

Robust Data-Driven Decision Making in Healthcare

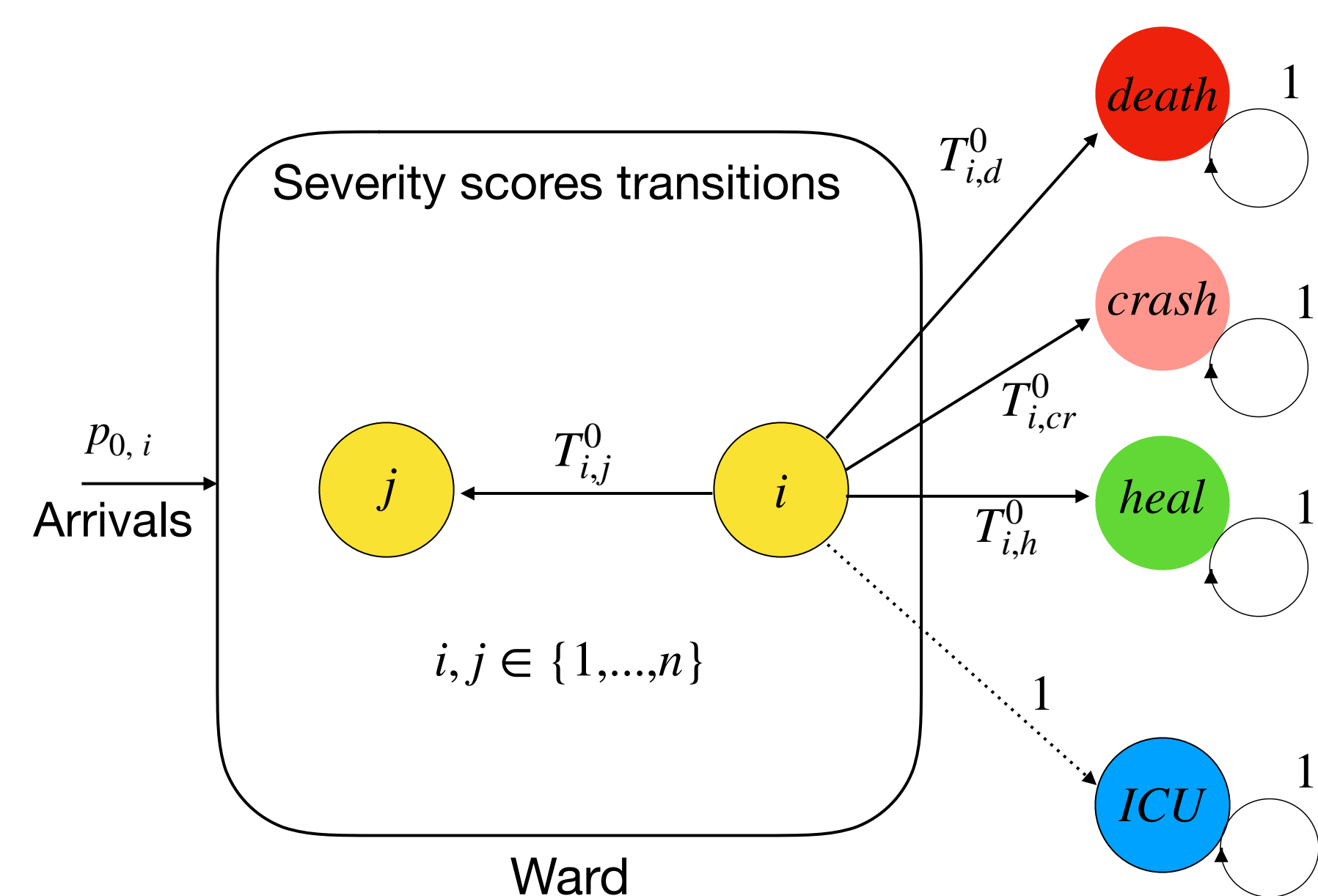
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Hospital management

- Ward vs Emergency room.
- Unplanned transfers: adversarial events.
- Early transfer to emergency room:
 - highly benefits risky patients,
 - might result in congestions.
- Patients who are transferred back to ward: worse mortality and Length-Of-Stay (LOS).
- From data: *risk scores* for each patient.
- Need for patient prioritization guidelines.

