

## ON THE LIMITING DISTRIBUTION FOR BERNOULLI TRIALS WITHIN A MARKOV CHAIN CONTEXT

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### ABSTRACT

Let  $X_1, X_2, \dots$  be a sequence of Bernoulli trials governed by a homogeneous third-order two-state Markov chain. The probability function of  $S_n$ , the number of occurrences in  $n$  successive trials, is obtained. In addition to this, assuming that steady state is already attained the limiting function of  $S_n$  is obtained under the condition that  $nP(X_i = 1) = u$  as  $n \rightarrow \infty$ . Finally we can note that this limiting probability function can be generalized in terms of Leguerre polynomials as already shown in the relevant literature.

KEY WORDS: Third-Order Markov Chain, Markov Bernoulli Sequence

### INTRODUCTION

It is well known that for the independent Bernoulli sequence, the limit of the probability function of  $S_n$  is Poisson with parameter  $u$ . In 1960, Edwards [3] formulated the problem as a Markov chain for the Bernoulli sequence with a correlation between trials and called such a sequence of dependent random variables "Markov Bernoulli sequence". The unconditional probabilities of this sequence are  $P(X_i = 1) = p$  and  $P(X_i = 0) = q = 1 - p$  for all  $i = 1, 2, \dots$ .

Wang [4] obtained the limiting probability function of  $S_n$  for the Bernoulli sequence governed by a first-order two-state Markov chain. Brainerd and Chang [1] derived the probability function of  $S_n$  in the case of the second-order Markov chain and Brainerd [2] obtained the limit of this probability function.

### THE DISTRIBUTION OF $S_n$ IN THE THIRD-ORDER CASE

Let  $X_1, X_2, \dots$  be a Markov Bernoulli sequence governed by a third-order Markov chain. Denote the unconditional probabilities of  $X_i$  by  $P(X_i = 1) = p$ ,  $P(X_i = 0) = q = (1-p)$  and the conditional

probabilities by  $P(X_i = 0 / X_{i-1} = 1) = \alpha$ ,  $P(X_i = 0 / X_{i-2} = 1, X_{i-1} = 0) = \beta$ ,  $P(X_i = 0 / X_{i-3} = 1, X_{i-2} = 0, X_{i-1} = 0) = \xi$ ,  $P(X_i = 0 / X_{i-1} = 0) = w$ ,  $P(X_i = 0 / X_{i-2} = 0, X_{i-1} = 0) = \lambda$ ,  $P(X_i = 0 / X_{i-3} = 0, X_{i-2} = 0, X_{i-1} = 0) = \delta$  for all  $i = 1, 2, \dots$ . These probabilities are independent of  $i$ . In the third-order Markov chain the following identities can be written immediately:

$$P(X_{i-1} = 0, X_i = 1) = P(X_{i-1} = 1, X_i = 0), \quad (1)$$

$$P(X_{i-2} = 0, X_{i-1} = 0, X_i = 1) = P(X_{i-2} = 1, X_{i-1} = 0, X_i = 0) \quad (2)$$

$$P(X_{i-3} = 0, X_{i-2} = 0, X_{i-1} = 0, X_i = 1) = P(X_{i-3} = 1, X_{i-2} = 0, X_{i-1} = 0, X_i = 0) \quad (3)$$

Let

$Y$  = The number of trials to observe the first occurrence of 1, after  $i$ . The conditional probabilities of  $Y$  are

