

# Results relating to a conjecture on the validity of a certain hypothesis test

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**SUMMARY:** We consider the classical problem of forming a confidence interval for the mean of a distribution with bounded support based on an iid sample. Gaffke (2005) proposed such an interval and established that it is asymptotically valid. The interval's remarkably tight bounds on the mean led Gaffke to offer two conjectures: 1) The CI has guaranteed coverage for all sample sizes (Gaffke's weaker conjecture), and 2) Further, even after relaxing the assumption of identical distributions, the CI remains valid simultaneously for all the underlying means (Gaffke's stronger conjecture). Dormant in the literature for many years, Gaffke's conjectures have received renewed attention in recent years (Waudby-Smith and Ramdas, 2024; Phan et al., 2021; Learned-Miller and Thomas, 2019). We do not offer a proof of the conjecture but instead offer a collection of related results, including properties of the test statistic and special cases of the conjecture.

Let  $n \geq 1$  pairs  $(a_i, b_i)$  be given such that  $0 \leq a_i \leq 1$ ,  $b_i \geq 1$ , and  $a_i < b_i$ ,  $i = 1, \dots, n$ . Let  $X_1, \dots, X_n$ , be mutually independent random variables with mean 1, with  $X_i$  supported on  $\{a_i, b_i\}$ ,  $i = 1, \dots, n$ , implying

$$X_i = \begin{cases} a_i & \text{w.p. } \frac{b_i-1}{b_i-a_i} \\ b_i & \text{w.p. } \frac{1-a_i}{b_i-a_i}. \end{cases}$$

Define the function  $K : \mathbb{R}^{(\mathbb{N})} \rightarrow \mathbb{R}$  as follows.

**Definition 1.** For  $Z_0, \dots, Z_n$  independent standard exponential random variables,

$$K(x_1, \dots, x_n) = \mathbb{P}\left(\sum_{i=1}^n (x_i - 1)Z_i < Z_0\right).$$

Gaffke (2005) makes the following conjecture:

**Conjecture 1.** For any  $n \in \mathbb{N}$  and  $\alpha \in [0, 1]$ ,

$$\mathbb{P}(K(X_1, \dots, X_n) \leq \alpha) \leq \alpha.$$

Gaffke (2005) relates this conjecture to the validity of a certain one-sided test for the mean of independent, not necessarily identically distributed random variables with known lower bounds. See Section 6.

# 1 Properties of $K$

Theorem 2 lists properties following directly from Definition 1.

**Theorem 2.** For reals  $x_1, \dots, x_n$ ,

1.  $0 \leq K(x_1, \dots, x_n) \leq 1$ .
2.  $K(x_1, \dots, x_n) = 1$  if  $\max_i x_i \leq 1$ , and  $K(x_1, \dots, x_n) \rightarrow \infty$  if  $\max_i x_i \rightarrow \infty$  and  $\min_i x_i$  is bounded below.
3.  $K(x_1, \dots, x_n)$  is symmetric in  $x_1, \dots, x_n$ .
4.  $K(x_1, \dots, x_n)$  is non-increasing in each  $x_i$ , and strictly decreasing if  $x_i > 1$  for some  $i$ .
5.  $K(x_1, \dots, x_n, y) \stackrel{\geq}{\leq} K(x_1, \dots, x_n)$  as  $y \stackrel{\leq}{\geq} 1$ .
6.  $K(y_1^{(t)}, \dots, y_n^{(t)})$  is non-increasing in  $t \geq 0$ , where  $y_i^{(t)}$  is given by the transformation  $x_i \mapsto y_i^{(t)} = 1 + t(x_i - 1)$ .

**Theorem 3.** For nonnegative reals  $x_1, \dots, x_n$ ,

1.  $\prod_{i: x_i \geq 1} \frac{1}{x_i} \leq K(x_1, \dots, x_n) \leq \prod_{i=1}^n \frac{1}{x_i}$ .
2. If  $x_i \geq 1, i = 1, \dots, n$ , then  $K(x_1, \dots, x_n) = \frac{1}{\prod_{i=1}^n x_i}$ .

*Proof.* Let  $Z_0, \dots, Z_n$  be independent standard exponentials, so their common cdf is  $q \mapsto \max(0, 1 - e^{-q})$ .

$$\begin{aligned}
 K(x_1, \dots, x_n) &= \mathbb{P}\left(\sum_{i=1}^n (x_i - 1)Z_i < Z_0\right) \\
 &= \mathbb{E}\left(\mathbb{P}\left(\sum_{i=1}^n (x_i - 1)Z_i < Z_0 \middle| \sum_{i=1}^n (x_i - 1)Z_i\right)\right) \\
 &= \mathbb{E}\left(\exp\left(-\sum_{i=1}^n (x_i - 1)Z_i\right); \sum_{i=1}^n (x_i - 1)Z_i \geq 0\right) + \mathbb{P}\left(\sum_{i=1}^n (x_i - 1)Z_i < 0\right). \quad (1)
 \end{aligned}$$

If  $x_i \geq 1, i = 1, \dots, n$ , then  $\sum_{i=1}^n (x_i - 1)Z_i > 0$  almost surely, and (1) is

$$\begin{aligned}
 &= \mathbb{E}\left(\exp\left(-\sum_{i=1}^n (x_i - 1)Z_i\right)\right) \\
 &= \prod_{i=1}^n \mathbb{E}\left(\exp(-(x_i - 1)Z_i)\right) \\
 &= \frac{1}{\prod_{i=1}^n x_i}.
 \end{aligned}$$

Otherwise, (1) is

$$\begin{aligned}
&\leq \mathbb{E}(\exp(-\sum_{i=1}^n (x_i - 1)Z_i); \sum_{i=1}^n (x_i - 1)Z_i \geq 0) + \mathbb{E}(\exp(-\sum_{i=1}^n (x_i - 1)Z_i); \sum_{i=1}^n (x_i - 1)Z_i < 0) \\
&= \mathbb{E}(\exp(-\sum_{i=1}^n (x_i - 1)Z_i)) \\
&= \prod_{i=1}^n \mathbb{E}(\exp(-(x_i - 1)Z_i)) \\
&= \frac{1}{\prod_{i=1}^n x_i}.
\end{aligned}$$

□

Theorem 5 gives an explicit formula for  $K$ .

**Definition 4.**

$$K_0 : \mathbb{R} \rightarrow (0, 1], \quad K_0(x) = \begin{cases} 1, & x \leq 1 \\ 1/x, & x > 1. \end{cases}$$

For  $x \geq 0$ ,  $K_0(x) = 1 \wedge (1/x)$ .

**Theorem 5.** For distinct  $x_1, \dots, x_n$ ,

$$K(x_1, \dots, x_n) = \sum_{i=1}^n K_0(x_i) \prod_{j=1, j \neq i}^n \frac{x_i - 1}{x_i - x_j}. \quad (2)$$

*Proof.* Fix  $x_1, \dots, x_n$ . The characteristic function of  $\sum_{i=1}^n (x_i - 1)Z_i - Z_0$  is

$$\phi(t) = \frac{1}{1 + it} \prod_{i=1}^n \frac{1}{1 - (x_i - 1)it}.$$

By a Fourier inversion formula (Gil-Pelaez, 1951),

$$K(x_1, \dots, x_n) = \frac{1}{2} - \frac{1}{\pi} \int_0^\infty \frac{\text{Im}(\phi(t))}{t} dt. \quad (3)$$

Let  $y_0 = -1$  and  $y_i = x_i - 1, i = 1, \dots, n$ , so  $\phi(t) = \prod_{i=0}^n (1 - iy_i t)^{-1}$  and  $\text{Im} \frac{1}{1 - iy_i t} = \frac{y_i t}{1 + y_i^2 t^2}$ .

The partial fraction decomposition of  $\phi(t)$  is

$$\phi(t) = \prod_{i=0}^n \frac{1}{1 - iy_i t} = \sum_{i=0}^n \frac{c_i}{1 - iy_i t}, \quad c_i = \frac{1}{\prod_{j:j \neq i} (1 - y_j/y_i)}.$$

The integral in (3) is

$$\begin{aligned}
\int_0^\infty \frac{\text{Im}(\phi(t))}{t} dt &= \int_0^\infty \sum_{i=0}^n \frac{c_i y_i t}{1 + y_i^2 t} \\
&= \sum_{i=0}^n c_i \arctan(y_i t) \Big|_0^\infty \\
&= \frac{\pi}{2} \sum_{i=0}^n \frac{\text{sgn}(y_i)}{\prod_{j:j \neq i} (1 - y_j/y_i)}.
\end{aligned} \tag{4}$$

Substituting (4) into (3),

$$\begin{aligned}
K(x_1, \dots, x_n) &= \frac{1}{2} \left( 1 - \sum_{i=0}^n \frac{\text{sgn}(y_i) y_i^n}{\prod_{j:j \neq i} (y_i - y_j)} \right) \\
&= \frac{1}{2} \left( 1 - \frac{(-1)^{n+1}}{\prod_{j=1}^n (-x_j)} - \sum_{i=1}^n \frac{\text{sgn}(x_i - 1) (x_i - 1)^n}{x_i \prod_{j:j \neq i} (x_i - x_j)} \right).
\end{aligned} \tag{5}$$

The identity

$$\sum_{i=1}^n \frac{(x_i - 1)^{n-1}}{\prod_{j:j \neq i} (x_i - x_j)} = 1$$

follows by interpreting the lhs as the Lagrange interpolating polynomial of  $x \mapsto 1$  at nodes  $x_1, \dots, x_n$ , evaluated at  $x = 1$ , allowing (5) to be written as

$$K(x_1, \dots, x_n) = \frac{1}{2} \sum_{i=1}^n \frac{(x_i - 1)^{n-1}}{\prod_{j:j \neq i} (x_i - x_j)} \left( 1 + \frac{1}{\prod_{j=1}^n x_j} - \frac{|x_i - 1|}{x_i} \right). \tag{6}$$

A similar identity,

$$\sum_{i=1}^n (1 - x_i)^{n-1} \prod_{j:j \neq i} \frac{-x_j}{x_i - x_j} = 1$$

follows by evaluating at 0 the Lagrange interpolating polynomial for  $x \mapsto (1 - x)^{n-1}$  at nodes  $x_1, \dots, x_n$ , implying

$$\sum_{i=1}^n \frac{(x_i - 1)^{n-1}}{\prod_{j:j \neq i} (x_i - x_j)} \frac{1}{\prod_{j=1}^n x_j} = \sum_{i=1}^n \frac{(x_i - 1)^{n-1}}{\prod_{j:j \neq i} (x_i - x_j)} \frac{1}{x_i}.$$

Therefore (6) is

$$K(x_1, \dots, x_n) = \sum_{i=1}^n \frac{(x_i - 1)^{n-1}}{\prod_{j:j \neq i} (x_i - x_j)} \frac{1}{2} \left( 1 + \frac{1}{x_i} - \frac{|x_i - 1|}{x_i} \right),$$

where

$$\frac{1}{2} \left( 1 + \frac{1}{x_i} - \frac{|x_i - 1|}{x_i} \right) = \begin{cases} 1, & x \leq 1 \\ 1/x, & x > 1. \end{cases}$$

□

## 1.1 Recursion formula and consequences

**Theorem 6.** Let  $f_0 : \mathbb{R} \rightarrow \mathbb{R}$  be given. Then a function  $f : \mathbb{R}^{(\mathbb{N})} \rightarrow \mathbb{R}$  satisfies for all distinct reals  $x_1, \dots, x_n$ , and distinct indices  $i$  and  $j$ ,

$$f(\mathbf{x}) = \begin{cases} \frac{x_i-1}{x_i-x_j}f(\mathbf{x}_{-j}) + \frac{x_j-1}{x_j-x_i}f(\mathbf{x}_{-i}), & n > 1 \\ f_0(x_1), & n = 1 \end{cases} \quad (7)$$

if and only if

$$f(\mathbf{x}) = \sum_{i=1}^n f_0(x_i) \prod_{j:j \neq i}^n \frac{x_i-1}{x_i-x_j}. \quad (8)$$

Then also, for  $n \geq 3$ ,

$$f(\mathbf{x}_{-3}) = \frac{x_1-x_3}{x_1-x_2}f(\mathbf{x}_{-2}) + \frac{x_2-x_3}{x_2-x_1}f(\mathbf{x}_{-1}),$$

that is,

$$(x_2-x_1)f(\mathbf{x}_{-3}) + (x_1-x_3)f(\mathbf{x}_{-2}) + (x_3-x_1)f(\mathbf{x}_{-1}) = 0. \quad (9)$$

*Proof.* Suppose first that  $f(x_1, \dots, x_n) = \sum_{i=1}^n f_0(x_i) \prod_{j:j \neq i} \frac{x_i-1}{x_i-x_j}$ . Then,

$$\begin{aligned} & \frac{x_1-x_3}{x_1-x_2}f(\mathbf{x}_{-2}) + \frac{x_2-x_3}{x_2-x_1}f(\mathbf{x}_{-1}) \\ &= \frac{x_1-x_3}{x_1-x_2} \sum_{i \neq 2} f_0(x_i) \prod_{j:j \neq i, j \neq 2} \frac{x_i-1}{x_i-x_j} + \frac{x_2-x_3}{x_2-x_1} \sum_{i \neq 1} f_0(x_i) \prod_{j:j \neq i, j \neq 1} \frac{x_i-1}{x_i-x_j} \\ &= \frac{x_1-x_3}{x_1-x_2} f_0(x_1) \prod_{j:j \neq 1, j \neq 2} \frac{x_1-1}{x_1-x_j} + \frac{x_2-x_3}{x_2-x_1} f_0(x_2) \prod_{j:j \neq 2, j \neq 1} \frac{x_2-1}{x_2-x_j} \\ &+ \frac{1}{x_1-x_2} \sum_{j \neq 1, j \neq 2} f_0(x_i) ((x_1-x_2) \prod_{j:j \neq i, j \neq 2} \frac{x_i-1}{x_i-x_j} + (x_3-x_2) \prod_{j:j \neq i, j \neq 1} \frac{x_i-1}{x_i-x_j}) \\ &= (x_1-x_3)f_0(x_1) \prod_{j \neq 1} \frac{x_1-1}{x_1-x_j} + (x_2-x_3)f_0(x_2) \prod_{j \neq 2} \frac{x_2-1}{x_2-x_j} \\ &+ \frac{1}{x_1-x_2} \sum_{i \neq 1, i \neq 2} f_0(x_i) ((x_1-x_3)(x_i-x_2) + (x_3-x_2)(x_i-x_1)) \prod_{j:j \neq i} \frac{x_i-1}{x_i-x_j} \\ &= f_0(x_1) \prod_{j \neq 1, j \neq 3} \frac{x_1-1}{x_1-x_j} + f_0(x_2) \prod_{j \neq 2, j \neq 3} \frac{x_2-1}{x_2-x_j} + \sum_{i \neq 1, i \neq 2, i \neq 3} f_0(x_i) \prod_{j:j \neq i, j \neq 3} \frac{x_i-1}{x_i-x_j} \\ &= \sum_{i \neq 3} f_0(x_i) \prod_{j:j \neq i, j \neq 3} \frac{x_i-1}{x_i-x_j} \\ &= f(\mathbf{x}_{-3}). \end{aligned}$$

The assumed form  $f(x_1, \dots, x_n) = \sum_{i=1}^n f_0(x_i) \prod_{j:j \neq i} \frac{x_i-1}{x_i-x_j}$  and so for any distinct  $i, j, k$ ,

$$\frac{x_i-x_k}{x_i-x_j}f(\mathbf{x}_{-j}) + \frac{x_j-x_k}{x_j-x_i}f(\mathbf{x}_{-i}) = f(\mathbf{x}_{-k}).$$

Therefore  $f$  satisfies (9).

