

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

Michalis Panayides

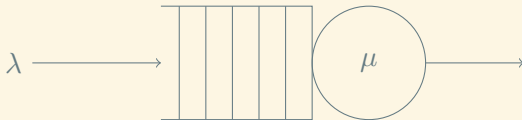


THIS.

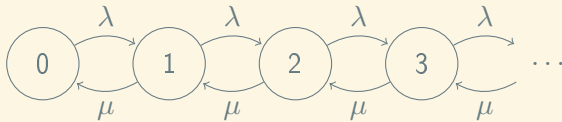
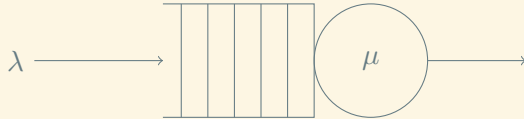
Supervisors:

Dr. Vince Knight,
Prof. Paul Harper

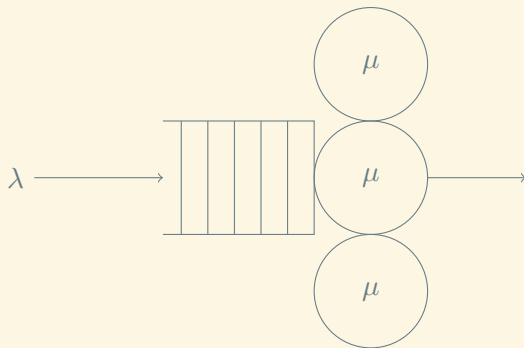
Queues - M/M/1



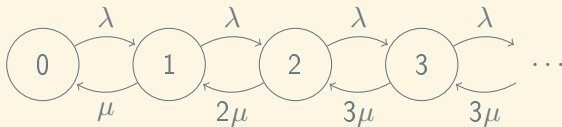
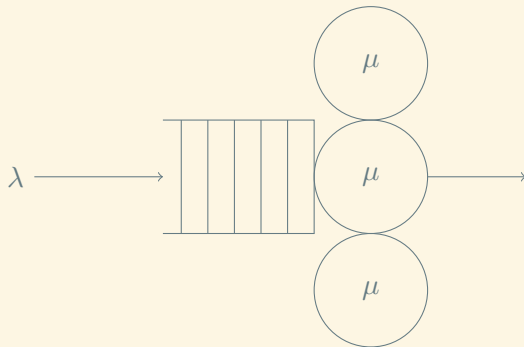
Queues - M/M/1



Queues - M/M/3



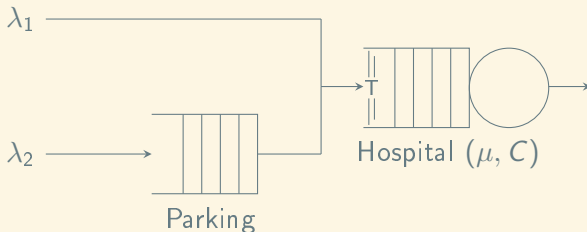
Queues - M/M/3



Queues - Custom network of queues



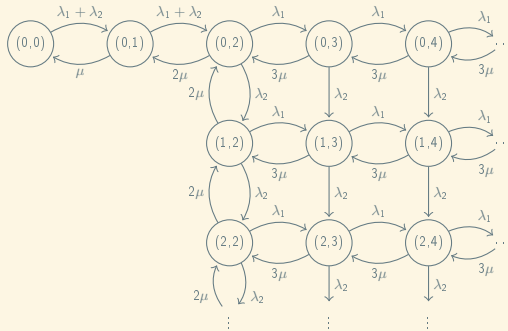
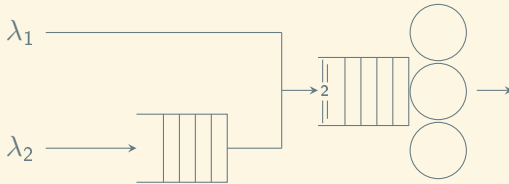
Queues - Custom network of queues



