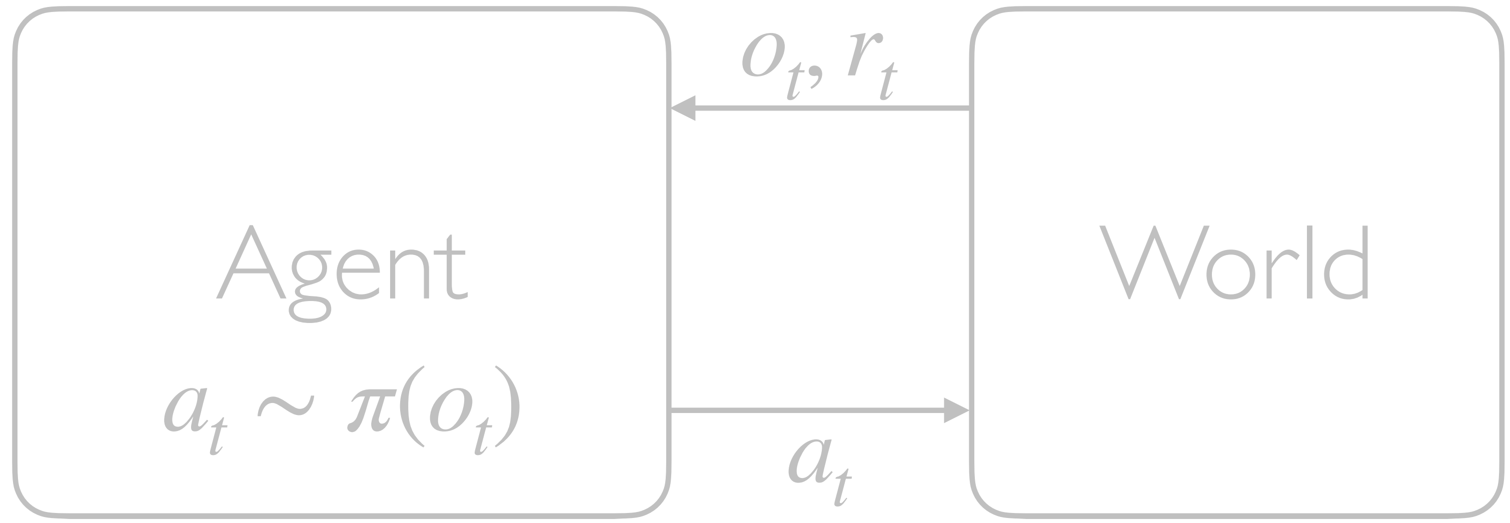
Reinforcement Learning

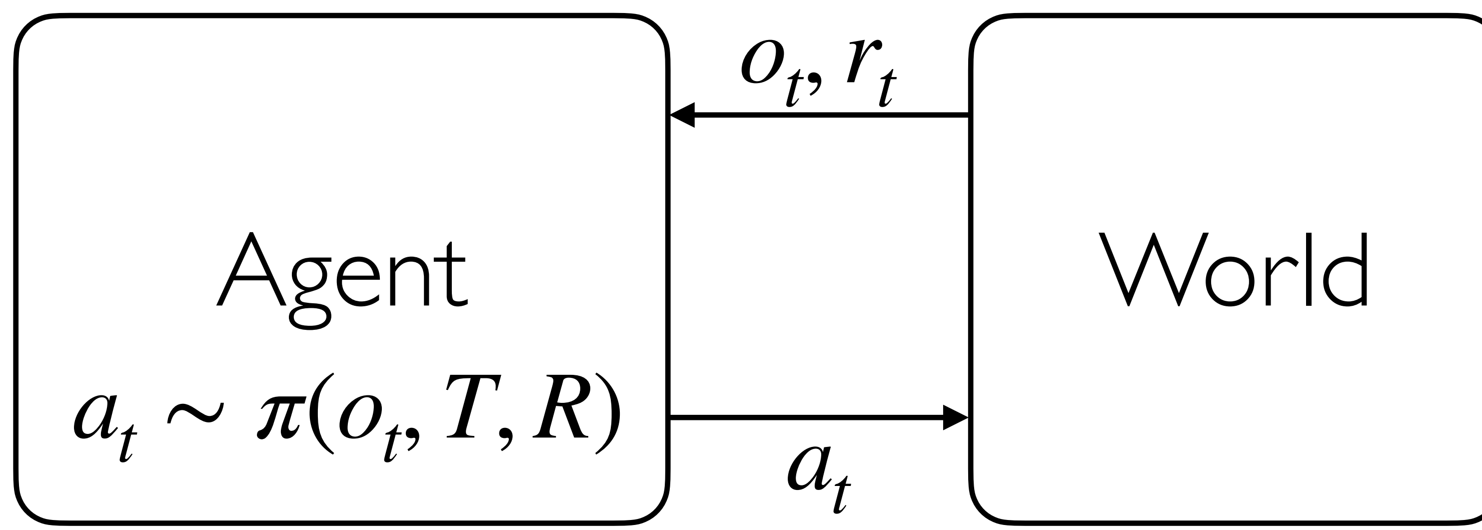
Solving MDPs

Policy: $a_t \sim \pi(o_t)$

Most General Case



More Specific Case



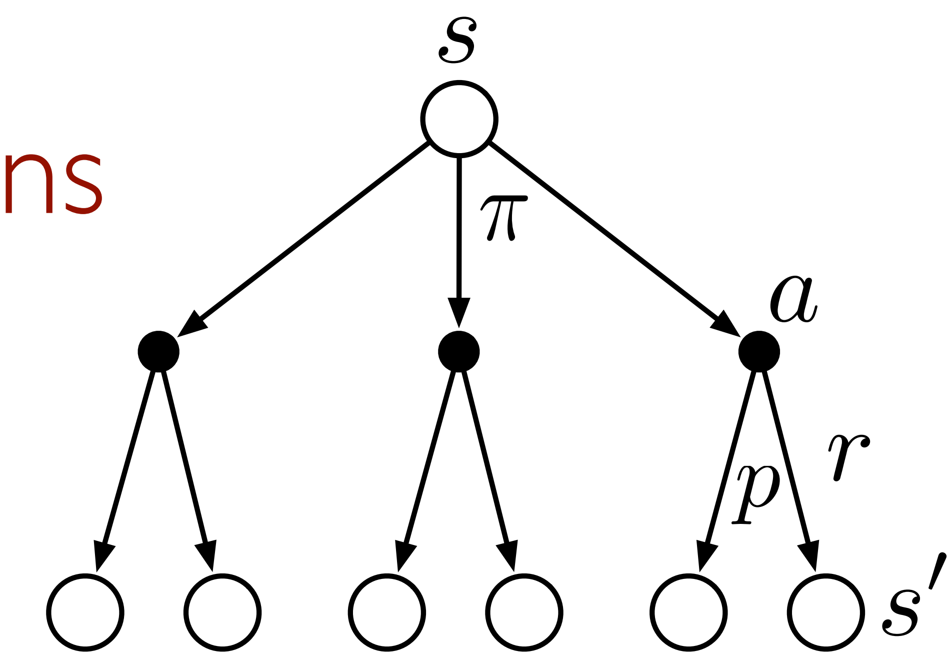
