# Diversity and overlap analysis in TCR populations

Michał Seweryn and Grzegorz A Rempała mseweryn@cph.osu.edu, grempala@cph.osu.edu



### Problem

Maintaining a proper diversity of T-cell receptor populations (TCR's) is crucial for the immune system's ability to recognize a vast variety of foreign antigens and to avoid autoagression. Due to large diversity of TCR's and the sampling error (of high-throughput sequencing) the standard diversity and overlap measures of the contingency table analysis are insufficient. Applying information theory here we have developed some new ones specifically for TCR data analysis.

## **Basic Concepts**

Each population of TCR's corresponds to a vector of counts  $\mathbf{c}_i = (c_{1,i}, \ldots, c_{m_i,i}), i = 1, \ldots, s$ . Let  $X = (X_1, \ldots, X_{m_i}), \sum_{k=1}^{m_i} X_k = n$  be a sample of size n. We define 'sample coverage'  $C := \sum_{l=1}^{m_i} p_l I_l$ , where  $I_l = 1$  if  $X_l > 0$  and  $I_l = 0$  otherwise and it's Good and Turing estimator  $\hat{C} = \frac{s_n(1)}{n}$ , where  $s_n(1)$  is the number of singletons.

## **Performance of new diversity indices**

We analyze two TCR datasets obtained from high-throughput sequencing experiments conducted in the molecular immunology lab of Prof Leszek Ignatowicz. One dataset consists of the so called "regulatory" T-cells  $(GFP^+)$  the second one of the so-called "naive" T-cells. Diversity and ENS (based on 500 repetitions) is reported relatively to the values in the complete set.

	<b>1</b>		V	L
	$n = 10^2$	$n = 10^{3}$	$n = 10^4$	$n = 10^{5}$
Stat/ENS	$\hat{C} = 0.30$	$\hat{C} = 0.62$	$\hat{C} = 0.83$	$\hat{C} = 0.94$
ISI	$0.34 \ (0.19, 0.45)$	$0.77 \ (0.52, 1.07)$	$0.94 \ (0.83, 1.08)$	0.95 (0.90, 0.99)
	0.34 ( $0.19, 0.45$ )	$0.77 \ (0.52, 1.07)$	$0.94 \ (0.83, 1.08)$	0.95(0.90, 0.99)
$H_{\hat{C}}$	$0.46\ (0.37,\!0.50)$	$0.74 (0.68,\!0.78)$	$0.92 (0.89,\!0.94)$	$0.96\ (0.95, 0.97)$
	0.07  (0.04, 0.08)	$0.27 (0.21,\!0.35)$	$0.65 \ (0.57, 0.74)$	$0.83 \ (0.78, 0.86)$
$H_{\hat{C}}^{(n)}$	$0.75 \ (0.49, 1.00)$	$0.90 \ (0.82, 0.98)$	$1.02 \ (1.00, 1.06)$	$1.01 \ (1.00, 1.02)$
	0.29 (0.077, 1.00)	$0.60\ (0.41, 0.90)$	$1.13\ (0.95, 1.35)$	$1.07 \ (1.01, 1.15)$
$H_1^{(n)}$	$0.73 \ (0.46, 1.04)$	$0.80\ (0.73, 0.89)$	0.92 (0.90, 0.95)	0.96 (0.95, 0.97)
1	$0.27 \ (0.06, 1.22)$	$0.39 \ (0.26, 0.56)$	$0.69 \ (0.60, 0.78)$	$0.84 \ (0.79, 0.88)$

Let  $\mathcal{F}_c$  be the fingerprint or diversity of the population c – a vector given by  $\mathcal{F}_c = (s(1), \ldots, s(\max_i c_i)), s(k) = card\{i : c_i = k\}$ . A nonnegative, real function of the fingerprint is called a measure (index) of diversity.