$$P(Y = 0 / X_i = 1) = 0,$$

$$P(Y = 1 / X_i = 1) = 1 - \alpha,$$

$$P(Y = 2 / X_i = 1) = \alpha (1 - \beta),$$

$\vdots$

$$P(Y = k / X_i = 1) = \alpha \beta \xi \delta^{k-4} (1 - \delta)$$

and

$$P(Y = 0 / X_i = 0) = 0,$$

$$P(Y = 1 / X_i = 0) = 1 - w,$$

$$P(Y = 2 / X_i = 0) = w (1 - \lambda),$$

$\vdots$

$$P(Y = k / X_i = 0) = w \lambda \delta^{k-3} (1 - \delta).$$

The probability generating functions of  $Y$  are for  $P(Y = k / X_i = 1)$

$$\begin{aligned} g_1(t) &= \sum_{k=0}^{\infty} P(Y = k / X_i = 1) t^k \\ &= \frac{(1-\alpha)t + [\alpha(1-\beta) - \delta(1-\alpha)]t^2 + [\alpha\beta(1-\xi) - \alpha\delta(1-\beta)]t^3}{1 - \delta t} + \\ &\quad \frac{[\alpha\beta\xi(1-\delta) - \alpha\beta(1-\xi)\delta]t^4}{1 - \delta t}, \end{aligned} \quad (4)$$

for  $P(Y = k / X_i = 0)$

$$g_0(t) = \sum_{k=0}^{\infty} P(Y = k / X_i = 0) t^k$$

$$= \frac{(1-w)t + [w(1-\lambda) - \delta(1-w)]t^2 + [w\lambda(1-\delta) - w\delta(1-\lambda)]t^3}{1 - \delta t},$$

and for  $P(Y = k)$

$$g(t) = \sum_{k=0}^{\infty} P(Y = k)t^k = P(X_i = 1) g_1(t) + P(X_i = 0) g_0(t)$$

$$= \frac{pt + p(\alpha - \delta)t^2 + p(\alpha\beta - \alpha\delta)t^3 + p[\alpha\beta(\delta - \delta)]t^4}{1 - \delta t} \quad (5)$$

where the following identities obtained from (1), (2) and (3) have been used:

$$\alpha p = q(1-w), \quad \alpha\beta p = (1-\lambda)wp, \quad \alpha\beta\delta p = \lambda wq(1-\delta). \quad (6)$$

Let

$Y_k =$  The number of trials to observe the  $k$ th occurrence of 1 after  $i$ th trial. At the initial trial  $X_i$  is 1 or 0. Thus we can write

$$Y_k = Y + (k - 1) Y.$$

$Y_k$  is equal to the sum of  $k$  independent random variables. The probability generating function of  $Y_k$  is for  $k \geq 1$

$$f_k(t) = \sum_{n=0}^{\infty} P(Y_k = n) t^n$$

$$= g(t) [g_1(t)]^{k-1}.$$

Since

$$P(S_n = k) = P(S_n \geq k) - P(S_n \geq k + 1)$$

$$= P(Y_k \leq n) - P(Y_{k+1} \leq n)$$

the probability generating function of  $S_n$  is of the form

$$G_k(t) = \sum_{n=0}^{\infty} P(S_n = k)t^n = \sum_{n=0}^{\infty} P(Y_k \leq n)t^n - \sum_{n=0}^{\infty} P(Y_{k+1} \leq n)t^n \quad (7)$$

$$= \frac{f_k(t)}{1-t} - \frac{f_{k+1}(t)}{1-t}$$

$$\begin{aligned}
 &= \frac{g(t) [g_1(t)]^{k-1} - g(t) [g_1(t)]^k}{1-t} \\
 &= \frac{g(t) [g_1(t)]^{k-1} [1 - g_1(t)]}{1-t} .
 \end{aligned}$$

