

Understanding the generator A

$A = \text{diag}(\lambda)(Q - I)$, so it can be written this way:

$$A = \begin{bmatrix} -\lambda(1) & \lambda(1)Q_{12} & \lambda(1)Q_{13} & \dots \\ \lambda(2)Q_{21} & -\lambda(2) & \lambda(2)Q_{23} & \\ & & -\lambda(3) & \\ & & & \dots \end{bmatrix}$$

Note:

- $-\lambda(i)$ on the diagonal is the rate of leaving state i
- $\lambda(i)Q_{ij}$ is the rate of leaving state i times the probability of jumping to state j . It is best thought of as the rate of jumping from state i to state j .

In applied problems, this can often be figured out directly.

- If state i is absorbing, then $\lambda(i) = 0$ and row i of A is zero, no matter what row i of Q is.
 - Each row of A sums to 0.
 - Knowing the matrix A , one can recover $\lambda(1), \lambda(2), \dots$, then divide each row by these to recover Q .
- So knowing A is equivalent to knowing both λ and Q .

Matlab

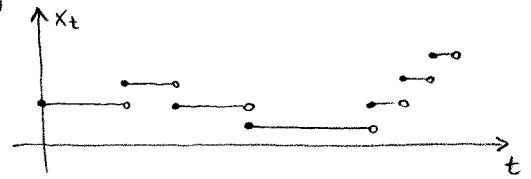
$$\text{lambda} = -\text{diag}(A);$$

$$Q = \text{inv}(\text{diag}(\text{lambda})) * (A + \text{diag}(\text{lambda}));$$

(assuming no states are absorbing)

Example Population with birth and death

Population size X_t is Markov, can go up or down by 1 for birth and death.



Get the parameters by writing down the generator first.

$$A = \begin{matrix} & \begin{matrix} 0 & 1 & 2 & 3 & \dots \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ 3 \\ \vdots \end{matrix} & \left[\begin{array}{cccc} 0 & \delta & 0 & 0 \\ 0 & 0 & \beta & 0 \\ \delta & -(\delta+\beta) & 0 & 0 \\ 0 & 2\delta & -(2\delta+\beta) & 0 \\ \vdots & \vdots & \vdots & \vdots \end{array} \right] \end{matrix} \leftarrow \text{rate of jumping is zero.}$$

Rate of jumping from 1 to 2 is β , the birth rate.
1 to 0 is δ , the death rate.

Make row 1 sum to 0.

Rate of jumping from 2 to 3 is 2β , twice the individual birth rate.
2 to 1 is 2δ , ...

Rate from i to $i+1$ is $i\beta$, i to $i-1$ is $i\delta$.

Read off parameters from A :

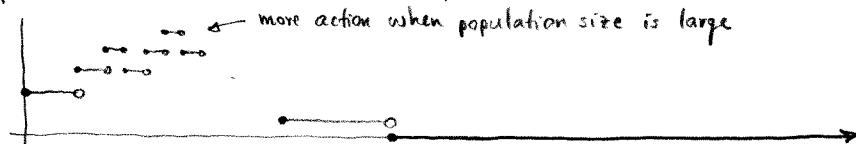
$$\lambda(i) = i(\beta + \delta) \quad \text{rate of leaving state } i$$

$$Q_{i,i+1} = \frac{A_{i,i+1}}{\lambda(i)} = \frac{i\beta}{i(\beta + \delta)} = \frac{\beta}{\beta + \delta}$$

$$Q_{i,i-1} = \frac{\delta}{\beta + \delta}$$

Drift depends on the relative size of β and δ .

Outcome:



0 is absorbing.

If you don't like that, allow

$$A = \begin{matrix} & \begin{matrix} 0 & 1 & 2 & 3 & \dots \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \end{matrix} & \left[\begin{array}{cccc} -\alpha & \alpha & 0 & 0 \\ \alpha & -(\alpha + \beta + \delta) & \beta & 0 \\ 0 & 2\alpha & -(2\alpha + \beta + \delta) & 0 \end{array} \right] \end{matrix}$$

immigration: new individuals arrive at rate α .

Still, no fundamental limit on population growth.

Kolmogorov's forward equation

$$\begin{aligned} \text{We know that } \frac{dP(t)}{dt} &= AP(t) = A \cdot e^{At} = A \sum_{n=0}^{\infty} \frac{A^n t^n}{n!} \\ &= \left(\sum_{n=0}^{\infty} \frac{A^n t^n}{n!} \right) A \\ &= e^{At} A \\ &= P(t) A, \end{aligned}$$

so P satisfies $\frac{dP(t)}{dt} = P(t) A$ as well, which is called Kolmogorov's forward equation.

