

## On Finite Tail $\sigma$ -Algebras\*

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### 1. Introduction

Let  $\xi = (\xi_t)_{t \in \Theta}$  be a stochastic process on a probability space  $(\Omega, \mathcal{H}, P)$  assuming values in an arbitrary measurable space  $(X, \mathcal{X})$ . Here  $\Theta$  is either  $N = \{0, 1, 2, \dots\}$  or the non-negative half line  $[0, \infty)$ .

Let  $\mathcal{H}_s^t$ ,  $s \leq t$ , denote the  $\sigma$ -algebra generated by the family  $(\xi_u)_{s \leq u \leq t}$ ,  $\mathcal{H}_s = \mathcal{H}_s^s$ , and  $\mathcal{H}_s^\infty$  = the least  $\sigma$ -algebra containing all the  $\sigma$ -algebras  $\mathcal{H}_s^t$ ,  $t \geq s$ .

The  $\sigma$ -algebra  $\mathcal{F} = \bigcap_{s \in \Theta} \mathcal{H}_s^\infty$  is called the *tail  $\sigma$ -algebra* of  $\xi$ .

A  $\sigma$ -algebra contained in  $\mathcal{H}$  will be said to be  $\delta$ -trivial (under  $P$ ),  $0 \leq \delta < 1$ , if the probability of any set belonging to it is either 0 or greater than or equal to  $1 - \delta$ . Clearly, a  $\delta$ -trivial  $\sigma$ -algebra is equivalent to a finite  $\sigma$ -algebra containing at most  $[(1 - \delta)^{-1}]$  atoms, and, conversely, any finite  $\sigma$ -algebra is  $\delta$ -trivial for some  $0 \leq \delta < 1$ . A 0-trivial  $\sigma$ -algebra will be simply called *trivial*. Notice that  $\delta$ -trivialness with  $\delta < \frac{1}{2}$  amounts to trivialness because  $0 < P(A) < 1$  would imply that both  $P(A)$  and  $P(A^c)$  are greater than  $\frac{1}{2}$ .

It is well known that if  $\xi$  is a sequence of independent random variables, then its tail  $\sigma$ -algebra is trivial (Kolmogorov's 0-1 law). Blackwell and Freedman [2] have proved that the same conclusion holds for homogeneous irreducible, aperiodic, recurrent, countable state, discrete parameter Markov chains. Recently, Cohn [3] has proved that the tail  $\sigma$ -algebra of any finite state, discrete parameter Markov chain (*homogeneous or not*) is  $\delta$ -trivial.

In this paper we characterize (Theorems 1 and 2) stochastic processes having a  $\delta$ -trivial tail  $\sigma$ -algebra, then we exhibit (Theorem 3) the simplification arising in the Markovian case.

Several applications to discrete state space Markov processes are made. Theorem 4 gives necessary and sufficient conditions for the  $\delta$ -trivialness of the tail  $\sigma$ -algebra in terms of the transition and absolute probabilities. Theorem 5 is a necessary and sufficient condition for the tail  $\sigma$ -algebra to be trivial under any initial distribution. Theorem 7 exhibits a class of Markov processes for which the strongly mixing property and the trivialness of the tail  $\sigma$ -algebra are equivalent. Finally, Theorems 6 and 8 extend the above quoted results in [2] and [3] to the continuous parameter case.

### 2. The General Case

The theorems below slightly extend some results by Bártfai and Révész [1] and Blackwell and Freedman [2].

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**Theorem 1.** Assume that

$$\limsup_{t \rightarrow \infty} \sup_{B \in \mathcal{K}_t^\infty} (P(A \cap B) - P(A)P(B)) \leq \delta P(A)$$

for any  $A \in \bigcup_{s \in \Theta} \mathcal{K}_0^s$ . Then  $\mathcal{T}$  is  $\delta$ -trivial.