Fully Observed System $o_t = s_t$

Known Transition Function $s_{t+1} \sim T(s_t, a_t)$

Known Reward Function $R(s_{t+1}, s_t, a_t)$

Recap

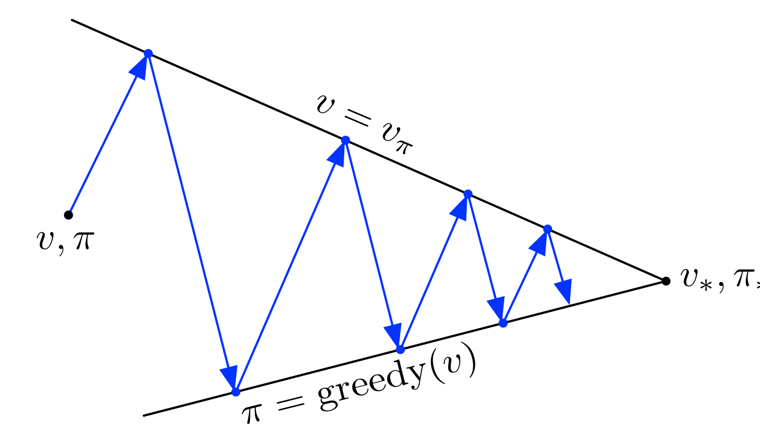
Computing $V_*(s)$ and $Q_*(s, a)$ for known MDPs.



