A Method for Analysing Complex Markovian Models

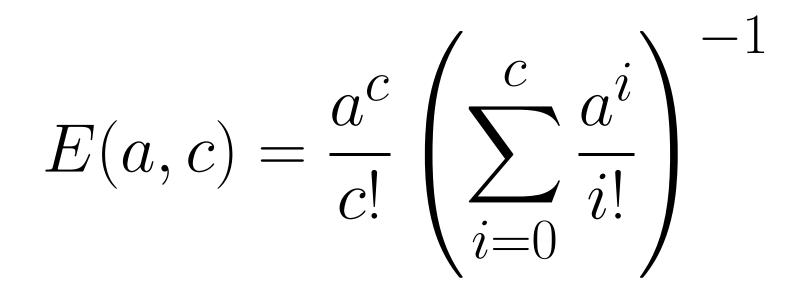
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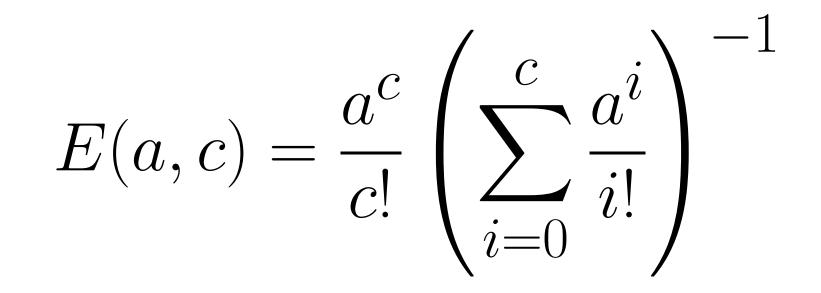


ARC CENTRE OF EXCELLENCE FOR MATHEMATICS

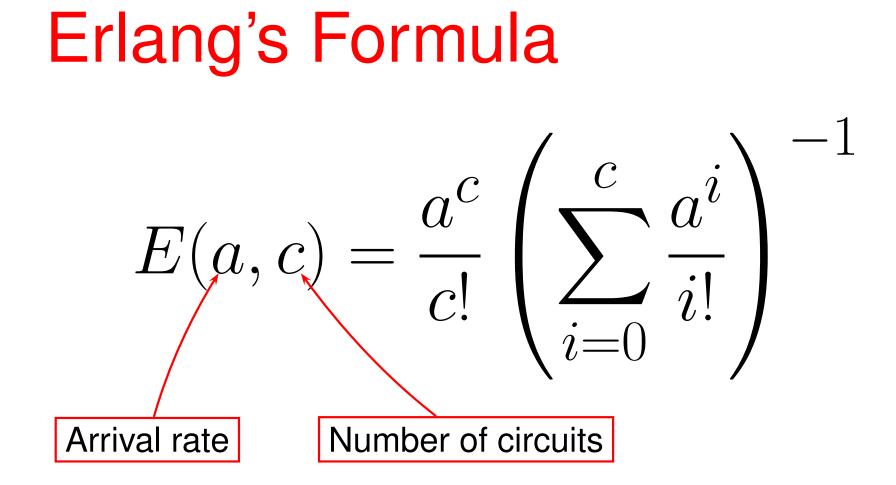
AND STATISTICS OF COMPLEX SYSTEMS



Erlang's Formula



Erlang's Formula $(a, c) = \frac{a^c}{c!} \left(\sum_{i=0}^{c} \frac{a^i}{i!} \right)$ E Arrival rate

