

A 3-player game theoretic model of a choice between two queueing systems with strategic managerial decision making

Michalis Panayides

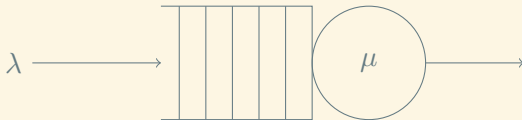


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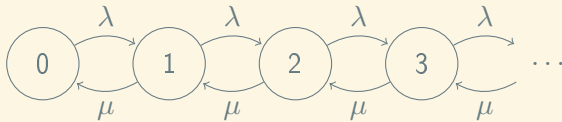
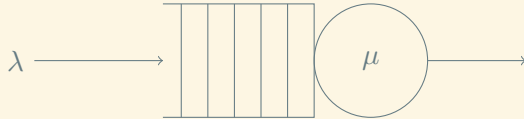
Supervisors:

Dr. Vince Knight,
Prof. Paul Harper

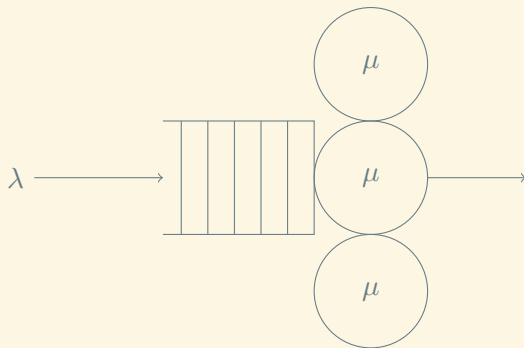
Queues - M/M/1



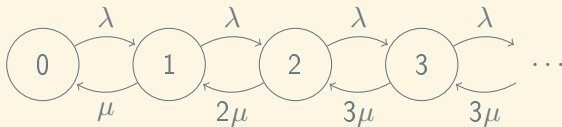
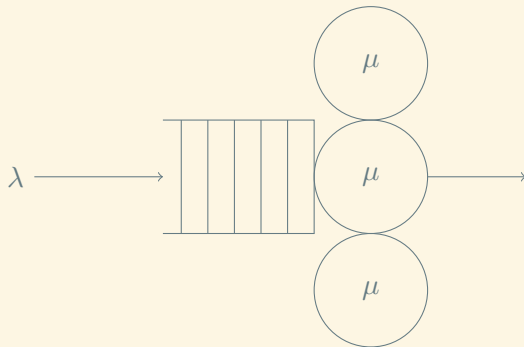
Queues - M/M/1



Queues - M/M/3



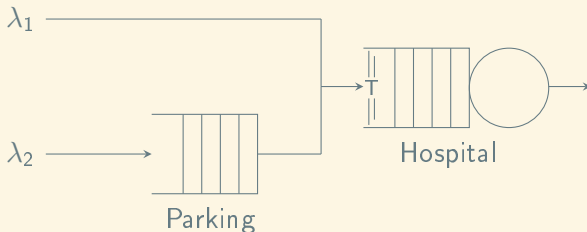
Queues - M/M/3



Queues - Custom network of queues



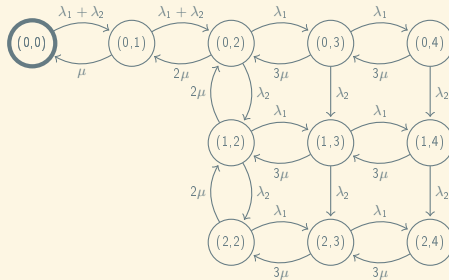
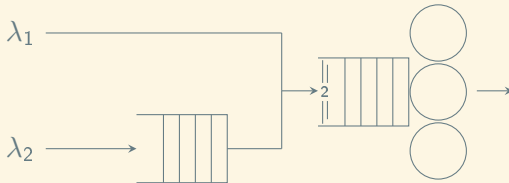
Queues - Custom network of queues



