

# Emergent Behaviour in Stochastic Queueing Systems

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# Overview

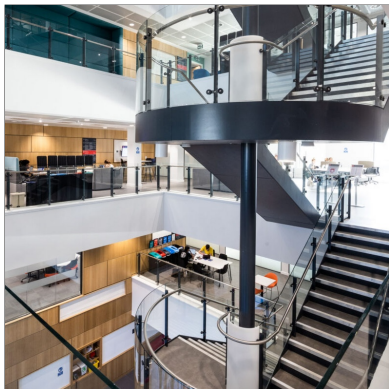
- i. Motivation - Abacws
- ii. Background to game theory & emergent behaviour
- iii. Discrete Event Simulation
- iv. Discrete Event Population Updates
- v. Recovering known results
- vi. Abacws jockeying scenario

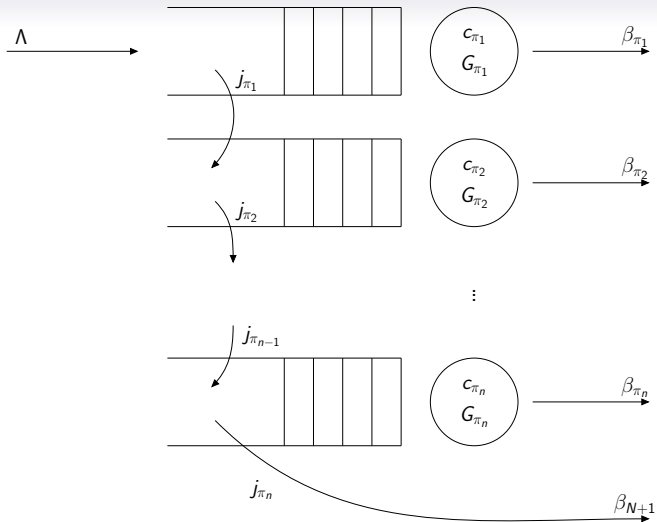
# Motivation & Inspiration

Using Replicator Dynamics to Model Seating Strategies in Abacws

Anthony Holman, Katherine Zverovich, Megan Allen and Rachel Banks

April 2024





$$s = (\pi, j)$$

$$s = (\pi = (3, 1, 2, 1), j = (0.5, 1.2, 0.4, 3.3))$$

Corresponds to:

- First queue at **node 3**, and wait a maximum of **0.5 time units**;
- If still waiting after for service **0.5 time units**, jockey to **node 1**, and wait a maximum of **1.2 time units**;
- If still waiting after for service **1.2 time units**, jockey to **node 2**, and wait a maximum of **0.4 time units**;
- If still waiting after for service **0.4 time units**, jockey to **node 1**, and wait a maximum of **3.3 time units**;
- If still waiting after for service **3.3 time units**, renege from the system.

## Fitness of a Strategy

$$f_s = e^{-\kappa \mathbb{E}(C)} = e^{-\kappa \left( \mathbb{E}(L)\beta + \sum_{k=0}^K (\mathbb{E}(W_{\pi_k}) + \mathbb{E}(T_{\pi_k})) \right)}$$

Where:

- $\kappa$  is the selection intensity,
- $L$  is a binary variable indicating if the customer was lost,
- $\beta_{N+1}$  is the cost of being lost,
- $\beta_{\pi_k}$  is the cost of being served at  $\pi_k$ ,
- $W_{\pi_k}$  is the waiting time at node  $\pi_k$ ,
- $T_{\pi_k} = \epsilon g_{\pi_k} + \beta_{\pi_k}$  service time plus cost of service at node  $\pi_k$ , if they were served there, 0 otherwise.

## Travel Times between Service Centres

$$c_1 = 2, \quad c_2 = 5$$

- $s_1 = ((1, 2), (5, 5))$
- $s_2 = ((2, 1), (6, 8))$
- $s_3 = ((2, 1, 2), (4, 3, 3))$

$$T = \begin{pmatrix} 0 & 10 \\ 7 & 0 \end{pmatrix}$$

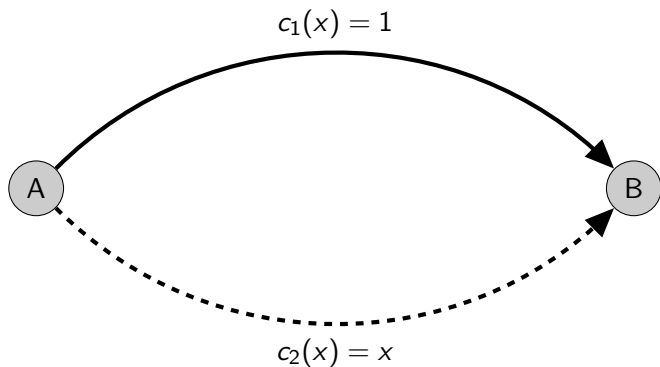
$$c_1 = 2, \quad c_2 = 5, \quad c_3 = 0$$

