Rényi's Divergence and Entropy Rates for Finite Alphabet Markov Sources

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***Abstract*—In this work, we examine the existence and the computation of the Rényi divergence rate, $\lim_{n\to\infty}\frac{1}{n}D_\alpha(p^{(n)}\|q^{(n)})$, between two time-invariant finite-alphabet Markov sources of arbitrary order and arbitrary initial distributions described by the probability distributions $p^{(n)}$ and $q^{(n)}$, respectively. This yields a generalization of a result of Nemetz where he assumed that the initial probabilities under $p^{(n)}$ and $q^{(n)}$ are strictly positive. The main tools used to obtain the Rényi divergence rate are the theory of nonnegative matrices and Perron–Frobenius theory. We also provide numerical examples and investigate the limits of the Rényi divergence rate as $\alpha \to 1$ and as $\alpha \downarrow 0$. Similarly, we provide a formula for the Rényi entropy rate $\lim_{n\to\infty}\frac{1}{n}H_\alpha(p^{(n)})$ of Markov sources and examine its limits as $\alpha \to 1$ and as $\alpha \downarrow 0$. Finally, we briefly provide an application to source coding.**

***Index Terms*—Kullback–Leibler divergence rate, nonnegative matrices, Perron–Frobenius theory, Rényi's divergence and entropy rates, Shannon and Hartley entropy rates, time-invariant Markov sources.**

I. INTRODUCTION

Let $\{X_1, X_2, \ldots\}$ be a first-order time-invariant Markov source with finite alphabet $\mathcal{X} = \{1, \ldots, M\}$. Consider the following two different probability laws for this source. Under the first law

$$\Pr\{X_1 = i\} =: p_i \quad \text{and} \quad \Pr\{X_{k+1} = j | X_k = i\} =: p_{ij}, \quad i, j \in \mathcal{X}$$

so that

$$p^{(n)}(i^n) := \Pr\{X_1 = i_1, \ldots, X_n = i_n\} = p_{i_1}p_{i_1i_2}\cdots p_{i_{n-1}i_n}, \quad i_1, \ldots, i_n \in \mathcal{X}$$

while under the second law the initial probabilities are q_i, the transition probabilities are q_{ij}, and the n-tuple probabilities are $q^{(n)}$. Let $p = (p_1, \ldots, p_M)$ and $q = (q_1, \ldots, q_M)$ denote the initial distributions under $p^{(n)}$ and $q^{(n)}$, respectively.

The Rényi divergence [20] of order α between two distributions $\hat{p}$ and $\hat{q}$ defined on $\mathcal{X}$ is given by

$$D_\alpha(\hat{p}\|\hat{q}) = \frac{1}{\alpha-1}\log\left(\sum_{i\in\mathcal{X}}\hat{p}_i^\alpha \hat{q}_i^{1-\alpha}\right)$$

where $0 < \alpha < 1$. This definition can be extended to $\alpha > 1$ if all $\hat{q}_i > 0$. The base of the logarithm is arbitrary. Similarly, the Rényi entropy of order α for $\hat{p}$ is defined as

$$H_\alpha(\hat{p}) = \frac{1}{1-\alpha}\log\left(\sum_{i\in\mathcal{X}}\hat{p}_i^\alpha\right)$$

Manuscript received April 5, 2000; revised October 28, 2000. This work was supported in part by the Natural Sciences and Engineering Research Council of Canada. The material in this correspondence was presented in part at the International Symposium on Information Theory and its Applications, Honolulu, HI, November 2000.

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Communicated by I. Csiszár, Associate Editor for Shannon Theory.
Publisher Item Identifier S 0018-9448(01)02853-X.

where $\alpha > 0$ and $\alpha \neq 1$. As $\alpha \to 1$, the Rényi divergence approaches the Kullback–Leibler divergence (relative entropy) given by

$$D(\hat{p}\|\hat{q}) = \sum_{i\in\mathcal{X}}\hat{p}_i\log\frac{\hat{p}_i}{\hat{q}_i}$$

and the Rényi entropy approaches the Shannon entropy.

The above generalized information measures and their subsequent variations [23] were originally introduced for the analysis of memoryless sources. One natural direction for further studies is the investigation of the Rényi divergence rate

$$\lim_{n\to\infty}\frac{1}{n}D_\alpha\left(p^{(n)}\|q^{(n)}\right)$$

where

$$D_\alpha\left(p^{(n)}\|q^{(n)}\right) = \frac{1}{\alpha-1}\log\left(\sum_{i^n\in\mathcal{X}^n}\left[p^{(n)}(i^n)\right]^\alpha\left[q^{(n)}(i^n)\right]^{1-\alpha}\right)$$

and of the Rényi entropy rate

$$\lim_{n\to\infty}\frac{1}{n}H_\alpha\left(p^{(n)}\right)$$

where

$$H_\alpha\left(p^{(n)}\right) = \frac{1}{1-\alpha}\log\left(\sum_{i^n\in\mathcal{X}^n}\left[p^{(n)}(i^n)\right]^\alpha\right)$$

for sources with memory, in particular Markov sources. Nemetz addressed these problems in [16], where he evaluated the Rényi divergence rate $\lim_{n\to\infty}\frac{1}{n}D_\alpha(p^{(n)}\|q^{(n)})$ between two Markov sources characterized by $p^{(n)}$ and $q^{(n)}$, respectively, under the restriction that the initial probabilities p and q are strictly positive (i.e., all p_i's and q_i's are strictly positive).

The Rényi divergence rate has played a significant role in certain hypothesis-testing questions [14], [16], [17]. Furthermore, the Rényi entropy and the Rényi entropy rate have revealed several operational characterizations in the problem of fixed-length source coding [7], [6], variable-length source coding [4], [5], [13], [19], error exponent calculations [8], and other areas [1]–[3], [18].

In this work, we generalize the Nemetz result by establishing a computable expression for the Rényi divergence rate between Markov sources with *arbitrary* initial distributions. We also investigate the questions of whether the Rényi divergence rate reduces to the Kullback–Leibler divergence rate as $\alpha \to 1$ and the interchangeability of limits between n and α as $n \to \infty$ and as $\alpha \downarrow 0$. To the best of our knowledge, these issues have not been addressed before. We provide sufficient (but not necessary) conditions on the underlying Markov source distributions $p^{(n)}$ and $q^{(n)}$ for which the interchangeability of limits as $n \to \infty$ and as $\alpha \to 1$ is valid. We also give an example of noninterchangeability of limits as $n \to \infty$ and as $\alpha \to 1$. We also show that the interchangeability of limits as $n \to \infty$ and $\alpha \downarrow 0$ always holds. We next address the computation and the existence of the Rényi entropy rate $\lim_{n\to\infty}\frac{1}{n}H_\alpha(p^{(n)})$ for a Markov source with distribution $p^{(n)}$ and examine its limits as $\alpha \downarrow 0$ and as $\alpha \to 1$.

The rest of this correspondence is organized as follows. In the following section, we review some definitions and relevant results from the theory of nonnegative matrices and Perron–Frobenius theory. In Section III, we provide a general formula for the Rényi divergence rate between $p^{(n)}$ and $q^{(n)}$, with no restriction on the initial probabilities p and q, and illustrate it numerically. The result is first proved for first-order Markov sources, and is then extended for Markov sources of arbitrary order. In Section IV, we show that if the probability transition matrix P associated with the Markov source under $p^{(n)}$ is irreducible and if both the initial probability q and the probability transition matrix Q associated with the Markov source under $q^{(n)}$ are positive (with strictly positive entries), then the Rényi divergence rate reduces to the Kullback–Leibler divergence rate as $\alpha \to 1$. We also show that the interchangeability of limits as $n \to \infty$ and as $\alpha \downarrow 0$ is always valid. In Section V, we address similar questions for the Rényi entropy rate and briefly illustrate it with an application to variable-length source coding. Finally, concluding remarks are stated in Section VI.

II. Nonnegative Matrices

We begin with some results about nonnegative matrices. Most of what follows may be found in [22] and [9].

Matrices and vectors are *positive* if all their components are positive and *nonnegative* if all their components are nonnegative. Throughout this section, A denotes an $M \times M$ nonnegative matrix $(A \geq 0)$ with elements a_{ij}. The ijth element of A^m is denoted by $a_{ij}^{(m)}$.