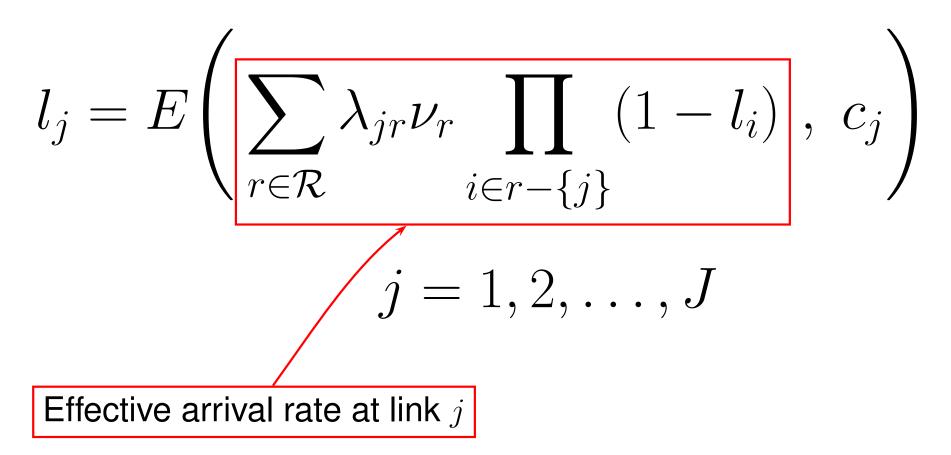


MASCOS

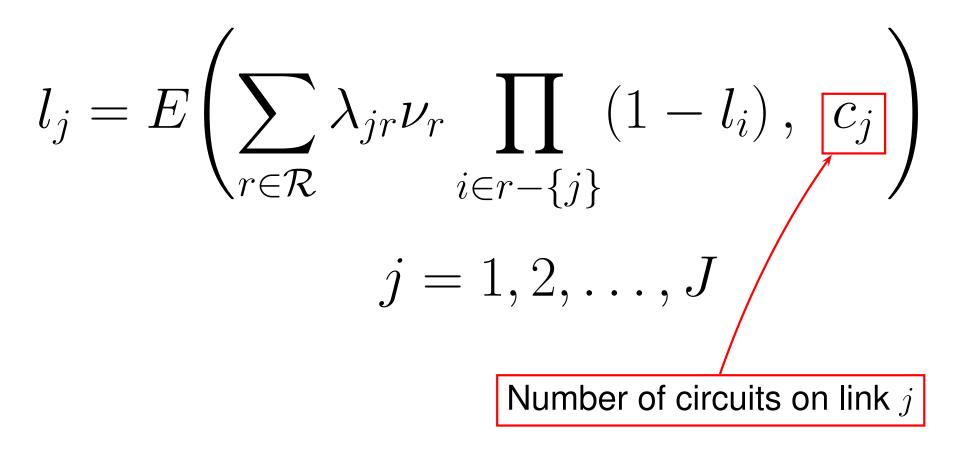
 $l_j = E\left(\sum_{r \in \mathcal{R}} \lambda_{jr} \nu_r \prod_{i \in r - \{j\}} (1 - l_i), c_j\right)$ $j=1,2,\ldots,J$

Erlang fixed point approximation $l_{j} = E\left(\sum_{r \in \mathcal{R}} \lambda_{jr} \nu_{r} \prod_{i \in r - \{j\}} (1 - l_{i}), c_{j}\right)$ $j = 1, 2, \dots, J$

Erlang fixed point approximation



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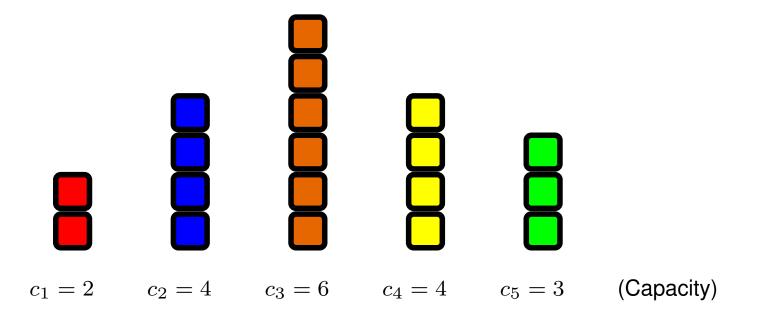


Consider any large-scale stochastic system whose natural state description is Markovian, yet its behaviour (equilibrium or time-dependent behaviour) is difficult to analyze.