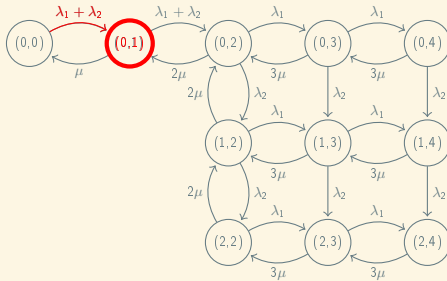
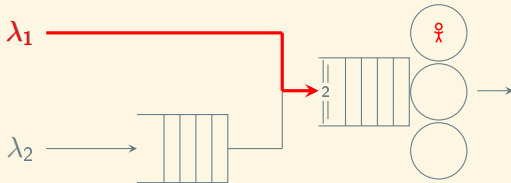
Parameters:

- ▶ λ_1 : Arrival rate of type 1 individuals
- ▶ λ_2 : Arrival rate of type 2 individuals
- ▶ μ : Service rate
- ▶ C : Number of servers
- ▶ T : Threshold

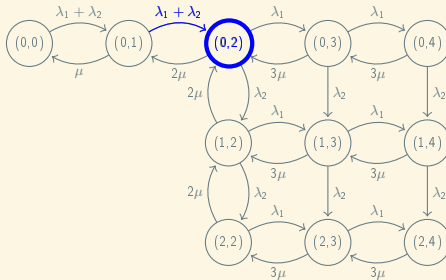
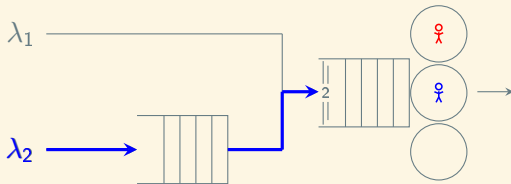
Markov Chain - Custom network



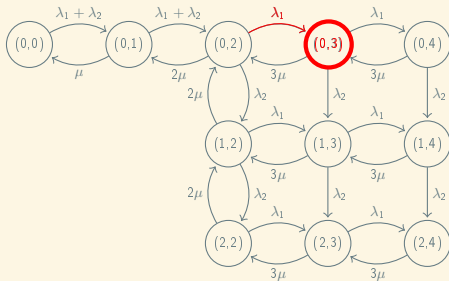
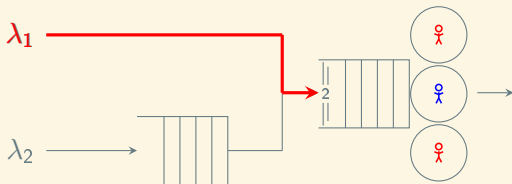
Markov Chain - Custom network



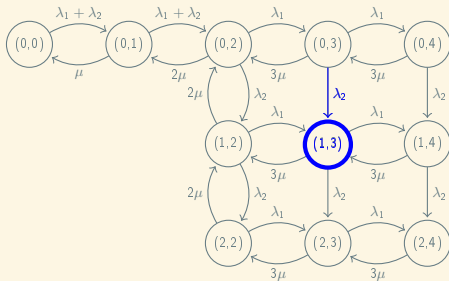
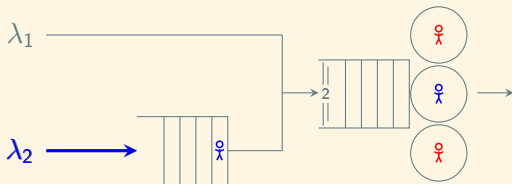
Markov Chain - Custom network



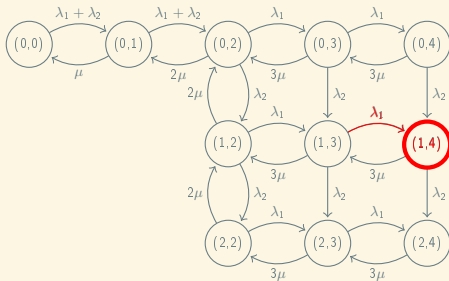
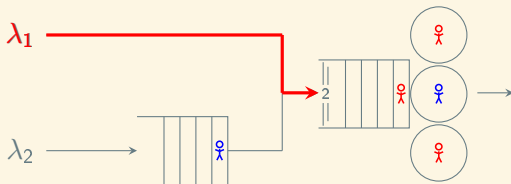
Markov Chain - Custom network