*Proof.* Let us first notice that the above limit does exist as the quantity under ‘lim’ does not increase when  $t$  increases. Moreover, it is non-negative because

$$P(A \cap B) - P(A)P(B) = -(P(A \cap B^c) - P(A)P(B^c)).$$

Passing to the proof of the theorem, it is easily seen that the assumption made implies that for any  $T \in \mathcal{T}$  and  $s \in \Theta$  we have

$$P(T | \mathcal{K}_0^s) - P(T) \leq \delta \quad \text{a. s.}$$

Now, by a well-known property (see e. g. [6], p. 409)  $P(T | \mathcal{K}_0^{s_n}) \rightarrow P(T | \mathcal{K}_0^\infty)$  a. s. for any increasing sequence  $(s_n)_{n \in \mathbb{N}}$  such that  $\lim_{n \rightarrow \infty} s_n = \infty$ . Therefore

$$P(T | \mathcal{K}_0^\infty) - P(T) \leq \delta \quad \text{a. s.}$$

Taking into account that  $T \in \mathcal{T} \subset \mathcal{K}_0^\infty$  and integrating the above inequality over  $T$  we obtain

$$P(T) - P^2(T) \leq \delta P(T),$$

whence either  $P(T) = 0$  or  $P(T) \geq 1 - \delta$ , q. e. d.

The proof of the next theorem is based on the following simple

**Proposition.** Let  $E_j \in \mathcal{K}$  be such that  $P(E_j) > 0$ ,  $1 \leq j \leq r$ . Then

$$P(A | E_j) \leq \frac{P(A)}{\min_{1 \leq k \leq r} P(E_k)}$$

for any  $A \in \mathcal{K}$  and  $1 \leq j \leq r$ .

*Proof.*<sup>1</sup> For any  $1 \leq j \leq r$  we can write

$$P(A) \geq P(A \cap E_j) = P(A | E_j) P(E_j) \geq P(A | E_j) \min_{1 \leq k \leq r} P(E_k). \quad \text{q. e. d.}$$

**Theorem 2.** Assume that  $\mathcal{T}$  is  $\delta$ -trivial. Then

$$\limsup_{t \rightarrow \infty} \sup_{B \in \mathcal{K}_t^\infty} (P(A \cap B) - P(A)P(B)) \leq \delta P(A)$$

for any  $A \in \mathcal{K}$ .

*Proof.* If  $\mathcal{T}$  is  $\delta$ -trivial the above Proposition implies that for any  $A \in \mathcal{K}$

$$P(A | \mathcal{T}) \leq (1 - \delta)^{-1} P(A) \quad \text{a. s.,}$$

whence

$$P(A | \mathcal{T}) - P(A) \leq \delta P(A | \mathcal{T}) \quad \text{a. s.} \tag{1}$$

<sup>1</sup> I am indebted to Dr. D. Williams for this simple proof.

Then, for  $A \in \mathcal{K}$  and  $B \in \mathcal{K}_t^\infty$  we can write

$$\begin{aligned} P(A \cap B) - P(A)P(B) &= \int_B [P(A|\mathcal{K}_t^\infty)(\omega) - P(A|\mathcal{T})(\omega)] P(d\omega) + \int_B [P(A|\mathcal{T})(\omega) - P(A)] P(d\omega). \end{aligned}$$

The first integral above is dominated by

$$\int_\Omega |P(A|\mathcal{K}_t^\infty)(\omega) - P(A|\mathcal{T})(\omega)| P(d\omega)$$

which by [6] loc. cit. tends to 0 as  $t \rightarrow \infty$ . By virtue of (1) the second integral is dominated by  $\delta P(A)$ , q.e.d.

### 3. The Markovian Case

3.1. When  $\xi$  is a Markov process a simplification occurs in Theorems 1 and 2. We have namely

**Theorem 3.** *Assume that  $\xi$  is a Markov process. Then in Theorems 1 and 2  $\sup_{B \in \mathcal{K}_t^\infty}$  can be replaced by  $\sup_{B \in \mathcal{K}_t}$ .*

*Proof.* We shall prove that

$$\begin{aligned} f(A) &= \sup_{B \in \mathcal{K}_t^\infty} (P(A \cap B) - P(A)P(B)) \\ &= \sup_{B \in \mathcal{K}_t} (P(A \cap B) - P(A)P(B)) = g(A) \end{aligned}$$

for any  $A \in \mathcal{K}_0^s$  with  $s < t$ .