We write $i \to j$ if $a_{ij}^{(m)} > 0$ for some positive integer m, and we write $i \not\to j$ if $a_{ij}^{(m)} = 0$ for every positive integer m. We say that i and j *communicate* and write $i \leftrightarrow j$ if $i \to j$ and $j \to i$. If $i \to j$ but $j \not\to i$ for some index j, then the index i is called *inessential* (or *transient*). An index which leads to no index at all (this arises when A has a row of zeros) is also called inessential. Also, an index that is not inessential is called *essential* (or *recurrent*). Thus, if i is essential, $i \to j$ implies $i \leftrightarrow j$, and there is at least one j such that $i \to j$.

With these definitions, it is possible to partition the set of indexes $\{1, 2, \ldots, M\}$ into disjoint sets, called *classes*. All essential indexes (if any) can be subdivided into *essential classes* in such a way that all the indexes belonging to one class communicate, but cannot lead to an index outside the class. Moreover, all inessential indexes (if any) may be divided into two types of *inessential classes*: *self-communicating* classes and *non-self-communicating* classes. Each self-communicating inessential class contains inessential indexes which communicate with each other. A non-self-communicating inessential class is a singleton set whose element is an index which does not communicate with any index (including itself).

A matrix is *irreducible* if its indexes form a single essential class; i.e., if every index communicates with every other index.

Proposition 1: By renumbering the indexes (i.e., by performing row and column permutations), it is possible to put a nonnegative matrix A in the *canonical form* as shown at the bottom of the page, where A_i, $i = 1, \ldots, g$, are irreducible square matrices, and in each row $i = h+1, \ldots, g$ at least one of the matrices $A_{i1}, A_{i2}, \ldots, A_{ii-1}$ is not zero. The matrix A_i for $i = 1, \ldots, h$ corresponds to the essential class C_i; while the matrix A_i for $i = h+1, \ldots, g$ corresponds to the self-communicating inessential class C_i. The other diagonal block submatrices which correspond to non-self-communicating classes C_i, $i = g+1, \ldots, l$, are 1×1 zero matrices. In every row $i = g+1, \ldots, l$ any of the matrices $A_{i1}, \ldots, A_{ii-1}$ may be zero.

A class C_j is *reachable* from another class C_i if $A_{ij} \neq 0$, or if for some $i_1, \ldots, i_c$, $A_{ii_1} \neq 0$, $A_{i_1 i_2} \neq 0, \ldots, A_{i_c,j} \neq 0$, where c is at most $l-1$ (since there are l classes). Thus, c can be viewed as the number of steps needed to reach class C_j starting from class C_i. Note that from the canonical form of A, the class C_j is reachable from class C_i if $A_{ij}^{(c)} \neq 0$ for some $c = 1, \ldots, l-1$, where $A_{ij}^{(c)}$ is the ijth submatrix of A^c.

Proposition 2 (Frobenius): If A is irreducible, then A has a real positive eigenvalue λ that is greater than or equal to the magnitude of each other eigenvalue. There is a positive left (right) eigenvector, $\boldsymbol{a}$ ($\boldsymbol{b}$), corresponding to λ, where $\boldsymbol{a}$ is a row vector and $\boldsymbol{b}$ is a column vector.

Proposition 3 [12, p. 508]: If A is irreducible, then the largest positive real eigenvalue has algebraic multiplicity 1.

Proposition 4 [12, p. 494]: If A has a positive eigenvector x, then for all $m = 1, 2, \ldots,$ and for all $i = 1, \ldots, M$ we have

$$\sum_{j=1}^{M} a_{ij}^{(m)} \leq \left[\frac{\max\limits_{1 \leq k \leq M} x_k}{\min\limits_{1 \leq k \leq M} x_k} \right] \rho^m(A)$$

where $A^m = (a_{ij}^{(m)})$ and $\rho(A) \stackrel{\Delta}{=} \max\{|\lambda| : \lambda \text{ eigenvalue of } A\}$ is the spectral radius of A.

The following corollary follows directly from the previous proposition by observing that

$$a_{ij}^{(m)} \leq \sum_{j=1}^{M} a_{ij}^{(m)}, \qquad \forall\, i = 1, \ldots, M \quad \text{and} \quad j = 1, \ldots, M.$$

Corollary 1: If A is irreducible, then $A^m \leq \lambda^m C$ (i.e., $a_{ij}^{(m)} \leq \lambda^m c_{ij}$), for all $m = 1, 2, \ldots$, where λ is the largest positive real eigenvalue of A and

$$C = \left(\frac{\max_{1 \leq k \leq M} x_k}{\min_{1 \leq k \leq M} x_k} \right)$$

is a matrix with identical entries that are independent of m.

Proposition 5 [15, p. 371]: The eigenvalues of a matrix are continuous functions of the entries of the matrix.

Proposition 6 [15, p. 396]: Let $A(\alpha)$ be an $M \times M$ matrix whose entries are all analytic functions of α in some neighborhood of α_0. Let λ be an eigenvalue of $A(\alpha_0)$ of algebraic multiplicity 1. Then $A(\alpha)$ has

$$A = \begin{bmatrix}
A_1 & \ldots & 0 & 0 & \ldots & 0 & \ldots & \ldots & 0 \\
0 & \ldots & 0 & 0 & \ldots & 0 & \ldots & \ldots & 0 \\
\ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\
0 & \ldots & A_h & 0 & \ldots & 0 & \ldots & \ldots & 0 \\
A_{h+11} & \ldots & A_{h+1h} & A_{h+1} & \ldots & 0 & \ldots & \ldots & 0 \\
\ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\
A_{g1} & \ldots & A_{gh} & A_{gh+1} & \ldots & A_g & \ldots & \ldots & 0 \\
A_{g+11} & \ldots & A_{g+1h} & A_{g+1h+1} & \ldots & A_{g+1g} & 0 & \ldots & 0 \\
\ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\
A_{l1} & \ldots & A_{lh} & A_{lh+1} & \ldots & A_{lg} & A_{lg+1} & \ldots & 0
\end{bmatrix}$$

an eigenvalue $\lambda(\alpha)$ which is an analytic function in the neighborhood of α_0 and for which $\lambda(\alpha_0) = \lambda$.

III. The Rényi Divergence Rate

A. First-Order Markov Sources

We assume first that the Markov source $\{X_1, X_2, \ldots\}$ is of order one. Later, we generalize the results for an arbitrary order k. With the same notation as presented at the beginning of the Introduction, the joint distributions of the random variables $(X_1, \ldots, X_n)$ under $p^{(n)}$ and $q^{(n)}$ are given, respectively, by

$$p^{(n)}(i^n) := \Pr\{X_1 = i_1, \ldots, X_n = i_n\} = p_{i_1} p_{i_1 i_2} \cdots p_{i_{n-1} i_n},$$

and

$$q^{(n)}(i^n) := \Pr\{X_1 = i_1, \ldots, X_n = i_n\} = q_{i_1} q_{i_1 i_2} \cdots q_{i_{n-1} i_n}.$$

Let

$$V(n, \alpha) = \sum_{i^n \in \mathcal{X}^n} \left[p^{(n)}(i^n)\right]^{\alpha} \left[q^{(n)}(i^n)\right]^{1-\alpha}.$$

Then

$$V(n, \alpha) = \sum p_{i_1}^{\alpha} q_{i_1}^{1-\alpha} p_{i_1 i_2}^{\alpha} q_{i_1 i_2}^{1-\alpha} \cdots p_{i_{n-1} i_n}^{\alpha} q_{i_{n-1} i_n}^{1-\alpha}$$

where the sum is over $i_1, \ldots, i_n \in \mathcal{X}$. Define a new matrix $R = (r_{ij})$ by

$$r_{ij} = p_{ij}^{\alpha} q_{ij}^{1-\alpha}, \qquad i, j = 1, \ldots, M.$$

Also, define two new $1 \times M$ vectors $\boldsymbol{s} = (s_1, \ldots, s_M)$ and $\mathbf{1}$ by

$$s_i = p_i^{\alpha} q_i^{1-\alpha}, \qquad \mathbf{1} = (1, \ldots, 1).$$

Then, clearly, $D_\alpha(p^{(n)} \| q^{(n)})$ can be written as

$$D_\alpha(p^{(n)} \| q^{(n)}) = \frac{1}{\alpha - 1} \log \boldsymbol{s} R^{n-1} \mathbf{1}^t \tag{1}$$

where $\mathbf{1}^t$ denotes the transpose of the vector $\mathbf{1}$. Without loss of generality, we will herein assume that there exists at least one $i \in \{1, \ldots, M\}$ for which $s_i > 0$, because otherwise (i.e., if $s_i = 0 \, \forall i$), $D_\alpha(p^{(n)} \| q^{(n)})$ is infinite. We also assume that $0 < \alpha < 1$; we can allow the case of $\alpha > 1$ if $q > 0$ and $Q > 0$ (where $Q = (q_{ij})$). Before stating our first main theorem, we prove the following lemma.

