Markovian decision-support model for patient-to-ward assignment problem in a random environment

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Outline



Patient to Ward Assignment problem



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• Approximate Dynanic Programming

Conclusion

Patient to Ward Assignment Problem

- A generalisation of the advanced patient scheduling problem (APAS).
- Patients are allocated to beds in different wards.
- We take into account the patients' needs, their priorities and the availability of resources.
- We construct a Markov Decision Problem (MDP), in which:
 - Also, decisions are made at the time of each time period of a fixed length,
 - Allocation decisions involved several arrived patients (of different type).
- Our goal is to find the optimal assignment of patients to wards at a minimum expected cost.

We use the following notations for our math model:

- $\mathcal{I} = \{1, 2, ..., I\}$: the set of all patient types and contains all required information,
- $\ensuremath{\mathcal{K}}$: the set of ward in the hospital,
- $\ensuremath{\mathcal{T}}$: the planning period,
- $\mathcal{B}_{\mathcal{K}}$: the number of beds in ward $k \in \mathcal{K}$,
- λ_i : the arrival rate of type-*i* patient,
- $Q_i(t)$: the random variable recording the number of arrivals of type-*i* patient during time *t*, and $Q_i(t) \sim Poi(\lambda_i t)$,
- q_i : the number of newly arrived type-*i* patients.

Notations

Random Departure

- Length of Stay (Latouche & Ramaswami, 1999): $LoS_{k,i} \sim PH(\gamma^{(k,i)}, \mathbf{P}^{(k,i)}),$
- Random departures during interval *t*: $Z_{k,i}(t) \sim Bin(n_{k,i}, p_{k,i}(t))$,

$$p_{k,i}(t) = Pr(LOS_{k,i} \le t) = 1 - \gamma^{(k,i)} \left(\mathbf{P}^{(k,i)} \right)^t \mathbf{1} \ \forall t \in \mathcal{T}, \quad (1)$$

• where 1 is a column vector of ones of appropriate size.

- State space:
 - The set of state space is denoted by \mathcal{S} ,
 - The information of the system at time *t* is given by s_t ∈ S, defined as s_t = ([n_{k,i}]_{K×I}, [q_i]_{1×I}),
 - where $n_{k,i}$ is the number of type-*i* patients in ward $k, i \in \mathcal{I}, k \in \mathcal{K}$.
- Action space:
 - The set of action space is denoted by $\ensuremath{\mathcal{A}},$
 - A decision $a \in A$ is defined as $a = ([x_{k,i}]_{\mathcal{K} \times \mathcal{I}}, [y_{k,\ell,i}]_{\mathcal{K} \times \mathcal{K} \times \mathcal{I}}),$
 - where x_{k,i} ≥ 0 is allocation decision and y_{k,ℓ,i} ≥ 0 patients of type-*i* transferred from ward k to ward ℓ.

MDP

Transition probabilities

The transition from s_t to $s' = ([n'_{k,i}]_{K \times I}, [q'_i]_{1 \times I})$ is defined by:

$$\Pr\{s'|(s_t, a_t)\} = \prod_i \Pr(Q_i(t) = q_i) \prod_{k,i} \Pr(Z_{k,i}(t) = z_{k,i})$$
(2)

- where
$$\mathsf{Pr}({m Q}_i(t)={m q}_i)=rac{(\lambda_i)^{{m q}_i}{m e}^{-\lambda_i}}{({m q}_i)!}, orall i\in\mathcal{I}.$$

Post-decision states

Making decision a_t while in state s_t will result in a post-decision $\bar{s}(n, q)$

$$\bar{n}_{k,i} = n_{k,i} + x_{k,i} + \sum_{k \in \mathcal{K}} y_{k,\ell,i} - \sum_{\ell \in \mathcal{K}} y_{k,\ell,i}.$$
(3)

where $x_{k,i}$ and $y_{k,\ell,i}$ are the decisions regarding the assignment and relocation of the patients, respectively.

MDP

The Optimality Equation

Using the value function $v : S \to \mathbb{R}^+_0$, we construct the Bellman's optimality equation

$$v(s) = \min_{a \in \mathcal{A}_s} \left\{ c(s, a) + \alpha \sum_{s' \in \mathcal{S}} \Pr\{s' | (s, a)\} v(s') \right\} \forall s \in \mathcal{S}, \quad (4)$$

where α is discount factor, and c(s, a) is an immediate cost associate action $a \in A_s$ in state $s \in S$.

MDP

The Set of Feasible Action Space

$$\min\{\sum_{k\in\mathcal{K}} \boldsymbol{C}_k, \boldsymbol{q}_i\} \leq \sum_{k=1}^K x_{k,i} \; \forall i$$

where C_k is the available beds in ward k,

$$\sum_{\ell=1}^{K} y_{k,\ell,i} \le n_{k,i} \tag{6}$$

$$\sum_{i=1}^{l} (x_{k,i} + n_{k,i}) + \sum_{\ell=1}^{K} \sum_{i=1}^{l} (y_{k,\ell,i} - y_{\ell,k,i}) \le m_k$$
(7)

 $y_{k,\ell,i} \leq n_{k,i} \times d_{k,\ell,i}, \ y_{\ell,k,i} \leq n_{\ell,i} \times d_{\ell,k,,i}, \ d_{k,\ell,i} + d_{\ell,k,,i} \leq 1,$ (8) where $z_{\ell,k,,i} \in \{0,1\}$ is an auxiliary variable.

(5)

- The realistic size of this MDP is computationally intractable,
- We use Approximate Dynamic Programming techniques to resolve this issue,
- We use the linear programming form of v(s) approximated by a set of basis functions similar to Gocgun and Puterman (2014)¹,
- A basis function Φ : S → ℝ is set of features that contain state's information.

¹Dynamic scheduling with due dates and time windows: an application to chemotherapy patient appointment booking. *Health Care Mange Sci*

We write the linear programming equivalent of Eq. (4) as

$$\max \sum_{s \in S} \omega(s) v(s) \tag{9}$$

subject to

$$c(s,a) + \alpha \sum_{s' \in S} \Pr\{s' | (s,a)\} v(s') \ge v(s) \ \forall a \in \mathcal{A}_s, \forall s \in S$$
(10)

where $\omega(s)$ represent the weights of the states in (5).

• We approximate the LP using basis functions:

$$\bar{\nu}(s) = W_0 + \sum_{k=1}^{K} W_k \Phi_k(s) \tag{11}$$

- where $\{W_k\}_{k=0}^{K} \in \mathbb{R}$ are weights that should be determined.

• We update the LP using this approximation

$$\max W_0 + \sum_{k=1}^{K} \left(\sum_{s \in S} \omega(s) \Phi_k(s) \right) W_k$$
(12)

subject to

$$c(s,a) \ge (1-\alpha)W_0 + \sum_{k=1}^{K} v_k(s,a)W_k \ \forall a \in \mathcal{A}_s, \forall s \in \mathcal{S}$$
 (13)

where

$$v_{k}(s, a) = \Phi_{k}(s) - \alpha \sum_{s' \in S} \Pr\{s' | (s, a)\} \Phi_{k}(s') \ge v(s)$$
(14)
$$\forall a \in \mathcal{A}_{s}, \forall s \in S$$

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Thank you!