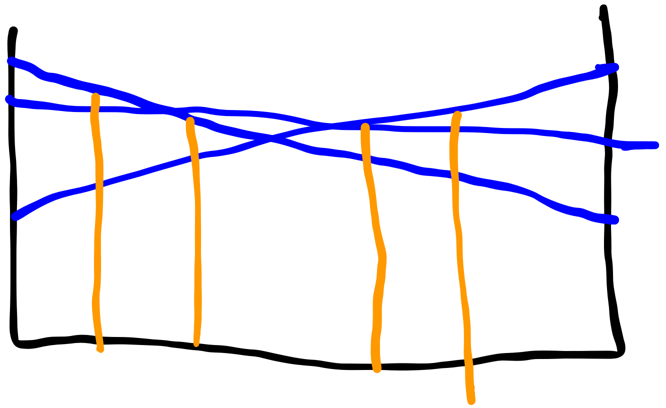

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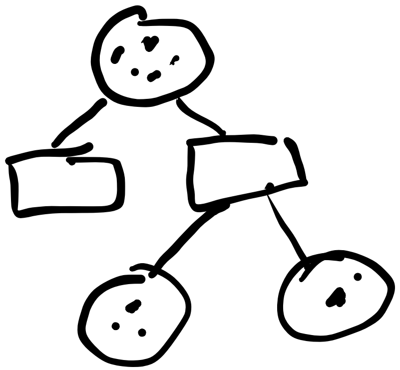

Simple Games

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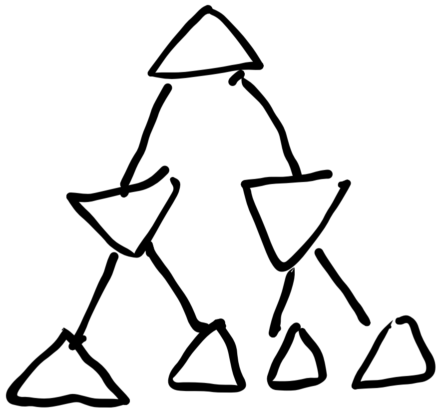
- Algorithms like fictitious play converge in special cases

Turn Taking Games

Turn Taking Games



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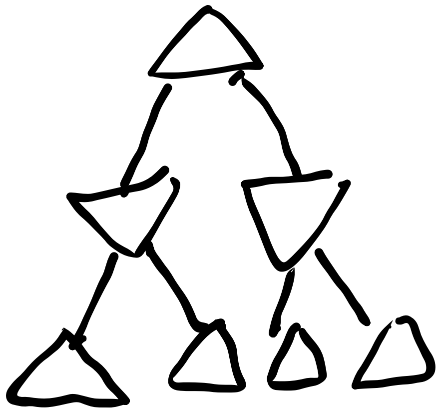

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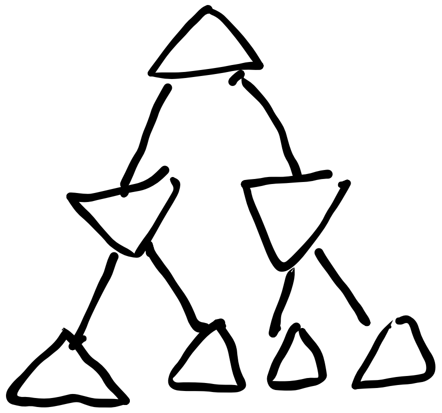
Turn Taking Games



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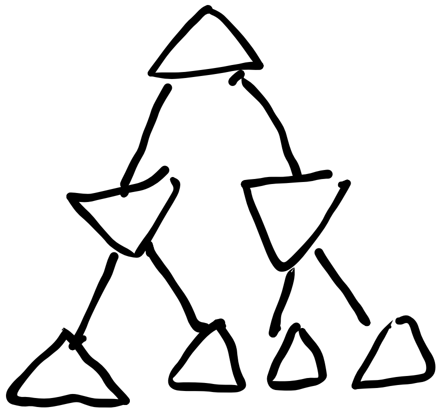
Turn Taking Games



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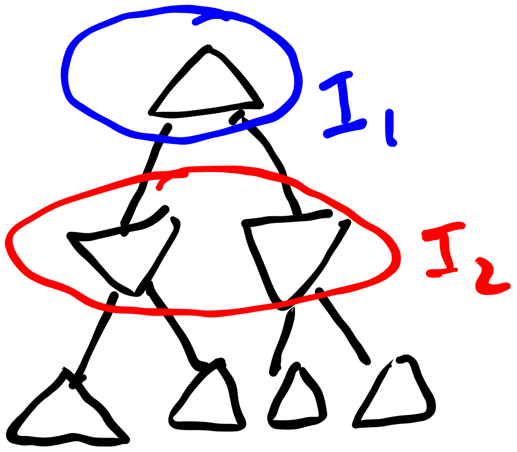