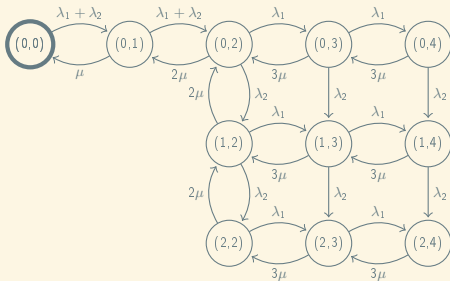
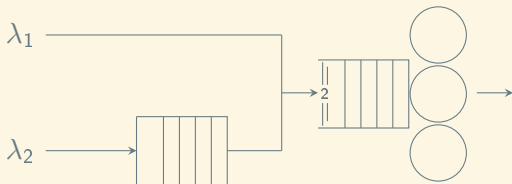
Parameters:

- ▶ 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

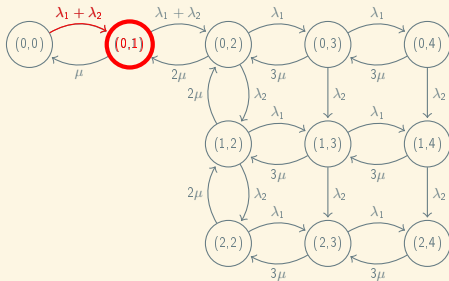
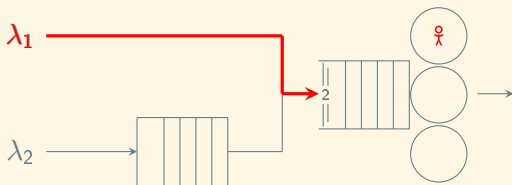
Markov Chain - Custom network



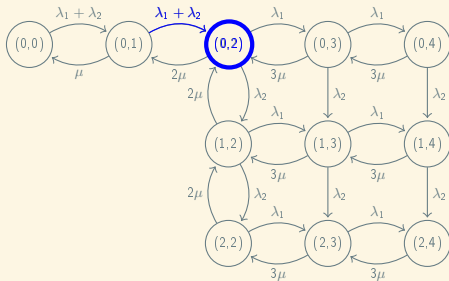
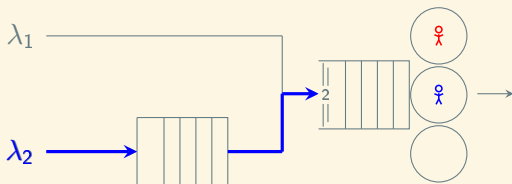
Markov Chain - Custom network - $N = 4, M = 2$



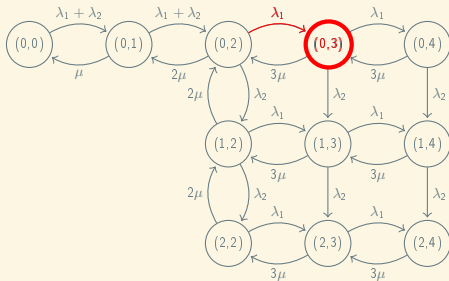
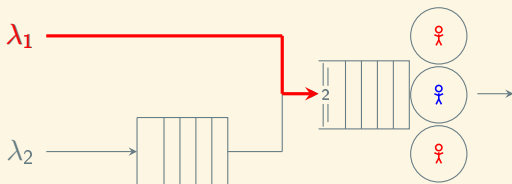
Markov Chain - Custom network - $N = 4, M = 2$



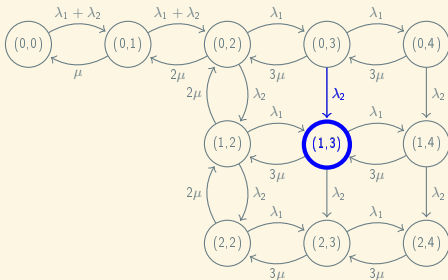
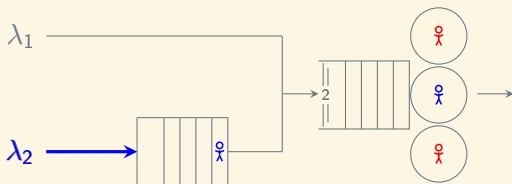
Markov Chain - Custom network - $N = 4, M = 2$