Backup diagrams, Bellman equations

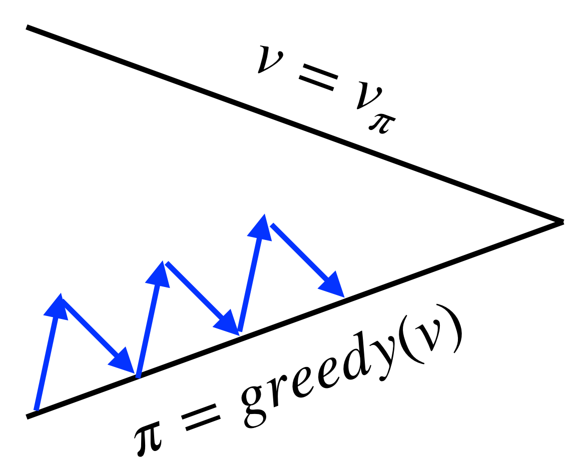
$$V_\pi(s) = \sum_a \pi(a \mid s) \sum_{s',r} p(s', r \mid s, a)\big(r + \gamma V_\pi(s')\big)$$

Policy Evaluation, Improvement



Value Iteration

$$V_{k+1}(s) = max_a \sum_{s',r} p(s', r \mid s, a)\big(r + \gamma V_k(s')\big)$$