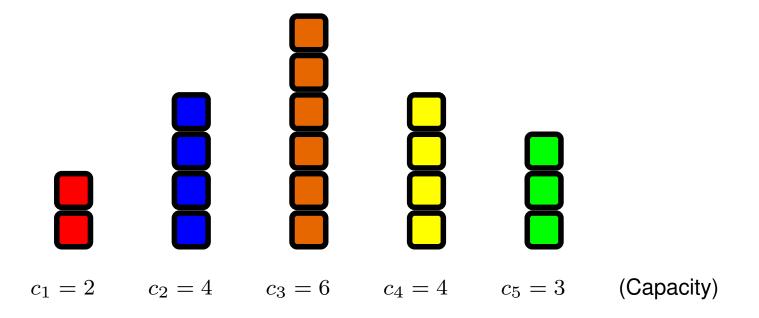
Can we find an alternative state description, together with an approximating transition structure, that can be analyzed more simply?

Our goal is to approximate quantities of interest and to assess the quality of the approximation.

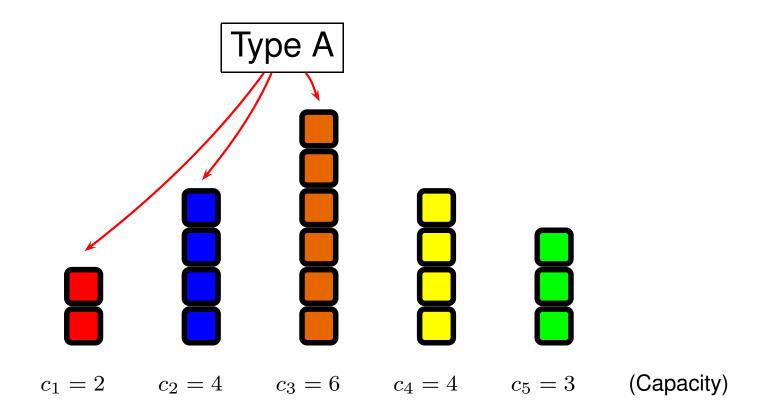
A collection of resources of different types and differing amounts (capacities)



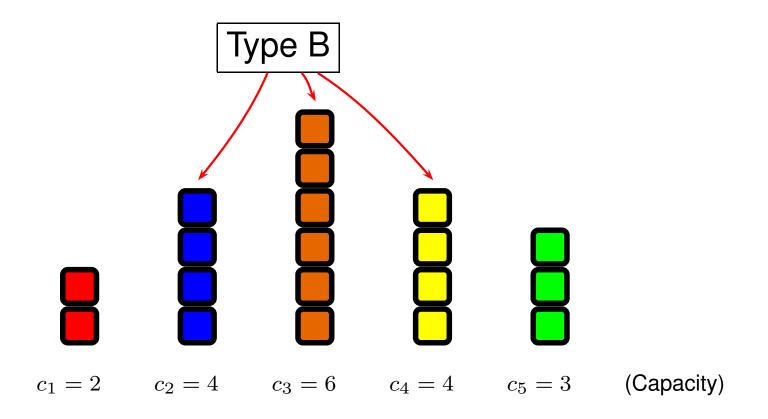
Customers of different types arrive as independent Poisson streams and request groups of resources



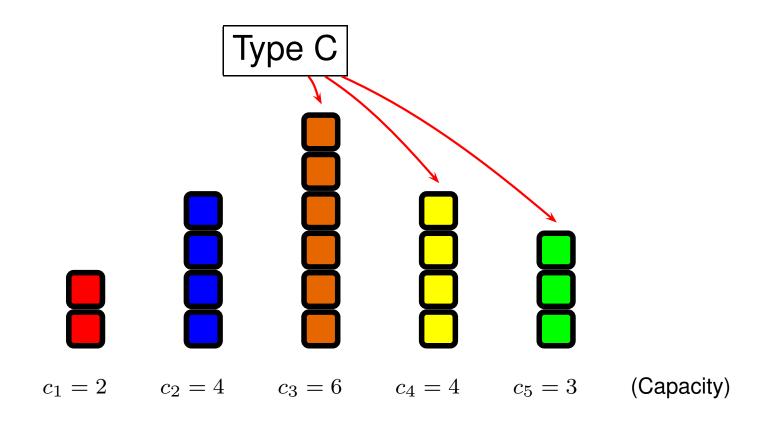
Customers are identified by *which* resources they require