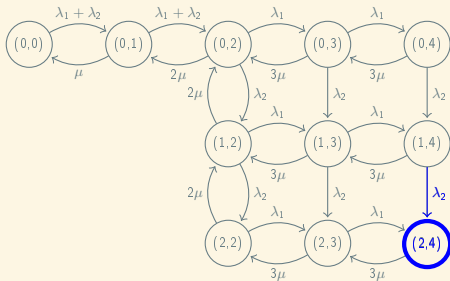
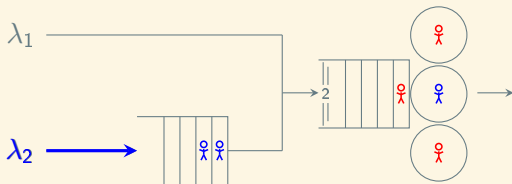
Markov Chain - Custom network



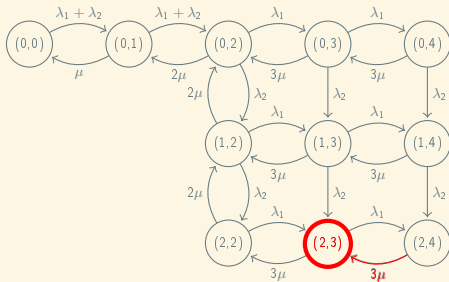
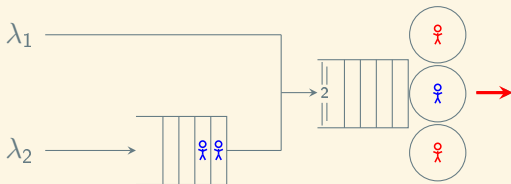
Markov Chain - Custom network



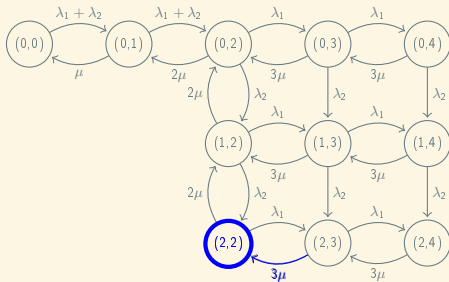
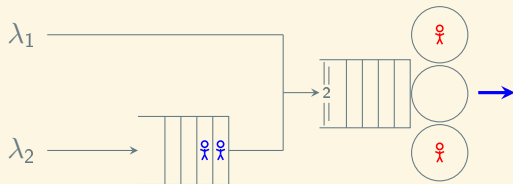
Markov Chain - Custom network



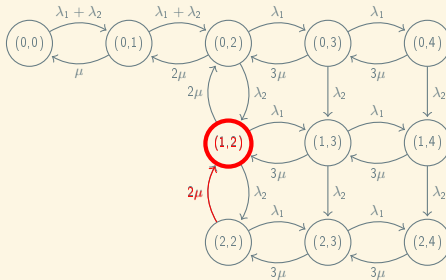
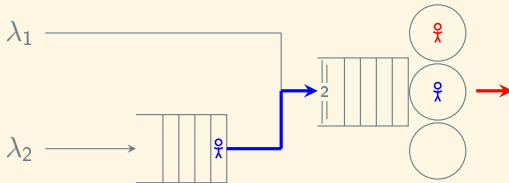
Markov Chain - Custom network