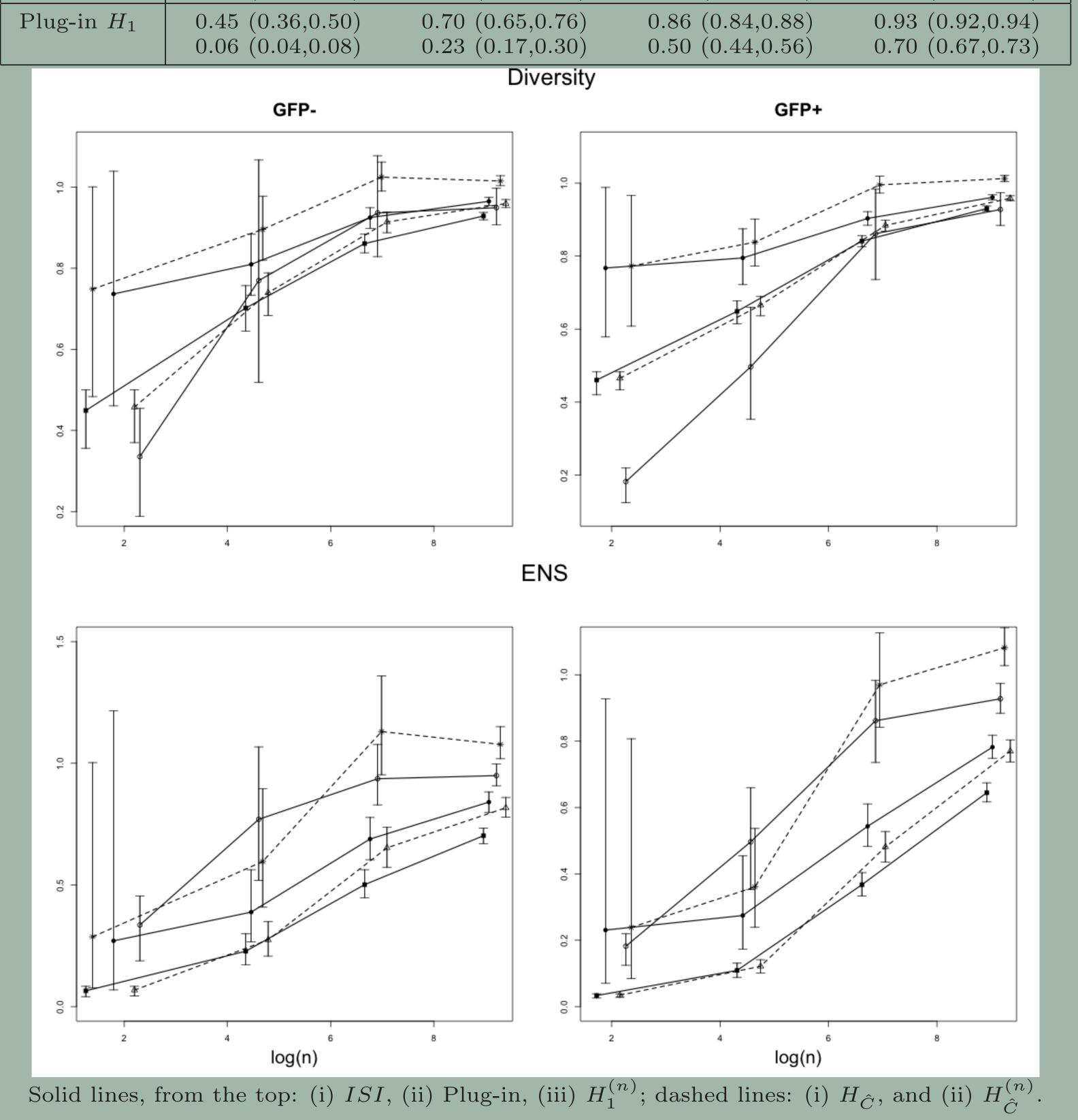
Set  $c_1, c_2, \ldots c_n$  to be populations and let  $supp(c_i)$  denote the support of  $c_i$ . The overlap between vectors  $c_1, \ldots, c_n$  is then  $\mathcal{O}_n = \bigcap_{k=1}^n supp(c_k)$ . Any nonnegative, real function G, such that  $G(\mathcal{O}_n c_1, \ldots, c_n)$ , is an overlap measure (index).

Let c - population and D - monotone diversity measure,  $\mathcal{F}_{I(m)}$  the fingerprint of a uniform population with m different receptors. We define ENS (effective number of species) as the smallest solution of the equation  $D(\mathcal{F}_{I(y)}) = D(\mathcal{F}_c)$ .