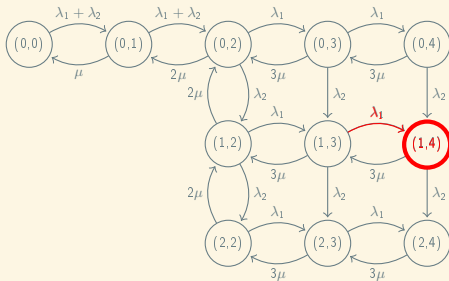
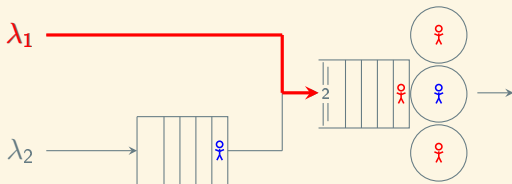
Markov Chain - Custom network - $N = 4, M = 2$



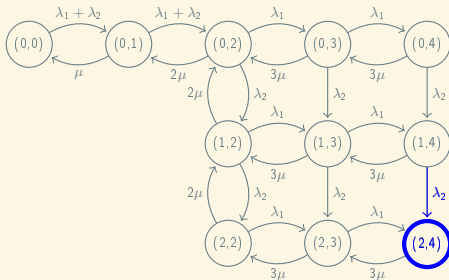
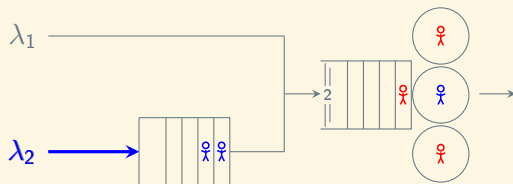
Markov Chain - Custom network - $N = 4, M = 2$



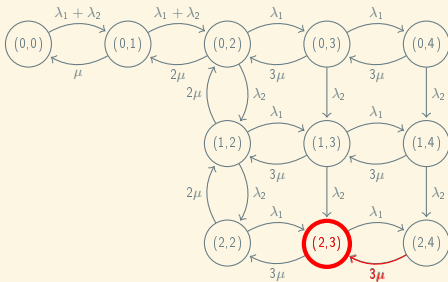
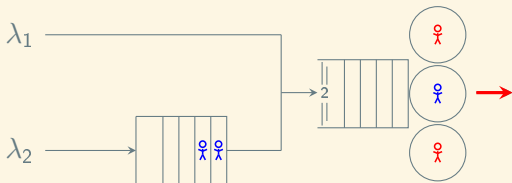
Markov Chain - Custom network - $N = 4, M = 2$



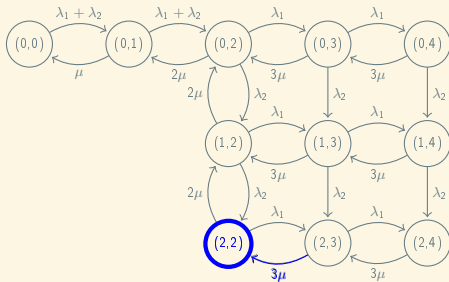
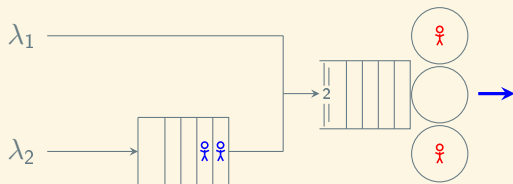
Markov Chain - Custom network - $N = 4, M = 2$