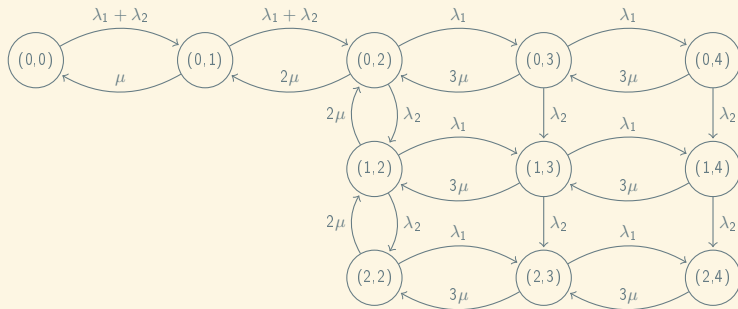
Markov Chain - Custom network



Markov Chain - Custom network



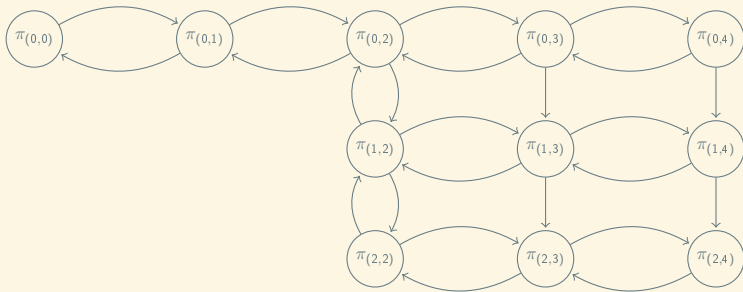
Steady state probabilities - Generator matrix



From \ To	(0,0)	(0,1)	(0,2)	(2,3)	(2,4)
(0,0)	$-\lambda_1 - \lambda_2$	$\lambda_1 + \lambda_2$	0	...	0
(0,1)	μ	$-\mu - \lambda_1 - \lambda_2$	$\lambda_1 + \lambda_2$...	0
(0,2)	0	2μ	$-2\mu - \lambda_1 - \lambda_2$...	0
...
(2,3)	0	0	0	$-\lambda_1 - 3\mu$	λ_1
(2,4)	0	0	0	3μ	-3μ

Steady state probabilities - Generator matrix (Q)

$$\pi = [\pi_{(0,0)} \quad \pi_{(0,1)} \quad \pi_{(0,2)} \quad \dots \quad \pi_{(2,3)} \quad \pi_{(2,4)}], \quad \sum \pi_{(u,v)} = 1$$

