Dynamic Patient Scheduling With Temporal Dependencies

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Problem

Allocating sparse medical resources to patients for Emergency and Critical Care: We focus on four primary aspects of resource allocation:

1. Efficiency to balance costs and benefits
2. Dynamic model to capture uncertainties that are naturally imposed in such environments
3. Temporal constraints, i.e., interdependencies between tasks/resources
4. Fairness among patients in need of any subset of resources

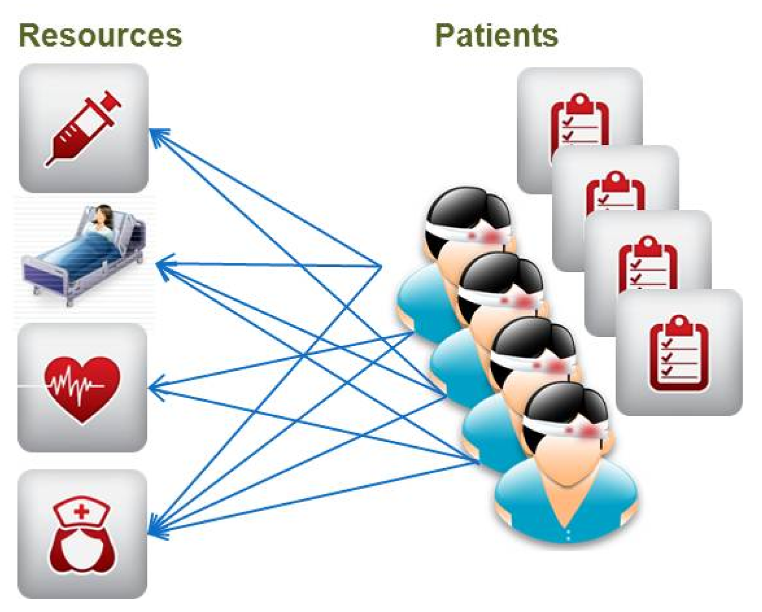
Motivation

- Problem is computationally intractable: current solutions cannot handle large-scale problems.
- Stochastic patient arrivals/departures and uncertain outcomes of medical steps.
- Health model of patients: different progression/diseases
- Temporal dependencies: Sequence in medical tasks (resources)

Interaction

Our model consists of two types of agents:

1. Patient agents model their local preferences and valuations over resources
2. Resource agents allocate the available timeslots to the patient agents



Key challenge: requiring **multiple** resources in a **temporal** order.

Approach

- Independent Markov Decision Processes (MDPs) that provide local individual optimal actions (which resource to request next) considering future expected outcomes
- Auction-based coordination mechanism to find close-to-optimal global allocation of the decentralized MDPs
- Efficiency is defined in terms of maximizing social welfare (utility of agents)

Algorithms for Resource and Patient Agents

Algorithm 1: Resource agents

Input: Set of resources R, set of bids
Output: Mapping of agents to timeslots
initialization;
foreach *Timeslot* t **do**
  resource: open up auction for t;
  $Bid_t \leftarrow \text{receive}(bid_j)$; `// bid from agent j`
  $j_t = \arg\max_{j \in N}\{bid_j\}$; `// awarding phase`
  $\text{alloc}(A_j, t)$;

Patient agents compute their **expected regret** for not obtaining a given resource as follows:

$$R_i(h, \mathbf{r}, a_i) = Q_i - \bar{Q}_i \quad (1)$$

$$Q_i \equiv \sum_{\mathbf{r}'_{-i}} \sum_{h'} P(h'|h, \mathbf{r}) V_i(r'_i, \mathbf{r}'_{-i}, h') \delta(\mathbf{r}_{-i}, \mathbf{r}'_{-i}) \quad (2)$$

where $\mathbf{r_{-i}}$ is the set of all resources except r_i and $\delta(x, y) = 1 \leftrightarrow x = y$ and 0 otherwise. This value is then submitted as the agent's bid (valuation over resource i) to the required resource.