Example Yule process

We did this earlier.

$$\begin{aligned} \frac{dP_{ij}(t)}{dt} &= (P(t)A)_{ij} = \begin{bmatrix} \dots & P_{i,j-1}(t) P_{j-1}(t) & \dots \\ \dots & P(t) & \dots \\ \dots & \dots & \dots \end{bmatrix} \begin{bmatrix} \dots \\ \dots \\ \dots \\ \lambda(j-1) \cdot 1 \\ \dots \\ \dots \\ \lambda(j) \end{bmatrix} \\ &= \lambda(j-1) P_{i,j-1}(t) - \lambda(j) P_{ij}(t) \end{aligned}$$

Interpretation:

rate of change of probability of being in state j is:

$$\begin{aligned} &(\text{rate of leaving } j-1)(\text{prob. of being in } j-1) \\ &- (\text{rate of leaving } j)(\text{prob. of being in } j) \end{aligned}$$

General interpretation

$$\begin{aligned} \frac{dP_{ij}(t)}{dt} &= (P(t)A)_{ij} \\ &= -\lambda(j) P_{ij}(t) + \sum_{k \neq j} \lambda(k) Q_{jk} P_{ik}(t) \\ &= \begin{array}{l} \text{decrease due to} \\ \text{leaving state } j \end{array} + \begin{array}{l} \text{increase due to the rate of} \\ \text{jumping into state } j \\ \text{from various states } k. \end{array} \end{aligned}$$

This is called the forward equation because it is based on where the process is at time t , which is looking forward in time.

Kolmogorov's backward equation

We derived $\frac{dP(t)}{dt} = AP(t)$ rigorously, but here is a way of thinking of this equation in terms of rates of change.

$$\frac{dP_{ij}(t)}{dt} = (AP(t))_{ij}$$

$$= \left(\begin{array}{c} i \\ \vdots \\ \lambda(i)Q_{ik} \quad \dots \quad -\lambda(i) \\ \vdots \\ j \end{array} \right) \left(\begin{array}{c} \vdots \\ P_{kj}(t) \\ \vdots \end{array} \right)_{ij}$$

$$= -\lambda(i) P_{ij}(t) + \sum_{k \neq i} \lambda(i) Q_{ik} P_{kj}(t)$$

$$= \begin{array}{l} \text{decrease due to the} \\ \text{rate of leaving} \\ \text{state } i \text{ at time } 0 \end{array} + \begin{array}{l} \text{rate of jumping from } i \text{ to } k \text{ at time } 0, \\ \text{then getting from } k \text{ to } j \\ \text{in time } t. \end{array}$$

This is harder to understand intuitively than the forward equation, I think.

475/575
11-30-2000
Reading Taylor & Karlin, Chapter VI.

They write things like (p. 339, Yule process)

$$P(X_{t+h} - X_t = 1 \mid X_t = n) = n \cdot \beta \cdot h + o(h) \text{ as } h \rightarrow 0.$$

(smaller than h)

Interpretation:

$$P(X_{t+h} = n+1 \mid X_t = n) = n\beta h + o(h)$$

$$P_{n,n+1}(h) = n\beta h + o(h)$$

$$\frac{P_{n,n+1}(h)}{h} = n\beta + \frac{o(h)}{h}$$

$$\lim_{h \rightarrow 0} \frac{P_{n,n+1}(h)}{h} = n\beta$$

$$\left. \frac{d}{dh} P_{n,n+1}(h) \right|_{h=0} = n\beta$$

For us,

$$\frac{d}{dt} P(t) = AP(t)$$

$$\left. \frac{d}{dt} P(t) \right|_{t=0} = AP(0) = A$$

$$\left. \frac{d}{dt} P_{n,n+1}(t) \right|_{t=0} = A_{n,n+1} = \lambda(n) Q_{n,n+1},$$

the rate of jumping from n to $n+1$.

Easy translator:

$$P(X_{t+h} = j \mid X_t = i) = \rho h + o(h) \text{ as } h \rightarrow 0$$

means that X jumps from i to j at rate ρ , so $A_{ij} = \rho$.