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Markov Games and POMGS

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- All players play simultaneously
- Transitions are stochastic
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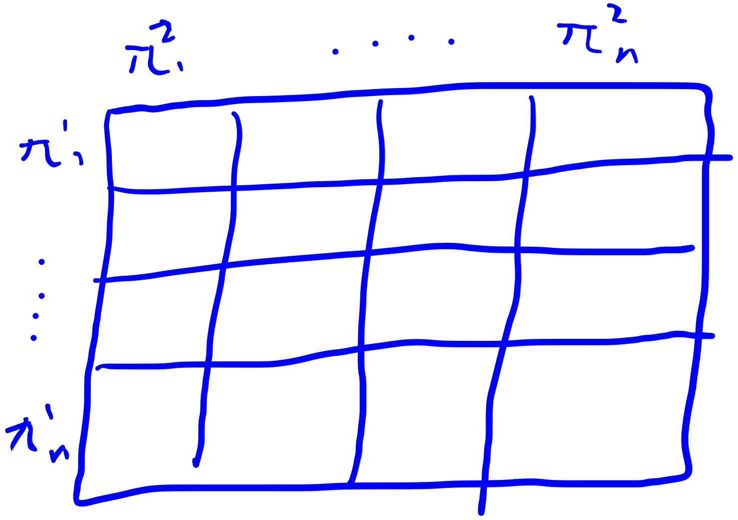

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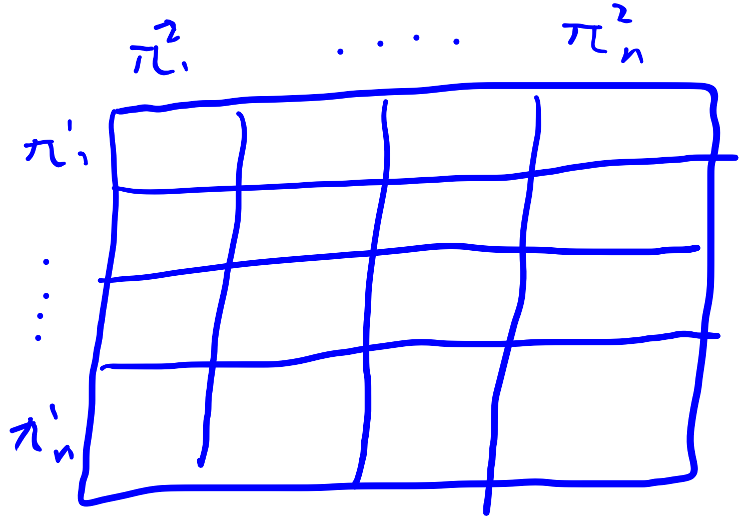

Partially Observable Markov Games

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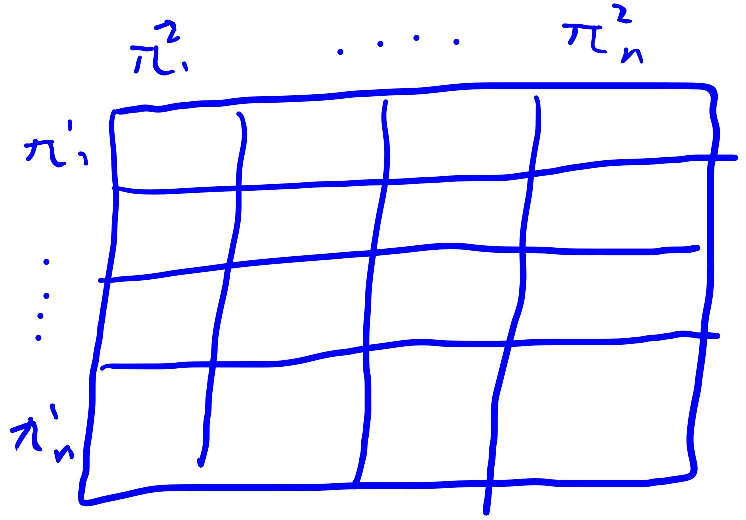

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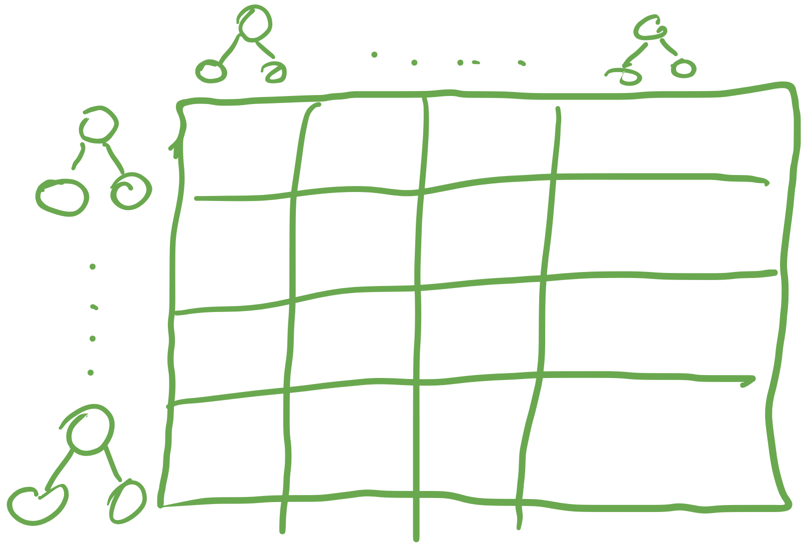

Fictitious Play in Markov Games

Recap

Recap

After DMU you have basic tools to deal with 4 Big Problems:

Recap

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1. Immediate and Future Rewards

Recap

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Recap

After DMU you have basic tools to deal with 4 Big Problems:

1. Immediate and Future Rewards
2. Unknown Models
3. Partial Observability
4. Other Agents

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DMU++