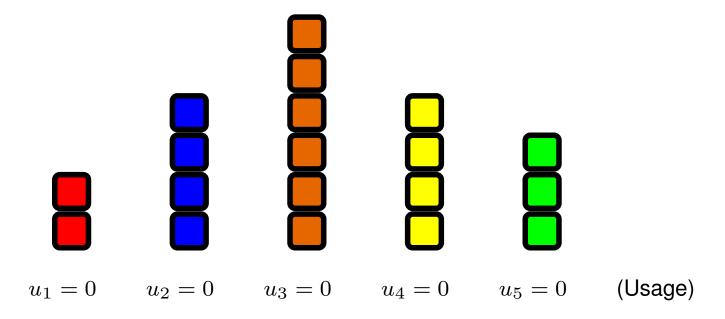
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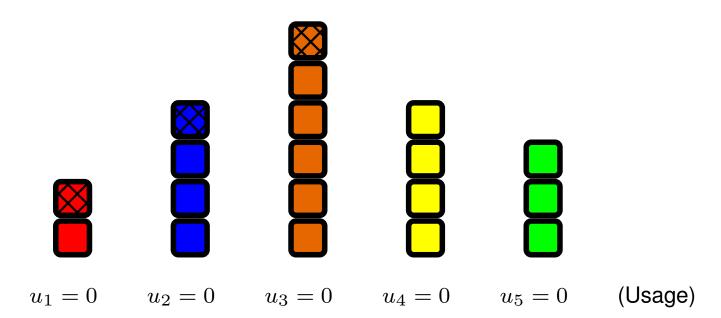
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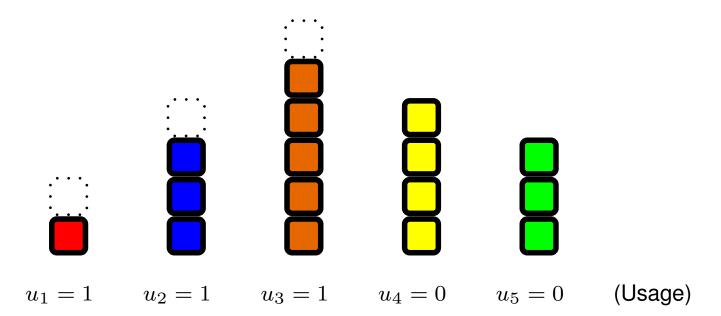
Resources are captured and held for a random period and released simultaneousness



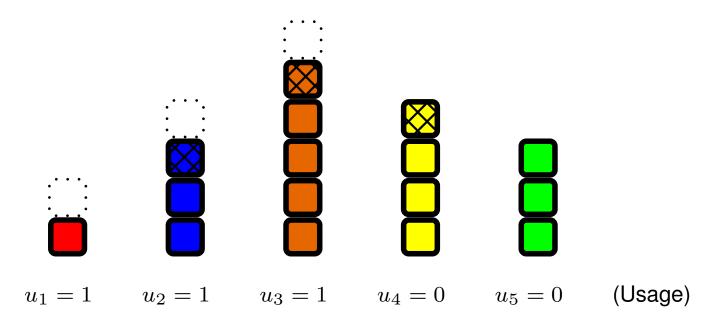
Type A $(n_A = 0)$ Type B $(n_B = 0)$ Type C $(n_C = 0)$