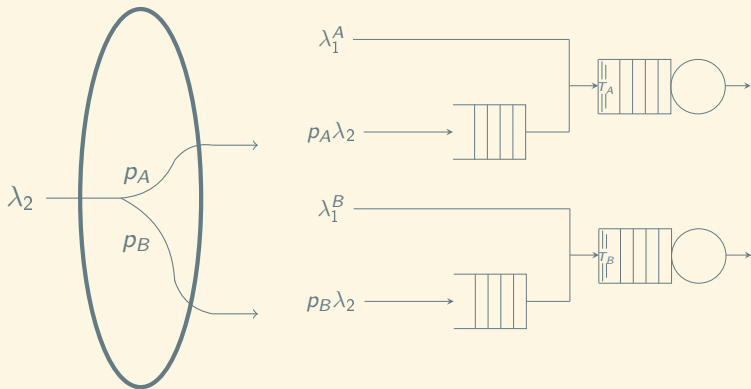


$$\frac{d\pi}{dt} = \pi Q = 0$$

Game - Definition

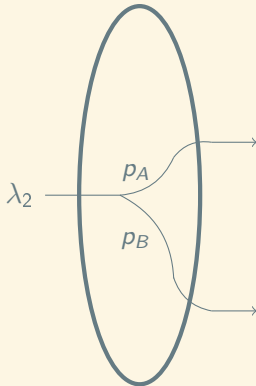


Game - Players and objectives

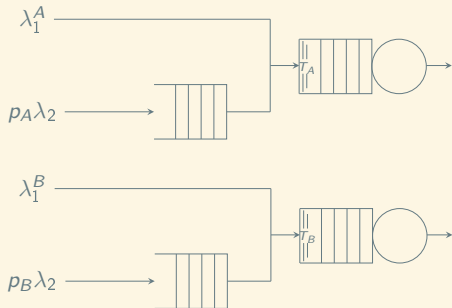


Game - Players and objectives

Blocking time



Proportion of individuals within time



Performance Measures - Blocking time

$$B = \frac{\sum_{(u,v) \in S_A^{(2)}} \pi(u,v) b(u,v)}{\sum_{(u,v) \in S_A^{(2)}} \pi(u,v)}$$

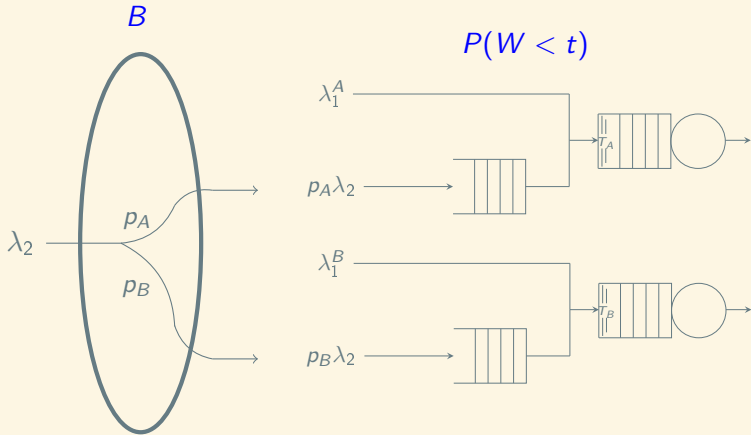
Performance Measures - Proportion within time

$$P(W < t) = \frac{\lambda_1 P_{L'_1}}{\lambda_2 P_{L'_2} + \lambda_1 P_{L'_1}} P(W^{(1)} < t) + \frac{\lambda_2 P_{L'_2}}{\lambda_2 P_{L'_2} + \lambda_1 P_{L'_1}} P(W^{(2)} < t)$$

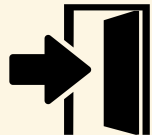
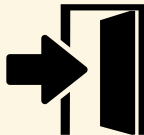
$$P(W^{(1)} < t) = \frac{\sum_{(u,v) \in S_A^{(1)}} P(W_{(u,v)}^{(1)} < t) \pi_{u,v}}{\sum_{(u,v) \in S_A^{(1)}} \pi_{u,v}}$$

$$P(W^{(2)} < t) = \frac{\sum_{(u,v) \in S_A^{(2)}} P(W_{(u,v)}^{(2)} < t) \pi_{u,v}}{\sum_{(u,v) \in S_A^{(2)}} \pi_{u,v}}$$