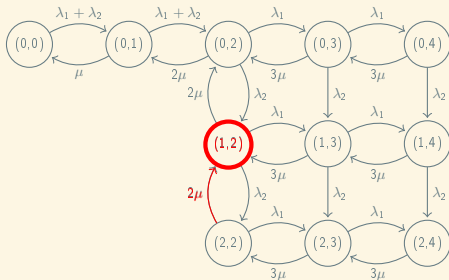
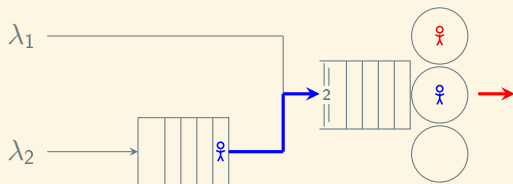
Markov Chain - Custom network - $N = 4, M = 2$



Markov Chain - Custom network - $N = 4, M = 2$



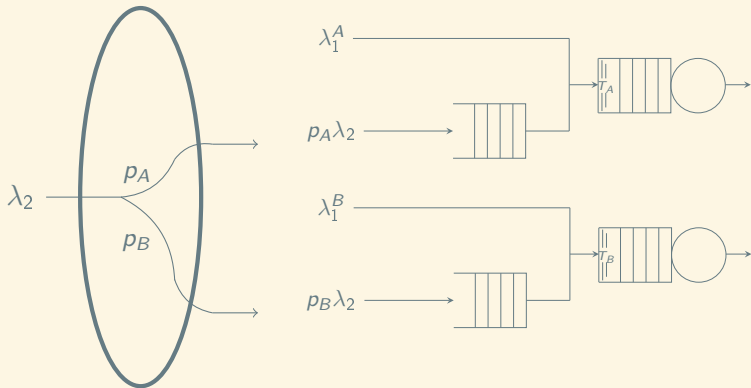
Markov Chain - Custom network - $N = 4, M = 2$



Game - Definition

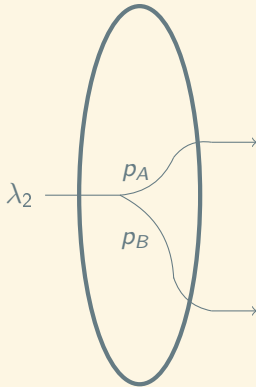


Game - Players and objectives

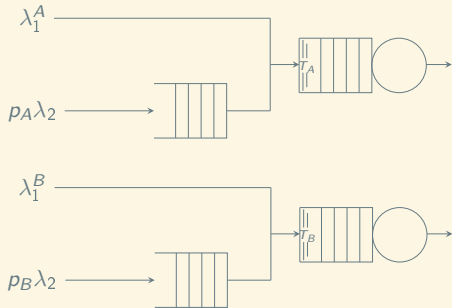


Game - Players and objectives

Blocking time



Proportion of individuals within target



Performance Measures - Blocking time

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

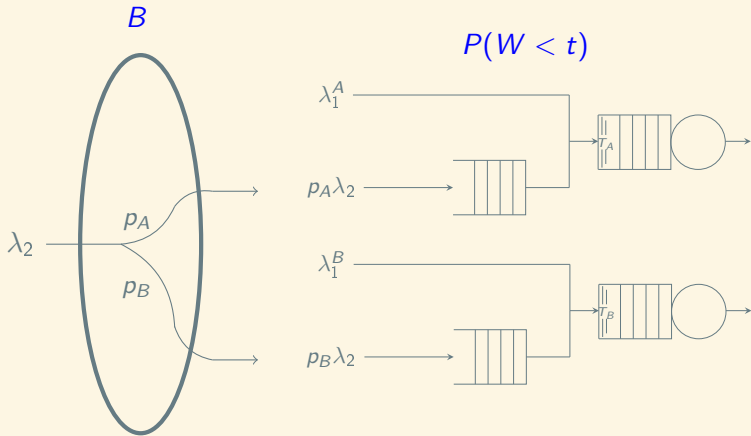
Performance Measures - Proportion within target