The value of the function

$$(x_1, \dots, x_n) \mapsto \sum_{i=1}^n f_0(x_i) \prod_{j:j \neq i} \frac{x_i - 1}{x_i - x_j}$$

is unaffected by the presence of any  $x_i$  that equals 1. Taking  $x_3 = 1$  in the above derivation shows that (8) satisfies the recursion (7). It satisfies the base case, as well, so it must equal  $f$ .  $\square$

Theorem 6 establishes the recursion for  $K$  using the sum-product formula (2), independently of the probabilistic definition of  $K$  in Definition 1. Kaminsky et al. (1984) established the recursion formula (7) for  $K$  as defined in Definition 1. By the preceding theorem, the result of Kaminsky et al. (1984) implies the conclusion of Theorem 5. We don't know if it was previously known that this recursion formula implies the sum-product formula (8). In the other direction, Theorem 5 gives an alternative proof of the result of Kaminsky et al. (1984) for standard exponentials, and strengthens it by (9).

Definition 1 shows that  $f$  is symmetric. Similarly, the formula (8), which is symmetric in  $x_i$ , also shows that the recursive definition (7) is well-defined, i.e., doesn't depend on the  $x_i, x_j$  chosen.

**Definition 7.**

$$p(x, y) : \mathbb{R}^2 \rightarrow \mathbb{R} : (x, y) \mapsto \frac{y - 1}{y - x}, \quad (10)$$

for  $x \neq y$ .

**Theorem 8.** 1. For reals  $x \geq 0, y \geq 0$ ,  $x$  and  $y$  on opposite sides of 1,

$$p(x, y) \leq K_0(x).$$

When  $x < 1, y > 1$ , equality occurs as  $y \rightarrow \infty$ . When  $x > 1, y < 1$ , equality occurs as  $y \rightarrow 0$ .

2. Given  $n \geq 1$ ,  $\mathbf{a} \in [0, 1]^n$ , and  $\mathbf{b} \in [0, \infty)^n$ ,

$$\prod_{i=1}^n p(b_i, a_i) \leq p\left(\prod_{i=1}^n b_i, \prod_{i=1}^n a_i\right),$$

with equality if and only if  $b_i = 1, i = 1, \dots, n$ , or  $a_i = 0, i = 1, \dots, n$ .

*Proof.* 1. If  $x \leq 1$ , the rhs is 1 while the lhs is a probability  $\leq 1$ . If  $x > 1$ , then  $y < 1$  and  $p(x, y) = 1 - (x - 1)/(x - y)$  is decreasing in  $y$ , and maximized at  $y = 0$ , when both sides of the inequality are  $1/x$ .

2.  $\prod_{i=1}^n \frac{1-a_i}{b_i-a_i} \leq \frac{1-\prod_{i=1}^n a_i}{\prod_{i=1}^n b_i - \prod_{i=1}^n a_i}$  if and only if  $\frac{\prod_{i=1}^n (1-a_i)}{1-\prod_{i=1}^n a_i} \leq \frac{\prod_{i=1}^n (1-\frac{a_i}{b_i})}{1-\prod_{i=1}^n \frac{a_i}{b_i}}$ , which holds since

$$f : [0, 1]^n / \mathbb{1}_n \rightarrow \mathbb{R} : (t_1, \dots, t_n) \mapsto \frac{\prod_{i=1}^n (1-t_i)}{1 - \prod_{i=1}^n t_i}$$

is non-increasing in each argument:

$$\frac{df}{dt_i} = \left( (-\prod_{j:j \neq i} (1-t_j))(1 - \prod_j t_j) + (\prod_j (1-t_j)) \prod_{j:j \neq i} t_j \right) (1 - \prod_j t_j)^{-2}$$

and the numerator is  $\leq 0$  if and only if  $1 \geq \prod_{j:j \neq i} t_j$ , with strict inequality unless  $t_j = 1, j = 1, \dots, n, j \neq i$ . □

**Theorem 9.** For distinct non-negative reals  $x, x_1, \dots, x_n$ ,

$$K_0(x)K(x_1, \dots, x_n) \leq K(x, x_1, \dots, x_n).$$

*Proof.* If  $x \leq 1$ , monotonicity of  $K$  implies

$$K_0(x)K(x_1, \dots, x_n) \leq K(x_1, \dots, x_n) \leq K(x, x_1, \dots, x_n).$$

Suppose  $b = x > 1$ . By induction on  $n$ . The base case requires  $1/bK(x_1) \leq K(b, x_1)$ . If  $x_1 \leq 1$ ,  $1/bK(x_1) = 1/b = K(b) \leq K(x_1, b)$ , while if  $x_1 \geq 1$ ,  $1/bK(x_1) = 1/(bx_1) = K(b, x_1)$ . Supposing the result holds for  $n-1$ , then

$$\begin{aligned} \frac{1}{b}K(x_1, \dots, x_n) &= \frac{1}{b}(p(x_n, x_1)K(x_1, \dots, x_{n-1}) + p(x_1, x_n)K(x_2, \dots, x_n)) \\ &\leq p(x_n, x_1)K(b, x_1, \dots, x_{n-1}) + p(x_1, x_n)K(b, x_2, \dots, x_n) \\ &= K(b, x_1, \dots, x_n). \end{aligned}$$

□

**Theorem 10.** Given  $\mathbf{a} \in [0, 1]^r, b_1 \geq 1, b_2 \geq 1$ ,

$$K_0(b_2)K(\mathbf{a}, b_1) \leq K(\mathbf{a}, b_1 b_2).$$

*Proof.* The conclusion is

$$\begin{aligned} 0 &\leq K(\mathbf{a}, b_1 b_2) - \frac{1}{b_2}K(\mathbf{a}, b_1) \\ 0 &\leq 1 + \prod_{i=1}^r p(a_i, b_1 b_2) \left( \frac{1}{b_1 b_2} - 1 \right) - \frac{1}{b_2} \left( \prod_{i=1}^r p(a_i, b_1) \left( \frac{1}{b_1} - 1 \right) + 1 \right) \\ 0 &\leq (b_2 - 1) \left( 1 - \prod_{i=1}^r p(a_i, b_1 b_2) \right) - \frac{b_1 - 1}{b_1} \left( \prod_{i=1}^r p(a_i, b_1 b_2) \right) - \prod_{i=1}^r p(a_i, b_1) \\ 0 &\leq (b_2 - 1) \left( 1 - g(b_1 b_2) \right) - \frac{b_1 - 1}{b_1} (g(b_1 b_2) - g(b_1)), \end{aligned} \tag{11}$$

where  $g$  is the nonnegative increasing function given by  $x \mapsto \prod_{i=1}^r \frac{x-1}{x-a_i}$ . We bound the two terms on the rhs of (11) using the log-derivative  $g'(x)/g(x) = \frac{1}{x-1} \sum_{i=1}^r \frac{1-a_i}{x-a_i}$ . For the first term,

$$\begin{aligned}
1 - g(b_1 b_2) &= \int_{b_1 b_2}^{\infty} g'(x) dx \\
&= \int_{b_1 b_2}^{\infty} \frac{1}{x-1} \sum_{i=1}^r \frac{1-a_i}{x-a_i} g(x) dx \\
&\geq g(b_1 b_2) \int_{b_1 b_2}^{\infty} \frac{1}{x-1} \sum_{i=1}^r \frac{1-a_i}{x-a_i} dx \\
&\geq g(b_1 b_2) \int_{b_1 b_2}^{\infty} \sum_{i=1}^r \frac{1-a_i}{(x-a_i)^2} dx \\
&= g(b_1 b_2) \sum_{i=1}^s \frac{1-a_i}{b_1 b_2 - a_i}.
\end{aligned}$$

For the second term,

$$\begin{aligned}
g(b_1 b_2) - g(b_1) &= \int_{b_1}^{b_1 b_2} \frac{1}{x-1} \sum_{i=1}^r \frac{1-a_i}{x-a_i} g(x) dx \\
&\leq \int_{b_1}^{b_1 b_2} \frac{1}{(x-1)^2} \sum_{i=1}^r (1-a_i) g(b_1 b_2) dx \\
&= g(b_1 b_2) \sum_{i=1}^r (1-a_i) \frac{b_1(b_2-1)}{(b_1-1)(b_1 b_2-1)}.
\end{aligned}$$

Therefore,

$$\begin{aligned}
&(b_2-1)(1-g(b_1 b_2)) - \frac{b_1-1}{b_1} (g(b_1 b_2) - g(b_1)) \\
&\geq g(b_1 b_2) \sum_{i=1}^s \frac{1-a_i}{b_1 b_2 - a_i} - g(b_1 b_2) \sum_{i=1}^r (1-a_i) \frac{b_1(b_2-1)}{(b_1-1)(b_1 b_2-1)} \\
&= (b_2-1)g(b_1 b_2) \left( \sum_{i=1}^r \frac{1-a_i}{b_1 b_2 - 1} - \sum_{i=1}^r \frac{1-a_i}{b_1 b_2 - a_i} \right) \\
&\geq 0,
\end{aligned}$$

since  $b_1 b_2 - 1 \leq b_1 b_2 - a_i, i = 1, \dots, r$ . □

The corresponding result for  $a' \in [0, 1]$ ,  $K_0(a')K(a, \mathbf{b}) \leq K(aa', \mathbf{b})$ , follows from the monotonicity property (Theorem 2) as in Theorem 9. Theorem 10 in conjunction with Theorem 23 below strengthens Theorem 9, in the special case where there is a single component  $x_i$  of  $\mathbf{x}$  that is  $\geq 1$ .



**Definition 11.** A “leaf node” is a vector lying in  $[0, 1]^{(\mathbb{N})}$  or in  $[1, \infty)^{(\mathbb{N})}$ . A “leaf node” of type “a” is an element of  $[0, 1]^{(\mathbb{N})}$ , a “leaf node” of type “b” is an element of  $[1, \infty)^{(\mathbb{N})}$ , and a “leaf node” is a leaf node of type “a” or of type “b”.

If  $x_i$  and  $x_j$  lie on opposite sides of the number 1 then  $p(x_i, x_j) = (x_j - 1)/(x_j - x_i)$  and  $p(x_j, x_i) = (x_i - 1)/(x_i - x_j)$  are both  $\geq 0$  and (7) is a convex combination. By iterating the recursion,  $K(x_1, \dots, x_n)$  can be expressed as a convex combination of the values of  $K$  on leaf nodes, namely, 1 and the reciprocal of products of b-values.

**Theorem 12.** Suppose  $f : \mathbb{R}^{(\mathbb{N})} \rightarrow \mathbb{R}$  satisfies the recursion (7). Then there are non-negative reals  $w_1, \dots, w_{m+n}$ ,  $\sum_{i=1}^{m+n} w_i = 1$ , such that

$$f(a_1, \dots, a_m, b_1, \dots, b_n) = \sum_{i=1}^m w_i f(a_1, \dots, a_i) + \sum_{i=1}^n w_{m+i} f(b_1, \dots, b_i), \quad (12)$$

where an empty sum is taken to be 0. The weights  $w_i$  depend on  $a_i$  and  $b_i$  only through the function  $p$  given in (10).

*Proof.* By induction on  $k = m + n$ . If  $k = 1, m = 0$ , or  $n = 0$ , then take  $w_1 = 1$ . Suppose that  $\min(m, n) > 0$ , and suppose the conclusion (12) holds for any  $m, n$  with  $m + n = k$ , and let  $(\mathbf{a}, \mathbf{b}) = (a_1, \dots, a_m, b_1, \dots, b_n)$ , be given with  $m + n = k + 1$ . Then,

$$\begin{aligned} f(\mathbf{a}, \mathbf{b}) &= p(a_m, b_n) f(a/a_{m-1}, b) + p(b_n, a_m) f(a, b/b_{n-1}) \\ &= p(a_m, b_n) \left( \sum_{i=1}^{m-1} w'_i f(a_1, \dots, a_i) + \sum_{i=1}^n w'_{m-1+i} f(b_1, \dots, b_i) \right) \\ &\quad + p(b_n, a_m) \left( \sum_{i=1}^m w''_i f(a_1, \dots, a_i) + \sum_{i=1}^{n-1} w''_{m+i} f(b_1, \dots, b_i) \right) \\ &= \sum_{i=1}^{m-1} f(a_1, \dots, a_i) (p(a_m, b_n) w'_i + p(b_n, a_m) w''_i) + p(b_n, a_m) w''_m f(a_1, \dots, a_m) \\ &\quad + \sum_{i=1}^{n-1} f(b_1, \dots, b_i) (p(a_m, b_n) w'_{m-1+i} + p(b_n, a_m) w''_{m+i}) + p(a_m, b_n) w'_{m-1+n} f(b_1, \dots, b_n), \end{aligned}$$

where  $w'_i$  and  $w''_i$  are non-negative,  $\sum_{i=1}^{m+n-1} w'_i = 1$ , and  $\sum_{i=1}^{m+n-1} w''_i = 1$ . Then

$$w_i = \begin{cases} p(a_m, b_n) w'_i + p(b_n, a_m) w''_i, & 1 \leq i \leq m-1 \\ p(b_n, a_m) w''_m, & i = m \\ p(a_m, b_n) w'_{i-1} + p(b_n, a_m) w''_i, & m+1 \leq i \leq m+n-1 \\ p(a_m, b_n) w'_{m-1+n}, & i = m+n \end{cases}$$

are nonnegative and sum to 1. □

When  $f$  in Theorem 12 is taken to be  $K$ , the conclusion is that there are  $w_1, \dots, w_n$ ,  $\sum_{i=1}^n w_i \leq 1$ ,  $w_i \geq 0$ , so that

$$K(a_1, \dots, a_m, b_1, \dots, b_n) = 1 - \sum_{i=1}^n w_i + \sum_{i=1}^n w_i / (b_1 \cdot \dots \cdot b_i). \quad (13)$$

The effect on  $f$  of scaling all arguments to or from 1 uniformly is determined by the effect on leaf vectors.

**Theorem 13.** *Let  $f$  be defined as in Theorem 6, and for  $\alpha \geq 0$  let  $h_\alpha : \mathbb{R} \rightarrow \mathbb{R} : x \mapsto 1 + \alpha(x - 1)$ . Then  $f(h_\alpha(x_1), \dots, h_\alpha(x_n))$  is monotonic in  $\alpha$  for any  $(x_1, \dots, x_n) \in \mathbb{R}^n$  iff it is for those  $(x_1, \dots, x_n) \in \mathbb{R}^n$  with  $x_i \leq 1$ , all  $i$ , and those with  $x_i \geq 1$ , all  $i$ .*

*Proof.* By Theorem 12  $f$  may be expressed as a convex combination of its values at vectors with all components  $\leq 1$  or all components  $\geq 1$ , with weights that depend on  $x_1, \dots, x_n$  only through  $p(\cdot, \cdot)$ . However,  $p(h_\alpha(x), h_\alpha(y)) = p(x, y)$ .  $\square$

## 1.2 $K$ leave-one-outs and $\Delta K$

Multiplying the lhs of the recursion formula (7) by  $1 = p(x_i, x_j) + p(x_j, x_i)$  gives

$$\left( \frac{x_i - 1}{x_i - x_j} + \frac{x_j - 1}{x_j - x_i} \right) K(\mathbf{x}) = \frac{x_i - 1}{x_i - x_j} K(\mathbf{x}_{-j}) + \frac{x_j - 1}{x_j - x_i} K(\mathbf{x}_{-i}),$$

which may be re-arranged as

$$\frac{K(\mathbf{x}_{-j}) - K(\mathbf{x})}{x_j - 1} = \frac{K(\mathbf{x}_{-i}) - K(\mathbf{x})}{x_i - 1}.$$

Therefore the ratio

$$\frac{K(\mathbf{x}_{-i}) - K(\mathbf{x})}{x_i - 1}$$

doesn't depend on the index of the omitted component  $x_i$ , only on  $x_1, \dots, x_n$ .

