Planning Treatment of Ischemic Heart Disease with POMDP

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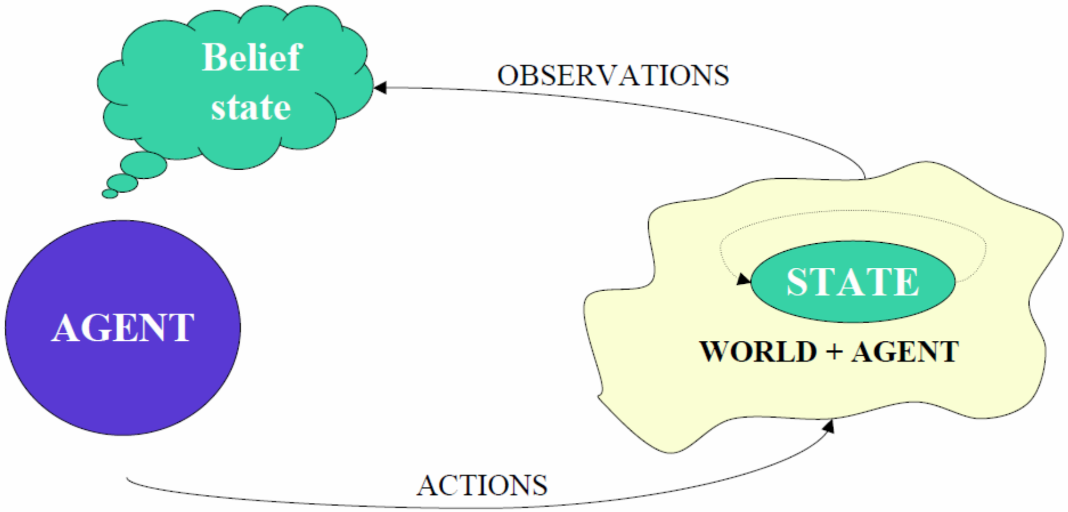
Review : POMDP



	Observable	Partially Observable
No Actions	Markov Process	Hidden Markov Model
Actions	MDP	POMDP

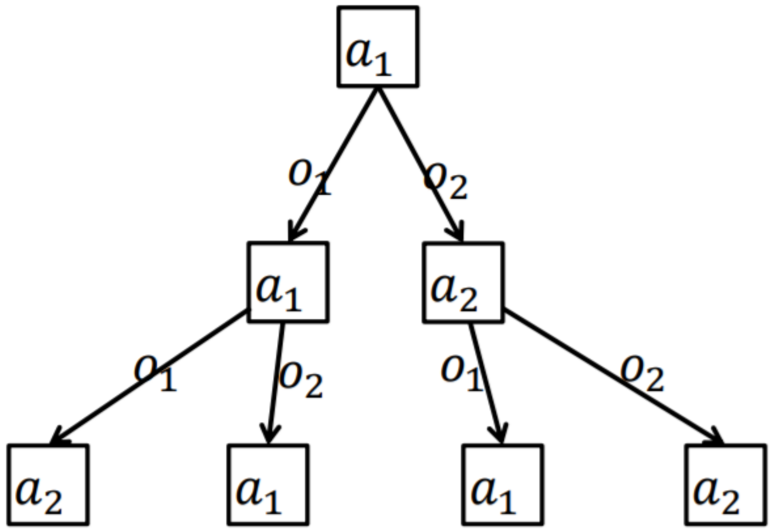
Given:
S : States / A : Finite set of Actions / R: Reward / P: transition Probability (as common MDP)

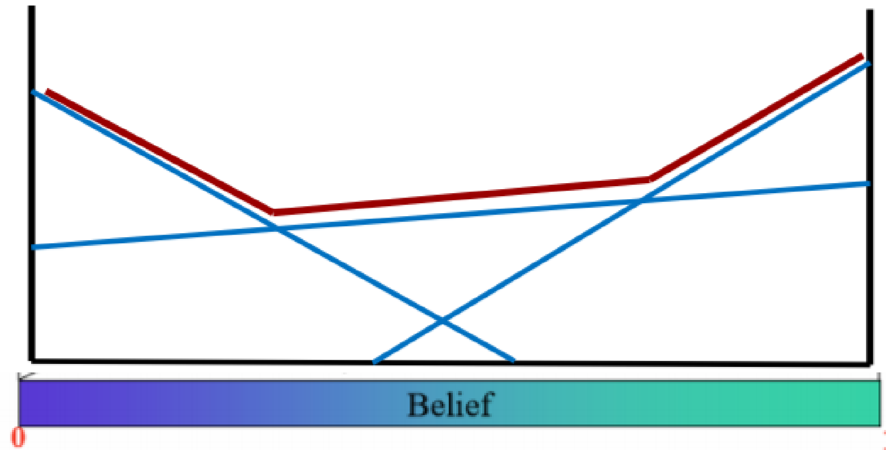
O(Ω): set of conditional observation Probabilities (Observation Function)
o: set of observations