Examples: pure death
birth & death

$$P(X_{t+h} = k-1 \mid X_t = k) = \mu_k h + o(h)$$

p. 345
p. 356

Numerical calculation of $P(t)$

$$\text{Let } A = \Lambda (-I + Q).$$

$$\text{Then } P(t) = e^{At}.$$

$$\text{For example, } P(1) = e^A,$$

$$P(2) = e^{2A} = (e^A)^2 = P(1) \cdot P(1)$$

$$P(3) = e^{3A} = (e^A)^3$$

Or, use a different time increment:

$$P(n \cdot \Delta t) = e^{n \cdot \Delta t \cdot A} = (e^{\Delta t A})^n.$$

The upshot is this:

1st: compute $e^{\Delta t A}$. Matlab `expm($\Delta t A$)`

2nd: simply raise this to higher powers.

Distribution of X_t

$$\mu(t) = \mu(0) \cdot P(t)$$

$$= \mu(0) \cdot e^{tA}$$

$$\mu(n \cdot \Delta t) = \mu(0) e^{n \cdot \Delta t A}$$

$$= \mu(0) \cdot (e^{\Delta t A})^n.$$

Begin with $\mu(0)$, repeatedly multiply on the right by $e^{\Delta t A}$.

Examples

Limiting distribution of $e^{\Delta t A}$ has one, as a M. chain transition matrix.

Invariant distribution of X_t

In the examples we have seen so far, the distribution of X_t has converged to a limiting distribution π very quickly as $t \rightarrow \infty$.

This is not surprising, since $P(n) = (e^A)^n$, just like raising the transition matrix of a Markov chain to a high power.

Besides, in many cases e^A has all positive entries, so not even periodicity is a problem.

The limiting distribution is an invariant distribution, as before.

Numerical calculation

There are several methods:

$$\pi = e^{At} \text{ for large } t, \quad \text{e.g.} \quad \text{expm}(A * 1000)$$

$$\pi = (e^A)^{1000}, \quad \text{using} \quad \text{expm}(A) ^ 1000$$

$$\pi = \text{invariant}(\text{expm}(A)) \text{ to find the invariant distribution for } P(1) = e^A.$$

Analytic calculation of the invariant distribution

An invariant distribution π would satisfy $\pi P(t) = \pi$ for all t .

Differentiating component by component would give $\frac{d}{dt}(\pi P(t)) = 0$.

But
$$\frac{d}{dt}(\pi P(t)) = \pi \frac{dP(t)}{dt} = \pi (AP(t)) = \pi AP(t).$$

This equals 0 for all t precisely when $\boxed{\pi A = 0}$.

This is more useful than $\pi P(t) = \pi$ since A is easier to obtain, either directly or from λ and Q .

Caution: solving $\pi A = 0$ will only give the solution up to a multiplicative constant. Be sure to normalize π to add up to 1, and make sure it has no negative entries.

Relationship to λ and Q

This is neat:

$$\pi A = \pi \Lambda (Q - I) = 0$$

$$\pi \Lambda Q - \pi \Lambda = 0$$

$$\pi \Lambda Q = \pi \Lambda.$$

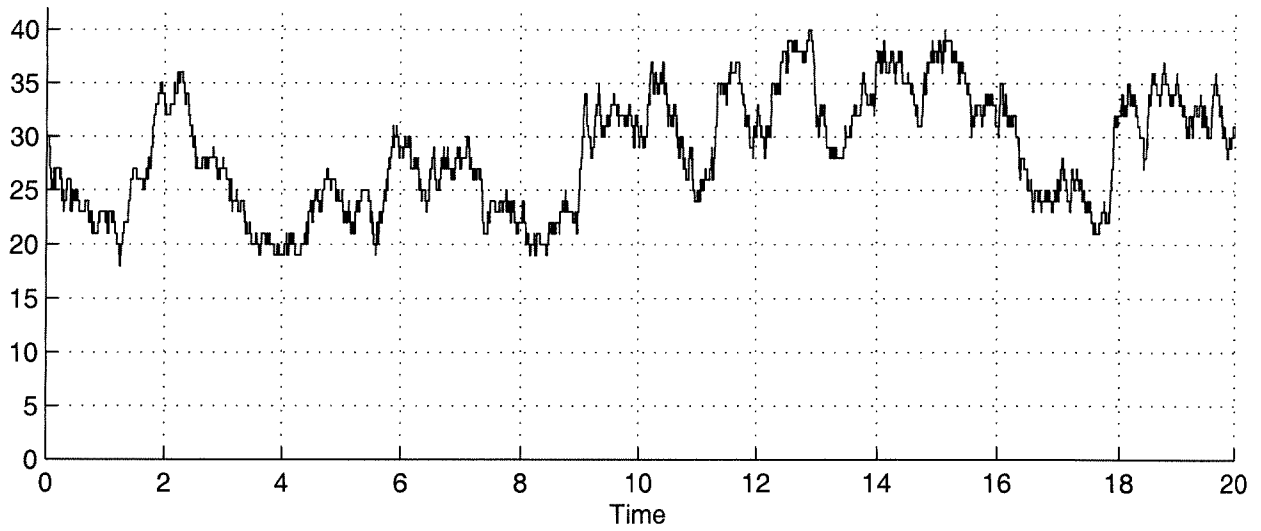
The equation may be written more simply as $\eta Q = \eta$.