**Definition 14.** *For reals  $x_1, \dots, x_n$ , distinct from 1,*

$$\Delta K(\mathbf{x}) = \frac{K(\mathbf{x}_{-i}) - K(\mathbf{x})}{x_i - 1}, 1 \leq i \leq n.$$

Combined with Theorem 2 and 16,  $K$  is seen to be Lipschitz in each component locally at 1 with Lipschitz constant  $\Delta K(\mathbf{x})$ :

$$|K(\mathbf{x}) - K(x_1, \dots, 1, \dots, x_n)| = \Delta K(\mathbf{x}) |x_i - 1|$$

**Theorem 15.**

$$\Delta K(\mathbf{x}) = \sum_{i=1}^n \Delta K_0(x_i) \prod_{j:j \neq i} p(x_j, x_i) \quad (14)$$

where

$$\Delta K_0 : \mathbb{R} \rightarrow [0, 1], \quad \Delta K_0(x) = \begin{cases} 0, & 0 < x < 1 \\ \frac{1}{x}, & x > 1 \\ \text{undefined}, & \text{otherwise.} \end{cases}$$

*Proof.* If  $0 < x < 1$ ,  $\Delta K(x) = (k(1) - 1)/(x - 1) = 0 = \Delta K_0(x)$ , and if  $x > 1$ ,  $\Delta K(x) = (k(1) - 1/x)/(x - 1) = 1/x = \Delta K_0(x)$ . By Theorem 6 the formula (14) follows on establishing the recursion (7) for  $\Delta K$ ,

$$p(x_1, x_n)\Delta K(\mathbf{x}_{-1}) + p(x_n, x_1)\Delta K(\mathbf{x}_{-n}) = \Delta K(\mathbf{x}). \quad (15)$$

Suppose  $n = 2$ . If  $x_1 < 1$  and  $x_2 < 1$ , both sides of (15) are 0. If  $x_1 > 1$  and  $x_2 > 1$ , (15) becomes

$$\frac{x_2 - 1}{x_2 - x_1} \frac{1}{x_2} + \frac{x_1 - 1}{x_1 - x_2} \frac{1}{x_2} = \frac{1}{x_1 x_2},$$

which also holds. If  $x_1 < 1$  and  $x_2 > 1$ , (15) becomes

$$p(x_1, x_2) \frac{1}{x_2} = \frac{1}{x_2 - 1} \left(1 - \frac{p(x_1, x_2)}{x_2} - p(x_2, x_1)\right),$$

which also holds. When  $n \geq 3$ ,

$$\begin{aligned} & p(x_1, x_n)\Delta K(\mathbf{x}_{-1}) + p(x_n, x_1)\Delta K(\mathbf{x}_{-n}) \\ &= p(x_1, x_n) \frac{K(\mathbf{x}_{-1,-2}) - K(\mathbf{x}_{-1})}{x_2 - 1} + p(x_n, x_1) \frac{K(\mathbf{x}_{-n,-2}) - K(\mathbf{x}_{-n})}{x_2 - 1} \\ &= \frac{1}{x_2 - 1} (K(\mathbf{x}_{-2}) - K(\mathbf{x})) \\ &= \Delta K(\mathbf{x}), \end{aligned}$$

using the recursion (7) for  $K$ . □

The approach used to define  $\Delta K$  can be iterated. The function  $\Delta K$  satisfies the recursion (7), so that as with  $K$  the ratio

$$\Delta^2 K(\mathbf{x}) = \frac{\Delta K(\mathbf{x}_{-i}) - \Delta K(\mathbf{x})}{x_i - 1}$$

must be independent of  $i$ . By the same method of proof as in Theorem 15,  $\Delta^2 K$  satisfies the formula

$$\Delta^2 K(\mathbf{x}) = \sum_{i=1}^n \Delta^2 K_0(x_i) \prod_{j:j \neq i} p(x_j, x_i)$$

where

$$\Delta^2 K_0 : \mathbb{R} \rightarrow [0, 1], \quad \Delta^2 K_0(x) = \begin{cases} 0, & 0 < x < 1 \\ \frac{1}{x(x-1)}, & x > 1 \\ \text{undefined}, & \text{otherwise.} \end{cases}$$

Therefore, as the leave-one-out

$$K(\mathbf{x}_{-i}) = (x_i - 1)\Delta K(\mathbf{x})$$

may be expressed as a linear function of  $x_i$  with coefficients independent of  $i$ , the “leave-two-out”

$$K(\mathbf{x}_{-i,-j}) = (x_i + x_j - 1)(\Delta K(\mathbf{x}) - \Delta^2 K(\mathbf{x})) - \Delta K(\mathbf{x}) + x_i x_j \Delta^2 K(\mathbf{x})$$

may be expressed as a quadratic function of  $x_i, x_j$  with coefficients independent of  $i, j$ , and so on.

Properties following from the formula (14):

**Theorem 16.** *For distinct non-negative reals  $x_1, \dots, x_n$ , different from 1,*

1.  $\Delta K(\mathbf{x}) = 0$  if  $\max_i x_i < 1$  and  $\Delta K(\mathbf{x}) = 1/\prod_i x_i$  if  $\min_i x_i > 1$ .
2. If  $\max_i x_i > 1$  then  $0 \leq \Delta K(\mathbf{x}) \leq 1/\min\{x_i : x_i > 1\}$ .

*Proof.* The formula (14) implies that  $\Delta K(\mathbf{x}) = 0$  if  $x_i \leq 1$ , all  $i$ . Since  $K_0$  and  $\Delta K_0$  agree on  $(1, \infty)$ , comparison of formulas (2) and (14) shows that  $K$  and  $\Delta K$  agree when  $x_i > 1$ , all  $i$ . Theorem 12 then implies that when  $\max_i x_i > 1$ ,  $\Delta K$  may be written as a convex combination of leaf nodes upper bounded by  $1/\min\{x_i : x_i > 1\}$ ,

$$\Delta K(\mathbf{a}, \mathbf{b}) = \sum_{i=1}^n w_i / (b_1 \cdot \dots \cdot b_i).$$

□

**Theorem 17.** *For distinct non-negative reals  $x_1 < \dots < x_n$ ,  $K(\mathbf{x}_{-i})$  is non-decreasing in  $i$ .*

*Proof.*

$$K(\mathbf{x}_{-i}) = K(\mathbf{x}) + \Delta K(\mathbf{x})(x_i - 1)$$

and by Theorem 16  $\Delta K(\mathbf{x}) \geq 0$ .

□

**Theorem 18.** *Let  $x_1, \dots, x_n$ , be distinct non-negative reals different from 1, and for  $\alpha \geq 0$  let  $h_\alpha$  be the homothety transformation given in Theorem 13. Then*

$$\Delta K(h_\alpha(\mathbf{x})) - \Delta K(\mathbf{x}) = K(h_\alpha(\mathbf{x})) - K(\mathbf{x}).$$

*Proof.* Let  $f$  be defined as the difference  $\Delta K - k$ . Then for  $\mathbf{x}$  as in the theorem statement,

$$f(\mathbf{x}) = \sum_{i=1}^n f_0(x_i) \prod_{j:j \neq i} p(x_j, x_i),$$

where

$$f_0 : \mathbb{R} \rightarrow \mathbb{R}, \quad f_0(x) = \begin{cases} 0, & 0 < x < 1 \\ 1, & x > 1 \\ \text{undefined}, & \text{otherwise.} \end{cases}$$

However, both  $p$  and  $f_0$  are invariant under  $h_\alpha$ .

□

**Theorem 19.** For distinct non-negative reals  $x_1, \dots, x_n$ ,

$$\min_i K(\mathbf{x}_{-i})^{\frac{n}{n-1}} \leq K(\mathbf{x}) \leq \max_i K(\mathbf{x}_{-i}).$$

The first inequality is tight iff  $x_i \leq 1$ , all  $i$ , or all  $x_i$  are equal. The second inequality is tight iff  $x_i \leq 1$ , all  $i$ .

*Proof.* The second inequality is

$$K(\mathbf{x}) \leq K(\mathbf{x}) + \Delta K(\mathbf{x})(\max_i x_i - 1).$$

If any  $x_i$  is  $\geq 1$  then the rhs is  $\geq K(\mathbf{x})$ , and the inequality gap vanishes iff  $\max_i x_i \downarrow 1$ . If  $x_i \leq 1$  for all  $i$  then both sides are  $= 1$ .

The first inequality is

$$K(\mathbf{x}) + (\min_i x_i - 1)\Delta K(\mathbf{x}) \leq K(\mathbf{x})^{\frac{n}{n-1}},$$

or

$$(1 - \min_i x_i)\Delta K(\mathbf{x}) \geq K(\mathbf{x})(1 - K(\mathbf{x})^{-\frac{1}{n}}).$$

If  $\min_i x_i \leq 1$ , the lhs is non-negative and the rhs is non-positive, with equality iff  $x_i \leq 1$ , all  $i$ . If  $x_i \geq 1$  for all  $i$  then the first inequality is

$$\left(\frac{\prod_{i=1}^n x_i}{\max_i x_i}\right)^{\frac{n}{n-1}} \leq \prod_{i=1}^n x_i$$

or  $\prod_{i=1}^n x_i \leq (\max_i x_i)^n$ , which holds with equality iff all  $x_i$  are equal.  $\square$

**Theorem 20.** For distinct non-negative reals  $x_1, \dots, x_m$ , and distinct non-negative reals  $y_1, \dots, y_n$ , all different from 1, if

$$\max_i K(\mathbf{x}_{-i}) \leq \min_i K(\mathbf{y}_{-i})$$

then

$$K(\mathbf{x}) \leq K(\mathbf{y}).$$

*Proof.* Since  $\Delta K(\mathbf{x}) \geq 0, \Delta K(\mathbf{y}) \geq 0$ ,

$$K(\mathbf{x}) \leq K(\mathbf{x}) + \Delta K(\mathbf{x})(\max_i x_i - 1) \leq K(\mathbf{y}) + \Delta K(\mathbf{y})(\min_i y_i - 1) \leq K(\mathbf{y})$$

unless  $x_i < 1$ , all  $i$ , or  $y_i > 1$ , all  $i$ , or both. If  $x_i < 1$ , all  $i$ , then  $1 = \max_i K(\mathbf{x}_{-i}) \leq \min_i K(\mathbf{y}_{-i})$  implies  $y_i \leq 1$ , all  $i$ , and  $K(\mathbf{y}) = 1 \geq K(\mathbf{x})$ . Suppose  $\min_i y_i > 1$ . Then  $K(\mathbf{y}) = \Delta K(\mathbf{y}) = 1/\prod_i y_i$ , and

$$\max_i K(\mathbf{x}_{-i}) \leq K(\mathbf{y}) + \Delta K(\mathbf{y})(\min_i y_i - 1) = K(\mathbf{y}) \min_i y_i = \frac{\min_i y_i}{\prod_i y_i}.$$

By Theorem 19

$$K(\mathbf{x}) \leq \max_i K(\mathbf{x}_{-i}) \leq (\max_i K(\mathbf{x}_{-i}))^{\frac{n}{n-1}} \leq \left(\frac{\min_i y_i}{\prod_i y_i}\right)^{\frac{n}{n-1}},$$

and the rightmost term is  $\leq K(\mathbf{y}) = 1/\prod_i y_i$  iff  $(\min_i y_i)^n \leq \prod_i y_i$ .  $\square$

**Theorem 21.** For distinct non-negative reals  $x_1, \dots, x_n$ , different from 1,

$$K(\mathbf{x}) = 1 - \sum_{i=1}^n (x_i - 1) \Delta K(x_1, \dots, x_i).$$

*Proof.* The  $n = 1$  case follows from the definitions of  $K_0$  and  $\Delta K_0$ . The  $n \geq 2$  case is

$$\begin{aligned} & 1 - K(\mathbf{x}) \\ &= 1 - K(x_1) + K(x_1) - K(x_1, x_2) + \dots + K(x_1, \dots, x_{n-1}) - K(x_1, \dots, x_n) \\ &= K(x_1/x_1) - K(x_1) + K((x_1, x_2)/x_2) - K(x_1, x_2) + \dots + K(\mathbf{x}_{-n}) - K(\mathbf{x}) \\ &= (x_1 - 1) \Delta K(x_1) + (x_2 - 1) \Delta K(x_1, x_2) + \dots + (x_n - 1) \Delta K(x_1, \dots, x_n). \end{aligned}$$

□

Whereas combining “a” values or “b” values can only increase  $p$  ((ref earlier theorem)), doing so can only decrease  $K$ .

**Lemma 22.** 1. Let  $\mathbf{a} = (a_1, \dots, a_r)$  with  $a_i \in [0, 1]$  for  $1 \leq i \leq r, r \geq 1$ . Let  $b_1 > 1, b_2 > 1$ . Then

$$K(\mathbf{a}, b_1, b_2) \leq K(\mathbf{a}, b_1 b_2)$$

with equality iff  $\mathbf{a} = \mathbf{1}$ .

2. Let  $\mathbf{b} = (b_1, \dots, b_s)$  with  $b_i \geq 1$  for  $1 \leq i \leq s, s \geq 1$ . Let  $a_1$  and  $a_2$  lie in  $[0, 1)$ . Then

$$K(a_1 a_2, \mathbf{b}) \leq K(a_1, a_2, \mathbf{b})$$

with equality iff  $\mathbf{b} = \mathbf{1}$ .

*Proof.* 1. Let  $\lambda_1 = b_1 - 1, \lambda_2 = b_2 - 1$ , and  $\lambda_{12} = \lambda_1 + \lambda_2 + \lambda_1 \lambda_2 = b_1 b_2 - 1$ . Let  $\Delta = \sum_{i=1}^r (1 - a_i) Z_i$ , where  $Z_i, i = 0, \dots, r$ , are independent standard exponentials. Then  $\Delta \geq 0$  a.s. Let

$$\begin{aligned} F_{\lambda_1 W_1 + \lambda_2 W_2} : q &\mapsto \max(0, 1 - \frac{\lambda_1 e^{-q/\lambda_1} - \lambda_2 e^{-q/\lambda_2}}{\lambda_1 - \lambda_2}) \text{ and} \\ F_{\lambda_{12} W_1} : q &\mapsto \max(0, 1 - e^{-q/\lambda_{12}}) \end{aligned}$$

denote the cdfs of  $\lambda_1 W_1 + \lambda_2 W_2$  and  $\lambda_{12} W_1$ , where  $W_1$  and  $W_2$  are independent standard exponentials.