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

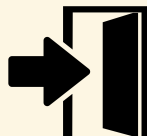
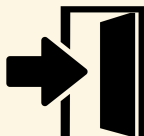
$$P(W^{(1)} < t) = \frac{\sum_{(u,v) \in S_A^{(1)}} P(W_{(u,v)}^{(1)} < t) \pi_{u,v}}{\sum_{(u,v) \in S_A^{(1)}} \pi_{u,v}}$$

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

Game - Players and objectives



Game - Strategies



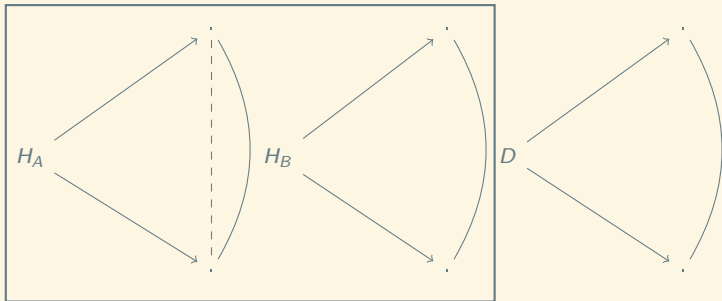
$$p_A, p_B \in [0, 1]$$

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

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

$$p_A + p_B = 1$$

Game - Formulation



Hospital's utility

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

Game - Payoff matrices

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

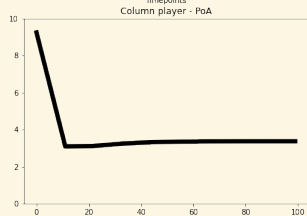
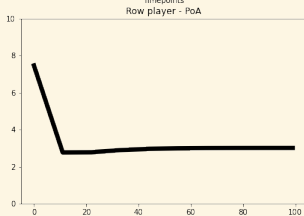
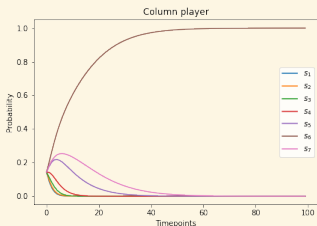
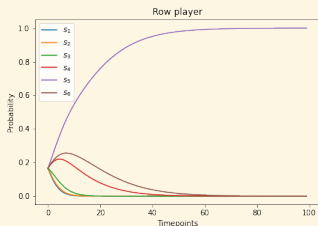
$$R = \begin{pmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,N_B} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,N_B} \\ \vdots & \vdots & \ddots & \vdots \\ p_{N_A,1} & p_{N_A,2} & \cdots & p_{N_A,N_B} \end{pmatrix}$$

Asymmetric Replicator Dynamics

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

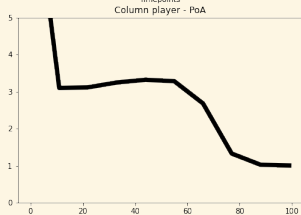
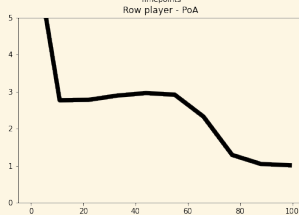
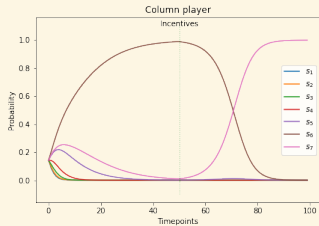
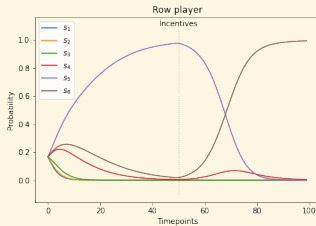
$$\frac{dy}{dt}_i = y_i((f_y)_i - \phi_y), \quad \text{for all } i$$

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!

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

✉ PanayidesM@cardiff.ac.uk

🐦 @Michalis_Pan

📺 @11michalis11