From (4) and (5) we can obtain  $pt[1-g_1(t)] = (1-t) g(t)$  and according to this equation,  $G_k(t)$  can be written

$$\begin{aligned}
 G_k(t) &= \frac{[g(t)]^2 [g_1(t)]^{k-1}}{pt} \\
 &= pt^k (a + bt + ct^2 + dt^3)^2 (f + ht + lt^2 + dt^3)^{k-1} \frac{(1-\delta)^{k+1}}{(1-\delta t)^{k+1}}
 \end{aligned} \tag{8}$$

where

$$\begin{aligned}
 a &= \frac{1}{1-\delta}, & b &= \frac{\alpha - \delta}{1-\delta}, & c &= \frac{\alpha\beta - \alpha\delta}{1-\delta}, & d &= \frac{\alpha\beta (\delta - \delta)}{1-\delta}, \\
 f &= \frac{1-\alpha}{1-\delta}, & h &= \frac{\alpha(1-\beta) - \delta(1-\alpha)}{1-\delta}, \\
 l &= \frac{\alpha\beta(1-\delta) - \alpha\beta(1-\beta)}{1-\delta}.
 \end{aligned}$$

In (8)  $(f + ht + lt^2 + dt^3)^{k-1}$  is the probability generating function of the multinomial distribution and  $(1-\delta)^{k+1}/(1-\delta t)^{k+1}$  is the probability generating function of the negative binomial distribution. From (7) it can be shown that  $P(S_n = k)$  is the coefficient of  $t^n$ .

The expansion of the  $G_k(t)$  allows us to write for  $k \geq 1$

$$P(S_n = k) = p[a^2 C_{n-k} + 2ab C_{n-k-1} + (b^2 + ac) C_{n-k-2} + (2ad + 2bc) C_{n-k-3} + (c^2 + 2bd) C_{n-k-4} + 2cd C_{n-k-5} + d^2 C_{n-k-6}], \tag{9}$$

and for  $k = 0$

$$P(S_n = 0) = P(X_i = 0, X_{i+1} = 0, \dots, X_{i+n} = 0) = q\omega\lambda\delta^{n-2} \tag{10}$$

where

$$C_{n-k-r} = \sum_{m=0}^{k-1} \sum_{i=0}^m \sum_{j=0}^i \binom{k-1}{j, i-j, m-i} \binom{k+n-k-m-i-j-r}{n-k-m-i-j-r} d^j l^{i-j} h^{m-i} f^{k-1-m} n^{-k-m-i-j-r} \delta \tag{11}$$

LIMITING PROBABILITY FUNCTION

If  $np = u$  is held fixed as  $n \rightarrow \infty$  from (6) we can write

$$1 - w = \frac{\alpha u}{n - u}, \quad 1 - \lambda = \frac{\alpha \beta u}{w(n-u)}, \quad 1 - \delta = \frac{\alpha \beta \xi u}{\lambda w (n - u)}. \quad (12)$$

The equations in (12) show that  $w, \lambda$  and  $\delta$  approach 1 as  $n \rightarrow \infty$  and we can also obtain

$$\lim_{n \rightarrow \infty} p = \lim_{n \rightarrow \infty} \frac{u}{n} = 0, \quad \lim_{n \rightarrow \infty} q = 1,$$

$$\lim_{n \rightarrow \infty} \delta^n = \lim_{n \rightarrow \infty} \left[ 1 - \frac{\alpha \beta \xi u}{\lambda w (n - u)} \right]^n = e^{-\alpha \beta \xi u}.$$

If we rearrange the expression (11) and let  $n \rightarrow \infty$  we obtain

$$C_k = \lim_{n \rightarrow \infty} \frac{C_{n-k-r}}{1-\delta} = \alpha \beta \xi u e^{-\alpha \beta \xi u} \sum_{m=0}^{k-1} \binom{k-1}{m} \frac{(1 - \alpha \beta \xi)^m (\alpha^2 \beta^2 \xi^2 u)^{k-1-m}}{(k - m)!}$$

which is independent of  $r$ . From (9) and (10) it can be written for  $k \geq 1$