By Definition 1 ,

$$K(a_1, a_r, b_1, b_2) - K(\mathbf{a}, b_1, b_2) = \mathbb{E}(F_{\lambda_1 W_1 + \lambda_2 W_2}(Z_0 + \Delta) - F_{\lambda_{12} W_1}(Z_0 + \Delta).)$$

The conclusion of the lemma follows on showing

$$F_{\lambda_1 W_1 + \lambda_2 W_2}(Z_0 + \delta) - F_{\lambda_{12} W_1}(Z_0 + \delta) \geq 0$$

for all non-random  $\delta \geq 0$ , with equality iff  $\delta = 0$ . Define  $h$  by

$$\begin{aligned} h(\delta) &= \mathbb{E}(F_{\lambda_1 W_1 + \lambda_2 W_2}(Z_0 + \delta) - F_{\lambda_{12} W_1}(Z_0 + \delta)) \\ &= \int_0^\infty (F_{\lambda_1 W_1 + \lambda_2 W_2}(z + \delta) - F_{\lambda_{12} W_1}(z + \delta)) e^{-z} dz \\ &= \frac{\lambda_{12}}{\lambda_{12} + 1} e^{-\delta/\lambda_{12}} - \frac{1}{\lambda_1 - \lambda_2} \left( \frac{\lambda_1^2}{\lambda_1 + 1} e^{-\delta/\lambda_1} - \frac{\lambda_2^2}{\lambda_2 + 1} e^{-\delta/\lambda_2} \right). \end{aligned}$$

By Rolle's theorem and induction, the sum of 3 exponential  $h(\delta)$  has at most 2 roots. The function  $h$  has a double root at 0, while  $h''(0) = 1/\lambda_{12} > 0$ . Therefore  $h$  increases from 0 in a neighborhood of 0. Moreover  $\lambda_{12} > \max(\lambda_1, \lambda_2)$  so that  $e^{-\delta/\lambda_{12}}$ , which has a positive coefficient, is the dominant term. As a result,  $h(\delta) \downarrow 0$  as  $\delta \rightarrow \infty$ , implying  $\delta = 0$  is the only root on  $[0, \infty)$ .

2. Let  $\lambda_1 = 1 - a_1$ ,  $\lambda_2 = 1 - a_2$ , and  $\lambda_{12} = 1 - a_1 a_2 = \lambda_1 + \lambda_2 - \lambda_1 \lambda_2$ . Let  $\Delta = \sum_{i=1}^r (1 - a_i) Z_i$ , where  $Z_i, i = 0, \dots, r$ , are independent standard exponentials. Then  $\Delta \geq 0$  a.s. Similarly to the first part,

$$K(a_1, a_2, \mathbf{b}) - K(a_1 a_2, \mathbf{b}) = \mathbb{E}(F_{\lambda_{12} W_1}(\Delta - Z_0) - F_{\lambda_1 W_1 + \lambda_2 W_2}(\Delta - Z_0)),$$

and the conclusion of the lemma follows on showing

$$\mathbb{E}(F_{\lambda_{12} W_1}(\Delta - Z_0) - F_{\lambda_1 W_1 + \lambda_2 W_2}(\Delta - Z_0)) \geq 0$$

for all non-random  $\delta \geq 0$ , with equality iff  $\delta = 0$ . Define  $h$  by

$$\begin{aligned} h(\delta) &= \mathbb{E}(F_{\lambda_1 W_1 + \lambda_2 W_2}(Z_0 + \delta) - F_{\lambda_{12} W_1}(Z_0 + \delta)) \\ &= \frac{\lambda_{12}}{\lambda_{12} - 1} e^{-\delta/\lambda_{12}} - \frac{1}{\lambda_1 - \lambda_2} \left( \frac{\lambda_1^2}{\lambda_1 - 1} e^{-\delta/\lambda_1} - \frac{\lambda_2^2}{\lambda_2 - 1} e^{-\delta/\lambda_2} \right). \end{aligned}$$

The remainder of the proof is the same as in the last part:  $h$  has at most 2 roots,  $h(0) = h'(0) = 0$ ,  $h''(0) > 0$ , and  $h(\delta) \downarrow 0$  as  $\delta \rightarrow \infty$ , implying  $h(\delta) > 0$  for  $\delta > 0$ . □

**Theorem 23.** Let  $\mathbf{x} = (x_1, \dots, x_n) \in \mathbb{R}_+^n$ . Let  $A = \{i : 0 \leq x_i < 1\}$  and  $B = \{i : x_i \geq 1\}$ . Suppose  $\{i, j\} \subset A$  or  $\{i, j\} \subset B$ ,  $x_i \neq 1, x_j \neq 1$ . Then

$$K(\mathbf{x}_{-i, -j}, x_i x_j) \leq K(\mathbf{x}),$$

with equality iff  $\mathbf{x}_{-i, -j} = \mathbf{1}$ .

*Proof.* The proof is by induction on  $\min(|A|, |B|)$ , with the cases  $\min(|A|, |B|) = 1$  and  $\min(|A|, |B|) = 2$  treated separately.

1.  $\min(|A|, |B|) = 0$ . Then  $\mathbf{x} = \mathbf{x}_A$  or  $\mathbf{x} = \mathbf{x}_B$ . If  $\mathbf{x} = \mathbf{x}_A$ , then  $K(\mathbf{x}) = 1 = K(\mathbf{x}_{-i, -j}, x_i x_j)$ . If  $\mathbf{x} = \mathbf{x}_B$ , then  $K(\mathbf{x}) = 1/\prod_i x_i = K(\mathbf{x}_{-i, -j}, x_i x_j)$ .

2.  $\min(|A|, |B|) = 1$ . By induction on  $\max(|A|, |B|)$ . If  $\max(|A|, |B|) = 1$  there is nothing to do.

Suppose that  $\max(|A|, |B|) = 2$ . Then either  $\mathbf{x}_A = a$  and  $\mathbf{x}_B = (b_1, b_2)$ , or  $\mathbf{x}_A = (a_1, a_2)$  and  $\mathbf{x}_B = b$ . In the first case,

$$\begin{aligned} K(a, b_1, b_2) - K(a, b_1 b_2) &= p(a, b_1)K(b_1, b_2) + p(b_1, a)K(a_1, b_2) - p(a, b_1 b_2)K(b_1 b_2) - p(b_1 b_2, a) \\ &= \frac{(1-a)^2(b_1-1)}{(b_1-a)(b_1 b_2-a)}p(a, b_2). \end{aligned}$$

If  $a = 1$ , the above line is 0, and otherwise it is  $> 0$ .

Next supposing  $\mathbf{x}_A = (a_1, a_2)$  and  $\mathbf{x}_B = b$ ,

$$\begin{aligned} K(a_1, a_2, b) - K(a_1 a_2, b) &= p(a_1, b)(p(a_2, b)/b + p(b, a_2)) + p(b, a_1) - p(a_1 a_2, b)/b - p(b, a_1 a_2) \\ &= \frac{(1-a_1)(1-a_2)(b-1)^2}{(b-a_1)(b-a_2)(b-a_1 a_2)}, \end{aligned}$$

which is non-negative and equal to 0 if and only if  $b = 1$ .

Suppose by way of induction that the conclusion of the theorem holds for some  $m \geq 2$ ,  $m = \max(|A|, |B|)$  and  $\min(|A|, |B|) = 1$ . We consider the case that  $|A| = m+1$  and  $|B| = 1$ , with the case  $|A| = 1, |B| = m+1$  being analogous. Then  $\{i, j\} \subset A$ , and there is  $u \in A$  distinct from  $i$  and  $j$ . Let  $B = \{v\}$ . By the inductive hypothesis and the  $\min(|A|, |B|) = 0$  case given above,

$$\begin{aligned} K(\mathbf{x}) &= K(\mathbf{x}_A, \mathbf{x}_B) = p(x_u, x_v)K(\mathbf{x}_{A/u}, x_v) + p(x_v, x_u)K(\mathbf{x}_A) \\ &\geq p(x_u, x_v)K(\mathbf{x}_{A/\{u, i, j\}}, x_i x_j, x_v) + p(x_v, x_u)K(\mathbf{x}_{A/\{i, j\}}, x_i x_j) \\ &= K(\mathbf{x}_{A/\{i, j\}}, x_i x_j, x_v). \end{aligned}$$

Equality holds above iff  $K(\mathbf{x}_{A/u}, x_v) = K(\mathbf{x}_{A/\{u, i, j\}}, x_i x_j, x_v)$  and  $K(\mathbf{x}_A) = K(\mathbf{x}_{A/\{i, j\}}, x_i x_j)$ , which holds iff  $\mathbf{x}_{A/\{i, j\}}$  are all 1 and  $\mathbf{x}_B = x_v = 1$ , by the inductive hypothesis.

3.  $\min(|A|, |B|) = 2$ . This case is given by Lemma 22.

Finally, suppose by way of induction that the conclusion of the theorem holds for some  $m \geq 2$ , and suppose  $\min(|A|, |B|) = m+1$ . We give the case that  $\{i, j\} \subset A$ , with the case that  $\{i, j\} \subset B$  being analogous. Let  $v \in B$ , and let  $u \in A$  be distinct from  $i$  and  $j$ . By the inductive hypothesis,

$$\begin{aligned} K(\mathbf{x}) &= K(\mathbf{x}_A, \mathbf{x}_B) = p(x_u, x_v)K(\mathbf{x}_{A/u}, \mathbf{x}_B) + p(x_v, x_u)K(\mathbf{x}_A, \mathbf{x}_{B/v}) \\ &\geq p(x_u, x_v)K(\mathbf{x}_{A/\{u, i, j\}}, x_i x_j, \mathbf{x}_B) + p(x_v, x_u)K(\mathbf{x}_{A/\{i, j\}}, x_i x_j, \mathbf{x}_{B/v}) \\ &= K(\mathbf{x}_{A/\{i, j\}}, x_i x_j, \mathbf{x}_B). \end{aligned}$$

Equality holds iff  $K(\mathbf{x}_{A/u}, \mathbf{x}_B) = K(\mathbf{x}_{A/\{u, i, j\}}, x_i x_j, \mathbf{x}_B)$  and  $K(\mathbf{x}_A, \mathbf{x}_{B/v}) = K(\mathbf{x}_{A/\{i, j\}}, x_i x_j, \mathbf{x}_{B/v})$ , which holds iff  $\mathbf{x}_{A/\{i, j\}}$  and  $\mathbf{x}_B$  are all 1, by the inductive hypothesis.  $\square$



**Theorem 24.** Given  $\mathbf{x} \in \mathbb{R}_+^n$  let  $A = \{i : x_i \leq 1\}$  and  $B = \{i : x_i > 1\}$ . If  $|B| = 1$ , then

$$(1 - K(\mathbf{x}))^{1-1/n}(1 - (1 - K(\mathbf{x}))^{1/n}) \leq \Delta K(\mathbf{x}) \leq K(\mathbf{x}).$$

Assuming  $A$  and  $B$  are fixed, the tight case of the first inequality occurs when  $\max\{x_i : i \in A\} = 0$  and the tight case of the second inequality occurs when  $\min\{x_i : i \in B\} = 1$ .

*Proof.* The second inequality follows from the convex combination representation given by Theorem 12 for  $K(\mathbf{x})$  and  $\Delta K(\mathbf{x})$ . The weights and the leaf nodes of type “b” in each of these representations are identical. The leaf nodes of type “a” all evaluate to 1 under  $K$  and to 0 under  $\Delta K$  unless all  $x_i, i \in A$ , are equal to 1.

For the first inequality, let  $a_1, \dots, a_{n-1}$  denote the components of  $\mathbf{x}$  indexed by  $A$  and let  $b$  denote the component indexed by  $B$ . Write

$$K(\mathbf{x}) = 1 - w + w/b,$$

where

$$w = \prod_{i=1}^{n-1} p(a_i, b) = \prod_{i=1}^n \frac{b-1}{b-a_i} \geq (1-1/b)^{n-1}.$$

The last inequality is tight if and only if all  $a_i$  are 0. Then  $1 - K(\mathbf{x}) = w(1-1/b) \geq (1-1/b)^n$ , i.e.,  $b \leq (1 - (1 - K(\mathbf{x}))^{1/n})^{-1}$ . Therefore,

$$\begin{aligned} \Delta K(\mathbf{x}) &= w/b \\ &= \frac{1 - K(\mathbf{x})}{b - 1} \\ &\geq (1 - K(\mathbf{x})) / ((1 - (1 - K(\mathbf{x}))^{1/n})^{-1} - 1) \\ &= (1 - K(\mathbf{x}))^{1-1/n}(1 - (1 - K(\mathbf{x}))^{1/n}). \end{aligned}$$

□

**Conjecture 2.** Given  $\mathbf{x} \in \mathbb{R}_+^n$ ,

$$(1 - K(\mathbf{x}))^{1-1/n}(1 - (1 - K(\mathbf{x}))^{1/n}) \leq \Delta K(\mathbf{x}).$$

The conjecture would be reduced to the case of a single “b”-type component in  $\mathbf{x}$  given by Theorem 24 if we were to establish that for any  $\mathbf{a} \in [0, 1]^r, \mathbf{b} \in [1, \infty)^s$  there is a scalar  $b$  such that  $K(\mathbf{a}, \mathbf{b}) = K(\mathbf{a}, b)$  and  $\Delta K(\mathbf{a}, \mathbf{b}) \geq \Delta K(\mathbf{a}, b)$ .

As  $t \mapsto K(\mathbf{a}, t)$  is strictly decreasing, define  $b^*$  as the unique scalar such that

$$K(\mathbf{a}, \mathbf{b}) = K(\mathbf{a}, b^*),$$

and let  $u^* = 1/b^*$ . Next, with reference to the decomposition (13), define  $W = \sum_{i=1}^n w_i$  and  $\bar{u} = W^{-1} \sum_{i=1}^n w_i / (b_1 \cdots b_i)$ , so that

$$\begin{aligned} K(\mathbf{a}, \mathbf{b}) &= 1 - W + W\bar{u} \\ \Delta K(\mathbf{a}, \mathbf{b}) &= W\bar{u}. \end{aligned}$$

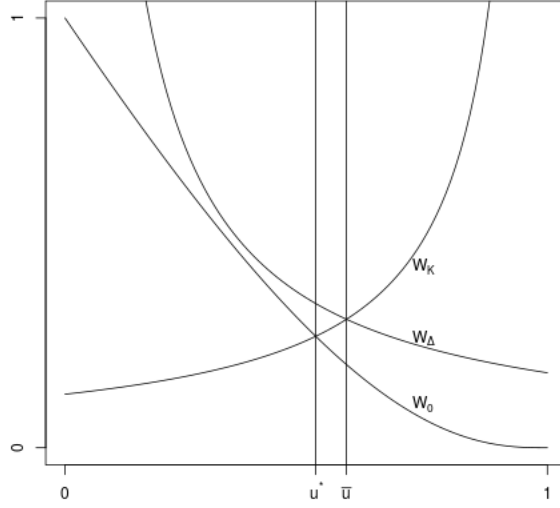


Figure 1: A sample visualization of the definitions involved in a sufficient condition for Conjecture 2.

Next, fixing  $\mathbf{a}$ ,  $K = K(\mathbf{a}, \mathbf{b})$ , and  $\Delta K = \Delta K(\mathbf{a}, \mathbf{b})$ , define

$$\begin{aligned} W_0 : u &\mapsto \prod_{i=1}^n p(a_i, 1/u) = \prod_{i=1}^n \frac{1-u}{1-a_i u} \\ W_K : u &\mapsto \frac{1-K}{1-u} \\ W_\Delta : u &\mapsto \frac{\Delta K}{u}. \end{aligned}$$

Then  $W_0$  and  $W_\Delta$  are strictly decreasing while  $W_K$  is strictly increasing. Furthermore,  $W_K(\bar{u}) = W_\Delta(\bar{u})$  and  $W_K(u^*) = W_0(u^*)$ . See Fig. 1.

Suppose it has somehow been established that  $u^* \leq \bar{u}$ . Then  $W_K(u^*) \leq W_K(\bar{u}) = W_\Delta(\bar{u})$ . Therefore

$$\begin{aligned} \Delta K(\mathbf{a}, 1/u^*) &= W_K(u^*)u^* \\ &\leq W_K(\bar{u})\bar{u} \\ &= \Delta K(\mathbf{a}, \mathbf{b}). \end{aligned}$$

By the definition of  $u^*$ ,  $K(\mathbf{a}, 1/u^*) = K(\mathbf{a}, \mathbf{b})$ , so  $1/u^*$  is the required scalar.

Therefore, Conjecture 2 would follow from Theorem 24 by establishing  $W_K(\bar{u}) \geq W_0(\bar{u})$ .