Lemma 1: If the matrix R is irreducible, then the Rényi divergence rate between $p^{(n)}$ and $q^{(n)}$ is given by

$$\lim_{n \to \infty} \frac{1}{n} D_\alpha(p^{(n)} \| q^{(n)}) = \frac{1}{\alpha - 1} \log \lambda$$

where λ is the largest positive real eigenvalue of R, and $0 < \alpha < 1$. Furthermore, the same result holds for $\alpha > 1$ if $q > 0$ and $Q > 0$.

Proof: By Proposition 2, let λ be the largest positive real eigenvalue of R with associated positive right eigenvector $\boldsymbol{b} > 0$. Then

$$R^{n-1} \boldsymbol{b} = \lambda^{n-1} \boldsymbol{b}. \tag{2}$$

Let $R^{n-1} = (r_{ij}^{(n-1)})$ and $\boldsymbol{b}^t = (b_1, b_2, \ldots, b_M)$. Also, let

$$b_L = \min_{1 \le i \le M} (b_i)$$

and

$$b_U = \max_{1 \le i \le M} (b_i),$$

Thus $0 < b_L \le b_i \le b_U \ \forall i$. Let $R^{n-1} \mathbf{1}^t = \boldsymbol{y}^t$ where $\boldsymbol{y} = (y_1, \ldots, y_M)$. Then, by (2)

$$\lambda^{n-1} b_i = \sum_{j=1}^{M} r_{ij}^{(n-1)} b_j \le \sum_{j=1}^{M} r_{ij}^{(n-1)} b_U = b_U y_i, \quad \forall i = 1, \ldots, M.$$

Similarly, it can be shown that $\lambda^{n-1} b_i \ge b_L y_i$, $\forall i = 1, \ldots, M$. Therefore,

$$\frac{b_i}{b_U} \le \frac{y_i}{\lambda^{n-1}} \le \frac{b_i}{b_L}, \qquad \forall i = 1, \ldots, M. \tag{3}$$

Since $\boldsymbol{s} R^{n-1} \mathbf{1}^t = \sum_{i=1}^{M} s_i y_i$, it follows directly from (3) that

$$\frac{\sum_i s_i b_i}{b_U} \le \frac{\boldsymbol{s} R^{n-1} \mathbf{1}^t}{\lambda^{n-1}} \le \frac{\sum_i s_i b_i}{b_L},$$

or

$$\frac{1}{n} \log \left(\frac{\sum_i s_i b_i}{b_U} \right) \le \frac{1}{n} \log \left(\frac{\boldsymbol{s} R^{n-1} \mathbf{1}^t}{\lambda^{n-1}} \right) \le \frac{1}{n} \log \left(\frac{\sum_i s_i b_i}{b_L} \right). \tag{4}$$

Note that s_i, b_i, b_U, b_L do not depend on n. Therefore, by (4)

$$\lim_{n \to \infty} \frac{1}{n} \log \left(\frac{\boldsymbol{s} R^{n-1} \mathbf{1}^t}{\lambda^{n-1}} \right) = 0$$

since it is upper- and lower-bounded by two quantities that approach 0 as $n \to \infty$. Hence

$$\begin{aligned} &\lim_{n \to \infty} \frac{1}{n} \log \left(\boldsymbol{s} R^{n-1} \mathbf{1}^t \right) \\ &\quad = \lim_{n \to \infty} \frac{1}{n} \log \lambda^{n-1} + \lim_{n \to \infty} \frac{1}{n} \log \left(\frac{\boldsymbol{s} R^{n-1} \mathbf{1}^t}{\lambda^{n-1}} \right) = \log \lambda \end{aligned}$$

and thus

$$\begin{aligned} \lim_{n \to \infty} \frac{1}{n} D_\alpha \left(p^{(n)} \| q^{(n)} \right) &= \lim_{n \to \infty} \frac{1}{n(\alpha - 1)} \log \left(\boldsymbol{s} R^{n-1} \mathbf{1}^t \right) \\ &= \frac{1}{\alpha - 1} \log \lambda. \end{aligned}$$ $\square$

We next use Lemma 1 and the canonical form of R to prove the following general result.

Theorem 1: Let $R_i, i = 1, \ldots, g$, be the irreducible matrices along the diagonal of the canonical form of the matrix R as shown in Proposition 1. Write the vector $\boldsymbol{s}$ as

$$\boldsymbol{s} = (\tilde{s}_1, \ldots, \tilde{s}_h, \tilde{s}_{h+1}, \ldots, \tilde{s}_g, s_{g+1}, \ldots, s_l)$$

where the vector $\tilde{s}_i$ corresponds to R_i, $i = 1, \ldots, g$. The scalars $s_{g+1}, \ldots, s_l$ correspond to non-self-communicating classes.

- Let λ_k be the largest positive real eigenvalue of R_k for which the corresponding vector $\tilde{s}_k$ is different from the zero vector, $k = 1, \ldots, g$. Let λ^* be the maximum over these λ_k's. If $\tilde{s}_k = 0$, $\forall k = 1, \ldots, g$, then let $\lambda^* = 0$.
- For each inessential class C_i with corresponding vector $\tilde{s}_i \ne 0$, $i = h+1, \ldots, g$, or corresponding scalar $s_i \ne 0$, $i = g+1, \ldots, l$, let λ_j be the largest positive real eigenvalue of R_j if class C_j is reachable from class C_i. Let $\lambda^\dagger$ be the maximum over these λ_j's. If $\tilde{s}_i = 0$ and $s_i = 0$ for every inessential class C_i, then let $\lambda^\dagger = 0$.

Let $\lambda = \max\{\lambda^*, \lambda^\dagger\}$. Then the Rényi divergence rate is given by

$$\lim_{n \to \infty} \frac{1}{n} D_\alpha \left(p^{(n)} \| q^{(n)} \right) = \frac{1}{\alpha - 1} \log \lambda$$

where $0 < \alpha < 1$. Furthermore, the same result holds for $\alpha > 1$ if $q > 0$ and $Q > 0$.

Proof: By Proposition 2, let λ_i be the largest positive real eigenvalue of R_i with associated positive right eigenvector $\tilde{b}_i > 0$, $i = 1, \ldots, g$. Let

$$\boldsymbol{b}^t = (\tilde{b}_1, \ldots, \tilde{b}_h, \tilde{b}_{h+1}, \ldots, \tilde{b}_g, 0, \ldots, 0),$$

where the zeros correspond to non self-communicating classes. By Proposition 1 we have the matrix shown at the bottom of the page. Then

$$\boldsymbol{s}R^{n-1}\boldsymbol{b} = \sum_{i=1}^{g} \tilde{s}_i R_i^{n-1}\tilde{b}_i + \sum_{i=h+1}^{g} \tilde{s}_i \left(R_{i1}^{(n-1)}\tilde{b}_1 + \cdots + R_{ii-1}^{(n-1)}\tilde{b}_{i-1}\right) + \sum_{i=g+1}^{l} s_i \left(R_{i1}^{(n-1)}\tilde{b}_1 + \cdots + R_{ig}^{(n-1)}\tilde{b}_g\right).$$

Rewrite the vector **1** as

$$\mathbf{1} = (\tilde{1}_1, \ldots, \tilde{1}_h, \tilde{1}_{h+1}, \ldots, \tilde{1}_g, 1, \ldots, 1)$$

where $\tilde{1}_i$, $i = 1, \ldots, g$, correspond to essential and inessential self-communicating classes and the 1's correspond to non-self-communicating classes. Let $R^{n-1}\mathbf{1}^t = \boldsymbol{y}^t$ where

$$\boldsymbol{y} = (\tilde{y}_1, \ldots, \tilde{y}_h, \tilde{z}_{h+1} + \tilde{y}_{h+1}, \ldots, \tilde{z}_g + \tilde{y}_g, \tilde{z}_{g+1}, \ldots, \tilde{z}_l)$$

and

$$\tilde{y}_i = R_i^{n-1}\tilde{1}_i^t, \qquad i = 1, \ldots, g$$

$$\tilde{z}_i = \sum_{j=1}^{i-1} R_{ij}^{(n-1)}\tilde{1}_j^t, \qquad i = h+1, \ldots, g$$

$$\tilde{z}_i = \sum_{j=1}^{g} R_{ij}^{(n-1)}\tilde{1}_j^t + \sum_{j=g+1}^{i-1} R_{ij}^{(n-1)}, \qquad i = g+1, \ldots, l.$$