Clearly,  $f(A) \geq g(A)$ . To prove the converse inequality let us notice that by the Markov property we can write

$$\begin{aligned} P(A \cap B) - P(A)P(B) &= P(A) \left[ \int_\Omega P(B|\mathcal{K}_t)(\omega) P_{t,A}(d\omega) - \int_\Omega P(B|\mathcal{K}_t)(\omega) P_t(d\omega) \right] \\ &= P(A) \int_\Omega P(B|\mathcal{K}_t)(\omega) (P_{t,A} - P_t)(d\omega), \end{aligned}$$

for any  $A \in \mathcal{K}_0^s$  such that  $P(A) \neq 0$ , and any  $B \in \mathcal{K}_t^\infty$ ,  $t > s$ , where  $P_t$  is the restriction of  $P$  at  $\mathcal{K}_t$  (i.e.  $P_t(E) = P(E)$  for any  $E \in \mathcal{K}_t$ ) and  $P_{t,A}(\cdot) = P_t(\cdot|A)$ . The inequality  $f(A) \leq g(A)$  is an immediate consequence of the above equation on account of the following

**Lemma.** *Let  $(\Omega, \mathcal{L}, \lambda)$  be a measure space and assume that the signed measure  $\lambda$  is finite and  $\sigma$ -additive and such that  $\lambda(\Omega) = 0$ . If  $h$  is any bounded real valued and  $\mathcal{L}$ -measurable function defined on  $\Omega$ , then*

$$\int_\Omega h(\omega) \lambda(d\omega) \leq (\text{ess sup } h - \text{ess inf } h) \sup_{L \in \mathcal{L}} \lambda(L).$$

The proof of this Lemma can be found in [5], p. 40, q.e.d.

3.2. Theorem 3 allows us to give a necessary and sufficient condition for  $\delta$ -trivialness of the tail  $\sigma$ -algebra of a Markov process in terms of its transition probabilities. For the sake of simplicity assume that the state space  $X$  is at most a countable set with elements  $i, j, \dots$ . Put  $p_i(t) = P(\xi(t) = i), i \in X$ , and

$$X(t) = \{i: p_i(t) > 0\}, \quad t \in \Theta.$$

Denote by  $p_{ij}(s, s + u), i, j \in X, s, u \in \Theta$  the transition probabilities of the process, that is

$$p_{ij}(s, s + u) = P(\xi(s + u) = j | \xi(s) = i).$$

On account of the well known fact that

$$\sup_{E \subset X} \sum_{i \in E} (u_i - v_i) = \frac{1}{2} \sum_{i \in X} |u_i - v_i|$$

for any two probability distributions  $(u_i)_{i \in X}$  and  $(v_i)_{i \in X}$  on  $X$ , Theorems 1, 2 and 3 yield

**Theorem 4.** *Assume that  $\xi$  is a Markov process with at most a countable set of states. Then*

1. *A necessary and sufficient condition for its tail  $\sigma$ -algebra to be  $\delta$ -trivial ( $\delta \geq \frac{1}{2}$ ) is that*

$$\lim_{u \rightarrow \infty} \sum_{j \in X} |p_{ij}(s, s + u) - p_j(s + u)| \leq 2\delta \tag{2}$$

for any  $s \in \Theta$  and  $i \in X(s)$ .

2. *A necessary and sufficient condition for its tail  $\sigma$ -algebra to be trivial is that*

$$\lim_{u \rightarrow \infty} \sum_{j \in X} |p_{ij}(s, s + u) - p_j(s + u)| = 0 \tag{3}$$

for any  $s \in \Theta$  and  $i \in X(s)$ .

