

# 1. Introducción

*Paper:*

## Relative Entropy Under Mappings by Stochastic Matrices

Joel E. Cohen, Yoh Iwasa, Gh. Rautu, Mary Beth Ruskai, Eugene Seneta, Gh. Zbaganu

*Relevance:*

- Can provide more information on bounding the rates of convergence to equilibrium of ergodic Markov chains and Markov processes

# 2. Preliminares

- give the definitions of the different types of random matrices
  - positive and nonnegative probability  $d$ -vectors
  - row/column stochastic matrix
  - scrambling matrix
- And I think we need the following definitions to give context for the contraction coefficient

**Definición: 2.1** → Symmetric Relative Entropy

**Definición: 2.2** → relative  $\phi$ -entropy

**Definición: 2.3**

Para cualquier  $m \times n$  matriz  $A$ , el coeficiente de ergodicity de Dobrushin se define

$$\alpha(A) = \min_{j,k} \sum_{i=1}^m \min(a_{ij}, a_{ik})$$

The complement  $1 - \alpha(A)$  is

$$\bar{\alpha}(A) \equiv 1 - \alpha(A) = \frac{1}{2} \max_{j,k} \sum_{i=1}^m |a_{ij} - a_{ik}|$$

and also satisfies

$$\bar{\alpha}(A) = \sup \left\{ \frac{\|A(x - y)\|_1}{\|x - y\|_1} : x \text{ and } y \text{ are positive } n\text{-vectors such that } x \neq y, \|x\|_1 = \|y\|_1 \right\}$$

- introduce  $g(t) = \phi(1, 1 + t)$  as a way to index the contraction coefficients

### 3. Resultados Principales

**Theorem 4.1:**  $0 \leq \eta_\phi(A) \leq \bar{\alpha}(A) \leq 1$

**Teorema: 4.1**

$$0 \leq \eta_\phi(A) \leq \bar{\alpha}(A) \leq 1$$

**Teorema: 5.4**

If  $g(w)$  is thrice differentiable in a neighborhood of 0 and  $g''(0) > 0$ , then  $\eta_{w^2}(A) \leq \eta_g(A)$ ; in particular,  $\eta_{w^2}(A) \leq \eta_{\log}(A)$

### 4. Elementos de las demostraciones

- Theorem 4.1
  - Introduce and explain theorem 3 and the corresponding lemas since theorem 4.1 depends on it
- Theorem 5.4
  - define homogeneous function
  - the rest seems pretty straight forward

### 5. Conclusión

Relación con el curso

- compare with what we've seen with DPI from  $KL$ -divergence and mutual information. Briefly, we have

$$\eta_\phi(A) = \sup \left\{ \frac{H_\phi(Ax, Ay)}{H_\phi(x, y)} : x \in P_n, y \in P_n, x \neq y \right\}$$

and also

$$\begin{aligned} A \text{ is scrambling} &\iff \eta_\phi(A) < 1 \\ &\iff H_\phi(x, y) < H_\phi(Ax, Ay) \quad \text{with equality if } A \text{ is permutation} \end{aligned}$$

So

$$X \xrightarrow{A} Y \xrightarrow{A'} Z \implies H_\phi(X, Y) < H_\phi(X, Z)$$

Seems like this connects easily to what we've seen if we define  $P_{X|Y} \equiv A$  and  $P_{Y|Z} \equiv A'$

- Compare relative  $g$ -entropy with  $f$ -divergence

- Extend symmetry to  $f$ -divergence

$$J_\phi(x, y) = H_\phi(x, y) + H_\phi(y, x) \longrightarrow J_f(x, y) = D_f(x, y) + H_f(y, x)$$