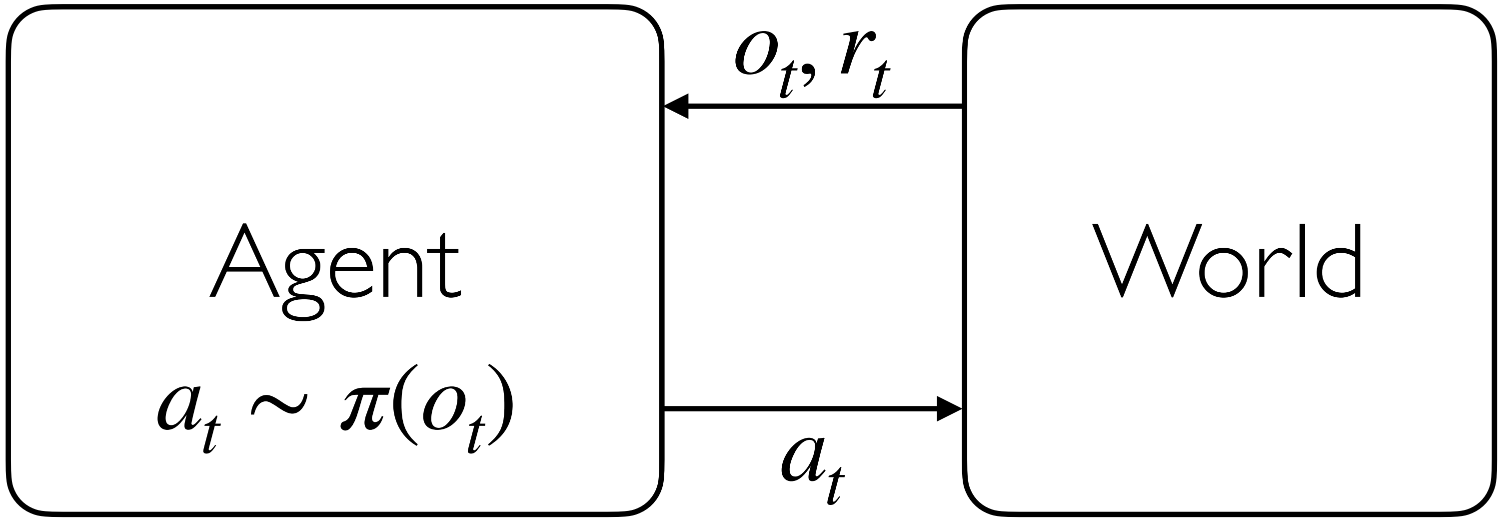
Solving MDPs

Policy: $a_t \sim \pi(o_t)$

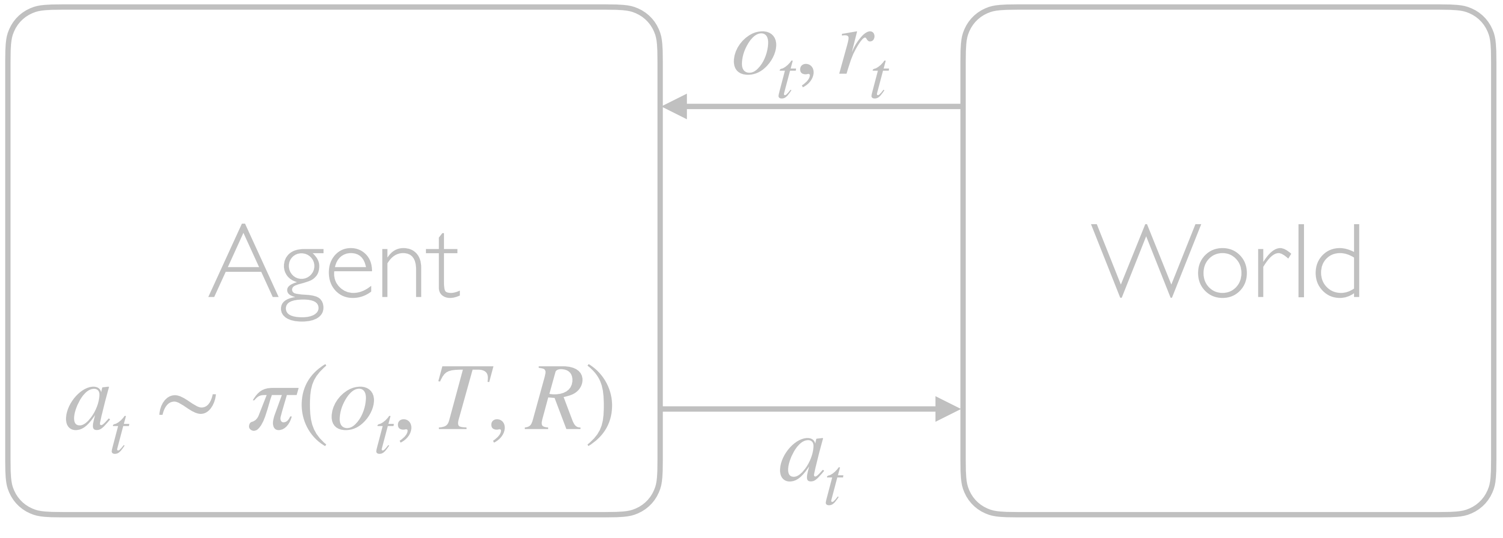
Most General Case

Fully Observed System:

