

Fundamental Theorem of Markov Chains:

①

For a finite, ergodic MC defined by P on Σ ,
there is a unique stationary distribution π .

Moreover, for all $i, j \in \Sigma$, $\lim_{t \rightarrow \infty} P^t(i, j) = \pi(j)$.

Ergodic: $\exists t^*$ s.t. $\forall i, j \in \Sigma, P^{t^*}(i, j) > 0$

Irreducible + aperiodic \Rightarrow ergodic

\uparrow
 $\forall i, j \exists t = t(i, j),$
 $P^t(i, j) > 0$

\uparrow
 $\forall i, \text{gcd}(T_i) = 0$
where $T_i = \{t : P^t(i, i) > 0\}$

Stationary distribution π means $\pi P = \pi$.

1. Existence of a stationary distribution:

(2)

Fix a state $k \in \Omega$.

Let $X_0 = k$.

Let T_k be the 1st return time to state k .

(Note, T_k is a random variable.)

For $i \neq k$, let $N_i = \#$ of visits to state i before T_k
(or at T_k).

& let $f_i(k) = E[N_i]$

and set $f_k(k) = 1$.

We'll show that: $f(k)P = f(k)$

where $f(k) = (f_1(k), f_2(k), \dots, f_N(k))$

where $N = |\Omega|$.

then by setting $u(i) = \frac{f_i(k)}{\sum_j f_j(k)}$

we have that $uP = u$ so u is a stationary distribution.

Fix a state $i \neq k$.

$$\begin{aligned}
\text{Then } f_i(k) &= \sum_{t=1}^{\infty} \Pr(X_t=i, T_k \geq t+1 \mid X_0=k) \\
&= \sum_{t=1}^{\infty} \Pr(X_t=i, T_k \geq t \mid X_0=k) \quad (\text{since } i \neq k) \\
&= P(k,i) + \sum_{t=2}^{\infty} \sum_{j \neq k} \Pr(X_t=i, X_{t-1}=j, T_k \geq t \mid X_0=k) \\
&= P(k,i) + \sum_{t=2}^{\infty} \sum_{j \neq k} \Pr(X_{t-1}=j, T_k \geq t \mid X_0=k) P(j,i) \\
&= P(k,i) + \sum_{j \neq k} \sum_{t=2}^{\infty} \Pr(X_{t-1}=j, T_k \geq t \mid X_0=k) P(j,i) \\
&= P(k,i) + \sum_{j \neq k} \sum_{t=1}^{\infty} \Pr(X_t=j, T_k \geq t+1 \mid X_0=k) P(j,i) \\
&= \cancel{P(k,k)} P(k,i) + \sum_{j \neq k} p_j(k) P(j,i) \\
&= \sum_j p_j(k) P(j,i)
\end{aligned}$$

thus, $f_i(k) = \sum_j p_j(k) P(j,i)$ so $f(k) = p(k) P$

We know the existence of a stationary distribution, ④
how to prove uniqueness?
& convergence (i.e., that it's a limiting distribution)?

Consider 2 copies (X_t) & (Y_t) with arbitrary initial states $X_0, Y_0 \in \mathcal{Z}$.

We'll define a coupling so that $\lim_{t \rightarrow \infty} \Pr(X_t \neq Y_t) = 0$

By ergodicity we know there exists t^* such that:
$$P^{t^*}(x, y) > 0 \text{ for all } x, y \in \mathcal{Z}.$$

Thus, there exists $\epsilon > 0$ s.t. for all $x, y \in \mathcal{Z}$,
$$P^{t^*}(x, y) \geq \epsilon.$$

We'll define a t^* -step coupling for X_t, Y_t .

Given $X_{k t^*}$ & $Y_{k t^*}$ for integer $k \geq 0$,

1. Run $X_{k t^*}$ for t^* steps.
2. If $Y_{k t^*} = X_{k t^*}$ then use same $X_t = Y_t$ for all $k t^* \leq t \leq (k+1)t^*$
3. Else, choose independent t^* step evolution $Y_{(k+1)t^*} \Rightarrow Y_{(k+1)t^*}$ for Y_t

(5)

$$\Pr(X_{(k+1)t^*} \neq Y_{(k+1)t^*} \mid X_{kt^*} \neq Y_{kt^*}) \leq 1 - \epsilon$$

thus, $\Pr(X_{kt^*} \neq Y_{kt^*} \mid X_0, Y_0) \leq (1 - \epsilon)^k$

$$\leq e^{-\epsilon k}$$

$$\rightarrow 0 \text{ as } k \rightarrow \infty$$

Setting $Y_0 \sim \mu$ (the stationary distribution we proved exist)

then $Y_t \sim \mu$ for all $t \geq 0$,

& $\lim_{t \rightarrow \infty} X_t = \mu$ so $X_t \rightarrow \mu$ for any $X_0 \in \mathcal{X}$.

& for all $X_0 \in \mathcal{X}$, all $j \in \mathcal{X}$,

$$\lim_{t \rightarrow \infty} \Pr(X_t = j \mid X_0 = i) = \mu(j)$$

i.e., $\lim_{t \rightarrow \infty} P^+(i, j) = \mu(j)$

Note, if we know $T_{\text{mix}}(\frac{1}{4})$ then let $t^* = T_{\text{mix}}(\frac{1}{4})$. ⁽⁶⁾

For any $X_0 \in \mathcal{X}$, for $Y_0 \sim \mu$ then

$$d_{\text{TV}}(X_{t^*}, Y_{t^*}) \leq \frac{1}{4}$$

Moreover for any $X_0 \in \mathcal{X}$, $Z_0 \in \mathcal{X}$,

$$d_{\text{TV}}(X_{t^*}, Z_{t^*}) \leq \frac{1}{2}$$

& \exists a t^* -step coupling of $(X_0, Z_0) \rightarrow (X_{t^*}, Z_{t^*})$

So that $\Pr(X_{t^*} \neq Z_{t^*}) \leq \frac{1}{2}$.

Hence, for any integer $k \geq 0$,

$$\Pr(X_{(k+1)t^*} \neq Z_{(k+1)t^*} \mid X_{kt^*} \neq Z_{kt^*}) \leq \frac{1}{2}$$

$$\& \Pr(X_{kt^*} \neq Z_{kt^*} \mid X_0, Z_0) \leq \frac{1}{2^k}$$

Thus, $T_{\text{mix}}(\epsilon) \leq T_{\text{mix}}(\frac{1}{4}) \log_2(\frac{1}{\epsilon})$.

$$\text{or } T_{\text{mix}}(\epsilon) \leq T_{\text{mix}}(\frac{1}{2\epsilon}) \ln(\frac{1}{\epsilon}).$$

Also, let $\tau_j = E[T_j] =$ mean return time
for state j

then
$$\mu(j) = \frac{1}{\tau_j}$$

(Can verify that this is a
stationary distribution.)