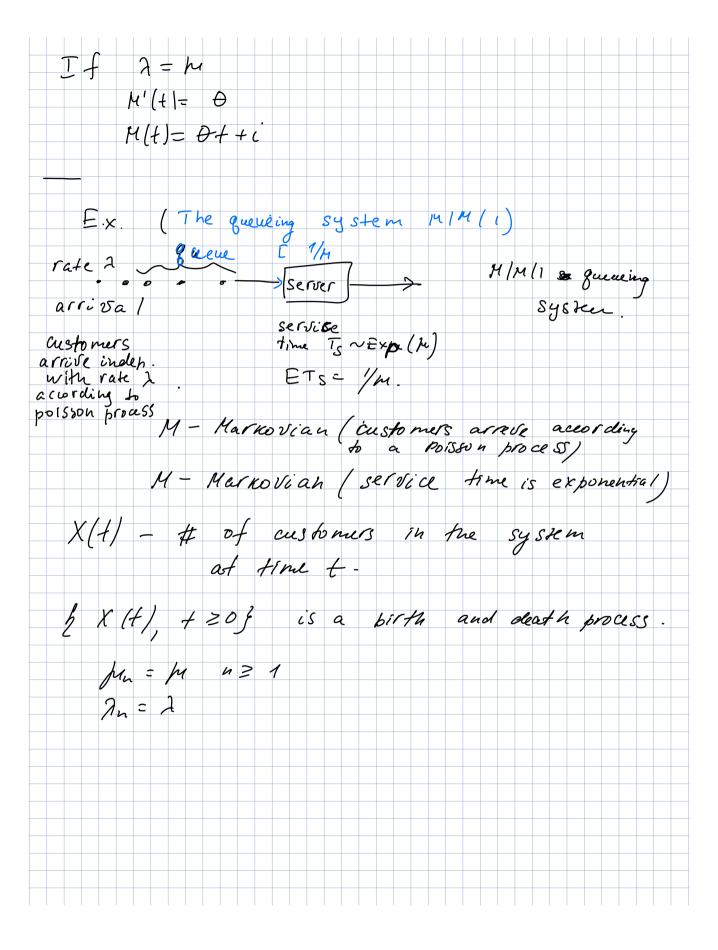
6.3.	Birth	and d	leath process	-
				in the system.
			ter system a	t exponentsal
(ii)	People	leare the	e system an	exponential
	7 _a -	pen time us	ntil next arm	·va/
	Tan	Exp (x.	next departure	, <u>,</u>
) F 7 =	
	Ta and	T _B are	in dependent	
Parameters:	I ma In=	- a	birth rate	
			process is a	continuous-time
MC				continuous-time
MC Sta vo	tes! 9	d death	process is a $process$ is a $process$ is a $process$ is a $process$ $process$ is a $process$	ha;
MC Sta Vo	-tes! 9 5 = λ6 = λ; + λ	d death	process is a	Continuous-time Pini = Mi \(\lambda_i + M_i\)
MC Sta vo	-tes! 9 5 = 25 = 2; + 1	d death	process is a $P_{0,i} = 1$ $P_{1,i+1} = \frac{\lambda_i}{\lambda_i + \mu_i}$	ha;

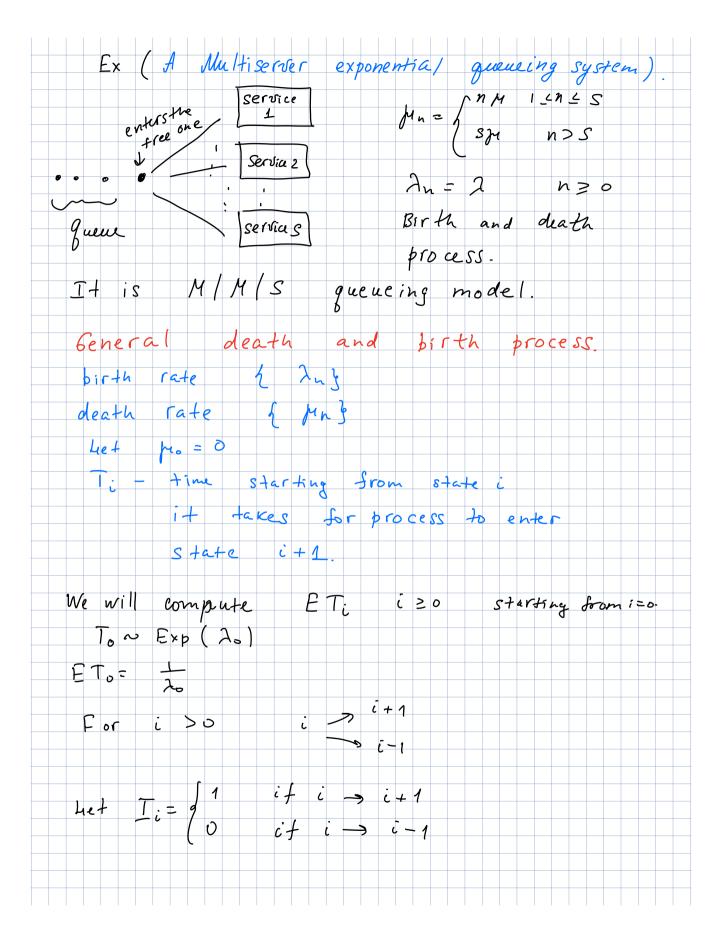
Ex. 6.2. Poisson process. Consider a birth and death process for which Departures never occur Time between successive arrivals $n \in \mathbb{Z}_p(\lambda)$ $ET_i = \frac{1}{\lambda}$ = > Poisson process. Ex. (A birth process with linear birth rate) Consider a population whose members can give pirth to new members but cant die. Each member acts independently of others T-Time until a measber gives a birth $n \to \infty$ (λ) + 4et X(1) be a population size at time t 7 hen { x (+), + > 0 } is a pure birth process $\lambda_n = n\lambda$ $n \ge 0$ The pure birth process is called Yulle process (6. Yule used it in math theory of evolution).