Therefore,

$$\boldsymbol{s}R^{n-1}\mathbf{1}^t = \sum_{i=1}^{g} \tilde{s}_i\tilde{y}_i + \sum_{i=h+1}^{g} \tilde{s}_i\tilde{z}_i + \sum_{i=g+1}^{l} s_i\tilde{z}_i. \tag{5}$$

As in the proof of Lemma 1, since $R_i\tilde{b}_i = \lambda_i\tilde{b}_i$, we can write

$$R_i^{n-1}\tilde{b}_i = \lambda_i^{n-1}\tilde{b}_i \le b_U\tilde{y}_i, \qquad i = 1, \ldots, g$$

where $b_U = \max_{1\le i\le g}(b_{U_i})$ and b_{U_i} is the largest component of $\tilde{b}_i$, $i = 1, \ldots, g$. Similarly,

$$R_i^{n-1}\tilde{b}_i = \lambda_i^{n-1}\tilde{b}_i \ge b_L\tilde{y}_i, \qquad i = 1, \ldots, g$$

where $b_L = \min_{1\le i\le g}(b_{L_i})$ and b_{L_i} is the smallest component of $\tilde{b}_i$, $i = 1, \ldots, g$. Therefore,

$$\frac{\lambda_i^{n-1}\tilde{b}_i}{b_U} \le \tilde{y}_i \le \frac{\lambda_i^{n-1}\tilde{b}_i}{b_L}, \qquad i = 1, \ldots, g.$$

Hence,

$$\frac{1}{b_U}\sum_{i=1}^{g} \tilde{s}_i\lambda_i^{n-1}\tilde{b}_i \le \sum_{i=1}^{g} \tilde{s}_i\tilde{y}_i \le \frac{1}{b_L}\sum_{i=1}^{g} \tilde{s}_i\lambda_i^{n-1}\tilde{b}_i.$$

Therefore, by (5)

$$\frac{1}{b_U}\sum_{i=1}^{g} \tilde{s}_i\lambda_i^{n-1}\tilde{b}_i + \sum_{i=h+1}^{g} \tilde{s}_i\tilde{z}_i + \sum_{i=g+1}^{l} s_i\tilde{z}_i \le \boldsymbol{s}R^{n-1}\mathbf{1}^t \le \frac{1}{b_L}\sum_{i=1}^{g} \tilde{s}_i\lambda_i^{n-1}\tilde{b}_i + \sum_{i=h+1}^{g} \tilde{s}_i\tilde{z}_i + \sum_{i=g+1}^{l} s_i\tilde{z}_i$$

or

$$\begin{aligned}
&\frac{1}{n}\log\left(\frac{1}{b_U}\sum_{i=1}^{g}\tilde{s}_i\left(\frac{\lambda_i}{\lambda}\right)^{n-1}\tilde{b}_i + \frac{1}{\lambda^{n-1}}\left(\sum_{i=h+1}^{g}\tilde{s}_i\tilde{z}_i + \sum_{i=g+1}^{l}s_i\tilde{z}_i\right)\right)\\
&\quad\le \frac{1}{n}\log\left(\frac{\boldsymbol{s}R^{n-1}\mathbf{1}^t}{\lambda^{n-1}}\right)\\
&\quad\le \frac{1}{n}\log\left(\frac{1}{b_L}\sum_{i=1}^{g}\tilde{s}_i\left(\frac{\lambda_i}{\lambda}\right)^{n-1}\tilde{b}_i + \frac{1}{\lambda^{n-1}}\left(\sum_{i=h+1}^{g}\tilde{s}_i\tilde{z}_i + \sum_{i=g+1}^{l}s_i\tilde{z}_i\right)\right)
\end{aligned}$$

where λ is as defined in the statement of the theorem. To show that $\frac{1}{n}\log\left(\frac{\boldsymbol{s}R^{n-1}\mathbf{1}^t}{\lambda^{n-1}}\right)$ converges to 0 as $n \to \infty$, it is sufficient to prove that the lower and upper bounds converge to 0. Since the lower and upper bounds are within a constant scaling of each other, it is enough to show that the lower bound converges to 0 as $n \to \infty$. Note that

$$\sum_{i=h+1}^{g}\tilde{s}_i\tilde{z}_i + \sum_{i=g+1}^{l}s_i\tilde{z}_i = \sum_{i=h+1}^{g}\sum_{j=1}^{i-1}\tilde{s}_iR_{ij}^{(n-1)}\tilde{1}_j^t + \sum_{i=g+1}^{l}\sum_{j=1}^{g}s_iR_{ij}^{(n-1)}\tilde{1}_j^t + \sum_{i=g+1}^{l}\sum_{j=g+1}^{i-1}s_iR_{ij}^{(n-1)}.$$

$$R^{n-1} = \begin{bmatrix}
R_1^{n-1} & \ldots & 0 & 0 & \ldots & 0 & \ldots & \ldots & 0\\
0 & \ldots & 0 & 0 & \ldots & 0 & \ldots & \ldots & 0\\
\ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots\\
0 & \ldots & R_h^{n-1} & 0 & \ldots & 0 & \ldots & \ldots & 0\\
R_{h+11}^{(n-1)} & \ldots & R_{h+1h}^{(n-1)} & R_{h+1}^{n-1} & \ldots & 0 & \ldots & \ldots & 0\\
\ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots\\
R_{g1}^{(n-1)} & \ldots & R_{gh}^{(n-1)} & R_{gh+1}^{(n-1)} & \ldots & R_g^{n-1} & \ldots & \ldots & 0\\
R_{g+11}^{(n-1)} & \ldots & R_{g+1h}^{(n-1)} & R_{g+1h+1}^{(n-1)} & \ldots & R_{g+1g}^{(n-1)} & 0 & \ldots & 0\\
\ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots\\
R_{l1}^{(n-1)} & \ldots & R_{lh}^{(n-1)} & R_{lh+1}^{(n-1)} & \ldots & R_{lg}^{(n-1)} & R_{lg+1}^{(n-1)} & \ldots & 0
\end{bmatrix}.$$

If $R_{ij}^{(n-1)} \neq 0$ for some n, then class C_j is reachable from class C_i (it is enough to check for $n = 2, \ldots, l$, since the number of classes is l). From the block form of R, if $R_{ij}^{(n-1)} \neq 0$, then it is a weighted sum involving products of powers of R_i and R_j (which are irreducible) and possibly some other submatrices (which are irreducible) along the diagonal[1] of R. By applying Corollary 1 to each of these irreducible submatrices if $\tilde{s}_i \neq 0$ or $s_i \neq 0$ (since $R_{ij}^{(n-1)}$ is multiplied by $\tilde{s}_i$ or s_i), the above expression is upper-bounded by linear combinations of powers of the largest eigenvalues of the submatrices along the diagonal of R for which $\tilde{s}_i \neq 0$, $i = h+1, \ldots, g$, or for which the corresponding class is reachable from class C_i, $i = g+1, \ldots, l$.

For example, in the case of the R as given in the footnote, $R_{21}^{(n-1)} \leq (n-1)\lambda^{n-2}C$, where $C > 0$ and its entries are independent of n. Hence,

$$\lim_{n\to\infty} \frac{1}{n} \log\left(\frac{1}{b_U} \sum_{i=1}^{g} \tilde{s}_i \left(\frac{\lambda_i}{\lambda}\right)^{n-1} \tilde{b}_i + \frac{1}{\lambda^{n-1}}\left(\sum_{i=h+1}^{g} \tilde{s}_i \tilde{z}_i + \sum_{i=g+1}^{l} s_i \tilde{z}_i\right)\right) = 0.$$

This follows from the fact that for large n, the argument of the logarithm is a polynomial expression of first degree in n, and

$$\lim_{n\to\infty} \frac{1}{n} \log(an+b) = 0.$$

If R has three submatrices along the diagonal, then from the block form of R, the matrix $R_{31}^{(n-1)}$ depends recursively on a weighted sum involving R_{21} and R_{32}. Therefore, it is bounded by $\lambda^{n-2}p(n)D$, where $p(n)$ is a polynomial of second degree in n, and $D > 0$ with entries independent of n.