(For any fixed  $s \in \Theta$  and  $i \in X(s)$  the quantity under 'lim' is a nonincreasing function of  $u$ .)

Notice that (2) with  $\delta < \frac{1}{2}$  must imply (3) (on account of Theorems 1, 2, and 3, too). I do not know a direct proof of this fact.

3.3. Until now the initial distribution of our Markov process,  $p_i(0) = P(\xi(0) = i), i \in X$ , has been kept fixed. Theorem 4 allows us to characterize Markov processes for which the tail  $\sigma$ -algebra is trivial under any initial distribution (the transition probabilities remaining the same). To this end put  $\bar{X}(0) = X$  and  $\bar{X}(t) = \{j: p_{ij}(0, t) > 0$  for some  $i \in X\}$  for  $t \neq 0$ .

**Theorem 5.** *Assume that  $\xi$  is a Markov process with at most a countable set of states. Then a necessary and sufficient condition for its tail  $\sigma$ -algebra to be trivial under any initial distribution is that*

$$\lim_{u \rightarrow \infty} \sum_{j \in X} |p_{ij}(s, s + u) - p_{kj}(s, s + u)| = 0 \tag{4}$$

for any  $s \in \Theta$  and  $i, k \in \bar{X}(s)$ .

*Proof.* Suppose first that the tail  $\sigma$ -algebra of  $\xi$  is trivial under any initial distribution. Taking as initial distribution that which assigns to each of the states  $i$  and  $k$  probability  $\frac{1}{2}$ , on account of (3) we obtain that

$$\lim_{u \rightarrow \infty} \sum_{j \in X} |p_{ij}(0, u) - p_{kj}(0, u)| = 0 \tag{5}$$

for any  $i, k \in X$ . Further, for any  $s \neq 0$  and  $i \in \bar{X}(s)$  for which  $p_{ii}(0, s) > 0$ , Eq. (3) implies that

$$\lim_{u \rightarrow \infty} \sum_{j \in X} |p_{ij}(s, s+u) - p_{ij}(0, s+u)| = 0. \tag{6}$$

Now it is easily seen that (5) and (6) imply (4).

Conversely, suppose that (4) holds and consider any initial distribution. As

$$p_{ij}(s, s+u) - p_j(s+u) = \sum_{l \in \bar{X}(s)} p_l(s) [p_{ij}(s, s+u) - p_{lj}(s, s+u)]$$

for any  $s \in \Theta$ ,  $i, j \in X$ , by dominated convergence and on account of (4) we have

$$\begin{aligned} \lim_{u \rightarrow \infty} \sum_{j \in X} |p_{ij}(s, s+u) - p_j(s+u)| \\ \leq \sum_{l \in \bar{X}(s)} p_l(s) \lim_{u \rightarrow \infty} \sum_{j \in X} |p_{ij}(s, s+u) - p_{lj}(s, s+u)| = 0 \end{aligned}$$

for any  $s \in \Theta$  and  $i \in \bar{X}(s) \supset X(s)$ .

But this means that (3) holds for the initial distribution we considered, q. e. d.

As an application of Theorem 5 we shall prove

**Theorem 6.** *Assume that  $\xi$  is a homogeneous continuous parameter Markov process with at most a countable set of states (i. e.  $p_{ij}(s, s+u) = p_{ij}(u)$  for any  $i, j \in X$ ,  $s, u \in \Theta$ ) that form a recurrent class. Then the tail  $\sigma$ -algebra of  $\xi$  is trivial under any initial distribution.*

*Proof.* By Theorem 5 it is sufficient to prove that

$$\lim_{u \rightarrow \infty} \sum_{j \in X} |p_{ij}(u) - p_{kj}(u)| = 0 \tag{6}$$

for any  $i, k \in X$ . But this is an immediate consequence of a theorem by Orey [7] establishing (6) for irreducible, recurrent, aperiodic, discrete parameter Markov chains, so that  $\sum_{j \in X} |p_{ij}(nh) - p_{kj}(nh)| \rightarrow 0$  as  $n \rightarrow \infty$  (through integral values) for any  $h > 0$ , and of the fact that the quantity under ‘lim’ in (6) is a nonincreasing function of  $u$ , q. e. d.