$$\begin{aligned} \lim_{n \rightarrow \infty} P(S_n = k) &= \lim_{n \rightarrow \infty} \frac{\frac{u}{n} [1 + (\alpha - \delta) + (\alpha \beta - \alpha \delta) + \alpha \beta (\xi - \delta)]^2}{\frac{\alpha \beta \xi}{\lambda w (n-u)}} \\ &= \frac{C_{n-k-r}}{1 - \delta} = \alpha \beta \xi C_k \\ &= \alpha^2 \beta^2 \xi^2 u e^{-\alpha \beta \xi u} \sum_{m=0}^{k-1} \frac{(k-1)!}{m!(k-1-m)!} \frac{(1-\alpha \beta \xi)^m (\alpha^2 \beta^2 \xi^2 u)^{k-1-m}}{(k - m)!}, \quad (13) \end{aligned}$$

and for  $k = 0$

$$\lim_{n \rightarrow \infty} P(S_n = 0) = \lim_{n \rightarrow \infty} \left( 1 - \frac{u}{n} \right) w \lambda \left[ 1 - \frac{\alpha \beta \xi u}{\lambda w (n-u)} \right]^{n-2} = e^{-\alpha \beta \xi u}.$$

In (13) by taking  $k-1-m = j$  it is obtained

$$\begin{aligned} \lim_{n \rightarrow \infty} P(S_n = k) &= \frac{\alpha^2 \beta^2 \xi^2 u (1-\alpha \beta \xi)^{k-1}}{k} e^{-\alpha \beta \xi u} \sum_{j=0}^{k-1} \frac{k!}{j! (j+1)! (k-1-m)!} \\ &\quad \left( \frac{\alpha^2 \beta^2 \xi^2 u}{1-\alpha \beta \xi} \right)^j. \quad (14) \end{aligned}$$

Since

$$L_r^{(1)}(y) = \sum_{i=0}^r \frac{(r+1)! (-y)^i}{(r-i)! i! (1+i)!}, \quad r = 0, 1, 2, \dots$$

is the first-order Leguerre polynomials (see [2]), it can be shown that (14) is of the form

$$\lim_{n \rightarrow \infty} P(S_n = k) = \frac{\alpha^2 \beta^2 \xi^2 u (1 - \alpha \beta \xi)^{k-1}}{k} e^{-\alpha \beta \xi u} L_{k-1}^{(1)} \left( -\frac{\alpha^2 \beta^2 \xi^2 u}{1 - \alpha \beta \xi} \right). \quad (15)$$

### CONCLUDING REMARKS

In the second-order Markov chain  $\xi = \delta = \lambda$ . For this case, from (15) we can obtain for  $k \geq 1$

$$\lim_{n \rightarrow \infty} P(S_n = k) = \frac{\alpha^2 \beta^2 u (1 - \alpha \beta)^{k-1}}{k} e^{-\alpha \beta u} L_{k-1} \left( -\frac{\alpha^2 \beta^2 u}{1 - \alpha \beta} \right), \quad (16)$$

and for  $k = 0$

$$\lim_{n \rightarrow \infty} P(S_n = k) = e^{-\alpha \beta u}$$

Expression (16) is the limiting probability function in [2] for the second order case.

Comparing (16) and (15) shows that we can write the following expression in the case of the  $v$  th-order Markov chain for  $k \geq 1$

$$\lim_{n \rightarrow \infty} P(S_n = k) = \frac{\alpha_1^2 \dots \alpha_v^2 u (1 - \alpha_1 \dots \alpha_v)^{k-1}}{k} e^{-\alpha_1 \dots \alpha_v u} L_{k-1}^{(1)} \left( -\frac{\alpha_1^2 \dots \alpha_v^2 u}{1 - \alpha_1 \dots \alpha_v} \right)$$

and for  $k = 0$

$$\lim_{n \rightarrow \infty} P(S_n = k) = e^{-\alpha_1 \dots \alpha_v u}$$

where for  $j = 1, 2, \dots, v$

$$\alpha_j = P(X_i = 0 / X_{i-j} = 1, \quad X_{i-j-1} = 0, \quad X_{i-1} = 0).$$

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