Model



- Markov model for transition among risk scores:

$$T_{i,j}^0 = \mathbb{P}(i \rightarrow j).$$

- Policy π : in risk score i , transfer or not.
- Goal: find π to maximize $Reward(\pi, \mathbf{T}^0)$.
- **Main limitation:** Parameter misspecification.
- Parameters \mathbf{T}^0 estimated from noisy data.
- Significantly suboptimal policy in practice.
- **Robust approach:** *safety region* \mathcal{U} ,

$$\mathbf{T}^0 \in \mathcal{U}.$$

Goal: find policy π that maximizes

$$\min_{\mathbf{T} \in \mathcal{U}} R(\pi, \mathbf{T})$$

Why do we care?

- Markov model: main decision tool for healthcare, along with decision trees.
- Previous works: uncertainty too conservative (assume parameters variations are unrelated.)
- Healthcare: uncertainty in parameters can be coupled.
Example: blood pressure and sugar level can have related effects on the dynamics of the risk scores.

Our model of uncertainty

- Uncertainty depends on a small number of “patient types” $(\mathbf{w}_1, \dots, \mathbf{w}_r) = \mathbf{W}$.
- Each patient is a combination of patient types:

$$\mathbf{T}_{i,\cdot} = \mathbf{W} \mathbf{u}_i.$$
- We assume patient types are *unrelated*:

$$(\mathbf{w}_1, \dots, \mathbf{w}_r) \in \mathcal{W}^1 \times \dots \times \mathcal{W}^r.$$
- **Key Idea:**
Coupled parameters \mathbf{T} are simple transformations of uncoupled underlying \mathbf{W} .

Methodology

Given the data:

- 1 Estimate $T_{i,j}^0$ with confidence σ .
- 2 Non-Negative Matrix Factorization for (u_i^k) and

$$(\mathbf{w}_1, \dots, \mathbf{w}_r) \in \mathcal{W}^1 \times \dots \times \mathcal{W}^r,$$

$$\mathcal{W}^i \subseteq B(\mathbf{w}_i, \kappa)_{\|\cdot\|_\infty} \cap B(\mathbf{w}_i, \tau)_{\|\cdot\|_1}.$$
- 3 Optimal nominal policies are deterministic.
- 4 Optimal robust policies are deterministic.
- 5 Efficient algorithm to compute robust policies.
- 6 **Key question:**
Do we improve the worst-case performance?

Application: early transfer of patients in hospital

- **Goal:** Compute robust transfer policies to the emergency room.
- Trade-off: congestion in emergency room *vs* patients recover faster in emergency room.
- Data set: $\approx 300,000$ patients hospitalizations \rightarrow estimated transitions $T_{i,j}$ and confidence intervals.
- **Result 1:** Deterioration of hospital performances.

	$mort_{est.}$ (%)	$mort_{worst}$ (%)	$LOS_{est.}$ (d)	LOS_{worst} (d)
Policy 1	5.87	6.03	3.87	4.01
Policy 2	6.08	6.42	3.92	4.06
Policy 3	6.21	6.64	3.95	4.02

Table 1: Comparison of different transfer policies performances (mortality rate, Length-Of-Stay) for small parameter deviations.

- **Result 2:** Optimal and interpretable transfer policies.
 \rightarrow *Threshold policies:* transfer all patients above a certain risk score.
In our experiments, there are 10 risk scores.

