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Partially observable Markov decision process (POMPD)

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Presentation 15
6.11.2020

MS-E2191 Graduate Seminar on Operations Research
Fall 2020

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POMDP

- **First used by Drake (1962)**
 - Study of monitoring of a discrete Markov source through a memoryless noisy channel
- **Why partial information?**
 - Structural systems are not identical to their designs
 - Direct, accurate measurements are not possible

POMDP

- Describes the problem when the transition laws of the core process under different control actions are known but the true state of the core process cannot be identified with certainty
 - Observable states Y (state space M) and true states X (state space S)
 - Control action during time t : a_t
- Relationship matrix: $\mathbf{R}(a_{t-1}) = [r_{ij}(a_{t-1})] \in \mathbb{R}^{|M| \times |S|}$ where $r_{ij}(a_{t-1}) = P[Y_t = j | X_t = i, a_{t-1}]$
- Transition matrix during $[t, t + 1)$ under control a_t : $\mathbf{P}(a_t) = [p_{ij}(a_t)] \in \mathbb{R}^{|S| \times |S|}$ where $p_{ij}(a_t) = P[X_{t+1} = j | X_t = i, a_t]$

Information vector

- Information vector $\mathbf{q}(t) = (q_1(t), \dots, q_N(t))$ where $q_i(0) = P[X_0 = i | d_t]$ where d_t is the history from 0 to t
- Information is updated: $\mathbf{q}_j^k(t+1) = (q_{j1}^k(t+1), \dots, q_{jN}^k(t+1))$ where

$$q_{ji}^k(t+1) = \frac{\sum_{l \in S} q_l(t) p_{li}(k) r_{ij}(k)}{\sum_{i \in S} [\sum_{l \in S} q_l(t) p_{li}(k)] r_{ij}(k)} := \frac{q(t) P_r^{j,k}}{\gamma(j | d_t, k)}$$

POMPD into MDP

- The sequence of information vectors $\{\mathbf{q}(t), t \in T\}$ is a Markov process for any fixed sequence of actions and it is completely "observable".
- Terminal cost $\mathbf{C}^0 = (C_1^0, \dots, C_N^0)^T$
- Immediate cost $\mathbf{C}_k = (C_{1k}, \dots, C_{Nk})^T$

- Value function for the problem

$$V^n(\mathbf{q}(t)) = \min_{k \in A} \left[\mathbf{q}(t) \mathbf{C}_k + \sum_{j \in M} \gamma(j|d_t, k) V^{n-1}(\mathbf{q}_j^k(t+1)) \right]$$

- For $n = 0$, $V^0(\mathbf{q}(t)) = \mathbf{q}(t) \mathbf{C}^0$

Multiple inspection strategies

- Inspection method is chosen from I
- Other costs (model specific)
 - Penalty cost $\mathbf{C}^P = (C_1^P, \dots, C_N^P)^T$
 - Inspection strategy cost $\mathbf{C}_l^I = (C_{l1}^I, \dots, C_{lN}^I)^T$
 - Discount factor β
- Recursive formulation

$$V^n(\mathbf{q}(t)) = \min_{k \in A, l \in I} \left[\mathbf{q}(t) \mathbf{C}_k + \beta \mathbf{q}(t) \mathbf{P}(k) (\mathbf{C}^P + \mathbf{C}_l^I) + \beta \sum_{j \in M(l)} \gamma(j|d_t, k, l) V^{n-1}(\mathbf{q}_j^{k,l}(t+1)) \right]$$

Example: Bridge repair

$$P(1) = \begin{bmatrix} 0.80 & 0.13 & 0.02 & 0.00 & 0.05 \\ 0.00 & 0.70 & 0.17 & 0.05 & 0.08 \\ 0.00 & 0.00 & 0.75 & 0.15 & 0.10 \\ 0.00 & 0.00 & 0.00 & 0.60 & 0.40 \\ 0.00 & 0.00 & 0.00 & 0.00 & 1.00 \end{bmatrix}$$

$$R(1) = (1,1,1,1,1)^T$$

$$C = \begin{bmatrix} 0 & 5 & 25 & 40 \\ 0 & 8 & 80 & 120 \\ 0 & 15 & 100 & 550 \\ 300 & 320 & 450 & 800 \\ 2000 & 2050 & 2500 & 4000 \end{bmatrix}$$

$$P(2) = \begin{bmatrix} 0.80 & 0.13 & 0.02 & 0.00 & 0.05 \\ 0.00 & 0.80 & 0.10 & 0.02 & 0.08 \\ 0.00 & 0.00 & 0.80 & 0.10 & 0.10 \\ 0.00 & 0.00 & 0.00 & 0.60 & 0.40 \\ 0.00 & 0.00 & 0.00 & 0.00 & 1.00 \end{bmatrix}$$

$$R(2) = \begin{bmatrix} 0.80 & 0.20 & 0.00 \\ 0.20 & 0.60 & 0.20 \\ 0.05 & 0.70 & 0.25 \\ 0.00 & 0.30 & 0.70 \\ 0.00 & 0.00 & 1.00 \end{bmatrix}$$

$$P(3) = \begin{bmatrix} 0.80 & 0.13 & 0.02 & 0.00 & 0.05 \\ 0.19 & 0.65 & 0.08 & 0.02 & 0.06 \\ 0.10 & 0.20 & 0.56 & 0.08 & 0.06 \\ 0.00 & 0.10 & 0.25 & 0.55 & 0.10 \\ 0.00 & 0.00 & 0.00 & 0.00 & 1.00 \end{bmatrix}$$