- $s_1 = ((1, 3, 2), (5, 10, 5))$
- $s_2 = ((2, 3, 1), (6, 7, 8))$
- $s_3 = ((2, 3, 1, 3, 2), (4, 7, 3, 10, 3))$



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## Example of a Game - Pigou's Routing Game



$x$  = proportion taking the shortcut

## Social (overall) Optimum

Strategy  $\hat{x}$  that minimises the sum of everyone's travel times:

$$\begin{aligned}\hat{x} &= \arg \min_x (1-x)c_1(x) + xc_2(x) \\ &= \arg \min_x x^2 - x + 1 \\ &= \frac{1}{2}\end{aligned}$$

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## Selfish Equilibrium

Strategy  $x^*$  that causes no reason to move, when travel times are equal:

$$\begin{aligned}c_1(x^*) &= c_2(x^*) \\ 1 &= x^*\end{aligned}$$

## Example of a Game - Stag Hunt

		Column Player	
		Stag	Hare
Row Player	Stag	(10, 10)	(1, 8)
	Hare	(8, 1)	(5, 5)

# Replicator Dynamics

If there is a population of players, with proportion  $x_s$  playing strategy  $s$ , all playing against each other, then:

$$\frac{dx_s}{dt} = x_s (f_s - \phi) \quad \text{for all } s \in S$$

where  $\phi = \sum_{s \in S} x_s f_s$  is the population's average fitness.

A stable population is when  $\frac{dx_s}{dt} = 0$  for all  $s \in S$ .

# Replicator Dynamics - Stag Hunt

Proportion of stag hunters =  $y$ , Proportion of hare hunters =  $1 - y$

$$f_{\text{stag}} = (10)(y) + (1)(1 - y) = 9y + 1$$

$$f_{\text{hare}} = (1)(y) + (5)(1 - y) = -4y + 5$$

$$\begin{aligned}\phi &= yf_{\text{stag}} + (1 - y)f_{\text{hare}} \\ &= y(9y + 1) + (1 - y)(-4y + 5) \\ &= 13y^2 - 8y + 5\end{aligned}$$

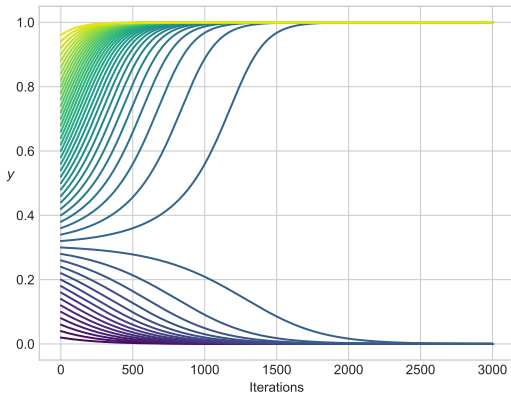
$$\begin{aligned}\frac{dy}{dt} &= y(f_{\text{stag}} - \phi) \\ &= y((9y + 1) - (13y^2 - 8y + 5)) \\ &= -13y^3 + 17y^2 - 4y\end{aligned}$$

$$y = 0, \quad y = \frac{4}{13}, \quad y = 1$$

# Numerical Methods

e.g. Euler method:

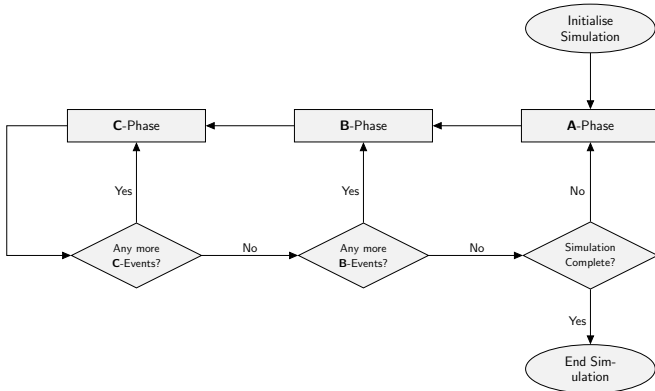
$$y_{t+1} = y_t + \frac{dy}{dt} \Delta t$$