Previous work – diversity and overlap indices Renyi's (and Shannon's) entropy  $H_{\alpha}(\mathcal{F}_c) = \frac{1}{1-\alpha} \log \left( \sum_k s(k) \left( \frac{k}{n} \right)^{\alpha} \right), \alpha \ge 0$ , and  $H_1(\mathcal{F}_c)$ Simpson's index  $ISI := \exp(H_2(\mathcal{F}_c))$ , Chao-Shen's index  $H_1(\mathcal{F}_c) = -\sum_k s(k) \frac{k}{n(1-(1-k/n)^n)}$ For two populations c, c' define Jaccard's index  $J(c, c') = \frac{\sum_i \min(c_i, c'_i)}{\sum_i (c_i + c'_i) - \sum_i \min(c_i, c'_i)}$ For  $(p_1, p_2)$  – pair of normalized populations: Morisita-Horn's index and Renyi's divergence  $MH(p_1, p_2) = \frac{2\sum_i p_{i,1} p_{i,2}}{\sum_i p_{i,1}^2 + \sum_i p_{i,2}^2}, \quad F_{\alpha}(p_1, p_2) = \frac{1}{\alpha - 1} \log \left( \sum_i \frac{p_{i,1}^{\alpha}}{p_{i,2}^{\alpha - 1}} \right), \alpha \ge 0$ 

# **Coverage corrected diversity indices**

Now we aim to estimate the diversity of a population of T-cells given sample  $\mathcal{X}$  of size n. We define a family of 'sample based' diversity measures which in a natural way overemphisize rare species in the case of undersampling error, we also use a Horvitz-Thompson type correction for bias. Let  $\hat{C}$  be the Good-Turing estimator of the sample coverage, we define



$$\hat{H}_{\alpha\hat{C}}(\mathcal{X}) = \frac{\log\left(\sum_{k} s_n(k) \left(\frac{k}{n}\right)^{\alpha\hat{C}}\right)}{1 - \alpha\hat{C}}, \quad \hat{H}_{\alpha\hat{C}}^{(n)}(\mathcal{X}) = \frac{\log\left(\sum_{k} \frac{s_n(k)k^{\alpha\hat{C}}}{n^{\alpha\hat{C}}(1 - (1 - k/n)^n)}\right)}{1 - \alpha\hat{C}}$$

Set  $\hat{p}$  to be the MLE of the normalized population vector p and  $\tilde{p} = \hat{C}\hat{p}$ . Let  $0 < \alpha < \infty$  and assume that  $H_{\alpha}(p) < \infty$ . If  $\alpha < 1$  or if  $\alpha > 1$  and  $\sum_{k} p_{k} \log^{r}(1/p_{k}) < \infty$  for some r > 0 then

$$H_{\alpha}^{(n)}(\tilde{\boldsymbol{p}}) \xrightarrow{a.s.} H_{\alpha}(\boldsymbol{p}) \quad \text{and} \quad H_{\hat{C}\alpha}^{(n)}(\tilde{\boldsymbol{p}}) \xrightarrow{a.s.} H_{\alpha}(\boldsymbol{p}). \quad \text{If } \alpha = 1, \text{ then } H_{1}^{(n)}(\tilde{\boldsymbol{p}}) \xrightarrow{a.s.} H_{1}(\boldsymbol{p}),$$
  
and on the set  $\{\hat{C} < 1 \text{ i.o.}\}, \ H_{\hat{C}}^{(n)}(\tilde{\boldsymbol{p}}) - \frac{\log R_{1}^{(n)}(\tilde{\boldsymbol{p}})}{1 - \hat{C}} \rightarrow H_{1}(\boldsymbol{p}), \text{ where } R_{1}^{(n)}(\tilde{\boldsymbol{p}}) := \sum \frac{\tilde{p}_{i}}{1 - (1 - \tilde{p}_{i})^{n}}$ 

#### New overlap indices

We consider a slightly more general form of the Morisita-Horn index, which allows it to put more weight on rare (resp. abundant) receptors. For  $(p_1, p_2)$  a pair of normalized populations and  $\alpha, \beta \in (0, \infty)$  the power-geometric (or PG) index of overlap is given by

$$PG_{\alpha,\beta}(\boldsymbol{p}_{1},\boldsymbol{p}_{2}) = \frac{\sum p_{i1}^{\alpha} p_{i2}^{\beta}}{\sum p_{i1}^{2\alpha} + \sum p_{i2}^{2\beta}}.$$

In analogy with the adjustment of diversity indices, and in the notation as above, we may consider  $PG_{\hat{C}_1 \alpha \hat{C}_2 \beta}^{(n)}(\tilde{p}_1, \tilde{p}_2)$  as the sample-coverage and Horvitz-Thompson adjusted PG index.

