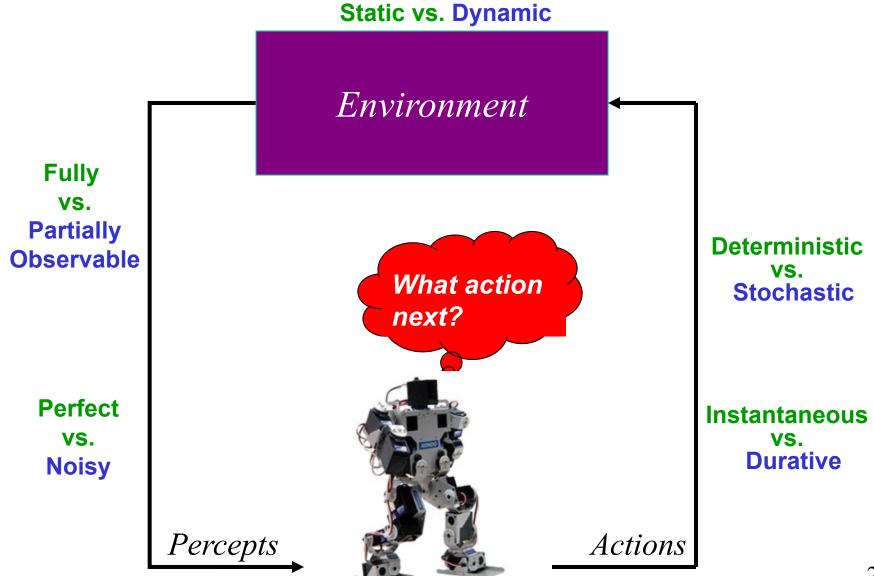
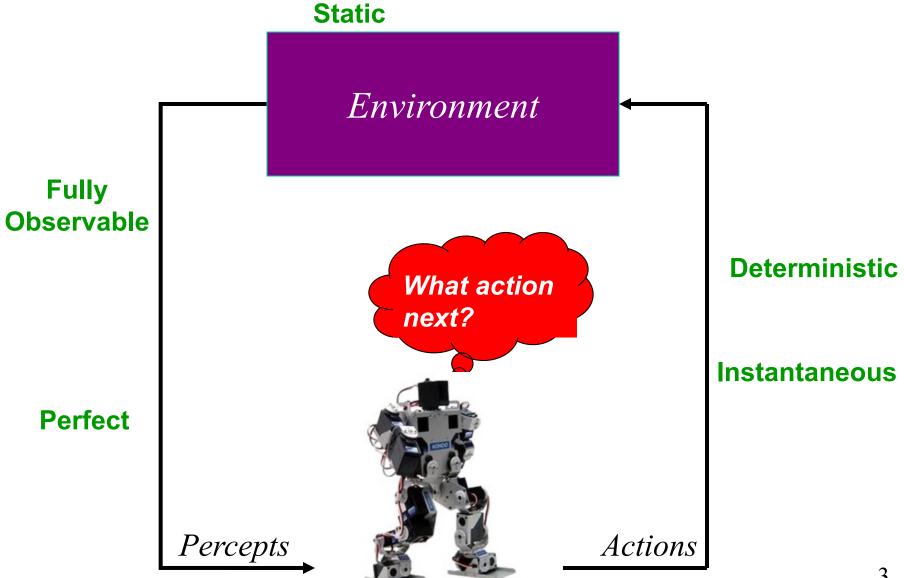
# Markov Decision Processes Chapter 17