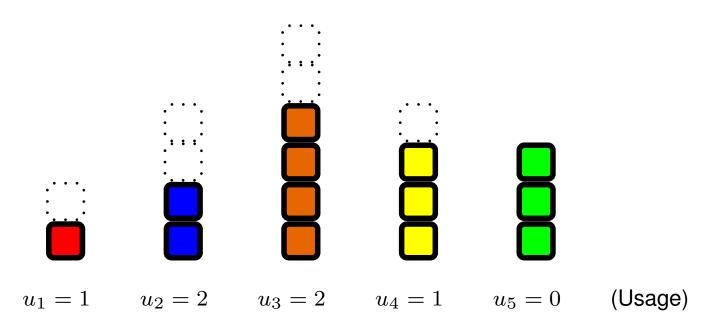
Type A
$$(n_A = 1)$$
Image: Constant of the second secon



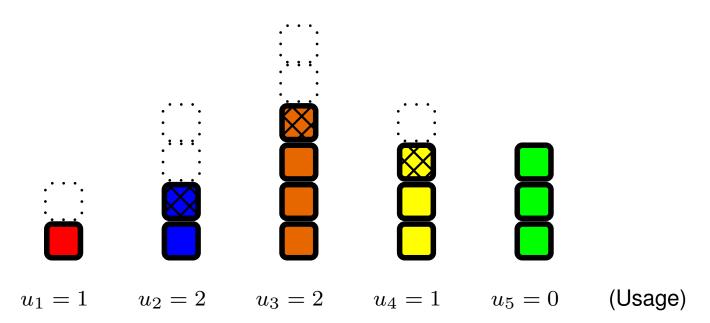
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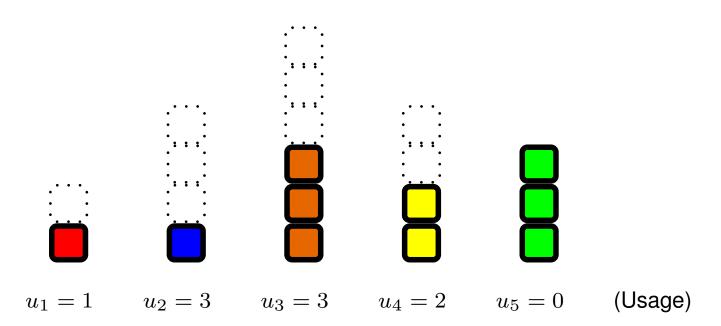
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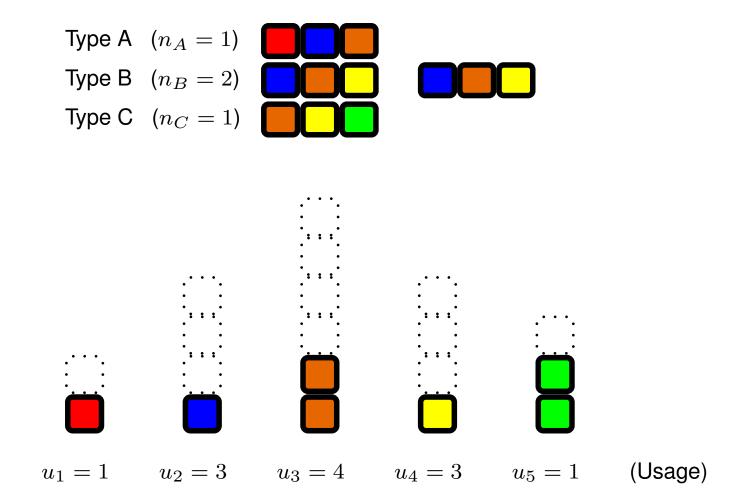