Stat $\hat{C}_1 = 0.25$ $\hat{C}_1 = 0.61$ $\hat{C}_1 = 0.83$ $\hat{C}_1 = 0.94$ $\hat{C}_2 = 0.16$ $\hat{C}_2 = 0.40$ $\hat{C}_2 = 0.70$ $\hat{C}_2 = 0.91$ PG $0.74 (0.00, 4.2)$ $0.76 (0.31, 1.31)$ $0.92 (0.80, 1.04)$ $0.99 (0.92, 1.6)$ I_1-ind $0.10 (0.00, 0.59)$ $0.40 (0.18, 0.62)$ $0.69 (0.62, 0.78)$ $0.91 (0.88, 0.92)$ L $0.12 (0.00, 0.73)$ $0.38 (0.20, 0.59)$ $0.64 (0.53, 0.74)$ $0.88 (0.84, 0.92)$ CJ $0.04 (0.00, 0.30)$ $0.24 (0.06, 0.62)$ $0.56 (0.37, 0.85)$ $0.81 (0.68, 1.02)$	$\hat{C}_2 = 0.16$ $\hat{C}_2 = 0.40$ $\hat{C}_2 = 0.70$ $\hat{C}_2 = 0.9$	
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	PG = 0.74 (0.00.4.2) = 0.76 (0.31.1.31) = 0.92 (0.801.04) = 0.99 (0.92.5)	)1
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	(0.00, 1.01) $(0.00, 1.01)$ $(0.00, 1.01)$	1.05)
CJ = 0.04 (0.00, 0.30) = 0.24 (0.06, 0.62) = 0.56 (0.37, 0.85) = 0.81 (0.68, 1.0)	$I_1$ -ind 0.10 (0.00,0.59) 0.40 (0.18,0.62) 0.69 (0.62,0.78) 0.91 (0.88,0)	).95)
	$L = 0.12 \ (0.00, 0.73) = 0.38 \ (0.20, 0.59) = 0.64 \ (0.53, 0.74) = 0.88 \ (0.84, 0.84)$	).94)
	CJ = 0.04 (0.00, 0.30) = 0.24 (0.06, 0.62) = 0.56 (0.37, 0.85) = 0.81 (0.68, 1)	01)
MH = 0.17 (0.00, 1.07) = 0.74 (0.23, 1.43) = 0.96 (0.73, 1.22) = 0.99 (0.92, 1.0)	MH = 0.17 (0.00, 1.07) = 0.74 (0.23, 1.43) = 0.96 (0.73, 1.22) = 0.99 (0.92, 1.43)	1.09)

Assume that 
$$\sum p_{i1}^{\alpha} < \infty$$
 and  $\sum p_{i2}^{\beta} < \infty$ , as well as  $\sum p_{i1} \log^{r_1} \frac{1}{p_{i1}} < \infty$  for some  $r_1 > 0$ , if  $\alpha > 1$  and  $\sum p_{i2} \log^{r_2} \frac{1}{p_{i2}} < \infty$  for some  $r_2 > 0$ , if  $\beta > 1$ . Then

 $PG_{\hat{C}_1\alpha,\hat{C}_2\beta}^{(n)}(\tilde{p}_1,\tilde{p}_2) \stackrel{a.s.}{\to} PG_{\alpha,\beta}(p_1,p_2).$ 