In general, for large n, the argument of the logarithm is a polynomial expression in the variable n of degree at most $l-1$ (l is the number of classes), and hence it follows that

$$\lim_{n\to\infty} \frac{1}{n} \log\left(\frac{1}{b_U} \sum_{i=1}^{g} \tilde{s}_i \left(\frac{\lambda_i}{\lambda}\right)^{n-1} \tilde{b}_i + \frac{1}{\lambda^{n-1}}\left(\sum_{i=h+1}^{g} \tilde{s}_i \tilde{z}_i + \sum_{i=g+1}^{l} s_i \tilde{z}_i\right)\right) = 0.$$

Therefore,

$$\lim_{n\to\infty} \frac{1}{n} \log\left(\frac{\boldsymbol{s}R^{n-1}\mathbf{1}^t}{\lambda^{n-1}}\right) = 0$$

and thus

$$\lim_{n\to\infty} \frac{1}{n} D_\alpha\left(p^{(n)} \| q^{(n)}\right) = \lim_{n\to\infty} \frac{1}{n(\alpha-1)} \log\left(\boldsymbol{s}R^{n-1}\mathbf{1}^t\right) = \frac{1}{\alpha-1} \log \lambda. \qquad \square$$

Remark: In [16], Nemetz showed that the Rényi divergence rate between two time-invariant Markov sources with *strictly positive* initial distributions is given by $\frac{1}{\alpha-1}\log\tilde{\lambda}$, where $\tilde{\lambda}$ is the largest positive real eigenvalue of R. Nemetz also pointed out that this assumption could be replaced by other conditions, although he did not provide them. Note that by Theorem 1, the Rényi divergence rate between two time-invariant Markov sources with *arbitrary* initial distributions is not necessarily equal to $\frac{1}{\alpha-1}\log\tilde{\lambda}$, where $\tilde{\lambda}$ is the largest positive real eigenvalue of R. However, if the initial distributions are strictly positive, which implies directly that $\boldsymbol{s} > 0$, then Theorem 1 reduces to the Nemetz result. This follows directly from the fact that, in this case, $\lambda = \lambda^* = \max\{\lambda_k\}$, $k = 1, \ldots, g$, and the fact that the determinant of a block lower triangular matrix is equal to the product of the determinants of the submatrices along the diagonal (thus, the largest eigenvalue of this matrix is given by $\max\{\lambda_k\}$).

[1]For example, if $R = \begin{bmatrix} R_1 & 0 \\ R_{21} & R_2 \end{bmatrix}$, then $R_{21}^{(n-1)} = \sum_{i=0}^{n-2} R_2^i R_{21} R_1^{n-i-2}$.

B. Numerical Examples

In this section, we use the natural logarithm. Let P and Q be two possible probability transition matrices for $\{X_1, X_2, \ldots\}$ defined as follows:

$$P = \begin{pmatrix} 1/4 & 3/4 & 0 & 0 & 0 \\ 1/3 & 2/3 & 0 & 0 & 0 \\ 0 & 0 & 1/2 & 1/2 & 0 \\ 0 & 0 & 1/5 & 4/5 & 0 \\ 0 & 1/6 & 1/2 & 0 & 1/3 \end{pmatrix}$$

$$Q = \begin{pmatrix} 1/5 & 4/5 & 0 & 0 & 0 \\ 1/6 & 5/6 & 0 & 0 & 0 \\ 0 & 0 & 1/4 & 3/4 & 0 \\ 0 & 0 & 1/2 & 1/2 & 0 \\ 0 & 1/2 & 1/3 & 0 & 1/6 \end{pmatrix}.$$

Let the parameter $\alpha = 1/3$. The largest eigenvalues of the three submatrices along the diagonal of R are, respectively, $\lambda_1 = 0.98676$, $\lambda_2 = 0.95937$, and $\lambda_3 = 0.20998$. Let $p = (0, 0, 3/4, 1/4, 0)$ and $q = (0, 0, 1/3, 2/3, 0)$ be two possible initial distributions under $p^{(n)}$ and $q^{(n)}$, respectively. For these given initial distributions, we get by Theorem 1 that $\lambda^* = \lambda_2$ and $\lambda^\dagger = 0$. Therefore, the Rényi divergence rate is $\ln(\lambda_2)/(\alpha-1) = 0.06221$. Note that λ_2 is *not* the largest eigenvalue of R. We also obtain the following.

n	$\frac{1}{n} D_\alpha\left(p^{(n)} \| q^{(n)}\right)$
1000	0.06227
2000	0.06224
3000	0.06223

Clearly, as n gets large, $\frac{1}{n} D_\alpha(p^{(n)} \| q^{(n)})$ is closer to the Rényi divergence rate. Note, however, that, in general, the function $\frac{1}{n} D_\alpha(p^{(n)} \| q^{(n)})$ is not monotonic in n.

Suppose that $\boldsymbol{s}$ has zero components on the first two classes. For example, let $p = (0, 1/4, 1/4, 0, 1/2)$ and $q = (1/4, 0, 0, 1/4, 1/2)$. In this case, $\lambda^* = \lambda_3$, and $\lambda^\dagger = \max\{\lambda_1, \lambda_2\}$ (the first and second classes are reachable from the third). Therefore, the Rényi divergence rate is $\ln(\lambda_1)/(\alpha-1) = 0.01999$. We also get the following.

n	$\frac{1}{n} D_\alpha\left(p^{(n)} \| q^{(n)}\right)$
1000	0.02223
2000	0.02111
3000	0.02074

Clearly, as n gets large $\frac{1}{n} D_\alpha(p^{(n)} \| q^{(n)})$ is closer to the Rényi divergence rate.

Suppose now that $\boldsymbol{s}$ has strictly positive components (as required in the Nemetz result). For example, let $p = (1/8, 1/4, 1/8, 1/4, 1/4)$ and $q = (1/10, 3/10, 2/10, 2/10, 2/10)$. In this case, $\lambda^* = \lambda^\dagger = \max\{\lambda_1, \lambda_2, \lambda_3\} = \lambda_1$. Therefore, the Rényi divergence rate is $\ln(\lambda_1)/(\alpha-1) = 0.01999$. Note that λ_1 is the largest eigenvalue of R which is expected since the components of $\boldsymbol{s}$ are strictly positive. We also get the following.

n	$\frac{1}{n} D_\alpha \left(p^{(n)} \| q^{(n)}\right)$
1000	0.02105
2000	0.02052
3000	0.02034

Clearly, as n gets large $\frac{1}{n} D_\alpha(p^{(n)} \| q^{(n)})$ is closer to the Rényi divergence rate.

C. kth-Order Markov Sources

Now, suppose that the Markov source has an arbitrary order k. Define $\{W_n\}$ as the process obtained by k-step blocking the Markov source $\{X_n\}$; i.e.,

$$W_n \triangleq (X_n, X_{n+1}, \ldots, X_{n+k-1}).$$

Then

$$\Pr(W_n = w_n | W_{n-1} = w_{n-1}, \ldots, W_1 = w_1) = \Pr(W_n = w_n | W_{n-1} = w_{n-1})$$

and $\{W_n\}$ is a first-order Markov source with M^k states. Let

$$p_{w_{n-1} w_n} \triangleq \Pr(W_n = w_n | W_{n-1} = w_{n-1}).$$

We next write the joint distributions of $\{X_n\}$ in terms of the conditional probabilities of $\{W_n\}$. For $n \geq k$, $V(n, \alpha)$, as defined before, is given by

$$V(n, \alpha) = \sum p_{w_1}^\alpha q_{w_1}^{1-\alpha} p_{w_1 w_2}^\alpha q_{w_1 w_2}^{1-\alpha} \cdots p_{w_{n-k} w_{n-k+1}}^\alpha q_{w_{n-k} w_{n-k+1}}^{1-\alpha}$$

where the sum is over $w_1, w_2, \ldots, w_{n-k+1} \in \mathcal{X}^k$. For simplicity of notation, let $(p_1, \ldots, p_{M^k})$ and $(q_1, \ldots, q_{M^k})$ denote the arbitrary initial distributions of W_1 under $p^{(n)}$ and $q^{(n)}$, respectively. Also let p_{ij} and q_{ij} denote the transition probability that W_n goes from index i to index j under $p^{(n)}$ and $q^{(n)}$, respectively, $i, j = 1, \ldots, M^k$. Define a new matrix $R = (r_{ij})$ by

$$r_{ij} = p_{ij}^\alpha q_{ij}^{1-\alpha}, \qquad i, j = 1, \ldots, M^k. \tag{6}$$

Also, define two new $1 \times M^k$ vectors $\boldsymbol{s} = (s_1, \ldots, s_{M^k})$ and $\mathbf{1}$ by

$$s_i = p_i^\alpha q_i^{1-\alpha}, \qquad \mathbf{1} = (1, \ldots, 1).$$

Then, clearly, $D_\alpha(p^{(n)} \| q^{(n)})$ can be written as

$$D_\alpha \left(p^{(n)} \| q^{(n)}\right) = \frac{1}{\alpha - 1} \log \boldsymbol{s} R^{n-k} \mathbf{1}^t$$

where $\mathbf{1}^t$ denotes the transpose of the vector $\mathbf{1}$. It follows directly that with the new matrix R as defined in (6), all the previous results also hold for a Markov source of arbitrary order.