Thus, if η is the invariant distribution for the jump matrix Q , then π equals $\eta \Lambda^{-1}$.

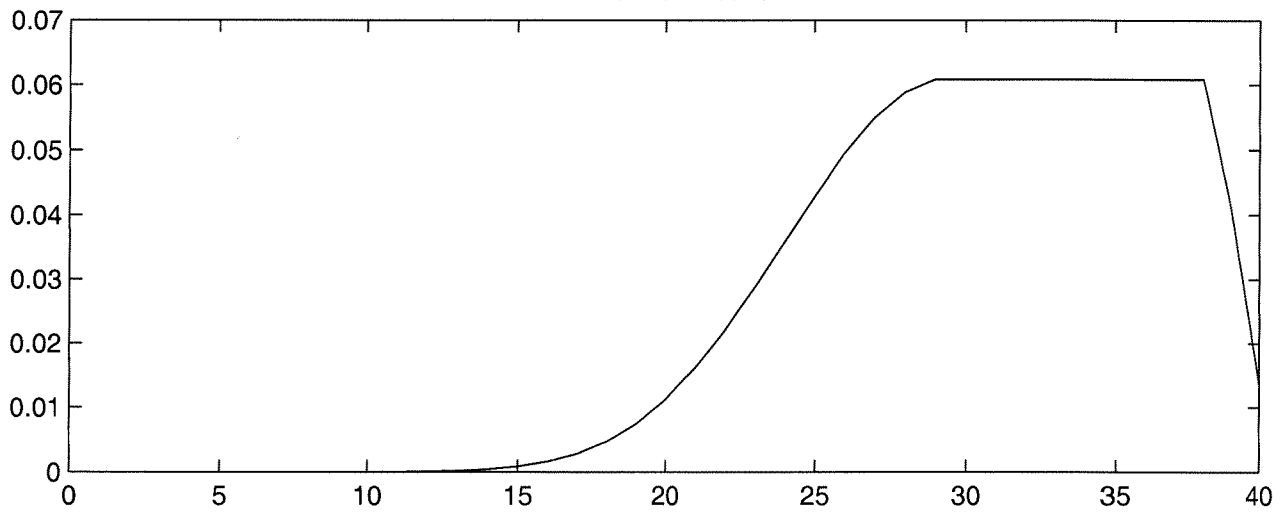
That is, η is what the invariant distribution would be if you considered jumps only, and Λ^{-1} weights each state according to the mean length of time spent there.

Caution: π still needs to be normalized!