Game - Players and objectives



Game - Strategies



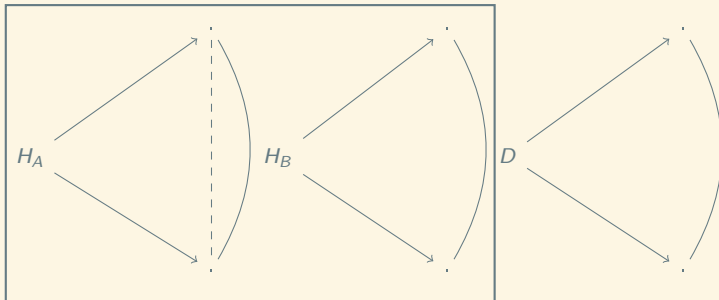
$$p_A, p_B \in [0, 1]$$

$$T_A \in [1, N_A]$$

$$T_B \in [1, N_B]$$

$$p_A + p_B = 1$$

Game - Formulation



Game - Payoff matrices

$$A = \begin{pmatrix} U_{1,1}^A & U_{1,2}^A & \cdots & U_{1,N_B}^A \\ U_{2,1}^A & U_{2,2}^A & \cdots & U_{2,N_B}^A \\ \vdots & \vdots & \ddots & \vdots \\ U_{N_A,1}^A & U_{N_A,2}^A & \cdots & U_{N_A,N_B}^A \end{pmatrix}, \quad B = \begin{pmatrix} U_{1,1}^B & U_{1,2}^B & \cdots & U_{1,N_B}^B \\ U_{2,1}^B & U_{2,2}^B & \cdots & U_{2,N_B}^B \\ \vdots & \vdots & \ddots & \vdots \\ U_{N_A,1}^B & U_{N_A,2}^B & \cdots & U_{N_A,N_B}^B \end{pmatrix}$$

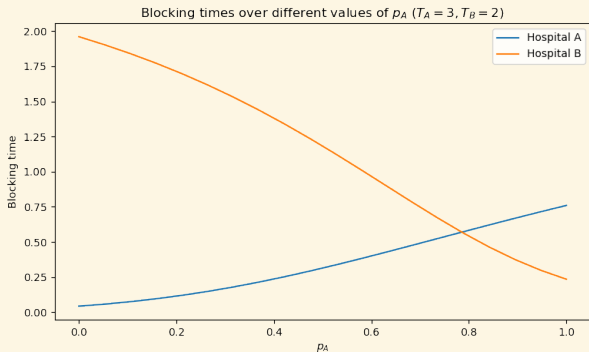
$$R = \begin{pmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,N_B} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,N_B} \\ \vdots & \vdots & \ddots & \vdots \\ p_{N_A,1} & p_{N_A,2} & \cdots & p_{N_A,N_B} \end{pmatrix}$$

Ambulance's Decision

$$R = \begin{pmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,N_B} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,N_B} \\ \vdots & \vdots & \ddots & \vdots \\ p_{N_A,1} & p_{N_A,2} & \cdots & p_{N_A,N_B} \end{pmatrix}$$

Ambulance's Decision

$$\begin{matrix} T_A = 3 \\ T_B = 2 \end{matrix} \rightarrow \begin{pmatrix} - & - & - & - \\ - & - & - & - \\ - & x & - & - \\ - & - & - & - \end{pmatrix} \rightarrow B_A(p_A) = B_B(1 - p_A)$$



Hospitals' Decision

$$A = \begin{pmatrix} U_{1,1}^A & U_{1,2}^A & \cdots & U_{1,N_B}^A \\ U_{2,1}^A & U_{2,2}^A & \cdots & U_{2,N_B}^A \\ \vdots & \vdots & \ddots & \vdots \\ U_{N_A,1}^A & U_{N_A,2}^A & \cdots & U_{N_A,N_B}^A \end{pmatrix}, \quad B = \begin{pmatrix} U_{1,1}^B & U_{1,2}^B & \cdots & U_{1,N_B}^B \\ U_{2,1}^B & U_{2,2}^B & \cdots & U_{2,N_B}^B \\ \vdots & \vdots & \ddots & \vdots \\ U_{N_A,1}^B & U_{N_A,2}^B & \cdots & U_{N_A,N_B}^B \end{pmatrix}$$

$$U_{T_A, T_B}^{(i)} = 1 - \left[(P(X^{(i)} < t) - 0.95)^2 \right]$$

Nash Equilibrium

$$R = \begin{pmatrix} 0.5 & 0.1 & 0 & 0 \\ 0.9 & 0.5 & 0.2 & 0 \\ 1 & 0.8 & 0.5 & 0.3 \\ 1 & 1 & 0.7 & 0.5 \end{pmatrix}$$

$$A = \begin{pmatrix} 0.99998394 & 0.99998394 & 0.99998394 & 0.99998394 \\ 0.99998955 & 0.99998848 & 0.99998649 & 0.9999845 \\ 0.99999952 & 0.9999987 & 0.99999596 & 0.99999199 \\ 0.99994372 & 0.99995113 & 0.99998603 & 0.99999911 \end{pmatrix}$$

$$B = \begin{pmatrix} 0.99998394 & 0.99998955 & 0.99999952 & 0.99994372 \\ 0.99998394 & 0.99998848 & 0.9999987 & 0.99995113 \\ 0.99998394 & 0.99998649 & 0.99999596 & 0.99998603 \\ 0.99998394 & 0.9999845 & 0.99999199 & 0.99999911 \end{pmatrix}$$

