

Notes - 1 April

Review from a question in class: why did we need a PGF last time? 1) Basic problem: finding $\Pi = \Pi P$, Π pmf. Π exists sometimes. Relation to being positive recurrent. 2) Basic problem: find a bounded solution of $Y = PY$ with a row/column “missing”, related to transient. Then we got to ex 3.3.8 - classic example: queuing theory. This example had several points: 1) Consider $\Pi = \Pi P$. Used generating functions. Came to the conclusion that Π exists $\iff \gamma = \sum_{k=0}^{\infty} k a_k < 1$, but only if chain is positive recurrent. So we needed to prove that the chain is positive recurrent so we can solve the problem. 2) We consider solution of $Y = PY, |Y_i| \leq 1$, with missing row/column (not full P). In this case using the fixed point theory we prove Y exists, but this holds iff chain is transient, which holds iff $\gamma > 1$. So, theorem is: positive recurrent if $\gamma < 1$, transient if $\gamma > 1$.

§3.4 - Limit Theorems

We explore the link between a stationary distribution and the behavior of P_{ij}^n as $n \rightarrow \infty$.

Example 3.4.1 - Consider ON/OFF system in ex 2.2.3 with $P = (1-p \text{ p} \ \& \ q \ 1-q)$ $0 \leq p \leq 1, 0 \leq q \leq 1$. When $0 < p, q < 1, P^n \rightarrow \frac{1}{p+q}(q \text{ p} \ \& \ q \text{ p})$ and we know there is a stationary distribution. Now suppose $p = q = 1$, the system changes states at every step. The stationary distribution satisfies $(\Pi_0, \Pi_1) = (\Pi_0, \Pi_1)(0 \ 1 \ \& \ 1 \ 0) \Rightarrow \Pi_0 = \Pi_1 = 1/2$. We can compute, e.g. $P_{00}^n = \{ 0 \text{ if } n \text{ even, } 1 \text{ if } n \text{ odd. There is no limiting behavior in this case. However the states are periodic with period 2.}$

Theorem 3.4.1 - For an irreducible, aperiodic Markov chain, (3.4.1) $P_{ij}^n \rightarrow \frac{1}{\mu_j}$ as $n \rightarrow \infty$ for all i, j (μ_j is the mean recurrence time). The limiting value is the same for all states i . $P^n \rightarrow (1/\mu_0 \ 1/\mu_0 \ \dots \& \ 1/\mu_1 \ 1/\mu_1 \ \dots \& \ \dots)^T = (1/\mu_0 \ 1/\mu_1 \ \dots \& \ 1/\mu_0 \ 1/\mu_1 \ \dots \& \ \dots)$.

Definition 3.4.1 - If there is a probability distribution q on the state space S such that $P_{ij}^n \rightarrow q_j$ for all $i, j \in S$ then q is a limit distribution of the chain.

Intuition: q_j describes the probability that the chain is in state j at some “late” time and by this time the chain has “forgotten” where it started. $P(X_n = j) = \sum_i P(X_0 = i) P_{ij}^n \rightarrow q_j$ regardless of the initial distribution of X_0 . Consequences:

Theorem 3.4.2 - (a) If the chain is transient or null recurrent, then $P_{ij}^n \rightarrow 0$ for all i, j . (b) If the chain is positive recurrent, then $P_{ij}^n \rightarrow \Pi_j = \mu_j^{-1}$, where Π is the unique stationary distribution.

Theorem 3.4.3 - If X_n is an irreducible chain with period d , then $Y_n = X_{nd}, n \geq 0$, is an aperiodic, irreducible chain, $P_{jj}^{nd} = P(Y_n = j | Y_0 = j) \rightarrow \frac{d}{\mu_j}$ as $n \rightarrow \infty$. Immediately from this follows the proof of theorem 3.1.6 (see notes).

Connection between limiting and stationary distributions: consider a Markov chain at some “late” time n . The stationary distribution gives the proportion of time spent in the different states up to time n .

The limit distribution gives the proportion of “time” spent in the various states at the large time, where we count by considering many realizations.

Example 3.4.2 - Consider ON/OFF system, ex 3.4.1 again. The stationary distribution $(1/2, 1/2)$ says that equal amounts of time are spent in each state up to some large time, say $n = 1000$. If we look precisely at $n = 1000$, the chain must return to its initial state. Multiple realizations give probability 1 to be in the initial state and 0 to be in the other.

Theorem 3.4.4 - An ergodic Markov chain has the property that it has both stationary and limiting distributions and these are equal.

Proof of theorem 3.4.1 - We treat different cases. The simplest case is a transient chain, because theorem 3.1.2 (3) implies $P_{ij}^n \rightarrow 0$ as $n \rightarrow \infty$ for all i, j . The recurrent cases are treated with “coupling”.

Definition - 3.4.2 - Let X_n, Y_n be independent Markov chains with common state space S and common probability transition matrix P . The coupled chain $Z_n = (X_n, Y_n)$ taking values in $S \times S$.

Theorem 3.4.5 - Z_n is a Markov chain with $P_{ij,kl} = P_{ik} P_{jl}$. If X_n, Y_n are irreducible and aperiodic, then Z_n is irreducible. Proof: $P_{ij,kl} = P(Z_{n+1} = (k, l) | Z_n = (i, j)) = P(X_{n+1} = k | X_n = i) \times P(Y_{n+1} = l | Y_n = j)$. X_n, Y_n aperiodic, irreducible \Rightarrow for any i, j, k, l there is an $N = N(i, j, k, l)$ such that $P_{ik}^n P_{jl}^n > 0, n \leq N$. Exercise: this implies Z_n is irreducible.

Comment: this is the only place we use the assumption X_n is aperiodic.

We assume X_n (in thm 3.4.1) is positive recurrent, so it has unique stationary distribution Π . (Consider $Y = X$ in the construction of Z .) Exercise: $Z_n = (X_n, Y_n)$ has a stationary distribution $\nu = (\nu_{ij}, i, j \in S), \nu_{ij} = \Pi_i \Pi_j$. This implies Z_n is also positive recurrent (due to stationary distribution). Choose $X_0 = i, Y_0 = j, Z_0 = (i, j)$. Choose $s \in S$. Set $T = \min(n \geq 1 : Z_n = (s, s))$. The recurrence of Z_n implies that

$P(T < \infty) = 1$ (exercise).