3.4. We close the study of the Markovian case with a remark about strongly mixing Markov processes.

An arbitrary stochastic process  $\xi$  is said to be *strongly mixing* if

$$\alpha(\tau) = \sup_{s \in \Theta} \sup_{A \in \mathcal{X}_s^0, B \in \mathcal{X}_{s+\tau}^\tau} (P(A \cap B) - P(A)P(B))$$

tends to zero as  $\tau \rightarrow \infty$ . On account of Theorem 1, the strong mixing property implies the trivialness of the tail  $\sigma$ -algebra. The theorem below exhibits a case for which the converse implication is also true.

**Theorem 7.2** Assume that  $\xi$  is a stationary homogeneous Markov process with at most a countable set of states (i.e.  $p_i(s) = \pi_i$ ,  $p_{ij}(s, s+u) = p_{ij}(u)$  for any  $i, j \in X$ ,  $s, u \in \Theta$ ). Then the strong mixing property is equivalent to the trivialness of the tail  $\sigma$ -algebra. Moreover,

$$\alpha(\tau) \leq \frac{1}{2} \sum_{i \in X} \pi_i \sum_{j \in X} |p_{ij}(\tau) - \pi_j|.$$

*Proof.* For any  $A \in \mathcal{K}_0^s$ ,  $B \in \mathcal{K}_{s+\tau}$  we have

$$P(A \cap B) - P(A)P(B) \leq \sum_{i \in X} \pi_i \left| \sum_{j \in B} (p_{ij}(\tau) - \pi_j) \right|$$

and the proof follows on account of Theorems 3 and 4, q.e.d.

The above theorem (together with Theorem 6) extends a result by Davydov [4].

#### 4. An Application to Finite State Markov Processes

By making use of Theorem 1 we shall now deduce a result first proved by Cohn [3] for the discrete parameter case.

**Theorem 8.** Assume that  $\xi = (\xi_t)_{t \in \Theta}$  is a finite state Markov process. Then its tail  $\sigma$ -algebra is  $\delta$ -trivial for some  $0 \leq \delta < 1$ .

*Proof.* Let  $E_i(t) = \{\xi_t = i\}$  and put as above  $p_i(t) = P(E_i(t))$ ,  $i \in X$ , and  $X(t) = \{i: p_i(t) > 0\}$ .

We shall prove that there is an increasing sequence  $(t_n)_{n \in N} \subset \Theta$  with  $\lim_{n \rightarrow \infty} t_n = \infty$  and there are two disjoint sets  $Y$  and  $Z$ ,  $Y \neq \emptyset$ ,  $Y \cup Z = X$  such that

$$\liminf_{n \rightarrow \infty} \min_{i \in X(t_n) \cap Y} p_i(t_n) = \gamma > 0$$

$$\text{and } \lim_{n \rightarrow \infty} \sum_{i \in Z} p_i(t_n) = 0. \quad ^3$$

Admitting that this is true, let us show that  $\delta$ -trivialness follows with  $\delta = 1 - \gamma$ . For given  $0 < \varepsilon < \gamma$  and  $A \in \bigcup_{t \in \Theta} \mathcal{K}_0^t$  choose an  $n$  large enough in order that  $A \in \mathcal{K}_0^{t_n}$ ,