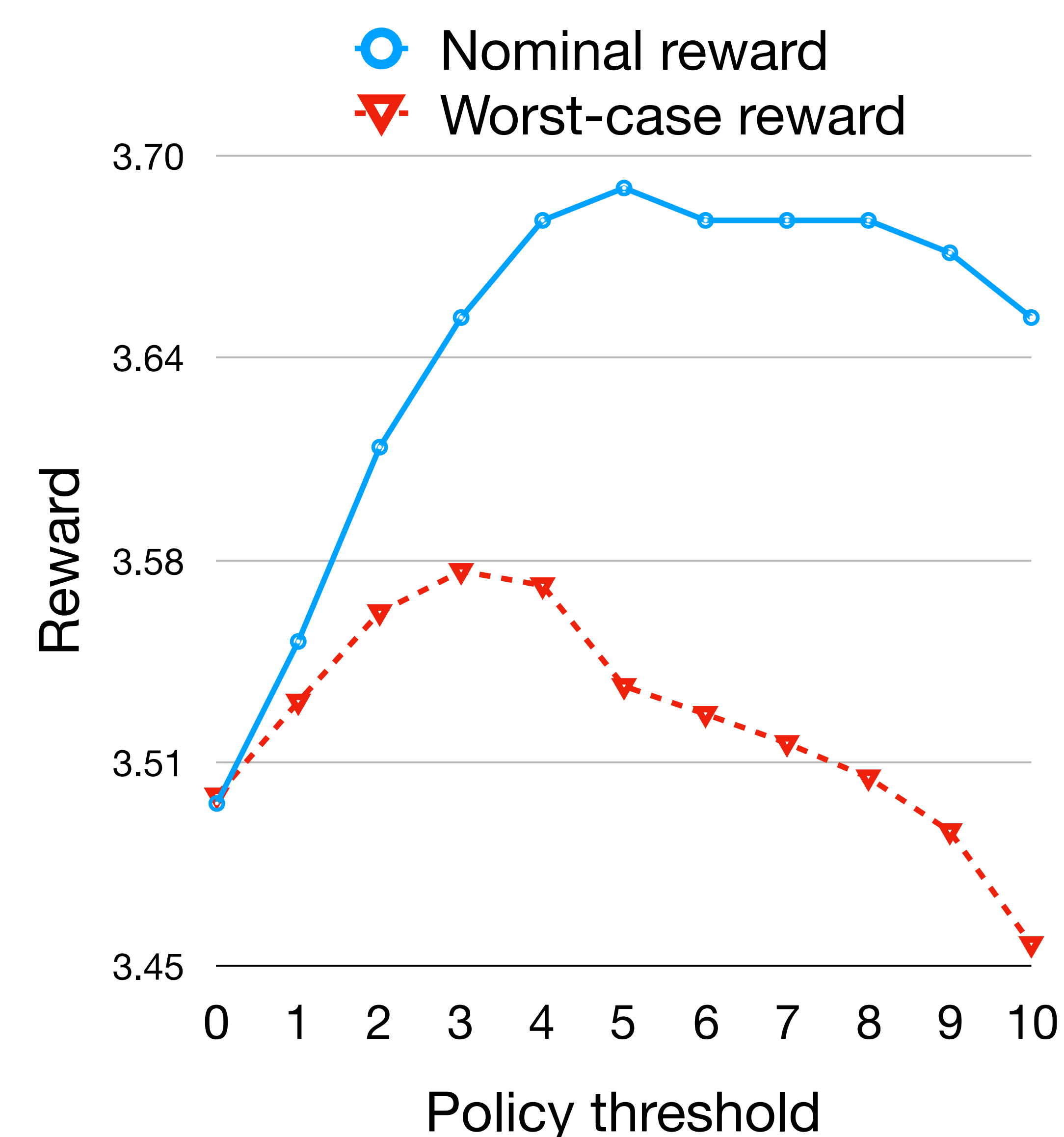


Figure 1: Performances of the 11 threshold policies. Comparison of the nominal (blue circle) and worst-case (red triangle) rewards.

Insights

- Hospital performances may deteriorate.
- Some transfer policies are more robust than the ‘naive’ best policy.
- The optimal nominal policy is *threshold*.
- The optimal robust policy is threshold too, with a lower threshold.

Future works

- Parameter estimation:
Compute better confidence bounds to reduce the parameter uncertainty?
- Actual implementation of the transfer policies in hospitals.
- Modeling:
Tractable *policy-dependent* uncertainty?
- Improve the risk scores estimation.

More at: www.columbia.edu/~jg3728/