Decision Under Uncertainty

Planning

UV - MAD

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Recap:

1st, state definition

- A collection of variables
- Each variables defined in a domain

Problem complexity: Search space

- Number of states (by combining domains)
- Number of succession of states

Recap:

2nd, A plan or policy

- Action to perform in each state
- Potentially modeled as a decision tree

How modeling successions of actions ?

Recap:

Problem: variables' evolution could-be uncertain

- **Bayesian Network**: model variables' dependency.

Require to define conditional distributions (matrices)

- **Dynamic Bayesian Network**: for variables with discrete time evolution

Providing a transition function

- Reachable states at time *t+1* weighted with probabilities

On ZombieDice

- *Bayesian Network*
- *Transition Function*

Optimizing Decision Making:

Bellman Equation (finit horizon):

$$a^{*} = argmax_{a} V^{h}(s,a) = r(s,a) + \sum_{s'} t(s,a,s') V^{h-1}(s')$$

- $t(s,a,s')$: transition function
- $r(s,a)$: reward function

Markov Decision Process: Tuple: S, A, t, r

Solving MDP:

Short term horizon algorithm:

At each time step:

- Evaluate all reachable states
- But on a restricted horizon

Monte-Carlo algorithm:

randomized search in constrained times

At each time step:

- Deep evaluation of state evolutions
- Limited in random trajectories

Optimal Solving

Offline exploration of every evolution trajectories

TD03: Decision Making

- From WillDie3 (correction of Dinamic Bayesian Network implementation for zombie dice)
- Optimize decision-making at horizon "1"

(compare immediate gains to probable gains)

- Optimize decision under a given horizon n

(recursive value function)

- Deeper horizon but with randomized evolution exploration