Ex. A linear growth model with immigration. $f_n = n f_1$ $h \ge 1$ growth model with immigrationi) Each individul in the population is assumed to give a birth at an exponential rate 2 2) There is an exponential rate of ingrease o Of the population due to immigration.

3) Deaths are assumed to occure at an exponential rate μ for each member of a population, so $\mu_n = n\mu$. Het X (t) be a population size at time t $\chi(0) = i$ M(t) = E X(t) M(t) - ?We will derive and solve a differential equation. M(t+L) = E(X(t+L)) - E(E(X(t+L)(X(t)))We ignor events whose probability is o(h) $X(t)+1 \quad \text{with prob.} \quad \left[\frac{\partial + X(t)}{\lambda}\right]h+o(h)$ $X(t+h) = \begin{cases} X(t)-1 & \text{with prob.} \\ X(t) & \text{with prob.} \end{cases} X(t) yh+o(h)$ $X(t) \quad \text{with prob.} \quad 1-\left[\frac{\partial + X(t)}{\lambda} + X(t)\right]h+o(h)$ Poisson process $P(N(t+h)-N(t)=1)=\lambda h + o(h)$ $P(N(t+h)-N(t)\geq 2)=o(h)$

Therefore E (X (++h) / X (+)) = X (+) + [0 + x (+) 2 - x (+) m] h+o(h) M(++h)= M(+) + (x-m) M(+) h + Oh + o(h) $\frac{M(++h)-M(+)}{h}=(\lambda-m)M(+)+O+O(h)$ $M'(1) = (\lambda - m) M(1) + D$ de fine $h(t) = (\lambda - m) H(t) + \Theta$ $\frac{h'(t)}{\lambda - h} = h(t)$ h'(+) = > - M dh = (7-m) d+ lu [h(+)] = (2-4) + + luc (x-4) t h(+)= Ke(1-m)+ (2-m M (+) +0= Ke To find K we use an initial conditions M(0) = C $\theta + (\lambda - m) i = K$ $M(t) = K e^{(\lambda - m)t} - \Theta = \frac{(\Theta + (\lambda - m)i)e}{\lambda - m}$ $K(t) = \frac{\Theta}{\lambda} - \frac{(\lambda - m)t}{\lambda} + ie^{(\lambda - m)t} \cdot \frac{\lambda + m}{\lambda}$ $M(t) = \frac{\Theta}{\lambda - m} \left(e^{(\lambda - m)t} - 1\right) + ie^{(\lambda - m)t} \cdot \frac{\lambda + m}{\lambda}$





$$E\left[T_{i} \mid T_{i} = 1\right] = \frac{1}{\lambda_{i} + h_{i}}$$

$$E\left[T_{i} \mid T_{i} = 0\right] = \frac{1}{\lambda_{i} + h_{i}} + E\left(T_{i-1}\right) + ET_{i}$$

$$E\left[T_{i} \mid T_{i} = 0\right] = \frac{1}{\lambda_{i} + h_{i}} + E\left(T_{i-1}\right) + ET_{i}$$

$$E\left[T_{i} \mid T_{i} = 0\right] = \frac{1}{\lambda_{i} + h_{i}} + E\left[T_{i} \mid T_{i}\right] + E\left$$

$$\begin{split} & \int \int_{\mathbb{R}^{n}} \int_{\mathbb{R}^{n$$

$$E \left(Var \left(T_{i} \mid T_{i} \right) \right) = E \left(Var \left(K_{i} \right) \right) + E \left[\left(-T_{i} \right) \mid Var \left(T_{i-1} \right) + War \right]$$

$$= \frac{1}{\lambda_{i} + \mu_{i}} + \frac{\mu_{i}}{\lambda_{i} + \mu_{i}} \left[Var \left(T_{i-1} \right) + Var \left(T_{i} \right) \right]$$

$$E : T_{i} = \frac{\lambda_{i}}{\lambda_{i} + \mu_{i}} = E \left(\mathbf{1} - T_{i} \right) = 1 - \frac{\lambda_{i}}{\lambda_{i} + \mu_{i}} = \frac{\mu_{i}}{\lambda_{i} + \mu_{i}}$$

$$Var \left(T_{i} \right) = \frac{1}{(\mu_{i} + \lambda_{i})^{2}} + \frac{\mu_{i}}{\mu_{i} + \lambda_{i}} \left[Var \left(T_{i-1} \right) + Var \left(T_{i} \right) \right] + \frac{\mu_{i}}{\lambda_{i}} + \frac{\lambda_{i}}{\lambda_{i}} \left[E \left(T_{i-1} \right) + E : T_{i} \right]^{2}$$

$$Var \left(T_{i} \right) = \frac{1}{\lambda_{i}} \left(\lambda_{i} + \mu_{i} \right) + \frac{\mu_{i}}{\lambda_{i}} \left[Var \left(T_{i-1} \right) + \frac{\mu_{i}}{\lambda_{i}} \right] + \frac{\mu_{i}}{\mu_{i} + \lambda_{i}} \left[E \left(T_{i-1} \right) + E : T_{i} \right]^{2}$$

$$Var \left(T_{0} \right) = \frac{\lambda_{i}}{\lambda_{i}} \quad we \quad can \quad get \quad Var \left(T_{i} \right)$$

$$Var \left(+ ime \quad go \quad \delta rom \quad \kappa \quad to \quad j \right) = \sum_{i} Var \left(T_{i} \right)$$

$$E : \kappa$$