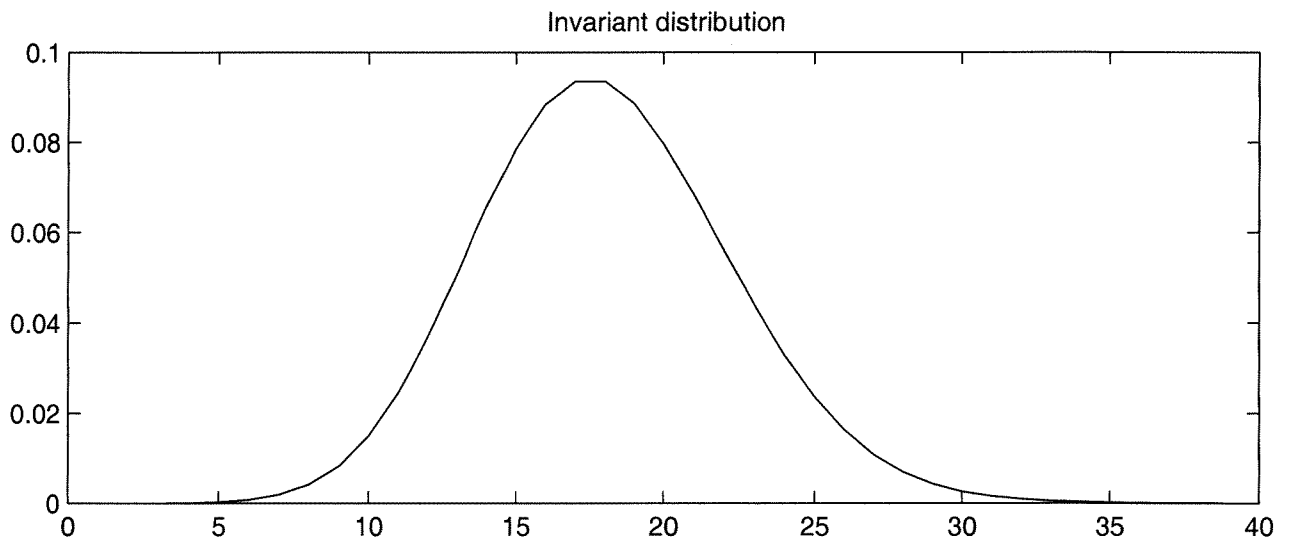
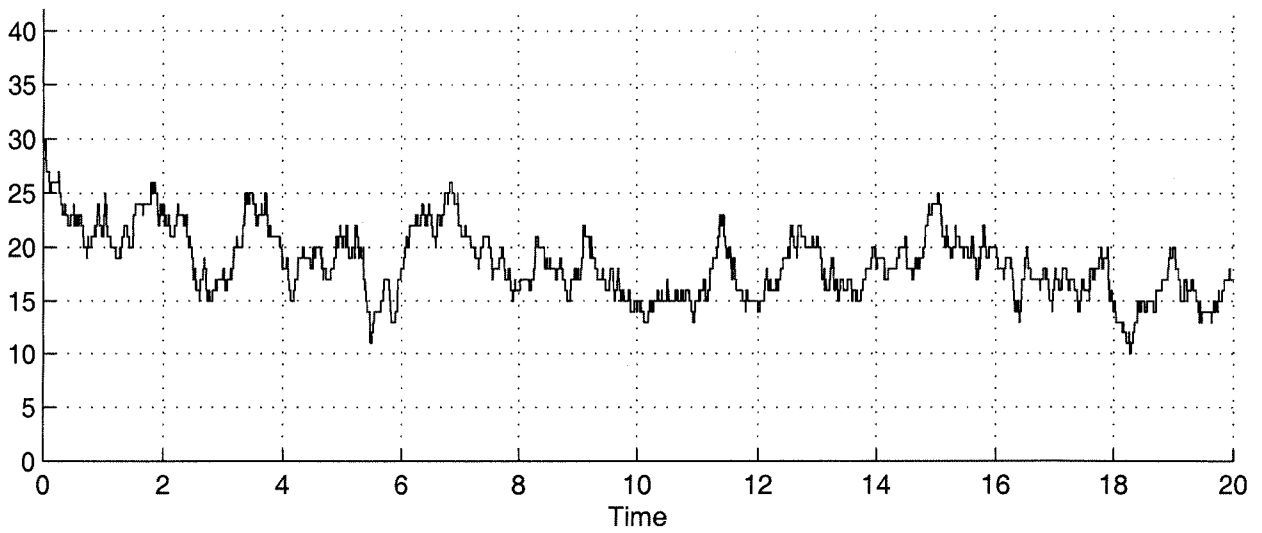
repair.m, $N = 40$, $M = 30$, $R = 3$, $\delta = 1$, $\rho = 10$



Invariant distribution



repair.m, $N = 40$, $M = 30$, $R = 3$, $\delta = 1$, $\rho = 6$



Inv. dist'n:

$$p_i = \text{invariant}(\text{expm}(A));$$

Cost

$$C(X_n)$$

$$C = \begin{bmatrix} 0 \\ 1 \\ \vdots \\ zr \\ ir \\ 30 \\ 0 + 3p \\ 0 \\ \vdots \\ 40 \end{bmatrix}$$

per unit time

plus cost of ~~main~~ having a repair shop.

Expected # working

Ways to improve the system

- more spares
- larger machi shop
- faster repairs
- better trucks