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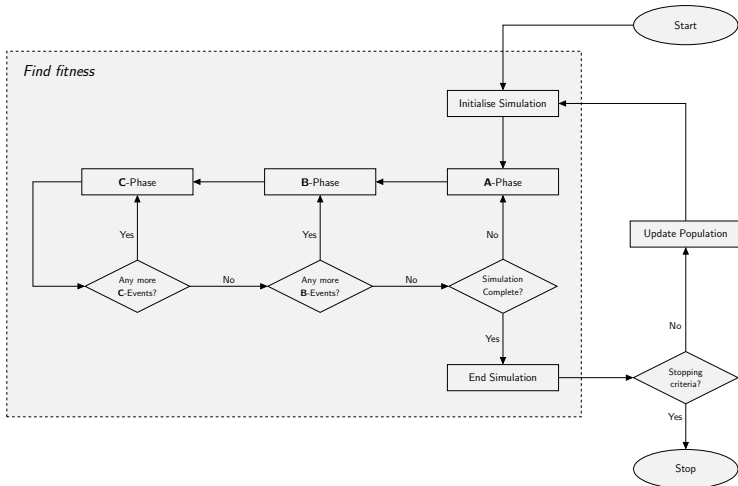
# Discrete Event Simulation



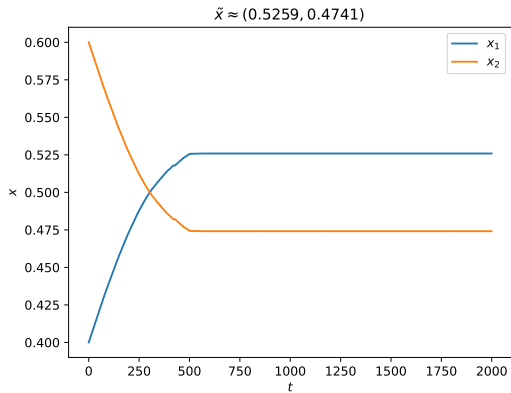


```
>>> import ciw
>>> N = ciw.create_network(
...     arrival_distributions=[ciw.dists.Exponential(5)],
...     service_distributions=[ciw.dists.Exponential(2)],
...     number_of_servers=[4]
... )
>>> ciw.seed(0)
>>> Q = ciw.Simulation(N)
>>> Q.simulate_until_max_time(1000)
>>> recs = Q.get_all_records()
>>> waits = [r.waiting_time for r in recs if r.arrival_date > 100]
>>> sum(waits) / len(waits)
0.0957353996505342
```

# Numerical Method with Discrete Event Simulation

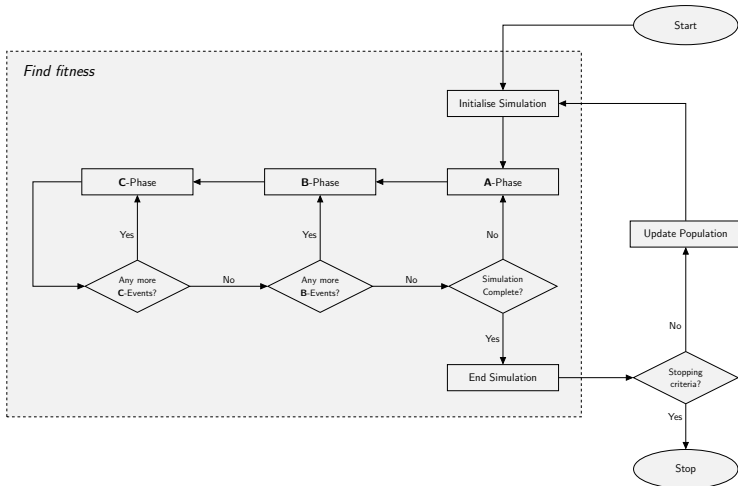


## Jockeying example:

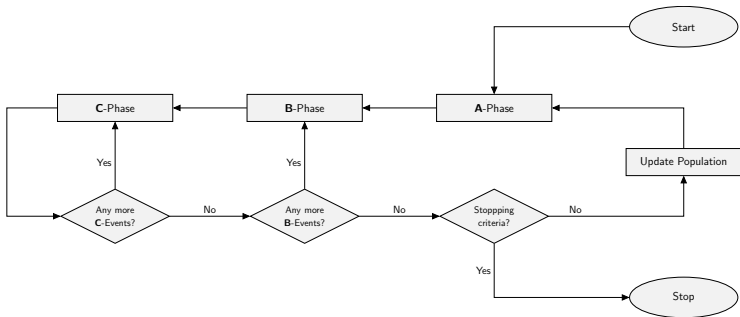


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# Numerical Method with Discrete Event Simulation