$o_t = s_t$



More Specific Case

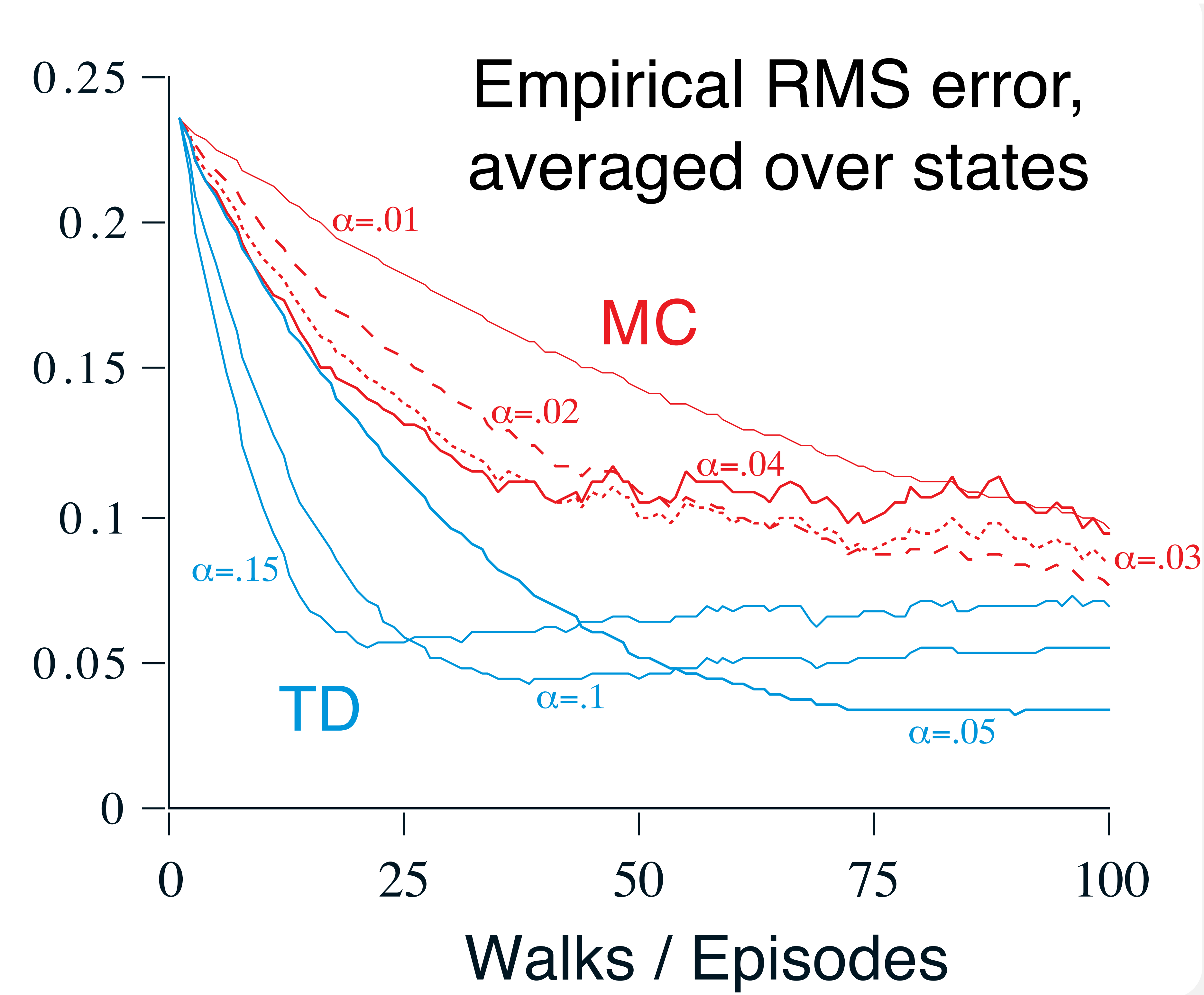


Fully Observed System $o_t = s_t$

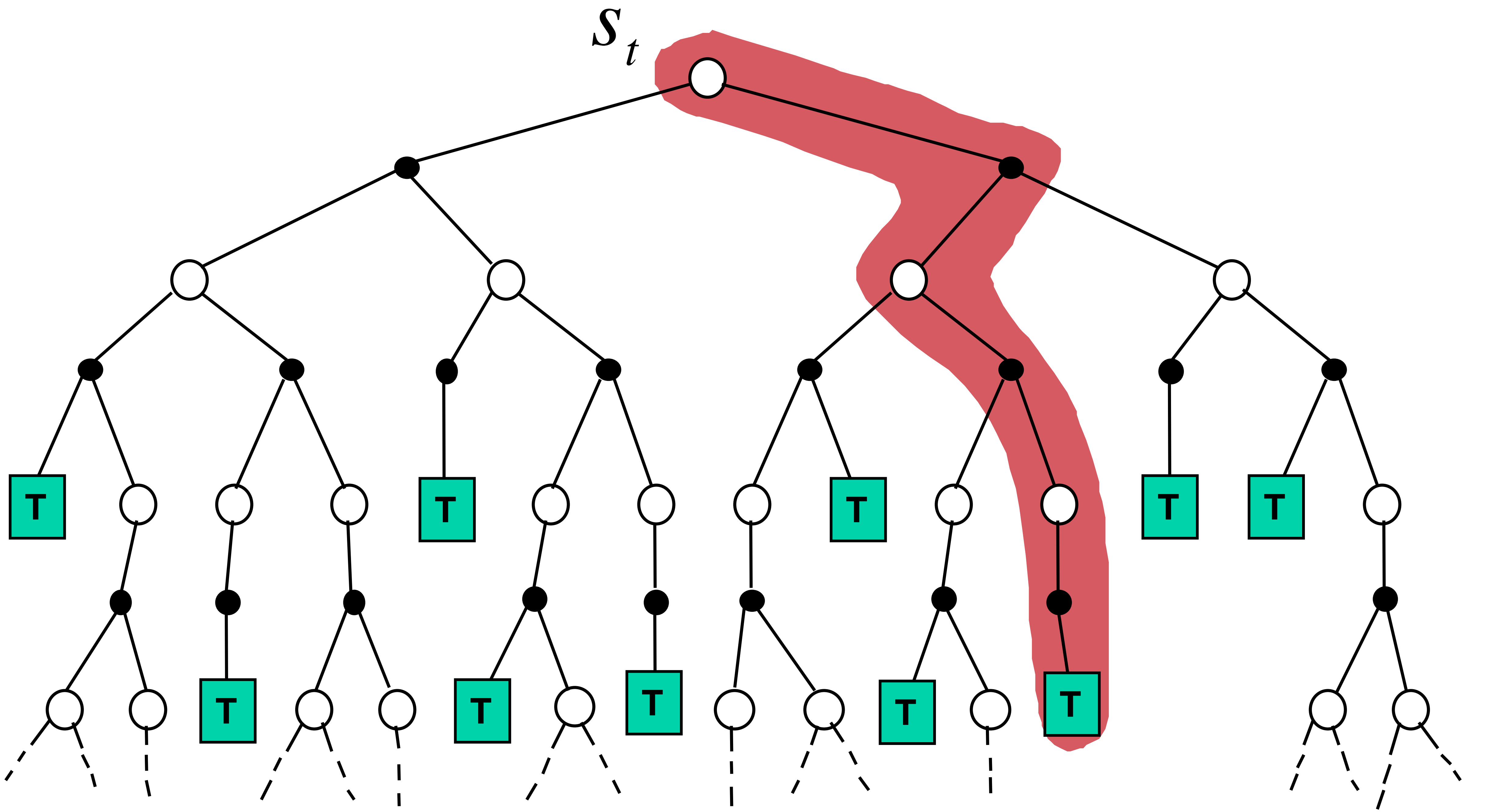
Known Transition Function $s_{t+1} \sim T(s_t, a_t)$