## 2 Special cases of Gaffke's strong conjecture and reductions

**Theorem 25** (Gaffke (2005, Lemma 4.1)). *Suppose  $n = 1$  or  $n = 2$ . Then Conjecture 1 holds.*

*Proof.* We exhibit the cdf of  $K$  directly and show that it is stochastically larger than a standard uniform cdf. Suppose  $n = 1$ . Then  $K(\mathbf{X}) = K(X_1) = 1$  w.p.  $p(a_1, b_1)$  and  $K(\mathbf{X}) = 1/b_1$  w.p.  $p(b_1, a_1)$ , so

$$\mathbb{P}(K(\mathbf{x}) \leq \alpha) = \begin{cases} 0, & \alpha \in [0, 1/b_1) \\ p(b_1, a_1), & \alpha \in [1/b_1, 1) \\ 1, & \alpha = 1. \end{cases}$$

Since  $p(b_1, a_1) \leq 1/b_1$ ,  $\mathbb{P}(K(\mathbf{x}) \leq \alpha) \leq \alpha$  for all  $\alpha$ .

Suppose  $n = 2$ . The state space of  $\mathbf{X} = (X_1, X_2)$  consists of  $(b_1, b_2), (a_1, b_2), (b_1, a_2), (a_1, a_2)$ . We assume that  $K(a_1, b_2) \leq K(b_1, a_2)$ , with the case of the opposite inequality being analogous. The cdf of  $K(X_1, X_2)$  is then

$$\mathbb{P}(K(X_1, X_2) \leq \alpha) = \begin{cases} 0, & \alpha \in [0, 1/(b_1 b_2)) \\ p(b_1, a_1)p(b_2, a_2), & \alpha \in [1/(b_1 b_2), K(a_1, b_2)) \\ p(b_2, a_2), & \alpha \in [K(a_1, b_2), K(b_1, a_2)) \\ p(b_2, a_2) + p(b_1, a_1)p(a_2, b_2), & \alpha \in [K(b_1, a_2), 1) \\ 1 & \alpha = 1. \end{cases}$$

We apply the monotonicity properties of  $p$ , namely  $p(a, b)$  is increasing in each argument and  $p(b, a)$  is decreasing in each argument, when  $a \in [0, 1]$  and  $b \geq 1$ . This monotonicity implies  $p(b_1, a_1)p(b_2, a_2) \leq 1/(b_1 b_2)$ , so that the cdf lies below  $\alpha$  through the second interval of constancy given above. In the third interval the cdf is  $p(b_2, a_2) \leq 1/b_2 \leq p(a_1, b_2)/b_2 + p(b_2, a_1) = K(a_1, b_2)$ , the second inequality following since the rhs is a convex combination of  $1/b_2$  and 1.

Consider finally the fourth interval, where the cdf is  $p(b_2, a_2) + p(b_1, a_1)p(a_2, b_2)$  and  $\alpha \geq K(b_1, a_2) = p(b_1, a_2) + p(a_2, b_1)/b_1$ . Suppose first  $b_1 \leq b_2$ . Then  $p(b_2, a_2) + p(b_1, a_1)p(a_2, b_2) \leq p(b_2, a_2) + p(a_2, b_2)/b_1$ . Since  $b_1 \leq b_2$  implies  $p(a_2, b_2) \geq p(a_2, b_1)$ , comparing the two convex combinations,  $p(b_2, a_2) + p(a_2, b_2)/b_1 \leq p(b_1, a_2) + p(a_2, b_1)/b_1 = K(b_1, a_2)$ . Suppose next that  $b_1 > b_2$ , so that  $p(a_1, b_1) > p(a_1, b_2)$ . Then rewriting the cdf value,  $p(b_2, a_2) + p(b_1, a_1)p(a_2, b_2) = p(b_1, a_1) + p(b_2, a_2)p(a_1, b_1) \leq p(b_1, a_1) + p(a_1, b_1)/b_2 \leq p(b_2, a_1) + p(a_1, b_2)/b_2 = K(a_1, b_2) \leq K(b_1, a_2)$ . Therefore,  $\mathbb{P}(K(\mathbf{x}) \leq \alpha) \leq \alpha$  for all  $\alpha$ .  $\square$

**Theorem 26** (Gaffke (2005, Lemma 2.2)). *Let  $\mathbf{a} = a\mathbf{1}, a \in [0, 1]$  and  $\mathbf{b} = b\mathbf{1}, b \geq 1, a \neq b$ . Then Conjecture 1 holds.*

*Proof.* Gaffke (2005) proves this result by showing that under the theorem assumptions another statistic, denoted there  $W$ , is stochastically larger than a standard uniform, and that  $K$  is in turn stochastically larger than  $W$ . A direct proof is below.

Let  $p = p(a, b) = (b-1)/(b-a)$ . Assume without loss that  $\alpha = K(a\mathbb{1}_r, b\mathbb{1}_s)$  where  $r \geq 0$ ,  $s \geq 0$ , and  $r + s = n$ .

The vectors  $\{a, b\}^n$  making up the probability space are ordered by the number of occurrences of  $a$ , or equivalently  $b$ , among their components: if  $r_1 > r_2$ , i.e.,  $s_1 < s_2$ , then by monotonicity

$$K(a\mathbb{1}_{r_1}, b\mathbb{1}_{s_1}) \leq K(a\mathbb{1}_{r_2}, b\mathbb{1}_{s_2}).$$

Therefore

$$\begin{aligned} \mathbb{P}(K(\mathbf{x}) \leq \alpha) &= \mathbb{P}(K(\mathbf{x}) \leq K(a\mathbb{1}_r, b\mathbb{1}_s)) \\ &= \sum_{i=0}^r \mathbb{P}(a\mathbb{1}_i, b\mathbb{1}_{s+r-i}) \\ &= \sum_{i=0}^r \binom{r+s}{i} p^i (1-p)^{r+s-i}. \end{aligned}$$

Using the martingale interpretation of  $K$  given in Section 3.1.1,

$$K(a\mathbb{1}_r, b\mathbb{1}_s) = \sum_{i=0}^{r-1} \binom{s+i}{i} p^i (1-p)^s + \sum_{i=0}^{s-1} \binom{r+i}{i} p^r (1-p)^i b^{i-s}.$$

By Theorem 8, we have  $1-p \leq 1/b$ , so  $K(a\mathbb{1}_r, b\mathbb{1}_s)$  is lower bounded by

$$\begin{aligned} &\sum_{i=0}^{r-1} \binom{s+i}{i} p^i (1-p)^s + \sum_{i=0}^{s-1} \binom{r+i}{i} p^r (1-p)^i b^{i-s} \\ &\geq \sum_{i=0}^{r-1} \binom{s+i}{i} p^i (1-p)^s + \sum_{i=0}^{s-1} \binom{r+i}{i} p^r (1-p)^i (1-p)^s \\ &= \sum_{i=0}^{r-1} \binom{s+i}{i} p^i (1-p)^s + p^r (1-p)^s \binom{r+s}{s-1}. \end{aligned}$$

By our choice of  $\alpha$  we have  $K(a\mathbb{1}_r, b\mathbb{1}_s) \in \{K(\mathbf{x}) \leq \alpha\}$ , so it suffices to establish the binomial inequality

$$\sum_{i=0}^r \binom{r+s}{i} p^i (1-p)^{r+s-i} \leq \sum_{i=0}^{r-1} \binom{s+i}{i} p^i (1-p)^s + p^r (1-p)^s \binom{r+s}{s-1}. \quad (16)$$

We use a probabilistic interpretation. Consider  $r+s$  independent Bernoulli trials with common success probability  $p$ . The left-hand side is

$$\begin{aligned} \sum_{i=0}^r \binom{r+s}{i} p^i (1-p)^{r+s-i} &= \mathbb{P}(\geq s \text{ failures in } r+s \text{ trials}) \\ &= \mathbb{P}(\geq s \text{ failures in } r+s-1 \text{ trials}) \\ &\quad + (1-p) \mathbb{P}(s-1 \text{ failures in the first } r+s-1 \text{ trials}). \end{aligned}$$

For  $s \geq 1$ , the second term is

$$\begin{aligned} (1-p) \mathbb{P}(s-1 \text{ failures in the first } r+s-1 \text{ trials}) &= p^r (1-p)^s \binom{r+s-1}{s-1} \\ &\leq p^r (1-p)^s \binom{r+s}{s-1}. \end{aligned}$$

The first term, by a union bound, is

$$\begin{aligned} \mathbb{P}(\geq s \text{ failures in } r+s-1 \text{ trials}) &= \mathbb{P}\left(\bigcup_{j=s}^{r+s-1} \{s \text{ failures and } j-s \text{ successes in the first } j \text{ trials}\}\right) \\ &\leq \sum_{j=s}^{r+s-1} \mathbb{P}(s \text{ failures and } j-s \text{ successes in the first } j \text{ trials}) \\ &= \sum_{j=s}^{r+s-1} \binom{j}{s} (1-p)^s p^{j-s} \\ &= (1-p)^s \sum_{i=0}^{r-1} \binom{s+i}{s} p^i \\ &= (1-p)^s \sum_{i=0}^{r-1} \binom{s+i}{i} p^i. \end{aligned}$$

Combining the two bounds yields (16). □

**Definition 27.** Let  $\mathbf{a} \in [0, 1]^n$ ,  $\mathbf{b} \in [0, \infty)^n$ ,  $n \geq 1$  be given. Let  $\mathbf{X} = (X_1, \dots, X_n)$  consist of independent random variables with mean 1, with  $X_i$  supported on  $\{a_i, b_i\}$ ,  $i = 1, \dots, n$ . For  $\mathbf{I} \in \{0, 1\}^{m \times n}$  with distinct rows  $\mathbf{I}_1, \dots, \mathbf{I}_m$ , define the  $m \times n$  matrix  $\mathbf{x}$  through

$$x_{ij} = x(\mathbf{I}_{ij}) = \begin{cases} a_j, & \text{if } \mathbf{I}_{ij} = 0 \\ b_j, & \text{if } \mathbf{I}_{ij} = 1. \end{cases}$$

with rows  $\mathbf{x}_i = \mathbf{x}_{I_i} = \mathbf{x}(\mathbf{I}_i) \in \prod_{j=1}^n \{a_j, b_j\}$

$$(\mathbf{x}(I_i))_j = \begin{cases} a_j & \text{if } I_{ij} = 0 \\ b_j & \text{if } I_{ij} = 1. \end{cases}$$

**Theorem 28.** Conjecture 1 is equivalent to the following assertion:

**Conjecture 1'.** For any  $n \geq 1$  and the  $2^{2^n}$  sets of distinct index sets  $I_1, \dots, I_m$ ,  $1 \leq m \leq 2^n$ ,

$$\sum_{i=1}^m \mathbb{P}((X_1, \dots, X_n) = \mathbf{x}_{I_i}) \leq \max_{1 \leq i \leq m} K(\mathbf{x}_{I_i}). \quad (17)$$

*Proof.* If Conjecture 1 is true, taking  $\alpha = \max_{1 \leq i \leq m} K(\mathbf{x}_{I_i})$ ,

$$\begin{aligned}
\sum_{i=1}^m \mathbb{P}(\mathbf{X} = \mathbf{x}_{I_i}) &\leq \sum_{I: K(\mathbf{x}_I) \leq \max_{1 \leq i \leq m} K(\mathbf{x}_{I_i})} \mathbb{P}(\mathbf{X} = \mathbf{x}_{I_i}) \\
&= \sum_{I: K(\mathbf{x}_I) \leq \alpha} \mathbb{P}(\mathbf{X} = \mathbf{x}_{I_i}) \\
&= \mathbb{P}(K(\mathbf{X}) \leq \alpha) \\
&\leq \alpha = \max_{1 \leq i \leq m} K(\mathbf{x}_{I_i}).
\end{aligned}$$

Conversely, letting  $\{I_1, \dots, I_m\} = \{I : K(\mathbf{x}_I) \leq \alpha\}$ ,

$$\begin{aligned}
\mathbb{P}(K(\mathbf{X}) \leq \alpha) &= \sum_{I: K(\mathbf{x}_I) \leq \alpha} \mathbb{P}(\mathbf{X} = \mathbf{x}_I) \\
&= \sum_{i=1}^m \mathbb{P}(\mathbf{X} = \mathbf{x}_{I_i}) \leq \alpha.
\end{aligned}$$

□

A schematic depiction of Conjecture 1' is, for all  $\mathbf{a} \in [0, 1]^n$ ,  $\mathbf{b} \in [1, \infty)^n$ ,  $\mathbf{I} \in \{0, 1\}^{m \times n}$ ,

$$\begin{aligned}
&\begin{array}{l} \mathbb{P}(x_{11}) \cdot \mathbb{P}(x_{12}) \cdots \mathbb{P}(x_{1,n}) \\ + \mathbb{P}(x_{21}) \cdot \mathbb{P}(x_{22}) \cdots \mathbb{P}(x_{2,n}) \\ \vdots \\ + \mathbb{P}(x_{m,1}) \cdot \mathbb{P}(x_{m,2}) \cdots \mathbb{P}(x_{m,n}) \end{array} \leq \bigvee \begin{array}{l} K(x_{11}, x_{12}, \dots, x_{1,n}) \\ K(x_{21}, x_{22}, \dots, x_{2,n}) \\ \vdots \\ K(x_{m,1}, x_{m,2}, \dots, x_{m,n}) \end{array} \quad (18)
\end{aligned}$$

## 2.1 Induction

For fixed  $j$ ,  $x_{ij} = x(\mathbf{I}_{ij})$  is either  $a_j$  or  $b_j$ , depending on whether  $\mathbf{I}_{ij} = 0$  or  $= 1$ . If the column only contains one of these two values, i.e., for some  $j$ ,  $1 \leq j \leq n$ ,  $x_{ij} = a_j$  for all  $i$ , or  $x_{ij} = b_j$  for all  $i$ ,  $1 \leq i \leq m$ , then factoring out this common value, say  $\mathbb{P}(x_{1,j})$ , reduces to the  $n - 1$  case,

$$\begin{aligned}
\sum_{i=1}^m \mathbb{P}(\mathbf{x}_i) &= \mathbb{P}(x_{1,j}) \sum_{i=1}^m \mathbb{P}(\mathbf{x}_{i,-j}) \\
&\leq \mathbb{P}(x_{1,j}) \max_{1 \leq i \leq m} K(\mathbf{x}_{i,-j})
\end{aligned}$$

and an application of Theorems 8 and 9 completes the inductive step,

$$\begin{aligned}
&\leq K_0(x_{1,j}) \max_{1 \leq i \leq m} K(\mathbf{x}_{i,-j}) \\
&\leq \max_{1 \leq i \leq m} K(\mathbf{x}_i).
\end{aligned}$$

Suppose therefore that for each  $j, 1 \leq j \leq n$ , there are  $i, i'$ , such that  $x_{i,j} = a_j, x_{i',j} = b_j$ . In terms of the matrix  $\mathbf{I}$  (Definition 27), the condition is that  $0 < \sum_{i=1}^m \mathbf{I}_{ij} < m, 1 \leq j \leq n$ . Then for any  $j, 1 \leq j \leq n$ , by the inductive hypothesis,

$$\begin{aligned} \sum_{i=1}^m \mathbb{P}(\mathbf{x}_i) &= \mathbb{P}(a_j) \sum_{i: x_{ij}=a_j} \mathbb{P}(x_{i,-j}) + \mathbb{P}(b_j) \sum_{i: x_{ij}=b_j} \mathbb{P}(x_{i,-j}) \\ &\leq \mathbb{P}(a_j) \max_{i: x_{ij}=a_j} K(\mathbf{x}_{i,-j}) + \mathbb{P}(b_j) \max_{i: x_{ij}=b_j} K(\mathbf{x}_{i,-j}). \end{aligned}$$