Nash Equilibria: $\frac{A}{(0, 0, 0.4, 0.6)}$ $\frac{B}{(0, 0, 0.4, 0.6)}$

Asymmetric Replicator Dynamics

$$\frac{dx}{dt}_i = x_i((f_x)_i - \phi_x), \quad \text{for all } i$$

$$\frac{dy}{dt}_i = y_i((f_y)_i - \phi_y), \quad \text{for all } i$$

Inefficiency measure

$$PoA = \frac{\max_{s \in E} Cost(s)}{\min_{s \in S} Cost(S)}$$

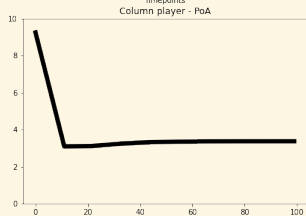
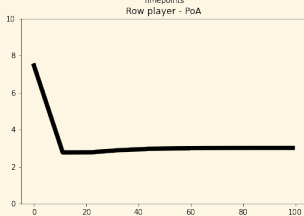
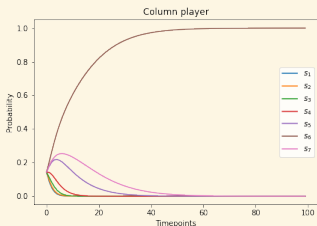
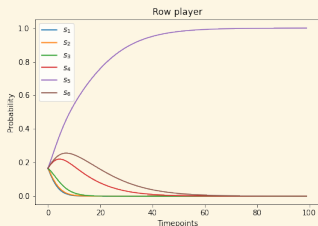
Inefficiency measure

$$PoA = \frac{\max_{s \in E} Cost(s)}{\min_{s \in S} Cost(S)}$$

$$PoA_A(s_r) = \frac{Cost(s_r)}{\min_{s \in S} Cost(S)},$$

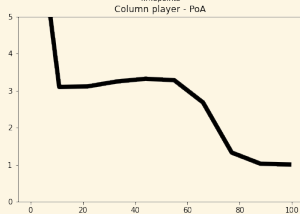
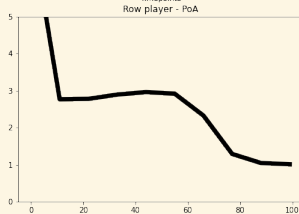
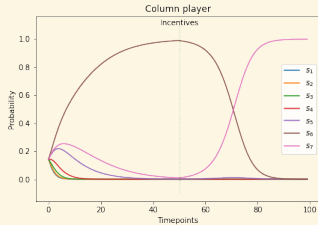
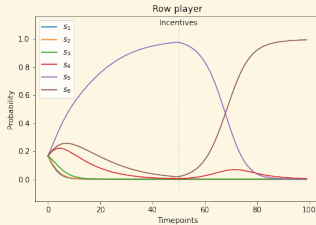
$$PoA_B(s_c) = \frac{Cost(s_c)}{\min_{s \in S} Cost(S)}$$

Learning algorithms - Asymmetric replicator dynamics



Inefficiencies can be learned and
emerge naturally

Learning algorithms - Asymmetric replicator dynamics



Targeted incentivisation of
behaviours can help escape
learned inefficiencies

Thank you!

“Inefficiencies can be learned and emerge naturally”

“Targeted incentivisation of behaviours can help escape learned inefficiencies”

```
$ pip install ambulance_game  
https://github.com/11michalis11/AmbulanceDecisionGame
```

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