Known Reward Function $R(s_{t+1}, s_t, a_t)$

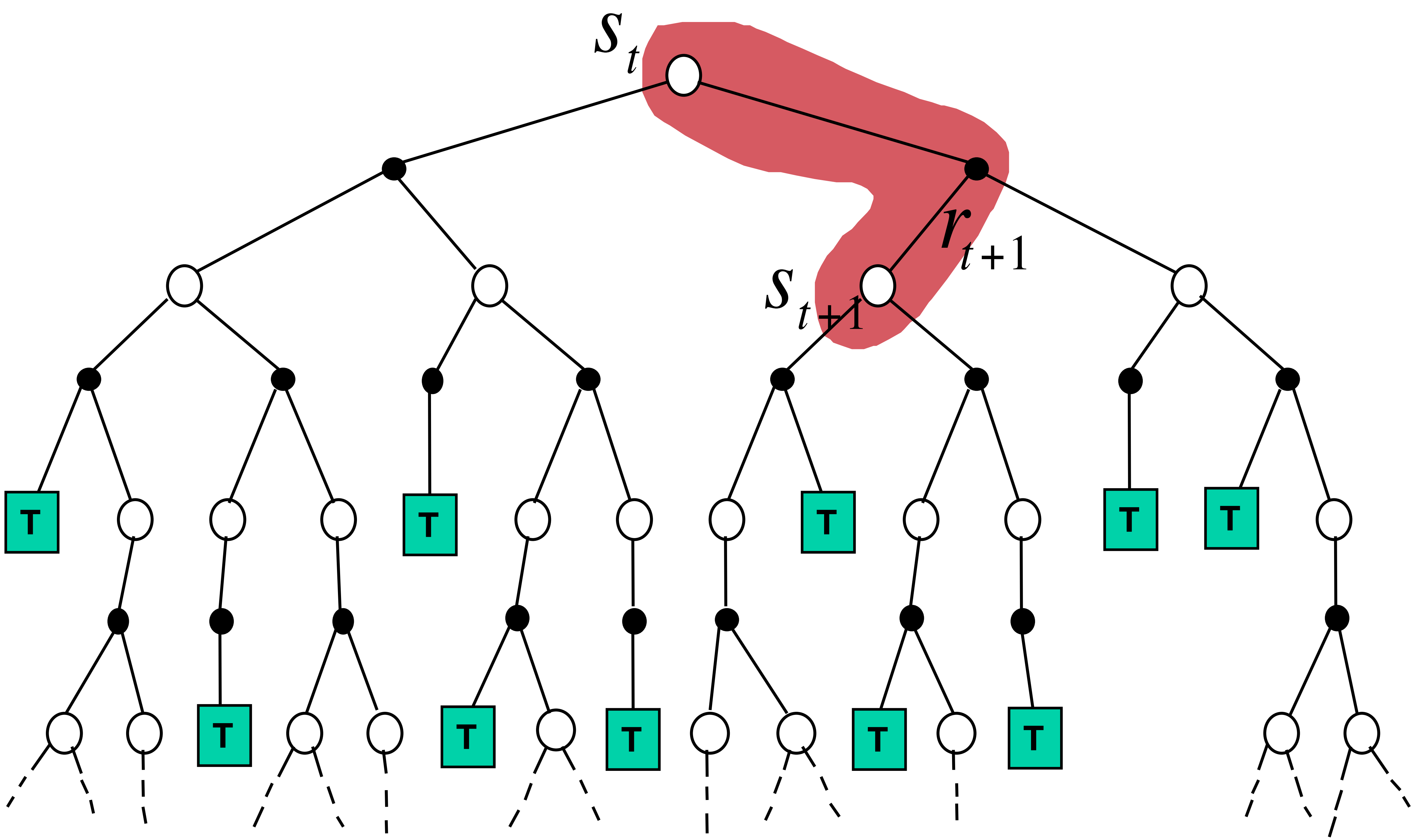
TD vs MC


Empirical RMS error, averaged over states
0.25
0.2
0.15
0.1
0.05
0
α=.01
α=.02
α=.04
α=.03
MC
α=.15
α=.1
α=.05
TD
0
25
50
75
100
Walks / Episodes