$\sum_{i \in Z} p_i(t_n) \leq \varepsilon$ , and  $\min_{i \in X(t_n) \cap Y} p_i(t_n) \geq \gamma - \varepsilon$ . Notice that our Proposition implies that whatever  $B \in \mathcal{K}$  we have

$$P(B) \geq (\gamma - \varepsilon) P(B | \mathcal{K}_{t_n})(\omega) \tag{7}$$

for almost all  $\omega$  not belonging to the event  $E'(t_n) = \bigcup_{i \in Z} E_i(t_n)$ , the probability of which is  $\leq \varepsilon$ . By the Markov property

$$P(A \cap B) - P(A)P(B) = \int_{A \cap E'(t_n)} + \int_{A \cap (E'(t_n))^c} (P(B | \mathcal{K}_{t_n})(\omega) - P(B)) P(d\omega)$$

for any  $B \in \mathcal{K}_s^\infty$  with  $s > t_n$ . The first integral above is dominated by  $\varepsilon$  and the second one, because of the estimate (7) for  $P(B)$ , is dominated by  $(1 - \gamma + \varepsilon)P(A)$ , so that

$$P(A \cap B) - P(A)P(B) \leq \varepsilon + (1 - \gamma + \varepsilon)P(A)$$

<sup>2</sup> Compare with Lemma 2 in [8] p. 207.

<sup>3</sup> This is one of the main points in Cohn's proof, too.

for any  $0 < \varepsilon < \gamma$  and any  $A \in \bigcup_{t \in \Theta} \mathcal{X}_0^t$  provided that  $B \in \mathcal{X}_s^\infty$  with  $s > t_n$ , where  $t_n$  depends upon both  $A$  and  $\varepsilon$ . But  $\delta$ -trivialness then follows at once from Theorem 1, with  $\delta = 1 - \gamma$ , because of the  $\lim_{t \rightarrow \infty}$  which occurs in the sufficient condition given there.

Coming back to the proof of the above statement in italics, let

$$\alpha = \liminf_{t \rightarrow \infty} \min_{i \in X(t)} p_i(t).$$

If  $\alpha > 0$ , clearly, we can take  $Y = X$ ,  $Z = \emptyset$ ,  $\gamma = \alpha$  and as  $(t_n)_{n \in N}$  any sequence through which the above ‘lim inf’ is reached. If  $\alpha = 0$ , let  $(a_n)_{n \in N} \subset \Theta$  be a sequence such that

$$\lim_{n \rightarrow \infty} \min_{i \in X(a_n)} p_i(a_n) = 0$$

and let  $i_n$  be a state such that

$$\min_{i \in X(a_n)} p_i(a_n) = p_{i_n}(a_n), \quad n \in N.$$

In the sequence  $(i_n)_{n \in N}$  at least one state, say 1, appears infinitely often. Therefore, for a subsequence  $(b_n)_{n \in N} \subset (a_n)_{n \in N}$  we have  $\lim_{n \rightarrow \infty} p_1(b_n) = 0$ , so that state 1 will be the first element of  $Z$ . Next let

$$\beta = \liminf_{n \rightarrow \infty} \min_{i \in X(b_n) - \{1\}} p_i(b_n).$$

If  $\beta > 0$ , we take  $Y = X - \{1\}$ ,  $Z = \{1\}$ ,  $\gamma = \beta$ , and  $t_n = b_n$ ,  $n \in N$ . If  $\beta = 0$ , we repeat the above procedure to include a new state, say 2, in  $Z$ , that is, we find a subsequence  $(c_n)_{n \in N} \subset (b_n)_{n \in N}$  such that  $\lim_{n \rightarrow \infty} p_2(c_n) = 0$ . We must stop before including all the states in  $Z$  as  $\sum_{i \in X} p_i(t) = 1$  for all  $t \in \Theta$ , q. e. d.

**Corollary.** *Let  $\xi$  be a finite state Markov process. Then, either*

$$\lim_{u \rightarrow 0} \sum_{j \in X} |p_{ij}(s, s+u) - p_j(s+u)| = 0$$

for any  $s \in \Theta$  and  $i \in X(s)$ , or

$$1 \leq \sup_{s \in \Theta} \sup_{i \in X(s)} \lim_{u \rightarrow 0} \sum_{j \in X} |p_{ij}(s, s+u) - p_j(s+u)| < 2.$$

*Proof.* Combine Theorems 4 and 8, q. e. d.

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