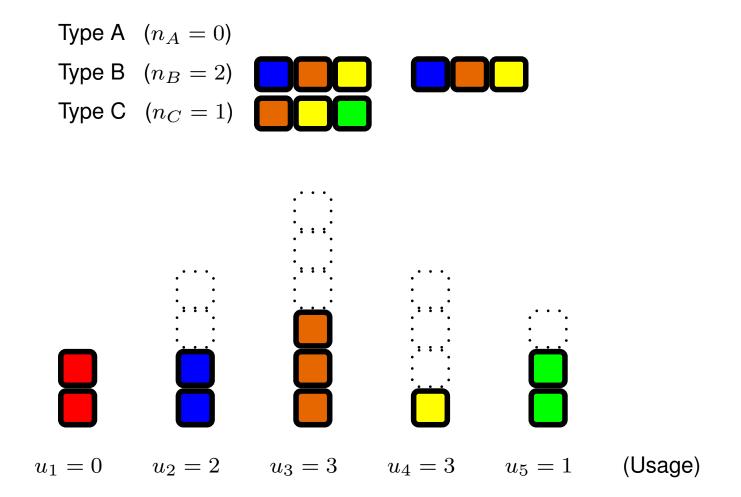
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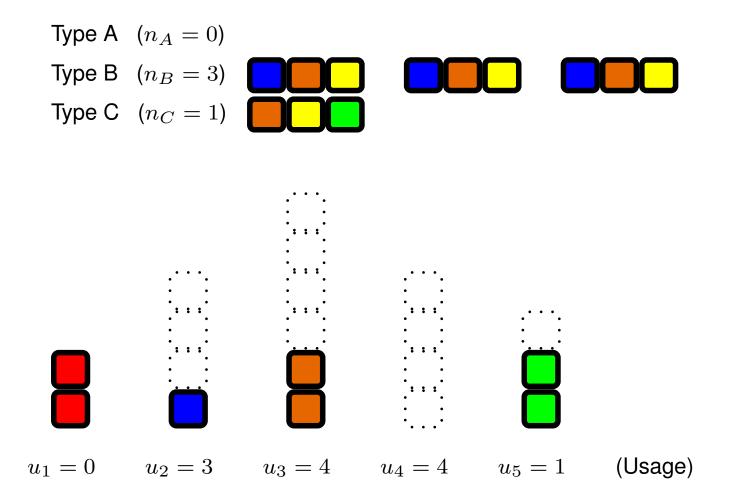


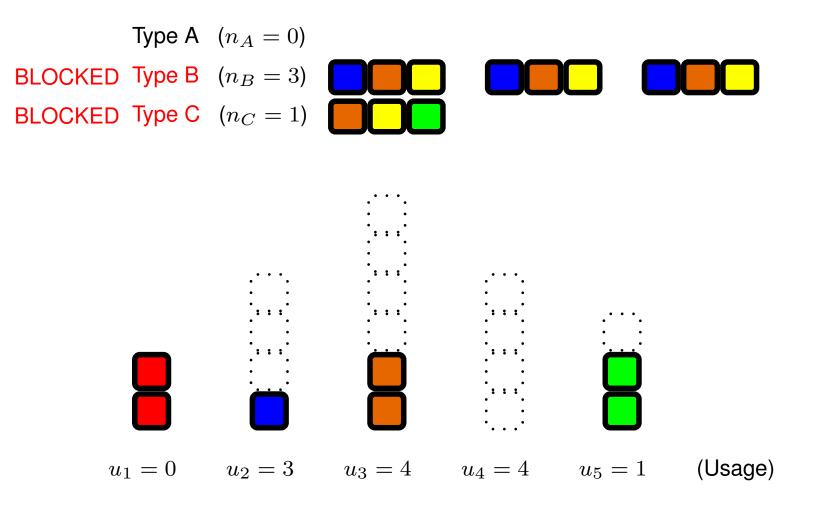
Type A
$$(n_A = 1)$$
Image: Constraint of the second sec











Type-B and Type-C customers are now blocked because there is no more

Let \mathcal{R} be the set of customer types and let $\mathbf{n} = (n_r, r \in \mathcal{R})$, where n_r is the number of type-r customers in the system.

Let $\mathbf{c} = (c_j, j = 1, ..., J)$ be the resource capacities, and $\Lambda = (\lambda_{jr})$ be the $J \times \mathcal{R}$ design matrix with $\lambda_{jr} = 1$ if resource *j* is used by type-*r* customers. The set of all states is then $S = \{\mathbf{n} \in \mathbb{Z}_+^{\mathcal{R}} : \Lambda \mathbf{n} \leq \mathbf{c}\}.$

If type-*r* customers arrive at rate ν_r (independent Poisson streams) and hold sets of resources for independent exponentially distributed times (with unit mean say), then $(\mathbf{n}_t, t \ge 0)$ is a Markov chain with transition rates:

$$q(\mathbf{n}, \mathbf{n} + \mathbf{e}_r) = \nu_r \qquad q(\mathbf{n}, \mathbf{n} - \mathbf{e}_r) = n_r$$

(here e_r is the unit vector with a 1 as its *r*-th entry).