A candidate for an inductive step in a proof of Conjecture 1' is showing

$$\min_{1 \leq j \leq n} (\mathbb{P}(a_j) \max_{i: x_{ij}=a_j} K(\mathbf{x}_{i,-j}) + \mathbb{P}(b_j) \max_{i: x_{ij}=b_j} K(\mathbf{x}_{i,-j})) \leq \max_{1 \leq i \leq m} K(\mathbf{x}_i). \quad (19)$$

**Lemma 29.** *Let  $\mathbf{a} \in [0, 1]^n$ ,  $\mathbf{b} \in [1, \infty)^n$ ,  $\mathbf{I} \in \{0, 1\}^{2 \times n}$ , and  $\mathbf{x} = \mathbf{x}(\mathbf{I})$  be given. Suppose  $\mathbf{x}_{11} = a_1$  and  $\mathbf{x}_{21} = b_1$ . Then*

$$\mathbb{P}(a_1)K(\mathbf{x}_{1,-1}) + \mathbb{P}(b_1)K(\mathbf{x}_{2,-1}) > \max(K(\mathbf{x}_1), K(\mathbf{x}_2)) \quad (20)$$

*if and only if  $a_1 \neq 1, b_1 \neq 1$ ,  $\Delta K(\mathbf{x}_1) < \Delta K(\mathbf{x}_2)$ , and*

$$a_1 - 1 < \frac{K(\mathbf{x}_1) - K(\mathbf{x}_2)}{|\Delta K(\mathbf{x}_1) - \Delta K(\mathbf{x}_2)|} < b_1 - 1.$$

*Proof.* The lhs of (20) strictly exceeding  $K(\mathbf{x}_1)$ , i.e.,

$$\begin{aligned} 0 &< (\mathbb{P}(a_1) - 1)K(\mathbf{x}_1) + (1 - \mathbb{P}(a_1))K(\mathbf{x}_2) + \frac{b_1 - 1}{b_1 - a_1}(a_1 - 1)\Delta K(\mathbf{x}_1) + \frac{1 - a_1}{b_1 - a_1}(b_1 - 1)\Delta K(\mathbf{x}_2) \\ &= \frac{1 - a_1}{b_1 - a_1}(K(\mathbf{x}_2) - K(\mathbf{x}_1)) + \frac{(1 - a_1)(b_1 - 1)}{b_1 - a_1}(\Delta K(\mathbf{x}_2) - \Delta K(\mathbf{x}_1)), \end{aligned}$$

is equivalent to  $a_1 \neq 1$  and

$$K(\mathbf{x}_1) - K(\mathbf{x}_2) < -(b_1 - 1)(\Delta K(\mathbf{x}_1) - \Delta K(\mathbf{x}_2)). \quad (21)$$

Similarly, assuming the lhs of (20) strictly exceeds  $K(\mathbf{x}_2)$  means  $b_1 \neq 1$  and

$$K(\mathbf{x}_1) - K(\mathbf{x}_2) > (1 - a_1)(\Delta K(\mathbf{x}_1) - \Delta K(\mathbf{x}_2)). \quad (22)$$

If  $\Delta K(\mathbf{x}_1) > \Delta K(\mathbf{x}_2)$  then (21) and (22) would together imply

$$1 - a_1 < \frac{K(\mathbf{x}_1) - K(\mathbf{x}_2)}{\Delta K(\mathbf{x}_1) - \Delta K(\mathbf{x}_2)} < -(b_1 - 1),$$

which is impossible since  $1 - a_1 \geq 0$  and  $b_1 - 1 \geq 0$ .  $\square$

**Theorem 30.** *Let  $\mathbf{a} \in [0, 1]^n$ ,  $\mathbf{b} \in [1, \infty)^n$ ,  $\mathbf{I} \in \{0, 1\}^{m \times n}$  be given, and suppose that Conjecture 1' holds for  $n - 1$ . Then if*

1. for some  $j, 1 \leq j \leq n, \sum_{i=1}^m \mathbf{I}_{ij} \in \{0, m\}$

the inequality (19) holds. Suppose  $0 < \sum_{i=1}^m \mathbf{I}_{ij} < m, 1 \leq j \leq n$ , and let  $i_a(j) = \arg \max_{i: \mathbf{I}_{ij}=0} K(\mathbf{x}_{i,-j})$  and  $i_b(j) = \arg \max_{i: \mathbf{I}_{ij}=1} K(\mathbf{x}_{i,-j})$  denote the indices of the two types of column maxima. The following are sufficient conditions for (19):

2. for any  $j, 1 \leq j \leq n, \sum_{i: x_{ij}=a_j} \mathbb{P}(\mathbf{x}_{i,-j}) \geq \sum_{i: x_{ij}=b_j} \mathbb{P}(\mathbf{x}_{i,-j})$

3. for any  $j, 1 \leq j \leq n, K(\mathbf{x}_{i_a(j),-j}) \geq K(\mathbf{x}_{i_b(j),-j})$

4. for any  $j, 1 \leq j \leq n, \Delta K(\mathbf{x}_{i_a(j)}) \geq \Delta K(\mathbf{x}_{i_b(j)})$

5. for all  $i, 1 \leq i \leq m$ , there is  $j, 1 \leq j \leq n$  such that  $\mathbf{I}_{ij} = 0$  and  $\mathbf{I}_{ij'} = 1, j' \neq j$ .

*Proof.* 1. The sufficiency of  $\sum_{i=1}^m \mathbf{I}_{ij} \in \{0, m\}$  is given in the discussion preceding the theorem.

2. If for some  $j, \sum_{i: x_{ij}=a_j} \mathbb{P}(\mathbf{x}_{i,-j}) \geq \sum_{i: x_{ij}=b_j} \mathbb{P}(\mathbf{x}_{i,-j})$  then since  $\mathbb{P}(a_j) + \mathbb{P}(b_j) = 1$ ,  $\mathbb{P}(a_j) \sum_{i: x_{ij}=a_j} \mathbb{P}(\mathbf{x}_{i,-j}) + \mathbb{P}(b_j) \sum_{i: x_{ij}=b_j} \mathbb{P}(\mathbf{x}_{i,-j}) \leq \mathbb{P}(a_j) \sum_{i: x_{ij}=a_j} \mathbb{P}(\mathbf{x}_{i,-j})$ . By the inductive hypothesis and Theorem 9, the rhs is  $\leq \mathbb{P}(a_j) \max_{i: x_{ij}=a_j} K(\mathbf{x}_{i,-j}) \leq \max_{i: x_{ij}=a_j} K(a_j, \mathbf{x}_{i,-j}) = \max_{i: x_{ij}=a_j} K(\mathbf{x}_i) \leq \max_{1 \leq i \leq m} K(\mathbf{x}_i)$ .

3. If for some  $j, \max_{i: x_{ij}=a_j} K(\mathbf{x}_{i,-j}) \geq \max_{i: x_{ij}=b_j} K(\mathbf{x}_{i,-j})$  then again by convexity

$$\mathbb{P}(a_j) \max_{i: x_{ij}=a_j} K(\mathbf{x}_{i,-j}) + \mathbb{P}(b_j) \max_{i: x_{ij}=b_j} K(\mathbf{x}_{i,-j}) \leq \max_{i: x_{ij}=a_j} K(\mathbf{x}_{i,-j})$$

and by monotonicity  $\max_{i: x_{ij}=a_j} K(\mathbf{x}_{i,-j}) \leq \max_{i: x_{ij}=a_j} K(\mathbf{x}_{i,-j}, a_j) = \max_{i: x_{ij}=a_j} K(\mathbf{x}_i) \leq \max_{1 \leq i \leq m} K(\mathbf{x}_i)$ .

4. Given by Lemma 29.

5. Let  $i_0 = \arg \max_{1 \leq i \leq m} \Delta K(\mathbf{x}_i)$  and let  $j_0$  be the index corresponding to  $i_0$  given by the condition. Then  $i_a(j_0) = i_0$ , and so  $\Delta K(\mathbf{x}_{i_a(j_0)}) = \Delta K(\mathbf{x}_{i_0}) \geq \Delta K(\mathbf{x}_{i_b(j_0)})$ , and sufficient condition (4) applies. □

**Corollary 31.** Suppose  $m = 1$  or  $m = 2$ . Then Conjecture 1' holds.

*Proof.* When  $m = 1$  the claim is that for any  $\mathbf{x} \in \prod_{i=1}^n \{a_i, b_i\}$ ,

$$\mathbb{P}(\mathbf{x}) \leq K(\mathbf{x}). \quad (23)$$

When  $n = 1$ , Theorem 25 implies (23). Assume (23) holds for  $n - 1$ , and let  $\mathbf{x} \in \prod_{i=1}^n \{a_i, b_i\}$  be given. Then by Theorems 8 and 9

$$\mathbb{P}(\mathbf{x}) \leq \mathbb{P}(x_1) K(\mathbf{x}_{-1}) \leq K(\mathbf{x}).$$

When  $m = 2$  the claim is that for any  $n \geq 1$  and  $\mathbf{I}_1 \in \{0, 1\}^n, \mathbf{I}_2 \in \{0, 1\}^n$ ,

$$\prod_{j=1}^n p(x(\mathbf{I}_{1j}), x(\bar{\mathbf{I}}_{1j})) + \prod_{j=1}^n p(x(\mathbf{I}_{2j}), x(\bar{\mathbf{I}}_{2j})) \leq \max(K(\mathbf{x}(\mathbf{I}_1)), K(\mathbf{x}(\mathbf{I}_2))). \quad (24)$$



Again the  $n = 1$  case is given by Theorem 25, so assume (24) holds for  $n - 1$ , and let  $\mathbf{I}_1 \in \{0, 1\}^n$  and  $\mathbf{I}_2 \in \{0, 1\}^n$  be given. If for some  $i, 1 \leq i \leq n$ ,  $x_i = y_i$  then  $\mathbb{P}(\mathbf{x}) + \mathbb{P}(\mathbf{y}) = \mathbb{P}(x_i)(\mathbb{P}(\mathbf{x}_{-i}) + \mathbb{P}(\mathbf{y}_{-i})) \leq \mathbb{P}(x_i) \max(K(\mathbf{x}_{-i}), K(\mathbf{y}_{-i})) \leq \max(K(\mathbf{x}), K(\mathbf{y}))$ , again by Theorems 8 and 9. Otherwise assume  $x_i \neq y_i, 1 \leq i \leq n$ . Then if  $\mathbf{x}$  is a leaf node so is  $\mathbf{y}$ , and one of them is then  $(a_1, \dots, a_n)$ , in which case the rhs of (24) is 1 and the inequality is satisfied. Therefore assume without loss of generality that  $(x_1, x_2) = (a_1, b_2), (y_1, y_2) = (b_1, a_2), a_1 \neq b_1, a_2 \neq b_2$ . In this case, Theorem 30 (5) establishes the inductive step.  $\square$

## 2.2 Cylinder sets on the probability space

Given a vector  $\mathbf{x} = \prod_{i=1}^n (a_i, b_i)$  with  $x_i = a_i$  for some index  $i$ , the monotonicity of  $K$  implies that changing  $x_i$  from  $a_i$  to  $b_i$  cannot increase  $K(\mathbf{x})$ . Therefore, adding to the lhs of (17) vectors obtaining by changes of this type can only tighten (17), increasing the lhs without affecting the rhs. Since any subset  $\{\mathbf{x} : K(\mathbf{x}) \leq \alpha\}$  of the probability space must be closed in this sense, there is no loss in generality in assuming in (17) that the lhs is closed.

**Theorem 32.** *Given  $\mathbf{I} \in \{0, 1\}^{m \times n}$ , suppose whenever  $\mathbf{I}_{ij} = 0$  for some  $i, j$ , there exists an  $i'$  such that  $\mathbf{I}_{i'j} = 1$  and  $\mathbf{I}_{i'j'} = \mathbf{I}_{ij}$  for  $j' \neq j$ . Then*

$$\sum_{i=1}^m \prod_{j=1}^n p(x(\mathbf{I}_{ij}), x(\bar{\mathbf{I}}_{ij})) = \mathbb{P}\left(\bigcup_{i=1}^m \bigcap_{j: \mathbf{I}_{ij}=1} \{X_j = b_j\}\right). \quad (25)$$

*Proof.* The lhs of (25) is the probability of the event

$$\bigcup_{i=1}^m \left( \left( \bigcap_{j: \mathbf{I}_{ij}=a_j} \{X_j = a_j\} \right) \bigcap \left( \bigcap_{j: \mathbf{I}_{ij}=b_j} \{X_j = b_j\} \right) \right), \quad (26)$$

and since  $((\bigcap_{j: \mathbf{I}_{ij}=a_j} \{X_j = a_j\}) \bigcap (\bigcap_{j: \mathbf{I}_{ij}=b_j} \{X_j = b_j\})) \subset \bigcap_{j: \mathbf{I}_{ij}=b_j} \{X_j = b_j\}$ , the lhs is  $\leq$  the rhs in (25). For the converse direction, fix  $i$  in  $1, \dots, m$ , and let  $B = \{j : \mathbf{I}_{ij} = 1\}$  and  $A = \{1, \dots, n\} / B = \{j : \mathbf{I}_{ij} = 0\}$ . The contribution of row  $i$  to the union event in the rhs of (25) is

$$\begin{aligned} \bigcap_{j: \mathbf{I}_{ij}=1} \{X_j = b_j\} &= \left( \bigcap_{j \in B} \{X_j = b_j\} \right) \bigcap \left( \bigcap_{k \in A} \{X_k = b_k\} \bigcup \{X_k = a_k\} \right) \\ &= \bigcap_{k \in A} \left( \left( \bigcap_{j \in B} \{X_j = b_j\} \right) \bigcap (\{X_k = b_k\} \bigcup \{X_k = a_k\}) \right) \\ &= \bigcup_{\mathbf{x} \in \prod_{k \in A} \{a_k, b_k\}} \left( \left( \bigcap_{j \in B} \{X_j = b_j\} \right) \bigcap \left( \bigcap_{k \in A} \{X_k = x_k\} \right) \right), \end{aligned}$$

where the outer intersection in the last line is taken over the  $2^{|A|}$  possible tuples  $\mathbf{x}$  formed by choosing  $a_k$  or  $b_k$  for each  $k \in A$ . By the assumed closure property, each event  $(\bigcap_{j \in B} \{X_j = b_j\}) \bigcap (\bigcap_{k \in A} \{X_k = x_k\})$  in the union belongs to (26).  $\square$

Therefore, another form of Conjecture 1 is:

**Conjecture 1''.** For any  $n \geq 1$ ,  $\mathbf{a} \in [0, 1]^n$ ,  $\mathbf{b} \in [1, \infty)^n$ ,  $\mathbf{X} \sim TP(\mathbf{a}, \mathbf{b}, \mathbf{1})$ , and distinct subsets  $J_1, \dots, J_m$ , of  $\{1, \dots, n\}$ ,

$$\mathbb{P}\left(\bigcup_{i=1}^m \bigcap_{j \in J_i} \{X_j = b_j\}\right) \leq \max_{1 \leq i \leq m} K((b_j)_{j \in J_i}, (a_j)_{j \notin J_i}).$$

Equivalently, for any  $n \geq 1$ ,  $\mathbf{a} \in [0, 1]^n$ ,  $\mathbf{b} \in [1, \infty)^n$ , independent Bernoulli random variables  $Y_1, \dots, Y_n$ , with  $\mathbb{P}(Y_i = 1) = 1 - \mathbb{P}(Y_i = 0) = p(b_i, a_i)$ , and distinct subsets  $J_1, \dots, J_m$ , of  $\{1, \dots, n\}$ ,

$$\mathbb{E}\left(\max_{1 \leq i \leq m} \prod_{j \in J_i} Y_j\right) \leq \max_{1 \leq i \leq m} K((b_j)_{j \in J_i}, (a_j)_{j \notin J_i}). \quad (27)$$