Algorithm 2: Consumer agents: bidding mechanism

Input: A condition profile including a set of needed resources
Output: Bid values, schedule
`// Initialization`
begin
  $\Lambda_R \sim Dir(\boldsymbol{\alpha_r})$; `// resource obtention`
  $\Omega_\psi \sim Dir(\boldsymbol{\alpha_\psi})$; `// succession model`
  Solve MDP;
while r *is nonempty* **do**
  forall the $r_i \in \mathbf{r}, a, \psi$ **do**
    $R_i(\psi, \mathbf{r}, a_i) = Q_i - \bar{Q}_i$
  foreach *Timeslot* t **do**
    $\mathbf{r}^t \leftarrow \mathbf{r}$;
    while $\mathbf{r}^t$ *is nonempty* $\wedge$ $schedule^t_j$ *is empty* **do**
      $i \leftarrow \arg\max_{i \in \mathbf{r}}\{R_i\}$;
      submit bid^i_j to resource i;
      if j *is winner* **then**
        $update(r_i, t)$;
        remove r_i from $\mathbf{r}$;
      else remove r_i from $\mathbf{r}^t$

Transition Model

The transition function $P(\mathbf{r}', h'|\mathbf{r}, h, a)$ is factored into two models:

- **Health progression** (Succession) model independent of other patients: $P(h'|\mathbf{r}, h)$
- **Resource acquisition** model dependent on patient distribution (demand load) and can be updated through learning: $P(\mathbf{r}'|\mathbf{r}, h, a)$

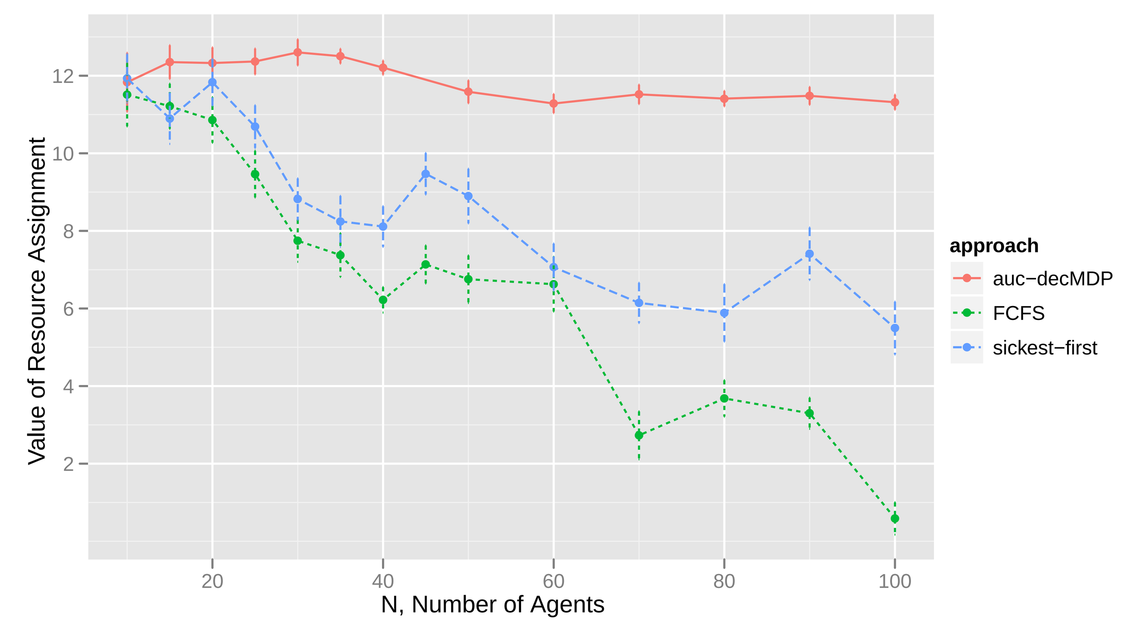
Social Welfare

We consider a utilitarian (or additive) social welfare function to evaluate the improvements in the society of agents:

$$\mathcal{SW}(\pi) = \sum_j \sum_{a \in \pi(s)} R^j(s^j, a^j) \quad (3)$$

where $\pi(s)$ is the allocation policy consisting of resource assignments (actions) at state vector s.

Results



We have simulated different scenarios: auction-based MDP (**auc-decMDP**), first-come-first-serve (**FCFS**), and **sickest-first** where agents obtain required resources based on their condition profiles. Our solution scales easily to 100 agents and 30 resources, giving a close-to-optimal allocation in dynamic domains.

Conclusion and Future Work

- AI solutions to dynamic scheduling improve throughput/efficiency at reduced cost
- Maximizing social welfare does not lead to fair allocation; future work: give up some efficiency to improve on equity
- Preference representation and bidding languages: ways to succinctly represent agents' valuations over bundles of resources

References

- Hosseini, H. Hoey, J. and Cohen,"R. 2011. Multi-agent Patient Scheduling Through Auctioned Decentralized MDPs". In Proceedings of the 6th INFORMS Workshop on Data Mining and Health Informatics 2011, p73–78.
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