IV. Interchangeability of Limits

A. Limit as $\alpha \to 1$

We herein show that although the Rényi divergence reduces to the Kullback–Leibler divergence as $\alpha \to 1$, the Rényi divergence rate does not necessarily reduce to the Kullback–Leibler divergence rate. Without loss of generality, we will herein deal with first-order Markov sources since any kth-order Markov source can be converted to a first-order Markov source by k-step blocking it. Let us first note the following result about the computation of the Kullback–Leibler divergence rate between two time-invariant Markov sources which follows based on [10, p. 68] and [12, Theorem 8.6.1].

Proposition 7: Let $\{X_1, X_2, \ldots\}$ be a time-invariant Markov source with finite alphabet $\mathcal{X}$. Let $p^{(n)}$ and $q^{(n)}$ be two n-dimensional probability distributions on $\mathcal{X}^n$. Let P and Q be the probability transition matrices associated with $p^{(n)}$ and $q^{(n)}$, respectively. Let q be the initial distribution with respect to $q^{(n)}$. If $Q > 0$, $q > 0$, and P is irreducible, then the Kullback–Leibler divergence rate between $p^{(n)}$ and $q^{(n)}$ is given by

$$\lim_{n \to \infty} \frac{1}{n} D\left(p^{(n)} \| q^{(n)}\right) = -H_p(\mathcal{X}) - \sum_{i,j} \pi_i p_{ij} \log q_{ij}$$

where

$$H_p(\mathcal{X}) \triangleq \lim_{n \to \infty} \frac{1}{n} H(p^{(n)}) = -\sum_{i,j} \pi_i p_{ij} \log p_{ij}$$

denotes the Shannon entropy rate of the source with respect to $p^{(n)}$, and π denotes the stationary distribution associated with $p^{(n)}$.

We first show the following lemma; a direct consequence of this lemma generalizes a result of [21, p. 21] for ergodic Markov sources to irreducible Markov sources.

Lemma 2: Let $A = (a_{ij})$ be an $n \times n$ matrix of rank $n - 1$ with the property that $\sum_j a_{ij} = 0$ for each i. Define c_i to be the cofactor of a_{ii}; i.e., the determinant of the matrix obtained from A by deleting the ith row and the ith column and let $c = (c_1, c_2, \ldots, c_n)$. Then c is a nonzero vector and satisfies $cA = 0$.

Proof: See the Appendix.

We next prove the following theorem.

Theorem 2: Given that $\alpha \in (0, 1) \cup (1, \infty)$, consider a time-invariant Markov source $\{X_1, X_2, \ldots\}$ with finite alphabet $\mathcal{X}$ and two possible distributions $p^{(n)}$ and $q^{(n)}$ on $\mathcal{X}^n$. Let P and Q be the probability transition matrices on $\mathcal{X}$ associated with $p^{(n)}$ and $q^{(n)}$, respectively. If the matrix P is irreducible, the matrix Q is positive, and the initial distribution q with respect to $q^{(n)}$ is positive then

$$\begin{aligned}\lim_{\alpha \to 1} \lim_{n \to \infty} \frac{1}{n} D_\alpha \left(p^{(n)} \| q^{(n)}\right) &= \lim_{n \to \infty} \lim_{\alpha \to 1} \frac{1}{n} D_\alpha \left(p^{(n)} \| q^{(n)}\right) \\ &= -H_p(\mathcal{X}) - \sum_{i,j} \pi_i p_{ij} \log q_{ij} \\ &= \sum_{i,j} \pi_i p_{ij} \log(p_{ij}/q_{ij})\end{aligned}$$

and, therefore, the Rényi divergence rate reduces to the Kullback–Leibler divergence rate as $\alpha \to 1$.

Proof: Since P is irreducible and Q is positive, then the matrix R (as defined in Section III) is irreducible. For convenience of notation, denote the largest positive real eigenvalue of R by $\lambda(\alpha, R)$. We know by Proposition 5 that each eigenvalue of R is a continuous function of elements of R. Note that since $Q > 0$, $R \to P$ as $\alpha \to 1$, and the largest eigenvalue of the stochastic matrix P is 1. Hence,

$$\lim_{\alpha \to 1} \lambda(\alpha, R) = 1.$$

Let a denote an arbitrary base of the logarithm. Then, by l'Hôpital's rule, we find that

$$\lim_{\alpha \to 1} \frac{\log \lambda(\alpha, R)}{\alpha - 1} = \frac{1}{\ln a} \lambda'(1, R) \triangleq \frac{1}{\ln a} \left.\frac{\partial \lambda(\alpha, R)}{\partial \alpha}\right|_{\alpha=1} \tag{7}$$

which is well defined by Proposition 6 since the algebraic multiplicity of $\lambda(\alpha, R)$ is 1 (R is irreducible) by Proposition 3. The equation defining the largest positive eigenvalue $\lambda(\alpha, R) = \lambda$ of R is

$$\begin{vmatrix} p_{11}^\alpha q_{11}^{1-\alpha} - \lambda & p_{12}^\alpha q_{12}^{1-\alpha} & \cdots & p_{1M}^\alpha q_{1M}^{1-\alpha} \\ p_{21}^\alpha q_{21}^{1-\alpha} & p_{22}^\alpha q_{22}^{1-\alpha} - \lambda & \cdots & p_{2M}^\alpha q_{2M}^{1-\alpha} \\ \vdots & \vdots & \ddots & \vdots \\ p_{M1}^\alpha q_{M1}^{1-\alpha} & p_{M2}^\alpha q_{M2}^{1-\alpha} & \cdots & p_{MM}^\alpha q_{MM}^{1-\alpha} - \lambda \end{vmatrix} = 0 \tag{8}$$

where $M = |\mathcal{X}|$. By differentiating this equation with respect to α, we get [15], [19]

$$D_1 + D_2 + \cdots + D_M = 0 \tag{9}$$

where D_i is the determinant obtained from (8) by replacing the ith row by

$$\big(p_{i1}^{\alpha} q_{i1}^{1-\alpha} \ln(p_{i1}/q_{i1}), \ldots, p_{ii}^{\alpha} q_{ii}^{1-\alpha} \ln(p_{ii}/q_{ii}) - \lambda'(\alpha), \ldots, p_{iM}^{\alpha} q_{iM}^{1-\alpha} \ln(p_{iM}/q_{iM})\big)$$

and leaving the other $M-1$ rows unchanged. In this equation, λ' denotes the derivative of λ with respect to α. Note that if we add in D_i all the other columns to the ith column, the value of the determinant remains unchanged. Therefore, for $\alpha = 1$ and hence $\lambda = 1$, D_i is the determinant

$$\begin{vmatrix} p_{11}-1 & \cdots & 0 & \cdots & p_{1M} \\ p_{21} & \cdots & 0 & \cdots & p_{2M} \\ \vdots & \vdots & 0 & \cdots & \vdots \\ p_{i-1,1} & \cdots & 0 & \cdots & p_{i-1,M} \\ p_{i1}\ln(p_{i1}/q_{i1}) & \cdots & S(X|i)-\lambda' & \cdots & p_{iM}\ln(p_{iM}/q_{iM}) \\ p_{i+1,1} & \cdots & 0 & \cdots & p_{i+1,M} \\ \vdots & \vdots & 0 & \cdots & \vdots \\ p_{M1} & \cdots & 0 & \cdots & p_{MM}-1 \end{vmatrix}$$

where

$$S(X|i) = \sum_{j=1}^{M} p_{ij} \ln(p_{ij}/q_{ij}).$$

A zero occurs in all the entries of the ith column except for the ith entry, since $\sum_{j=1}^{M} p_{lj} = 1$. We conclude that

$$D_i = \big(S(X|i) - \lambda'(1)\big)\, c_i \tag{10}$$

where c_i is the $M-1 \times M-1$ cofactor of $p_{ii}-1$ in the determinant of (8) for the case $\alpha = 1$, given by

$$c_i = \begin{vmatrix} p_{11}-1 & \cdots & p_{1,i-1} & \cdots & p_{1M} \\ p_{21} & \cdots & p_{2,i-1} & \cdots & p_{2M} \\ \vdots & \cdots & \cdots & \cdots & \vdots \\ p_{i-1,1} & \cdots & p_{i-1,i-1}-1 & \cdots & p_{i-1,M} \\ p_{i+1,1} & \cdots & p_{i+1,i-1} & \cdots & p_{i+1,M} \\ \vdots & \cdots & \cdots & \cdots & \vdots \\ p_{M1} & \cdots & p_{M,i-1} & \cdots & p_{MM}-1 \end{vmatrix}.$$