**Lemma 33.** Given  $\mathbf{a} \in [0, 1]^n$  and  $\mathbf{b} \in [1, \infty)^n$ , let  $B = \prod_{i=1}^n b_i$ . Then

$$\prod_{i=1}^n \frac{B - 1}{B - a_i} \leq 1 - \prod_{i=1}^n \frac{1 - a_i}{b_i - a_i}.$$

In the notation of (10)

$$\prod_{i=1}^n p(a_i, B) \leq 1 - \prod_{i=1}^n p(b_i, a_i).$$

*Proof.* Suppose  $b > 1, \beta > 1$ , and  $a \in [0, 1]$ . Since  $\frac{d^2}{db^2}(b - a_1)(\beta/b - a_2) = -\frac{2\beta a_1}{b^3} < 0$ ,  $b \mapsto (b - a_1)(\beta/b - a_2)$  is concave, implying  $b \mapsto \frac{1 - a_1}{b - a_1} \frac{1 - a_2}{\beta/b - a_2}$  is convex on  $[1, \beta]$ . Therefore

$$\frac{1 - a_1}{b - a_1} \frac{1 - a_2}{\beta/b - a_2} \leq \max\left(\frac{1 - a_2}{\beta - a_2}, \frac{1 - a_1}{\beta - a_1}\right).$$

Suppose by way of induction that  $a_{n+1} \in [0, 1)$  and  $b_{n+1} > 0$  are given and that

$$\prod_{i=1}^n \frac{1 - a_i}{b_i - a_i} \leq \max_{1 \leq i \leq n} \frac{1 - a_i}{\prod_{j=1}^n b_j - a_i}.$$

An application of the inductive hypothesis along with the base case with  $\beta = \prod_{j=1}^{n+1} b_j$  yields

$$\begin{aligned} \prod_{i=1}^{n+1} \frac{1 - a_i}{b_i - a_i} &\leq \max_{1 \leq i \leq n} \frac{1 - a_i}{\prod_{j=1}^n b_j - a_i} \frac{1 - a_{n+1}}{b_{n+1} - a_{n+1}} \\ &= \max_{1 \leq i \leq n} \frac{1 - a_i}{\beta/b_{n+1} - a_i} \frac{1 - a_{n+1}}{b_{n+1} - a_{n+1}} \\ &\leq \max_{1 \leq i \leq n} \max\left(\frac{1 - a_i}{\beta - a_i}, \frac{1 - a_{n+1}}{\beta - a_{n+1}}\right) \\ &= \max_{1 \leq i \leq n+1} \frac{1 - a_i}{\beta - a_i}. \end{aligned}$$

Therefore,

$$1 - \prod_{i=1}^n \frac{1 - a_i}{b_i - a_i} \geq 1 - \max_{1 \leq i \leq n} \frac{1 - a_i}{\prod_{j=1}^n b_j - a_i} = \min_{1 \leq i \leq n} \frac{\prod_{j=1}^n b_j - 1}{\prod_{j=1}^n b_j - a_i} \geq \prod_{i=1}^n \frac{\prod_{j=1}^n b_j - 1}{\prod_{j=1}^n b_j - a_i}.$$

□

**Theorem 34.** Suppose  $\mathbf{a} \in [0, 1]^n$ ,  $\mathbf{b} \in [1, \infty)^n$ , and  $J_1, \dots, J_m$ , are disjoint subsets of  $\{1, \dots, n\}$ . Then Conjecture 1'' holds.

*Proof.* Let  $i$  be fixed,  $1 \leq i \leq m$ , and let  $J = \cup_{j=1}^m J_j$ . Among the  $m$  terms maximized over on the rhs of (18) there is, corresponding to  $J_i$ ,  $K((b_j)_{j \in J_i}, (a_j)_{j \notin J_i})$ . For  $j, 1 \leq j \leq m$ , denote  $B_j = \prod_{k \in J_j} b_k$ . By Theorem 23 and (7)

$$\begin{aligned} K((b_j)_{j \in J_i}, (a_j)_{j \notin J_i}) &\geq K(B_i, (a_j)_{j \notin J_i}) \\ &= \frac{1}{B_i} \prod_{j \in J/J_i} p(a_j, B_i) + 1 - \prod_{j \in J/J_i} p(a_j, B_i). \end{aligned} \quad (28)$$

The last expression is a convex combination of 1 and the smaller  $1/B_i$ . The lhs of (18) may also be written as a convex combination by conditioning on whether  $\bigcap_{k \in J_j} \{X_k = b_k\}$  occurs for at least one  $j$  different from  $i$ ,

$$\prod_{j:j \neq i} (1 - \mathbb{P}(\bigcap_{k \in J_j} \{X_k = b_k\})) \mathbb{P}(\bigcap_{j \in J_i} \{X_j = b_j\}) + 1 - \prod_{j:j \neq i} (1 - \mathbb{P}(\bigcap_{k \in J_j} \{X_k = b_k\})).$$

The lhs is a convex combination of 1 and  $\mathbb{P}(\bigcap_{j \in J_i} \{X_j = b_j\})$  and by Theorem 8 the latter is  $\leq \prod_{j \in J_i} 1/b_j = 1/B_i$ . Therefore, if the lhs of (18) were strictly larger than the right hand side, and therefore also larger than (28), necessarily

$$\begin{aligned} \prod_{j:j \neq i} (1 - \mathbb{P}(\bigcap_{k \in J_j} \{X_k = b_k\})) &< \prod_{j \in J/J_i} p(a_j, B_i), \text{ i.e.,} \\ \prod_{j:j \neq i} (1 - \prod_{k \in J_j} p(b_k, a_k)) &< \prod_{j:j \neq i} \prod_{k \in J_j} p(a_k, B_i). \end{aligned}$$

Applying Lemma 33,

$$\prod_{j:j \neq i} \prod_{k \in J_j} p(a_k, B_j) < \prod_{j:j \neq i} \prod_{k \in J_j} p(a_k, B_i).$$

Therefore, for some  $j$  different from  $i$ ,  $\prod_{k \in J_j} p(a_k, B_j) < \prod_{k \in J_j} p(a_k, B_i)$ , implying that for some  $j$  different from  $i$ ,  $B_j < B_i$ , i.e.,

$$B_i > \min_{j:j \neq i} B_j.$$

If this inequality held for each  $i$  we would reach a contradiction as some  $B_i, 1 \leq i \leq m$ , must be minimal. Therefore, the lhs of (18) does not exceed at least one of the terms on the rhs of (18). □

**Theorem 35.** Suppose  $\mathbf{a} \in [0, 1]^n$ ,  $\mathbf{b} \in [1, \infty)^n$ , and  $J_1$  and  $J_2$  are subsets of  $\{1, \dots, n\}$ . Then Conjecture 1'' holds.

*Proof.* The lhs of (18) is

$$\begin{aligned}
& \mathbb{P}\left(\bigcap_{j \in J_1} \{X_j = b_j\} \bigcup \bigcap_{j \in J_2} \{X_j = b_j\}\right) \\
&= \mathbb{P}\left(\bigcap_{j \in J_1} \{X_j = b_j\}\right) + \mathbb{P}\left(\bigcap_{j \in J_2} \{X_j = b_j\}\right) - \mathbb{P}\left(\bigcap_{j \in J_1} \{X_j = b_j\} \bigcap \bigcap_{j \in J_2} \{X_j = b_j\}\right) \\
&= \mathbb{P}\left(\bigcap_{j \in J_1 \cap J_2} \{X_j = b_j\}\right) (\mathbb{P}\left(\bigcap_{j \in J_2/J_1} \{X_j = b_j\}\right) + (1 - \mathbb{P}\left(\bigcap_{j \in J_2/J_1} \{X_j = b_j\}\right)) \mathbb{P}\left(\bigcap_{j \in J_1/J_2} \{X_j = b_j\}\right)) \\
&= \prod_{j \in J_1 \cap J_2} p(b_j, a_j) \left( \prod_{j \in J_2/J_1} p(b_j, a_j) + (1 - \prod_{j \in J_2/J_1} p(b_j, a_j)) \prod_{j \in J_1/J_2} p(b_j, a_j) \right).
\end{aligned}$$

The rhs of (18) is

$$\max(K((a_j)_{j \in J_2/J_1}, (b_j)_{j \in J_1}), K((a_j)_{j \in J_1/J_2}, (b_j)_{j \in J_2})).$$

If (18) does not hold, then in particular the lhs would strictly exceed  $K((a_j)_{j \in J_2/J_1}, (b_j)_{j \in J_1})$ . Then by Theorem 23, denoting  $B_1 = \prod_{j \in J_1} b_j$ ,

$$\prod_{j \in J_2/J_1} p(b_j, a_j) + (1 - \prod_{j \in J_2/J_1} p(b_j, a_j)) \prod_{j \in J_1/J_2} p(b_j, a_j) > \frac{K((a_j)_{j \in J_2/J_1}, B_1)}{\prod_{j \in J_1 \cap J_2} p(b_j, a_j)}.$$

By repeated application of Theorem 10,

$$\begin{aligned}
\prod_{j \in J_1 \cap J_2} p(b_j, a_j) K\left(\prod_{j \in J_1/J_2} b_j, (a_j)_{j \in J_2/J_1}\right) &\leq \prod_{j \in J_1 \cap J_2} K_0(b_j) K\left(\prod_{j \in J_1/J_2} b_j, (a_j)_{j \in J_2/J_1}\right) \\
&\leq K(B_1, (a_j)_{j \in J_2/J_1}).
\end{aligned}$$

Therefore a violation of (18) would imply

$$\begin{aligned}
& \prod_{j \in J_2/J_1} p(b_j, a_j) + (1 - \prod_{j \in J_2/J_1} p(b_j, a_j)) \prod_{j \in J_1/J_2} p(b_j, a_j) \\
&> K\left(\prod_{j \in J_1/J_2} b_j, (a_j)_{j \in J_2/J_1}\right) \\
&= 1 - \prod_{j \in J_2/J_1} p(a_j, \prod_{k \in J_1/J_2} b_k) + \frac{1}{\prod_{k \in J_1/J_2} b_k} \prod_{j \in J_2/J_1} p(a_j, \prod_{k \in J_1/J_2} b_k).
\end{aligned}$$

The remainder is as in the proof of Theorem 34. Comparing terms of the two convex combinations, the above inequality implies

$$\prod_{j \in J_2/J_1} p(b_j, a_j) > \frac{1}{\prod_{k \in J_1/J_2} b_k} \prod_{j \in J_2/J_1} p(a_j, \prod_{k \in J_1/J_2} b_k)$$

and

$$1 - \prod_{j \in J_2/J_1} p(b_j, a_j) < \prod_{j \in J_2/J_1} p(a_j, \prod_{k \in J_1/J_2} b_k).$$

The second inequality, by Lemma 33, implies  $\prod_{k \in J_2/J_1} b_k < \prod_{k \in J_1/J_2} b_k$ , which in turn implies  $\prod_{k \in J_2} b_k < \prod_{k \in J_1} b_k$ . Repeating the argument with the rhs term  $K((a_j)_{j \in J_1/J_2}, (b_j)_{j \in J_2})$  rather than  $K((a_j)_{j \in J_2/J_1}, (b_j)_{j \in J_1})$ , or just from symmetry considerations, a violation of (18) would lead also to  $\prod_{k \in J_1} b_k < \prod_{k \in J_2} b_k$ , a contradiction.  $\square$

The proofs of Theorems 34 and 35 show that, when  $lhs(\mathbf{a}, \mathbf{b}, \mathbf{I})$  has the special structure assumed by those theorems, the inequality (18) may be tightened by replacing each  $K((a)_{j \notin J_i}, (b)_{j \in J_i})$  on the rhs with  $K((a)_{j \notin J_i}, \prod_{j \in J_i} b_j)$ .

A drawback of working with the second form of Conjecture 1 given in Theorem 28 is that it obscures which special cases are useful to establish. For example, in the condition given in Theorem 30 that for some  $j$ ,  $\sum_{i: x_{ij}=a_j} \mathbb{P}(\mathbf{x}_{i,-j}) \geq \sum_{i: x_{ij}=b_j} \mathbb{P}(\mathbf{x}_{i,-j})$ , strict inequality cannot hold for any subset of the probability space of the form  $\mathbb{P}(K(\mathbf{x}) \leq \alpha)$ ,  $\alpha \in (0, 1)$ , as established in Section 2.2. On the other hand, the sufficient conditions given in Theorem 30 appear more effective than those given by Theorems 34 and 35 for data-generating processes we have considered. See Fig. 2.

Theorems 8 and 23 show that “compressing” type “a” and type “b” arguments separately, i.e., replacing them by their products, can only increase  $p$  and can only decrease  $K$ . It follows that compressing redundant arguments in can only tighten the inequality Conjecture 1”.

**Theorem 36.** *With  $\mathbf{a}$ ,  $\mathbf{b}$ , and  $J_1, \dots, J_m$ , as in Conjecture 1”, let the  $m \times n$  matrix  $\mathbf{I}$  be given by*

$$\mathbf{I}_{ij} = \begin{cases} 1 & j \in J_i \\ 0 & j \notin J_i \end{cases}.$$

*Then it may be assumed in Conjecture 1” that the columns of  $\mathbf{I}$  are unique.*

*Proof.* Let  $K_1, \dots, K_p$  be a partition of  $\{1, \dots, n\}$  that collects together identical columns of  $\mathbf{I}$ , i.e.,  $i, j \in K_k$ ,  $1 \leq k \leq p$ , if and only if  $\mathbf{I}_{li} = \mathbf{I}_{lj}$ ,  $1 \leq l \leq m$ . Let  $a'_i = \prod_{j \in K_i} a_j$  and  $b'_i = \prod_{j \in K_i} b_j$ ,  $1 \leq i \leq p$ . Let  $J'_i = \{j : K_j \subset J_i\}$ ,  $1 \leq i \leq m$ , which is well-defined since for any  $i, j$ ,  $1 \leq i \leq m$ ,  $1 \leq j \leq p$ , either  $K_j \subset J_i$  or  $K_j \cap J_i = \emptyset$ . Let  $Y'_1, \dots, Y'_p$ , be  $p$  independent Bernoulli random variables with parameters  $p(b'_1, a'_1), \dots, p(b'_p, a'_p)$ . Supposing that Conjecture 1” holds, we establish that

$$\mathbb{E} \max_{1 \leq i \leq m} \prod_{j \in J_i} Y_j \leq \mathbb{E} \max_{1 \leq i \leq p} \prod_{j \in J'_i} Y'_j \leq \max_{1 \leq i \leq m} K((a'_j)_{j \notin J'_i}, (b'_j)_{j \in J'_i}) \leq \max_{1 \leq i \leq m} K((a_j)_{j \notin J_i}, (b_j)_{j \in J_i}) \quad (29)$$

The middle inequality is the conjectured inequality (27). The rightmost inequality follows from Theorem 23. For the leftmost inequality, pick one of  $K_1, \dots, K_p$ , say  $K_1$ . Let  $L_1 = \{i :$

$K_1 \subset J_i\}$ ,  $M_1 = \{i : K_1 \cap J_i = \emptyset\}$ , so  $L_1 \cup M_1 = \{1, \dots, n\}$ .