The chain has stationary distribution

$$p(\mathbf{n}) = B \prod_{r \in \mathcal{R}} \frac{\nu_r^{n_r}}{n_r!}, \qquad \mathbf{n} \in S,$$

where $B = B(\mathbf{c})$ is a normalizing constant.

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However, this cannot (usually) be computed in polynomial time.

Expected rates

We have a large-scale stochastic system whose natural state description is Markovian, yet its behaviour (equilibrium or time-dependent behaviour) is difficult to analyze.

Idea (Peter Taylor, 1996). Find an alternative state description, together with an approximating transition structure, that can be analyzed more simply. For this description, *impose* a Markovian assumption: the rates of transition are given by the expected rates of the corresponding transitions of the original chain:

$$q'(u,v) = \mathcal{E}_p\left(\sum_{\mathbf{m}\in A(\mathbf{n}(t))} q(\mathbf{n}(t),\mathbf{m})\right),\,$$

where $n \to A(n)$ is all transitions out of n that give rise to a $u \to v$ transition in the new structure.

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Modified idea.

$$q'(u,v) = \mathbf{E}_{\pi^{(0)}} \left(\sum_{\mathbf{m} \in A(\mathbf{n}(t))} q(\mathbf{n}(t),\mathbf{m}) \middle| \mathbf{n}(t) \in \underline{A}_u \right),$$

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Repeat the procedure.

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- π will provide good estimates of quantities of interest
- π will provide the best estimate of a particular quantity of interest among members of a class of distributions (for example, product-form distributions)
- to delimit conditions under which the approximations are good

Focus on the *usage* $\mathbf{u} = (u_j, j = 1, ..., J)$. The process $(\mathbf{u}_t, t \ge 0)$ is not (usually) Markovian. Let

$$\pi(\mathbf{u}) = \prod_{j=1}^{J} \pi_j(u_j), \quad \pi_j(u) = \frac{a_j^u}{u!} \left(\sum_{v=0}^{c_j} \frac{a_j^v}{v!}\right)^{-1} (u = 0, \dots, c_j)$$

where the a_j 's are to be determined. Then,

$$q'(\mathbf{u}, \mathbf{u} + \mathbf{e}_k) = \mathcal{E}_{\pi} \left(\sum_{r \in \mathcal{R}: k \in r} \nu_r \prod_{i \in r - \{k\}} \mathbb{1}_{\{U_i < c_i\}} \middle| U_k = u_k \right)$$

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where $l_i = \pi_i(c_i)$.

Similarly,

$$q'(\mathbf{u},\mathbf{u}-\mathbf{e}_k) = \mathbf{E}_{\pi}\left(u_k \mathbf{1}_{\{U_k=u_k\}} \middle| U_k=u_k\right) = u_k.$$

Similarly,

$$q'(\mathbf{u},\mathbf{u}-\mathbf{e}_k) = \mathbf{E}_{\pi}\left(u_k \mathbf{1}_{\{U_k=u_k\}} \middle| U_k=u_k\right) = u_k.$$

The limiting set of resource blocking probabilities $\mathbf{l} = (l_j, j = 1, ..., J)$ will satisfy

$$l_j = E\left(\sum_{r \in \mathcal{R}} \lambda_{jr} \nu_r \prod_{i \in r - \{j\}} (1 - l_i), c_j\right),$$

where

$$E(a,c) = \frac{a^c}{c!} \left(\sum_{v=0}^c \frac{a^v}{v!}\right)^{-1}.$$
 (Erlang's formula)

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- Plenty of scope for mathematical developments (for example, fixed point theory)