After substituting (10) in (9) and solving for $\lambda'(1)$, we obtain by (7) that

$$\lim_{\alpha\to 1} \frac{\log \lambda(\alpha, R)}{\alpha - 1} = \frac{1}{\ln a}\lambda'(1, R) = \frac{1}{\ln a}\sum_{i=1}^{M} \pi_i S(X|i) \tag{11}$$

where

$$\pi_i = \frac{c_i}{\sum_j c_j}.$$

As $\alpha \to 1$, $R \to P$; let $A = P - I$. Since the stationary distribution of the irreducible matrix R is unique, the rank of A is $n-1$ because the nullity of A is 1 in this case. Hence, the conditions in Lemma 2 are satisfied. Therefore, $cA = 0$, which is equivalent to $cP = c$. Note that c is the nonnormalized stationary distribution of P and (11) is just the Kullback–Leibler divergence rate between P and Q by Proposition 7. □

The following example illustrates that the Rényi divergence rate does not necessarily reduce to the Kullback–Leibler divergence rate if the conditions of the previous theorem are not satisfied.

Example: Given that $\alpha \in (0, 1) \cup (1, \infty)$, let P and Q be as follows:

$$P = \begin{pmatrix} 1/4 & 3/4 & 0 \\ 3/4 & 1/4 & 0 \\ 0 & 0 & 1 \end{pmatrix} \qquad Q = \begin{pmatrix} 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \end{pmatrix}.$$

Suppose that $p^{(n)}$ is stationary with stationary distribution $(b/2, b/2, 1-b)$, where $0 < b < 1$ is arbitrary. Also, suppose that the initial distribution q is positive. Then following [11, p. 40], a simple computation yields that the Kullback–Leibler divergence rate is given by $\log_2 3 - 2b + (3b/4)\log_2 3$, where the logarithm is to the base 2.

The eigenvalues of R are

$$\lambda_1 = 1/(3^{1-\alpha})$$
$$\lambda_2 = 4^{-\alpha}/(3^{1-\alpha}) + 4^{-\alpha}/(3^{1-2\alpha})$$

and

$$\lambda_3 = 4^{-\alpha}/(3^{1-\alpha}) - 4^{-\alpha}/(3^{1-2\alpha}).$$

Note that $\boldsymbol{s} > 0$ and that, if $0 < \alpha < 1$, $\max_{1\le i\le 3}\{\lambda_i\} = \lambda_2$. By Theorem 1, the Rényi divergence rate is $(\alpha-1)^{-1}\log_2 \lambda_2$. By l'Hôpital's rule, we get that

$$\lim_{\alpha\uparrow 1} (\alpha-1)^{-1}\log_2 \lambda_2 = (7/4)\log_2 3 - 2.$$

Therefore,

$$\lim_{\alpha\uparrow 1}\lim_{n\to\infty} \frac{1}{n} D_\alpha\left(p^{(n)} \| q^{(n)}\right) = (7/4)\log_2 3 - 2.$$

On the other hand, if $\alpha > 1$, $\max_{1\le i\le 3}\{\lambda_i\} = \lambda_1$. Therefore, the Rényi divergence rate is given by $(\alpha-1)^{-1}\log_2 \lambda_1$. Clearly,

$$\lim_{\alpha\downarrow 1} (\alpha-1)^{-1}\log_2 \lambda_1 = \log_2 3.$$

Hence,

$$\lim_{\alpha\downarrow 1}\lim_{n\to\infty} \frac{1}{n} D_\alpha\left(p^{(n)} \| q^{(n)}\right) = \log_2 3.$$

Therefore, the interchangeability of limits is not valid since

$$\lim_{\alpha\uparrow 1}\lim_{n\to\infty} \frac{1}{n} D_\alpha\left(p^{(n)} \| q^{(n)}\right) < \lim_{n\to\infty}\lim_{\alpha\to 1} \frac{1}{n} D_\alpha\left(p^{(n)} \| q^{(n)}\right) < \lim_{\alpha\downarrow 1}\lim_{n\to\infty} \frac{1}{n} D_\alpha\left(p^{(n)} \| q^{(n)}\right).$$

B. Limit as $\alpha \downarrow 0$

We obtain the following result.

Theorem 3: Let $\alpha \in (0, 1)$. Consider a time-invariant Markov source $\{X_1, X_2, \ldots\}$ with finite alphabet $\mathcal{X}$ and two possible distributions $p^{(n)}$ and $q^{(n)}$ on $\mathcal{X}^n$. Let P and Q be the probability transition matrices on $\mathcal{X}$ associated with $p^{(n)}$ and $q^{(n)}$, respectively. Then

$$\lim_{\alpha\downarrow 0}\lim_{n\to\infty} \frac{1}{n} D_\alpha\left(p^{(n)} \| q^{(n)}\right) = \lim_{n\to\infty}\lim_{\alpha\downarrow 0} \frac{1}{n} D_\alpha\left(p^{(n)} \| q^{(n)}\right).$$

Proof: By Theorem 1, we have

$$\lim_{n\to\infty} \frac{1}{n} D_\alpha\left(p^{(n)} \| q^{(n)}\right) = \frac{1}{\alpha - 1}\log \lambda(\alpha, R).$$

By Proposition 5, $\lambda(\alpha, R) \to \lambda(0, R)$ as $\alpha \downarrow 0$. Hence,

$$\lim_{\alpha\downarrow 0}\lim_{n\to\infty} \frac{1}{n} D_\alpha\left(p^{(n)} \| q^{(n)}\right) = -\log \lambda(0, R).$$

On the other hand,

$$\lim_{\alpha\downarrow 0} \frac{1}{n} D_\alpha\left(p^{(n)} \| q^{(n)}\right) = \frac{1}{n} \log \hat{\boldsymbol{s}} Y \mathbf{1}^t$$

where $\hat{\boldsymbol{s}} = \lim_{\alpha\downarrow 0} \boldsymbol{s}$ and $Y = \lim_{\alpha\downarrow 0} R$. Therefore, by again applying Theorem 1 to Y, we get

$$\lim_{n\to\infty} \lim_{\alpha\downarrow 0} \frac{1}{n} D_\alpha\left(p^{(n)} \| q^{(n)}\right) = -\log \lambda(0, R).$$

Hence the interchangeability of limits is always valid between n and α as $n \to \infty$ and as $\alpha \downarrow 0$. $\square$

V. The Rényi Entropy Rate

The existence and the computation of the Rényi entropy rate of an arbitrary time-invariant finite alphabet Markov source can be deduced from the existence and the computation of the Rényi divergence rate. Indeed, if $q^{(n)}$ is stationary memoryless with uniform marginal distribution then for any $\alpha > 0$, $\alpha \neq 1$

$$D_\alpha\left(p^{(n)} \| q^{(n)}\right) = n \log M - H_\alpha\left(p^{(n)}\right).$$

Therefore,

$$\lim_{n\to\infty} \frac{1}{n} D_\alpha\left(p^{(n)} \| q^{(n)}\right) = \log M - \lim_{n\to\infty} \frac{1}{n} H_\alpha\left(p^{(n)}\right).$$

Hence, the existence and the computation of the Rényi entropy rate follows directly from Theorem 1. Actually, $\lim_{n\to\infty} \frac{1}{n} H_\alpha(p^{(n)})$ can be computed directly from Theorem 1 by determining λ with $R = (p_{ij}^\alpha)$ and $s_i = p_i^\alpha$, and setting

$$\lim_{n\to\infty} \frac{1}{n} H_\alpha(p^{(n)}) = \frac{1}{1-\alpha} \log \lambda.$$

A formula for the Rényi entropy rate was established earlier in [18] and [19], but only for the particular case of ergodic finite alphabet time-invariant Markov sources.