Mausam

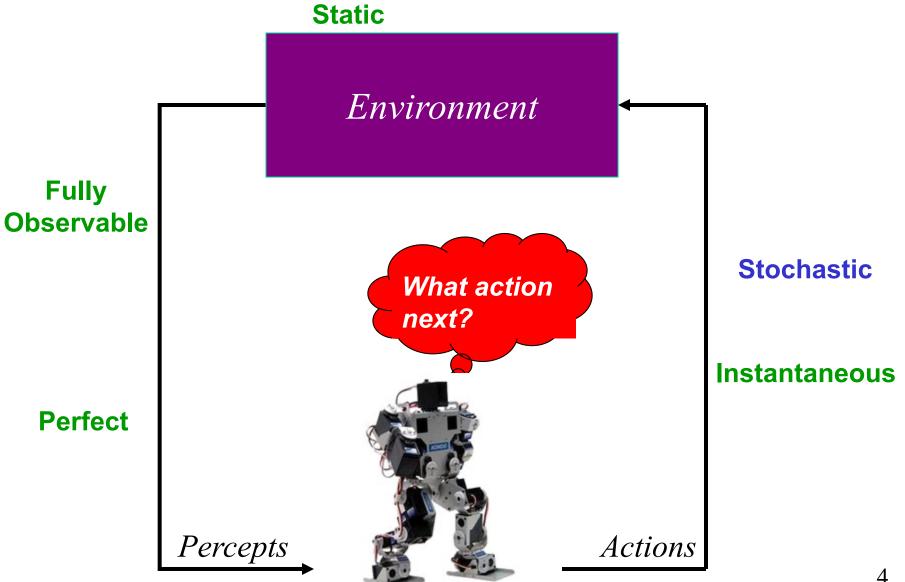
## **Planning Agent**



# **Search Algorithms**



## Stochastic Planning: MDPs



## MDP vs. Decision Theory

- Decision theory episodic
- MDP -- sequential

# Markov Decision Process (MDP)

S: A set of states factored **Factored MDP** 4. A set of actions 7(s,a,s'): transition model C(s,a,s'): cost model absorbing/ **G**: set of goals non-absorbing s₀: start state y: discount factor  $\mathcal{R}(s,a,s')$ : reward model

#### Objective of an MDP

- Find a policy  $\pi: \mathcal{S} \to \mathcal{A}$
- which optimizes
  - minimizes discounted or expected cost to reach a goal expected reward
  - maximizes undiscount. expected (reward-cost)
- given a \_\_\_\_ horizon
  - finite
  - infinite
  - indefinite
- assuming full observability

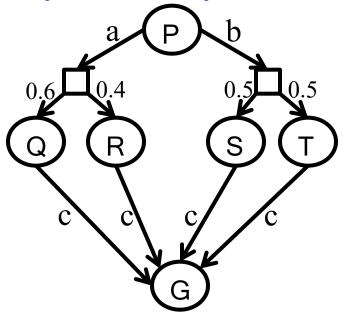
## Role of Discount Factor (γ)

- Keep the total reward/total cost finite
  - useful for infinite horizon problems
- Intuition (economics):
  - Money today is worth more than money tomorrow.
- Total reward:  $r_1 + \gamma r_2 + \gamma^2 r_3 + \dots$
- Total cost:  $c_1 + \gamma c_2 + \gamma^2 c_3 + ...$

## Examples of MDPs

- Goal-directed, Indefinite Horizon, Cost Minimization MDP
  - $\langle S, A, T, C, G, S_0 \rangle$
  - Most often studied in planning, graph theory communities
- Infinite Horizon, Discounted Reward Maximization MDP
  - <S, A, T, R, γ> most popular
  - Most often studied in machine learning, economics, operations research communities
- Oversubscription Planning: Non absorbing goals, Reward Max. MDP
  - $\langle S, A, T, G, R, s_0 \rangle$
  - Relatively recent model

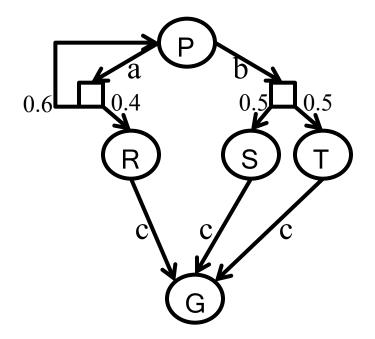
# Acyclic vs. Cyclic MDPs



$$C(a) = 5$$
,  $C(b) = 10$ ,  $C(c) = 1$ 

**Expectimin works** 

- V(Q/R/S/T) = 1
- V(P) = 6 action a



Expectimin doesn't work •infinite loop

- V(R/S/T) = 1
- Q(P,b) = 11
- Q(P,a) = ????
- suppose I decide to take a in P
- Q(P,a) = 5 + 0.4\*1 + 0.6Q(P,a)
- **→** = 13.5