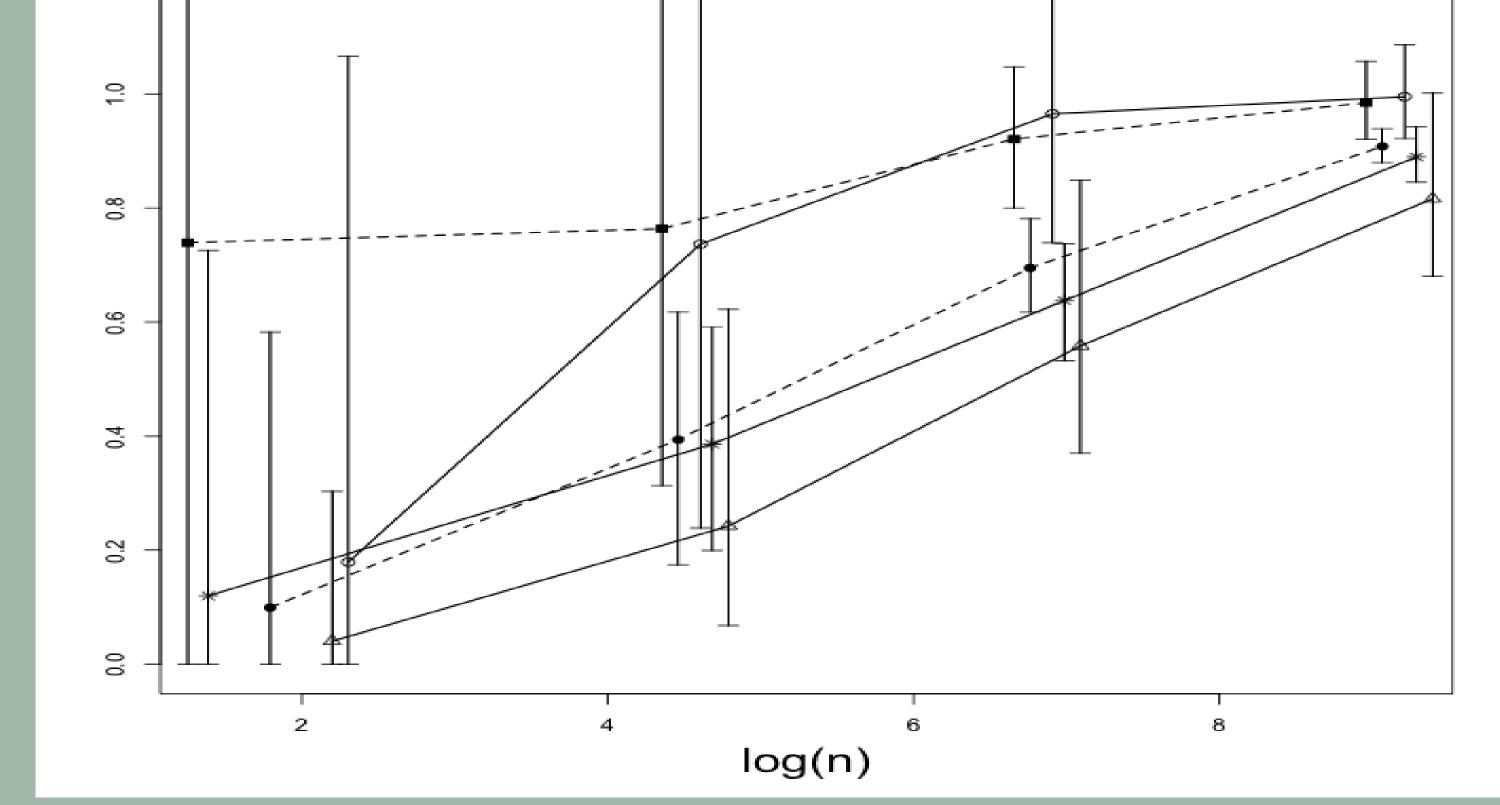
Moreover, we consider a different approach based on  $(m \times n)$  contingency table  $C = [c_{ij}]$  with columns representing *n* different population and rows representing *m* receptors. Let  $P = [p_{ij}] := [\frac{c_{ij}}{\sum_{kl} c_{kl}}]$  be the normalized matrix with columns  $p_1, p_2, \ldots, p_n, p_{i\circ} = \sum_j p_{ij}, p_{\circ j} = \sum_i p_{ij}$ and  $P_{\circ} = (p_{\circ 1}, \ldots, p_{\circ n}), P^{\circ} = (p_{1\circ}, \ldots, p_{m\circ})$ , as well as  $Q = P_{\circ} \bigotimes P^{\circ} := [p_{i\circ} p_{\circ j}]$ . Define

 $I_{\alpha}(\boldsymbol{C}) = 1 - F_{\alpha}(\boldsymbol{P}, \boldsymbol{Q}) / H_{2-\alpha}(\boldsymbol{P}_{\circ}) \text{ and } Q_{\alpha}(\boldsymbol{C}) = 1 - I_{\alpha}(\boldsymbol{C}).$ 

Note that for  $\alpha \in (0,2)$  we have  $0 \leq Q_{\alpha}(C) \leq 1$ ,  $Q_{\alpha}(C) = 0$  iff  $p_1 = p_2 = \cdots = p_n$  and if the vectors  $c_1, c_2, \ldots, c_n$  form an orthogonal system, then  $Q_{\alpha}(C) = 1$ . Let  $\hat{P}$  be the empirical MLE of P, then we also have that  $I_{\alpha}(\hat{P}) \stackrel{a.s.}{\to} I_{\alpha}(P)$ .

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Solid lines: (i) MH (open circles), (ii) L (stars) and (iii) CJ (triangles); dashed lines (i)  $PG_{\hat{C}_1,\hat{C}_2}^{(n)}$  (squares), and I-index (filled circles).