# DEPU - Discrete Event Population Updates

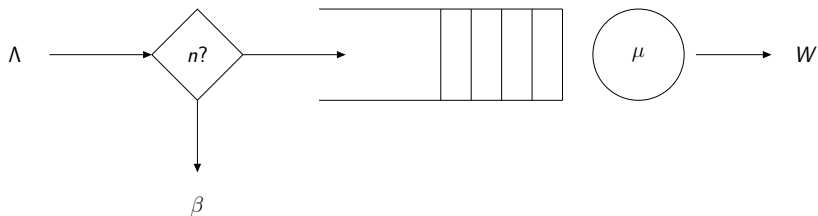


$$f_{s,i+1} \leftarrow (1 - \alpha)f_{s,i} + \alpha f^*$$



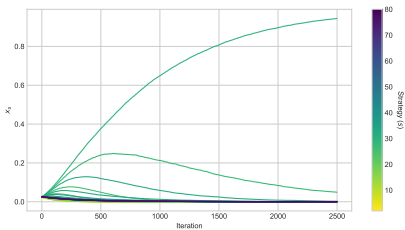
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# Naor (1969)



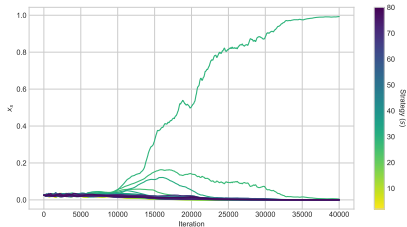
Emergent strategy:  $n = \beta\mu$

## Numerical Method + Simulation



( $\approx 5$  hours)

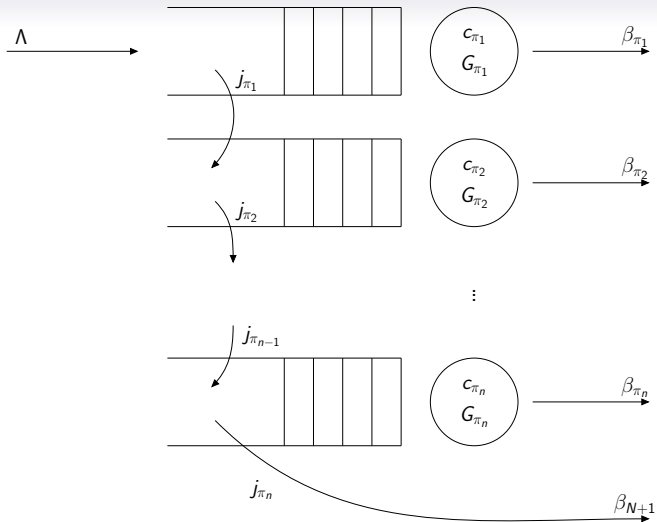
## DEPU



( $\approx 5$  minutes)

$$\Lambda = 30, \mu = 20, \beta = 1.5$$

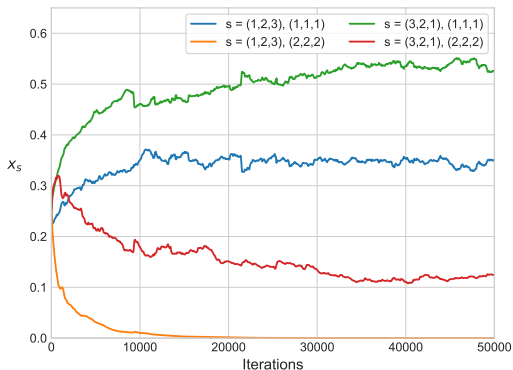
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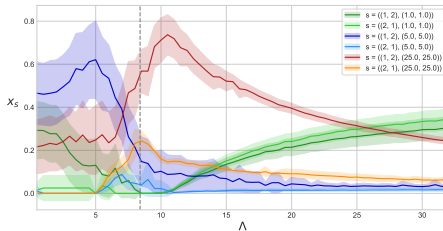
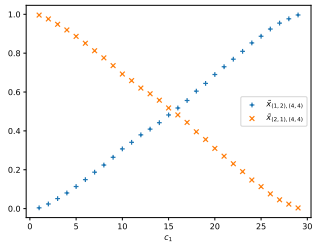
$$s = (\pi, j)$$

# Applying DEPU

- $\Lambda = 32$ ,
- $c_1 = 1, c_2 = 3, c_3 = 1$ ,
- $\mu_1 = 4, \mu_2 = 8, \mu_3 = 12$ ,
- $\beta_1 = \beta_2 = \beta_3 = 0$ ,
- $\beta_4 = 5$ ,
- $\epsilon = 0$ ,
- $\kappa = 0.2$ ,
- $s_1 = ((1, 2, 3), (1, 1, 1))$ ,
- $s_2 = ((1, 2, 3), (2, 2, 2))$ ,
- $s_3 = ((3, 2, 1), (1, 1, 1))$ ,
- $s_4 = ((3, 2, 1), (2, 2, 2))$ ,
- $\Delta t = 0.01$ ,
- $\alpha = 0.1$ ,



# Effect of Parameters



## Next steps...

- Investigate other update rules
- Incorporate variability in fitness function