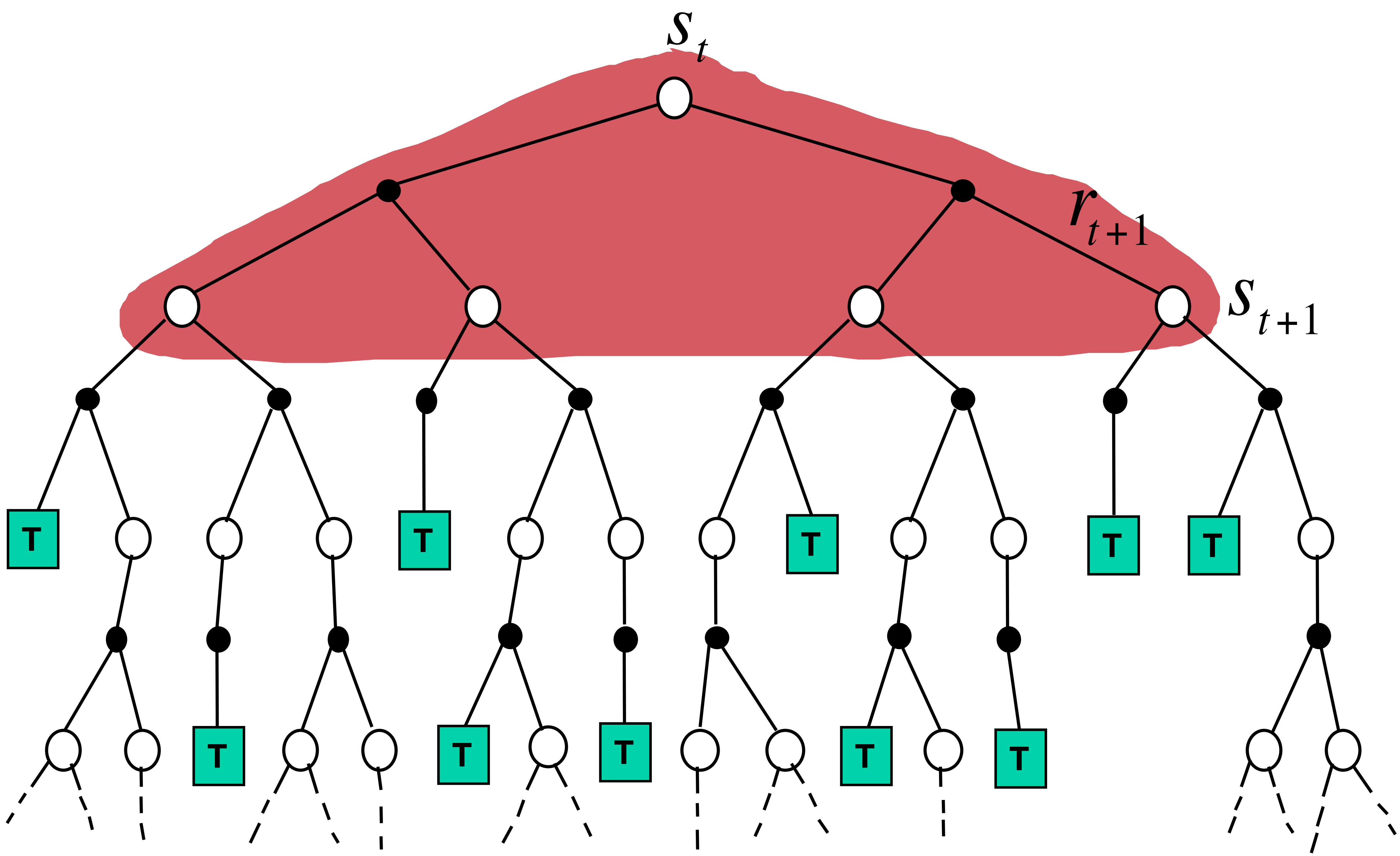
MC Backup

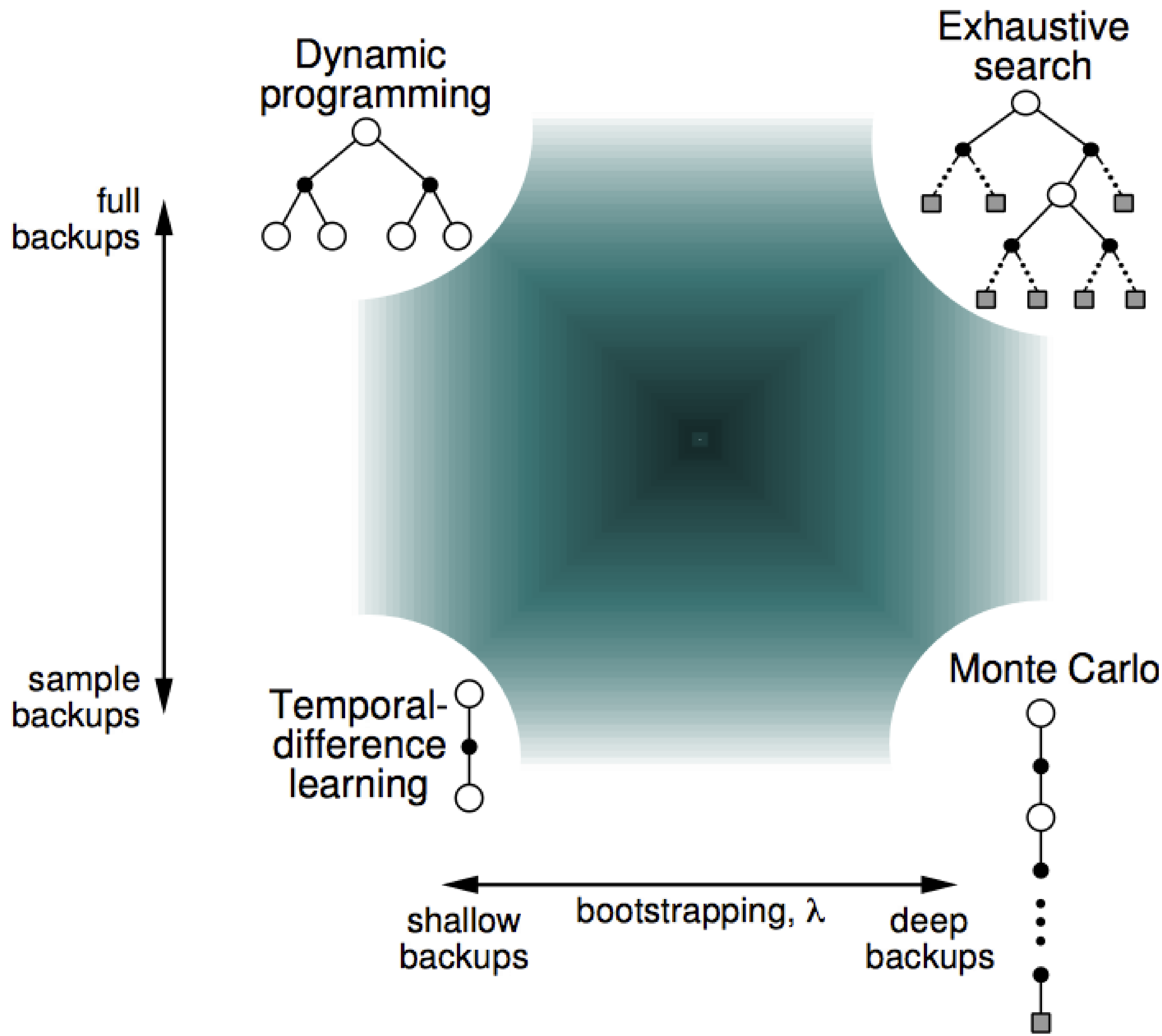


TD(0) Backup



Dynamic Programming Backup




Dynamic programming
Exhaustive search
full backups
sample backups
Temporal-difference learning
Monte Carlo
shallow backups
bootstrapping, λ
deep backups

Recap

- Model Free Policy Evaluation
  - Monte Carlo, TD(0), TD(λ)
- Model Free Control
  - On-policy: ϵ-greedy, SARSA, SARSA(λ)
  - Off-policy: Q-Learning

Model Free RL

Model Free Policy Evaluation

Model Free Control

Playing Atari with Deep Reinforcement Learning

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