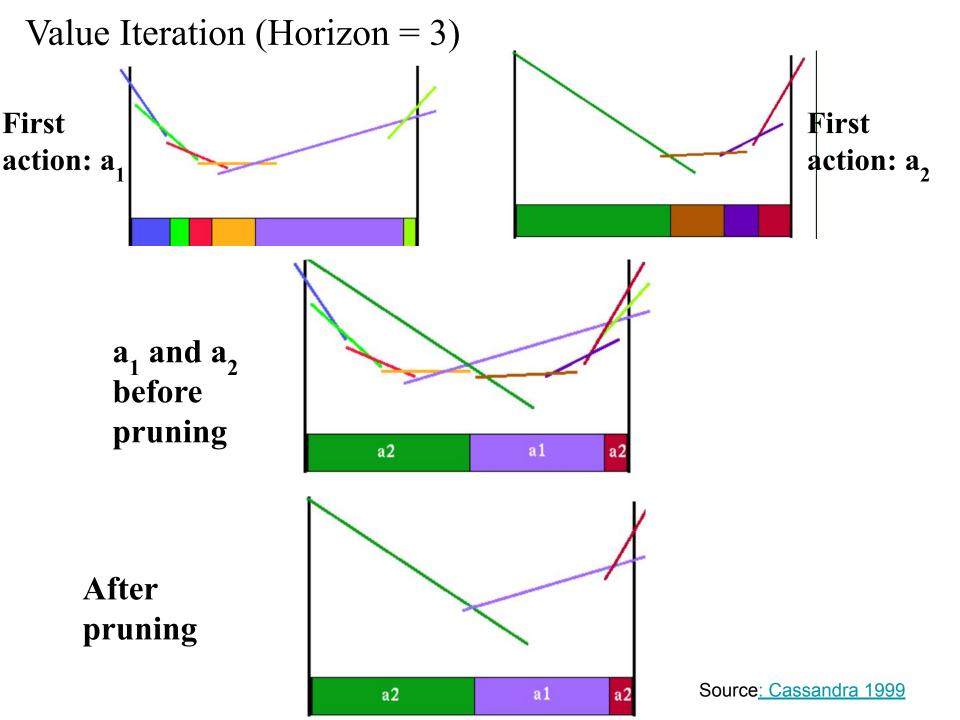
16-782

Planning & Decision-making in Robotics Planning under Uncertainty: Partially Observable Markov Decision Processes (POMDP) (cont.)

Alex LaGrassa Robotics Institute Carnegie Mellon University



Algorithm sketch

```
Initialize list of plans and \alpha's while true:
```

Compute all strategies

Update each $\alpha_p(s) = \sum_{s} P(s'|s,a)[R(s,a,s') + \gamma \sum_{o} P(o|s'a)\alpha_{p,o}(s')]$

Remove dominated plans

If the maximum difference between $V_t(b)$ and $V_{t-1}(b) < \epsilon(\gamma)$: break

Return V

Exact POMDP value iteration

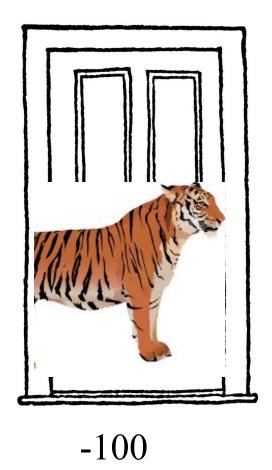
- Value functions remain PWLC
- Value functions over longer horizons do **not** necessarily become more complex
- Can still be quite expensive
 - Generation
 - Pruning

Other methods for solving POMDPs

- <u>Point-based Value Iteration</u> approximation
- Sampling points from reachable belief space (<u>SARSOP</u>)
- Maintain sparse representation of belief tree online (<u>DESPOT</u>)
- Monte Carlo sampling of states and histories (<u>POMCP</u>)

Generally difficult to do long-horizon planning with POMDPs

Tiger problem





States:

 S_l, S_r

Actions:

left right listen

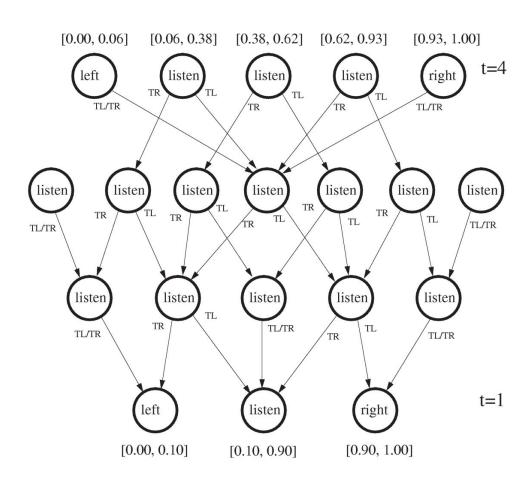
Transition model:

Either left or right results in reset $s_1:0.5 s_r:0.5$

Observations:

TL, TR $P(TL | s_1) = 0.85$ converse for s_r

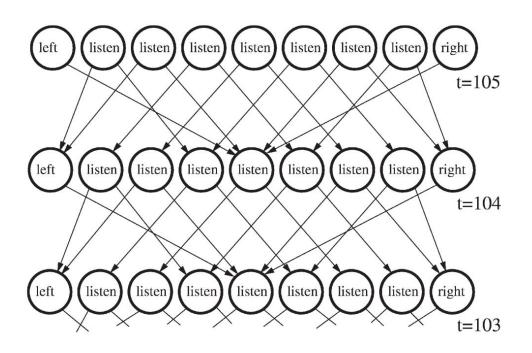
Tiger problem: policy structure for horizon=3



- Open door if fairly certain
- Q: no arrows into 2 nodes at t=3 Why?
- Most sets of observations end in opening a door for the optimal policy

L.P. Kaelbling et al. Planning and acting in partially observable stochastic domains. 1998

Tiger problem: policy structure for long horizon



- For $0 < \gamma < 1$ future rewards are less important
- What is the policy?
- Optimal policy is stationary

Summary

- The finite-horizon value function is PWLC
- POMDPs can be solved exactly in some cases
 - Finite horizon
 - Not too many actions/observations
- Problem structure can be exploited