Although the Rényi entropy reduces to the Shannon entropy, the Rényi entropy rate does not necessarily reduce to the Shannon entropy rate as $\alpha \to 1$. From the results about the interchangeability of limits for the Rényi divergence rate, it follows easily that the Rényi entropy rate always reduces to the Hartley entropy rate as $\alpha \downarrow 0$ $(\lim_{n\to\infty} \frac{1}{n} H_0(p^{(n)}))$, and if the Markov source is irreducible, it reduces to the Shannon entropy rate as $\alpha \to 1$.

In [19], we established an operational characterization for the Rényi entropy rate by extending the variable-length source coding theorem in [5] for discrete memoryless sources to ergodic Markov sources. Using the above expression for the Rényi entropy rate, this source coding theorem can be easily extended to arbitrary time-invariant Markov sources. We also note that, by the results on the interchangeability of limits, the coding theorem does not necessarily reduce to the Shannon lossless source coding theorem as $\alpha \to 1$. It does reduce to the Shannon coding theorem if, for example, the Markov source is irreducible.

VI. Concluding Remarks

In this work, we derived a formula for the Rényi divergence rate between two time-invariant finite-alphabet Markov sources of arbitrary order and arbitrary initial distributions. We also investigated the limits of the Rényi divergence rate as $\alpha \to 1$ and as $\alpha \downarrow 0$. Similarly, we examined the computation and the existence of the Rényi entropy rate for Markov sources and investigated its limits as $\alpha \to 1$ and as $\alpha \downarrow 0$. We also observed that an operational characterization for the Rényi entropy rate can be established by extending a variable-length source coding theorem for memoryless sources to the case of Markov sources.

Appendix

Proof of Lemma 2:

Step 1: First we prove that $c \neq 0$. The first $n-1$ columns of A are linearly independent, because, otherwise, the rank of A is less or equal to $n-2$ since the sum of the columns of A is 0. Thus, there is at least one nonzero determinant Δ of size $(n-1)\times(n-1)$ which can be formed by deleting one row and the nth column of A which follows from the fact that the determinant of a matrix is 0 iff the columns are linearly dependent. Let the deleted row be the kth row. If $k = n$, $\Delta = c_n$ and so $c \neq 0$. If $k < n$, add all the columns except the nth column to the kth column; this does not change the value of the determinant Δ. Because $\sum_j a_{ij} = 0$, the elements of the kth column are now $-a_{1n}, -a_{2n}, \ldots, -a_{nn}$. Multiply the elements of this column by -1 and move this column to the rightmost position. This yields a new determinant with value $\pm\Delta$ because these operations affect only the sign of the determinant. However, the new determinant is just c_k, so that once again, $c \neq 0$. Thus, at least one of the cofactors c_i is nonzero. Without loss of generality assume that $c_n \neq 0$. Next we prove that $cA = 0$.

Step 2: Consider the $n-1$ equations

$$\sum_{i=1}^{n} a_{ij} x_i = 0, \qquad j \in \{1, 2, \ldots, n-1\}. \tag{12}$$

Note that $\sum_{i=1}^n a_{ij} x_i = 0$ is equivalent to $\sum_{i=1}^{n-1} a_{ij} x_i = -a_{nj} x_n$. Since $c_n \neq 0$, we can use Cramer's rule [15, p. 60] to solve these equations for $x_1, \ldots, x_{n-1}$ in terms of x_n as follows:

$$x_k = -x_n \frac{D_k}{c_n} \tag{13}$$

where D_k is given in the equation at the bottom of the page, and where the elements from the nth column have replaced the elements of the kth column. If we add the other rows to the kth row (note that the determinants are transposed here) and use the fact that $\sum_j a_{ij} = 0$ we get a new kth row

$$-a_{1n}, -a_{2n}, \ldots, -a_{k-1,n}, -a_{nn}, -a_{k+1,n}, \ldots, -a_{n-1,n}.$$

After moving the kth row and the kth column to the last row and column position, respectively, it follows that $D_k = -c_k$. From (13), if we put $x_n = c_n$, then $x_k = c_k$ for all $k \in \{1, 2, \ldots, n\}$. Because $\sum_j a_{ij} = 0$, any solution of (12) is a solution of the same equation for $j = n$. Thus, $c = (c_1, \ldots, c_n)$ satisfies $cA = 0$. $\square$

$$D_k = \begin{vmatrix} a_{11} & a_{21} & \cdots & a_{k-1,1} & a_{n1} & a_{k+1,1} & \cdots & a_{n-1,1} \\ a_{12} & a_{22} & \cdots & a_{k-1,2} & a_{n2} & a_{k+1,2} & \cdots & a_{n-1,2} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ a_{1,n-1} & a_{2,n-1} & \cdots & a_{k-1,n-1} & a_{n,n-1} & a_{k+1,n-1} & \cdots & a_{n-1,n-1} \end{vmatrix}$$

ACKNOWLEDGMENT

The authors wish to thank the anonymous referees for their useful suggestions.

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One Stochastic Process and Its Application to Multiple Access in Supercritical Region

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***Abstract*—A discrete-argument stochastic process is presented. The process is a generalization of the Çinlar semiregenerative process [5] and process $\eta(t)$ given in [17]. For this process, the theorem, which is similar to the Smith regenerative process theorem, is given. We use this theorem to find the transmission rate and mean packet delay for stack and part-and-try random multiple access algorithms in their supercritical regions. For part-and-try algorithm, the results are new. For stack algorithm, we give a new method of finding the rate and delay.**

***Index Terms*—Packet multiple access, random process.**

I. INTRODUCTION

In this correspondence, we present a discrete-argument stochastic process which is useful in random multiple-access problems. The process is a generalization of the semiregenerative process [5] and process $\eta(t)$ given in [17]. The presented process is called the generalized process $\eta(t)$.

Similarly to the regenerative process, the generalized process $\eta(t)$ consists of independent cycles. But cycles are not stochastically the same; similarly as in both the semiregenerative process [5] and process $\eta(t)$ given in [17]. There are a number (maybe an infinite number) of stochastically different processes ε the beginnings of which can be candidates for the next cycle. The candidates are enumerated. A candidate number is called the type of process ε. The type for the next cycle is chosen randomly depending on the given type and length of the previous cycle. As in process $\eta(t)$ given in [17], but not as in the semiregenerative process [5], the time of cycle end is not necessarily the Markov moment of $\eta(t)$. However, contrary to both the semiregenerative process [5] and process $\eta(t)$ given in [17], the processes ε beyond their cycles can be dependent. Also, the cycle can depend on the processes ε beyond their cycles. Such dependencies are essential in some applications. For example, they are essential in our consideration of stack algorithm in Section III.

Two such applications are given in this correspondence. In the first, we consider the delay D and transmission rate R of the random packet-multiple-access stack algorithm [18], [16]. If the Poisson packet traffic arrival rate λ is less than $\lambda_{\rm cr} \approx 0.36$, the stack algorithm has a finite average packet delay [18]. The delay as a function of λ was found in [21], [6], and [13] for traffic arrival rate $\lambda < \lambda_{\rm cr} \approx 0.360177\ldots$. When $\lambda \geq \lambda_{\rm cr}$ (this is the supercritical region of rates), the stack algorithm has infinite average delay because some arriving packets do not achieve successful transmission at all. However, there exists a certain portion of arriving packets which are successful. The rate of successfully transmitted packets R as a function of λ for $\lambda \geq \lambda_{\rm cr}$ was found in [12]. The average delay of successfully transmitted packets D as a function of λ for $\lambda \geq \lambda_{\rm cr}$ was found in [22]. The method, which was applied to finding R in [12] and D in [22], uses linear and nonlinear functional equations and their recursive solutions [7].

In this correspondence, we give a different approach for finding R and D when $\lambda \geq \lambda_{\rm cr}$. The approach interprets the stochastic processes, which describe the stack algorithm, as the generalized process $\eta(t)$ and

Manuscript received May 25, 2000.
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Communicated by I. Csiszár, Associate Editor for Shannon Theory.
Publisher Item Identifier S 0018-9448(01)02999-6.