$$R(3) = \begin{bmatrix} 0.90 & 0.10 & 0.00 & 0.00 & 0.00 \\ 0.05 & 0.90 & 0.05 & 0.00 & 0.00 \\ 0.00 & 0.05 & 0.90 & 0.05 & 0.00 \\ 0.00 & 0.00 & 0.05 & 0.95 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 1.00 \end{bmatrix}$$

$$C_1^I = (0,0,0,0,0)^T$$

$$C_2^I = (4,4,4,4,4)^T$$

$$C_3^I = (18,18,18,18,18)^T$$

$$C^P = (0,0,0,0,0)^T$$

$$C^0 = (0,0,0,0,0)^T$$

$$P(4) = \begin{bmatrix} 0.80 & 0.13 & 0.02 & 0.00 & 0.05 \\ 0.80 & 0.13 & 0.02 & 0.00 & 0.05 \\ 0.80 & 0.13 & 0.02 & 0.00 & 0.05 \\ 0.80 & 0.13 & 0.02 & 0.00 & 0.05 \\ 0.80 & 0.13 & 0.02 & 0.00 & 0.05 \end{bmatrix}$$

α -vectors

$$V^n(\mathbf{q}(t)) = \min_{k \in A, l \in I} \left[\mathbf{q}(t) \mathbf{C}_k + \beta \mathbf{q}(t) \mathbf{P}(k) \mathbf{C}_l^I + \beta \sum_{j \in M(l)} \gamma(j|d_t, k, l) V^{n-1}(\mathbf{q}_j^{k,l}(t+1)) \right]$$

- Now $V^0(\mathbf{q}(t)) = \mathbf{q}(t) \mathbf{C}^0 = 0$
- Then V^1 can be calculated separately for each k and l
- For example when $k = 1$ and $l = 1$
 - $V^1(\mathbf{q}(t)) = \mathbf{q}(t) \mathbf{C}_1 + \beta \mathbf{q}(t) \mathbf{P}(1) \mathbf{C}_1^I = \mathbf{q}(t) (\mathbf{C}_1 + \beta \mathbf{P}(1) \mathbf{C}_1^I) := \mathbf{q}(t) \boldsymbol{\alpha}_1^{1,1}$
- Recursively, when $k = 2$ and $l = 1$
 - $V^2(\mathbf{q}(t)) = \mathbf{q}(t) \mathbf{C}_2 + \beta \mathbf{q}(t) \mathbf{P}(2) \mathbf{C}_1^I + \beta \sum_{j \in M(1)} \gamma(j|d_t, 2, 1) V^1\left(\frac{\mathbf{q}(t) \mathbf{P}_r^{j,2,1}}{\gamma(j|d_t, 2, 1)}\right) = \mathbf{q}(t) \mathbf{C}_2 + \beta \mathbf{q}(t) \mathbf{P}(2) \mathbf{C}_1^I + \beta \sum_{j \in M(1)} \mathbf{q}(t) \mathbf{P}_r^{j,2,1} \boldsymbol{\alpha}_1^{2,1} = \mathbf{q}(t) (\mathbf{C}_2 + \beta \mathbf{P}(2) \mathbf{C}_1^I + \beta \sum_{j \in M(1)} \mathbf{P}_r^{j,2,1} \boldsymbol{\alpha}_1^{2,1}) := \mathbf{q}(t) \boldsymbol{\alpha}_2^{2,1}$
- General recursive formulation is found in White (1993)

Example: Optimal decisions

- Calculate the α -vectors recursively for each action and inspection possibilities for all the needed time steps (n)
- When the information $\mathbf{q}(t)$ is known, choose the optimal maintenance decision k' and inspection strategy l' from the corresponding α -vector giving smallest value of $\mathbf{q}(t)\alpha_n^{k,l}$
- Update the information according to the outcome of the inspection j .
- Choose optimal decisions based on the value of $\mathbf{q}_j^{k',l'}(t)\alpha_{n-1}^{k,l}$

Conclusions

- Pros
 - Solution method can answer to the difficulties which the continuous state space creates
 - *Information vector is not discrete*
- Cons
 - Calculations of α -vectors might take time, if many possible control actions, information strategies and solutions for long term are needed

References

Corotis, R. B., Hugh Ellis, J., & Jiang, M. (2005). Modeling of risk-based inspection, maintenance and life-cycle cost with partially observable Markov decision processes. *Structure and Infrastructure Engineering*, 1(1), 75-84.

White, D. J. (1993). *Markov Decision Processes*. John Wiley & Sons.

Homework

Use the slides of the presentation (notation) and the article of Corotis et. al (2005) (numeric values) to answer the following questions.

1. Explain what $\mathbf{q}_2^{1,3}(t + 1)$ is. Calculate the $\mathbf{q}_2^{1,3}(t + 1)$ when $\mathbf{q}(t) = (0.85, 0.10, 0.05, 0, 0)$
2. Explain what $\alpha_1^{3,2}$ is. Calculate the $\alpha_1^{3,2}$ vector when $\beta = 0.99$.

Solutions can be calculated either by hand or with Excel, Matlab or R.

Return solutions until Friday 13th of November to jussi.leppinen@aalto.fi.

Need help: Send email or message in Telegram (@jussi_lep)