Added for POMDP

Review : POMDP

Given Initial Belief State b0

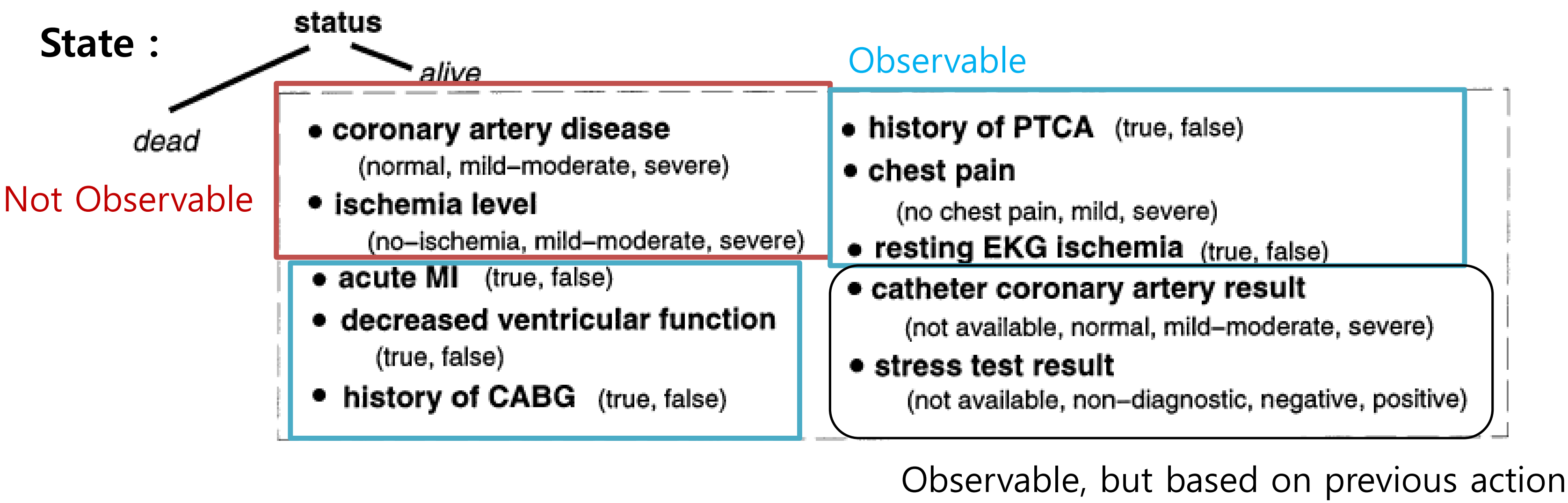




Example of two state POMDP

- Each policy in the tree corresponds with the linear equation, and it is proven that the upper layer of this piecewise linear & Convex value function.
- Main obstacle of implementing POMDP is that solving for finite horizon POMDP has complexity of PSPACE-complete(time-complexity grows in an exponential rate)

Ischemic Heart Disease Problem



- Process state variables represent their subset of whole states which is consistent with the Value Function equation and summarize all the information from previous steps.
- (To reduce complexity)

- **Action Sets:**

treatment actions	*investigative actions*
• no action (wait) • medication treatment • angioplasty (PTCA) • coronary artery bypass graft surgery (CABG)	• stress test • coronary angiogram

Ischemic Heart Disease Problem

Use of Hierarchical Bayesian Belief Network

$$b'(s_j) = \mathrm{P}(s_j \mid o, a, b) = \frac{P(o \mid s_j, a) \sum_{s_i \in S} P(s_j \mid s_i, a) b(s_i)}{\sum_{s_j \in S} P(o \mid s_j, a) \sum_{s_i \in S} P(s_j \mid s_i, a) b(s_i)}$$

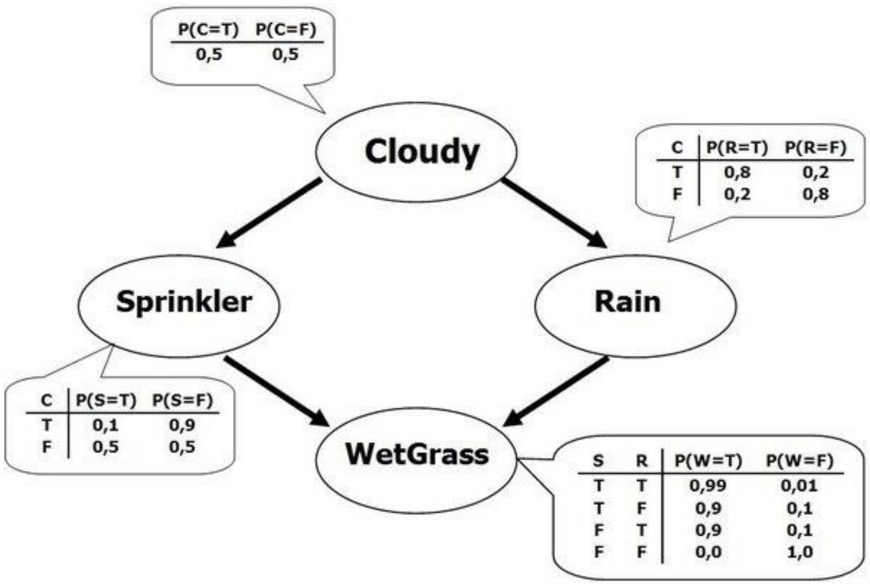
What actual POMDP transition probability looks like.

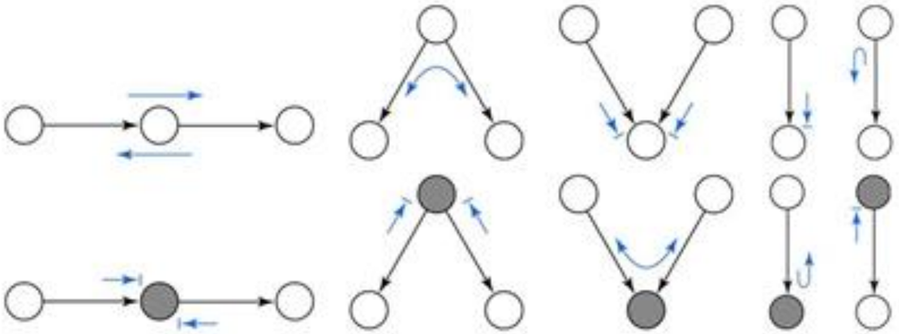
$$\begin{aligned} & P(status = alive,\ CAD = severe / action,\ PRS) \\ & \quad = P(status = alive / action,\ PRS) \\ & \qquad \cdot P(CAD = severe / action,\ PRS,\ status = alive). \end{aligned}$$

PRS: Previous states

Ischemic Heart Disease Problem

Brief Review of Bayesian Belief Networks



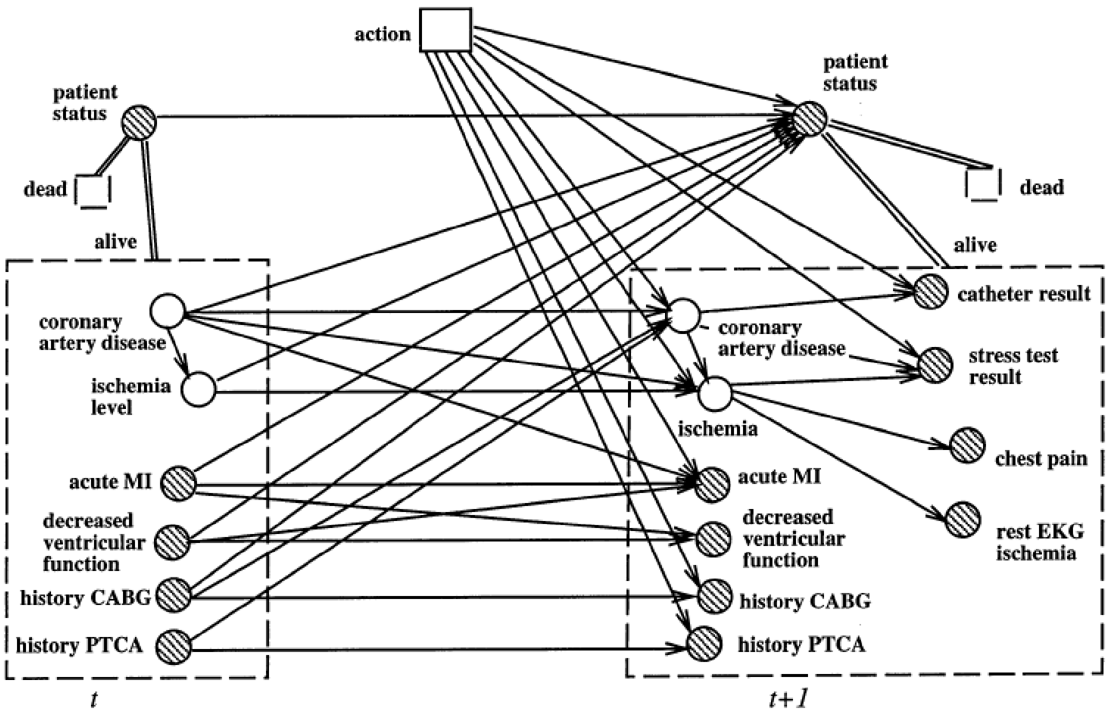


Graph showing the dependency relations.

Very handy to find whether two variables are independent(Bayesian Ball Algorithm in Common Parent/Cascading structure/V-structure)
F.Y.I.: https://www.youtube.com/watch?v=ZMG_LxhTzzk
http://slideplayer.com/slide/6184067/

Ischemic Heart Disease Problem

Use of Hierarchical Bayesian Belief Network



$$P(status = alive,\ CAD = severe \mid action,\ PRS)$$
$$= P(status = alive \mid action,\ PRS)$$
$$\cdot\ P(CAD = severe \mid action,\ PRS,\ status = alive).$$

PRS: Previous states

Ischemic Heart Disease Problem

Reward(Cost) :

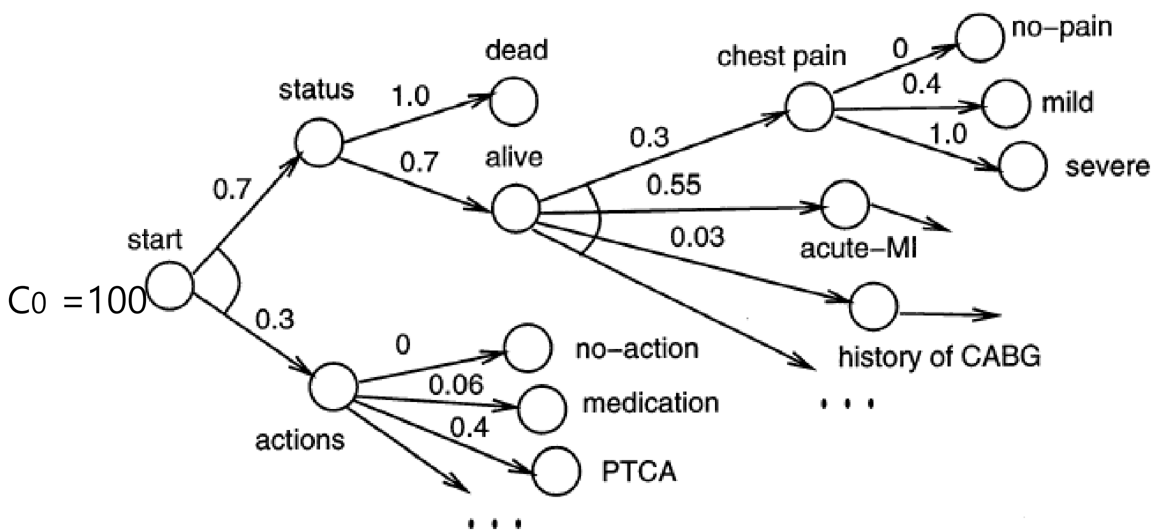


Fig. 7. Model used for the acquisition of costs for the ischemic heart disease model. Links with arcs represent the *AND model*, links without arcs represent the *XOR model*. Numbers represent weights assigned to the lower level components.

Reward for action and state is independent in this case

$$R(\text{chest-pain-severe}) = -C_0 \cdot w_{\text{status}} \cdot w_{\text{alive}} \cdot w_{\text{chest-pain}} \cdot w_{\text{chest-pain-severe}},$$

$$R(s,a,s') = R(s') + R(a)$$

Ischemic Heart Disease Problem

Solving the problem:

- Adapting hybrid information states: acute MI, decreased ventricular function, history of CABG, history of PTCA are Observable states while some others are unobservable.(hidden states)

$$\{o_d, b_d\} \ \{h_1, h_2, \ldots, h_j, \ldots, h_q\}$$

hj : set of all possible combinations of values of hidden process state variables.

$$V_i(\{o_d, b_d\}) = \max_{\alpha \in \Gamma_i^{od}} \sum_{j=1}^{q} \alpha(h_j) b_d(h_j)$$

Γ_i^{od} is a set of linear functions defining V_i

Subscript d denotes the process state variables

- Two Heuristics based on above Value Function was implemented.(Incremental Linear Function Method/Fast Informed Bound Method)

Ischemic Heart Disease Problem: Conclusion

- Despite that and the need to estimate a large number of parameters, the model and obtained solutions demonstrated behavior that was in most instances clinically reasonable and justifiable seen by cardiologists.
- Two methods showed very similar recommendation on action
- Does not cover all ischemic heart disease domain, so it should be detailed further
- The process of **defining probability parameters** proved difficult and time consuming.
- May adopt many other techniques widely used in Machine Learning context.

- Several modifications were taken into the model to alleviate the complexity of the actual problem.

Thank you