$$\begin{aligned}
& \mathbb{E} \max_{1 \leq i \leq m} \prod_{j \in J_i} Y_j \\
&= \mathbb{E}(\max_{1 \leq i \leq m} \prod_{j \in J_i} Y_j \mid \prod_{j \in K_1} Y_j = 1) \mathbb{P}(\prod_{j \in K_1} Y_j = 1) + \mathbb{E}(\max_{1 \leq i \leq m} \prod_{j \in J_i} Y_j \mid \prod_{j \in K_1} Y_j = 0) \mathbb{P}(\prod_{j \in K_1} Y_j = 0) \\
&= \mathbb{E}(\max(\max_{i \in L_1} \prod_{j \in J_i/K_1} Y_j, \max_{i \in M_1} \prod_{j \in J_i} Y_j)) \prod_{i \in K_1} p(b_i, a_i) + \mathbb{E}(\max(0, \max_{i \in M_1} \prod_{j \in J_i} Y_j))(1 - \prod_{i \in K_1} p(b_i, a_i)) \\
&= \mathbb{E}(\max(0, \max_{i \in M_1} \prod_{j \in J_i} Y_j)) \\
&\quad + \prod_{i \in K_1} p(b_i, a_i) (\mathbb{E}(\max(\max_{i \in L_1} \prod_{j \in J_i/K_1} Y_j, \max_{i \in M_1} \prod_{j \in J_i} Y_j)) - \mathbb{E}(\max(0, \max_{i \in M_1} \prod_{j \in J_i} Y_j))). \quad (30)
\end{aligned}$$

Since  $Y_i \in \{0, 1\}$ ,  $1 \leq i \leq n$ ,

$$\mathbb{E}(\max(\max_{i \in L_1} \prod_{j \in J_i/K_1} Y_j, \max_{i \in M_1} \prod_{j \in J_i} Y_j)) - \mathbb{E}(\max(0, \max_{i \in M_1} \prod_{j \in J_i} Y_j)) \geq 0.$$

Therefore, Theorem 8 implies (30) is

$$\begin{aligned}
& \leq \mathbb{E}(\max(0, \max_{i \in M_1} \prod_{j \in J_i} Y_j)) + p(b'_1, a'_1) (\mathbb{E}(\max(\max_{i \in L_1} \prod_{j \in J_i/K_1} Y_j, \max_{i \in M_1} \prod_{j \in J_i} Y_j)) - \mathbb{E}(\max(0, \max_{i \in M_1} \prod_{j \in J_i} Y_j))) \\
&= \mathbb{E}(\max(\max_{i \in L_1} Y'_1 \prod_{j \in J_i/K_1} Y_j, \max_{i \in M_1} \prod_{j \in J_i} Y_j) \mid Y'_1 = 0) \\
&\quad + p(b'_1, a'_1) (\mathbb{E}(\max(\max_{i \in L_1} Y'_1 \prod_{j \in J_i/K_1} Y_j, \max_{i \in M_1} \prod_{j \in J_i} Y_j) \mid Y'_1 = 1) \\
&\quad - \mathbb{E}(\max(\max_{i \in L_1} Y'_1 \prod_{j \in J_i/K_1} Y_j, \max_{i \in M_1} \prod_{j \in J_i} Y_j) \mid Y'_1 = 0)) \\
&= \mathbb{E} \max(Y'_1 \max_{i \in L_1} \prod_{j \in J_i/K_1} Y_j, \max_{i \in M_1} \prod_{j \in J_i} Y_j).
\end{aligned}$$

Iterating for any remaining  $K_i, i > 1$ , yields the leftmost inequality in (29).  $\square$

In terms of the index sets  $J_1, \dots, J_m$ , given in Conjecture 1'', the assumption that **I** have no repeated columns amounts to assuming that any given pattern of inclusion and exclusion among the  $J_i$  produces a singleton. E.g., there is a single index that belongs to  $J_1$  and no other  $J_i$ , there is a single index that belongs to  $J_1$  and  $J_2$  and no other  $J_i$ , etc. Given  $m$ , Theorem 36 implies that only  $n \leq 2^m$  need be considered in Conjecture 1''. When  $m$  is low, as in Corollary 31 or Theorem 35, the Conjecture 1 may be established by explicitly writing out the possible cumulative distribution functions of  $K$ .

Finally, the form of the lhs in (27) connects Conjecture 1'' to reliability theory. A standard bound there leads to a sufficient condition for the conjecture.

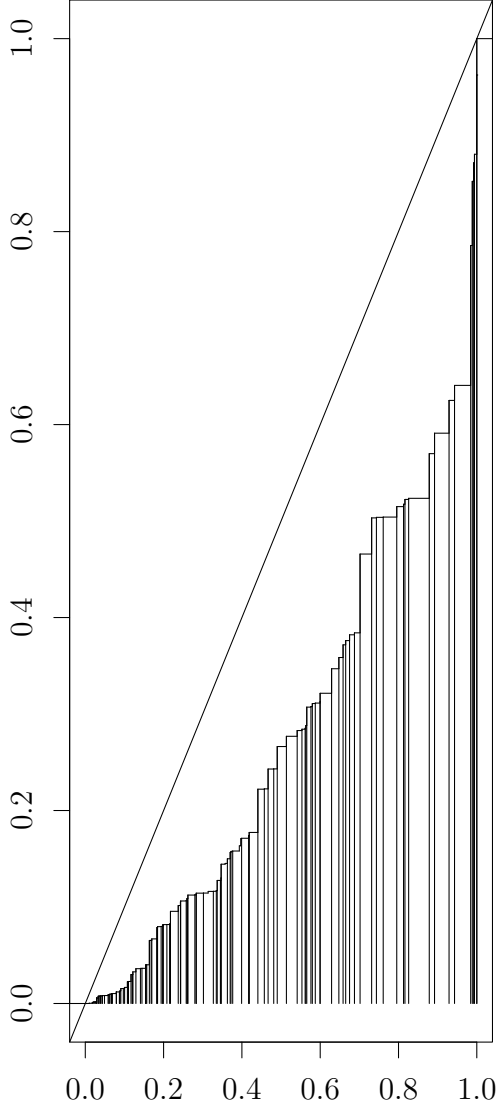
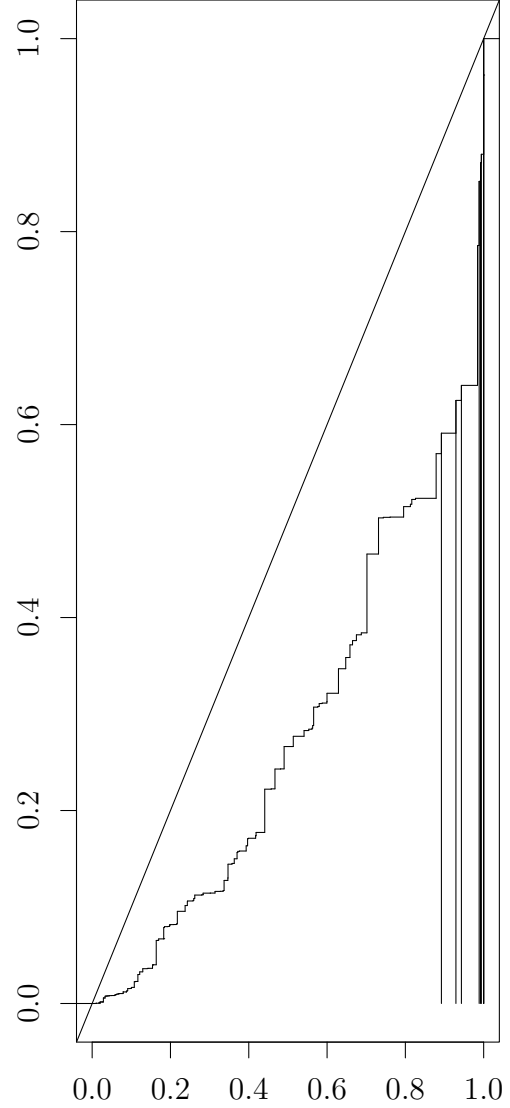
**Theorem 30****Theorems 34 and 35**

Figure 2: An illustration of the effectiveness of the special cases of Conjecture 1 given by Theorem 30. The cdf of  $K$  for a random choice of  $2n$  support points for  $X_1, \dots, X_n$  is plotted. Indicated in the figures are those of the  $2^n$  support points of  $K$  for which Conjecture 1 is established by Theorem 30 (left) and Theorems 34 and 35 (right). Here  $n = 7$ , the lower support points  $a_1, \dots, a_n$  are sampled uniformly on the unit interval and the upper support points  $b_1, \dots, b_n$  are sampled according to standard exponential random variables, shifted to lie in  $[1, \infty)$ .

**Theorem 37.** For any  $n \geq 1$ ,  $\mathbf{a} \in [0, 1]^n$ ,  $\mathbf{b} \in [1, \infty)^n$ ,  $\mathbf{X} \sim TP(\mathbf{a}, \mathbf{b}, \mathbf{1})$ , and distinct subsets  $J_1, \dots, J_m$ , of  $\{1, \dots, n\}$ ,

$$\mathbb{E}(\max_{1 \leq i \leq m} \prod_{j \in J_i} Y_j) \leq 1 - \prod_{i=1}^m (1 - \prod_{j \in J_i} p(b_j, a_j)).$$

*Proof.* The  $m$  random variables  $1 - \prod_{j \in J_i} Y_j$ ,  $1 \leq j \leq m$ , are “associated” in the sense of Esary et al. (1967), and therefore

$$\begin{aligned} 1 - \mathbb{P}(\max_{1 \leq i \leq m} \prod_{j \in J_i} Y_j) &= \mathbb{E} \min_{1 \leq i \leq m} (1 - \prod_{j \in J_i} Y_j) \\ &= \mathbb{E} \prod_{i=1}^m (1 - \prod_{j \in J_i} Y_j) \\ &\geq \prod_{i=1}^m \mathbb{E}(1 - \prod_{j \in J_i} Y_j) \\ &= \prod_{i=1}^m (1 - \prod_{j \in J_i} p(b_j, a_j)). \end{aligned}$$

□

## 3 Interpretations of $K$

### 3.1 Stochastic process

#### 3.1.1 Martingale

Recursion (7) invites a martingale formulation of  $K$ . Fix  $r \geq 0, s \geq 0, \mathbf{a} \in [0, 1]^r, \mathbf{b} \in [0, \infty)^s$ . Define discrete-time integer-valued processes  $I(t)$  on  $0, \dots, r$ , and  $J(t)$  on  $0, \dots, s$  as follows. For  $t = 0$ ,  $I(0) = J(0) = 0$ . For  $t > 0$ ,

$$(I(t+1), J(t+1)) = \begin{cases} (I(t), J(t)) & \text{w.p. 1 if } I(t) = r \text{ or } J(t) = s \\ (I(t) + 1, J(t)) & \text{w.p. } p(a_{I(t)}, b_{J(t)}) \text{ if } I(t) < r \text{ and } J(t) < s \\ (I(t), J(t) + 1) & \text{w.p. } p(b_{J(t)}, a_{I(t)}) \text{ if } I(t) < r \text{ and } J(t) < s. \end{cases}$$

Then  $K((\mathbf{a})_{I(t)}^r, (\mathbf{b})_{J(t)}^s)$  is a bounded discrete-time martingale. When  $I(t) = r$  or  $J(t) = s$ ,  $K((\mathbf{a})_{I(t+1)}^r, (\mathbf{b})_{J(t+1)}^s) = K((\mathbf{a})_{I(t)}^r, (\mathbf{b})_{J(t)}^s)$  deterministically, and when both  $I(t) < r$  and  $J(t) < s$ ,

$$\begin{aligned} &\mathbb{E}(K((\mathbf{a})_{I(t+1)}^r, (\mathbf{b})_{J(t+1)}^s) | K((\mathbf{a})_{I(t)}^r, (\mathbf{b})_{J(t)}^s)) \\ &= p(a_{I(t)}, b_{J(t)}) K((\mathbf{a})_{I(t+1)}^r, (\mathbf{b})_{J(t)}^s) + p(b_{J(t)}, a_{I(t)}) K((\mathbf{a})_{I(t)}^r, (\mathbf{b})_{J(t+1)}^s) \\ &= K((\mathbf{a})_{I(t)}^r, (\mathbf{b})_{J(t)}^s). \end{aligned}$$

Define the bounded stopping time  $T$  by the event  $I(t) = r$  or  $J(t) = s$ . Then

$$K(\mathbf{a}, \mathbf{b}) = \mathbb{E} K((\mathbf{a})_{I(T)}^r, (\mathbf{b})_{J(T)}^s).$$



### 3.1.2 Markov chain and gambling interpretation

Let  $a_1, a_2, \dots$  be a sequence in  $[0, 1]$  and  $b_1, b_2, \dots$  a sequence in  $[1, \infty)$ . Define a discrete-time process  $R_t$  on  $\mathbb{Z}$  with increments  $\pm 1$  as follows. At  $t = 0$ ,  $R_0 = 0$ . If at time  $t$ ,  $R$  has taken  $U$  up steps and  $D$  down steps then

$$R_{t+1} = \begin{cases} R_t + 1 & \text{w.p. } p(b_{U+1}, a_{D+1}) \\ R_t - 1 & \text{w.p. } p(a_{D+1}, b_{U+1}). \end{cases}$$

Since  $U + D = t$  and  $U - D = r_t$ ,  $U = (R_t + t)/2$  and  $D = (t - R_t)/2$ , and so  $R_t$  is a time- and space-inhomogeneous Markov chain. Given natural numbers  $r$  and  $s$ , define the “payoff” of the sample path as follows. Let  $\mathbf{a} = (a_i)_{i=1}^r$  and  $\mathbf{b} = (b_i)_{i=1}^s$ . Let  $T_U$  and  $T_D$  denote the hitting times for  $R_t = -t + 2s$  and  $R_t = t - 2r$ . When  $T_U = T_D \wedge T_U$ ,  $R_{T_D \wedge T_U}$  has made  $s$  up moves and  $T_U - s$  down moves, and the payoff is defined to be  $K(a_{D+1}, \dots, a_r) = 1$ . When  $T_D = T_D \wedge T_U$ ,  $R_{T_D \wedge T_U}$  has made  $r$  down moves and  $T_D - r$  up moves, and the payoff is defined to be  $K(b_{U+1}, \dots, b_s) = (\prod_{i=U+1}^s b_i)^{-1}$ . Then  $K(\mathbf{a}, \mathbf{b})$  is the expected payoff.

Player  $A$  begins with chips  $a_1, \dots, a_r$  and player  $B$  with chips  $b_1, \dots, b_s$ . The object of the game is to bankrupt the other player. In each of a sequence of rounds the two players put up a chip and a coin is flipped with probability  $p(b_U, a_D) = \frac{1-a_D}{b_U-a_D}$  of landing heads, where  $D$  and  $U$  represent the number of rounds  $A$  and  $B$ , respectively, have previously won. The value of a chip staked in a round is therefore related to its relative distance from 1. If the coin does land heads,  $A$  wins the current round, and  $B$  loses his chip; otherwise  $B$  wins and  $A$  loses his chip. Hitting  $R_t = -t + 2s$  represents bankruptcy for  $B$ ,  $R_t = t - 2r$  for  $A$ . At bankruptcy, the other player cashes in his remaining chips, and  $K$  is the valuation, e.g.,  $K((\mathbf{b})_{i=U+1}^s) = (\prod_{i=U+1}^s b_i)^{-1}$  if  $B$  wins.  $K(\mathbf{a}, \mathbf{b})$  represents the expected payoff for the winner. See Fig. 3.

The symmetry of  $K$  says that strategy doesn’t matter. A player can play chips in any order without affecting the expected payoff.

## 3.2 Interpolating polynomials

The formula (2) may be interpreted as the value of a polynomial interpolant and, relatedly, divided differences.

Given  $f : \mathbb{R} \rightarrow \mathbb{R}$  and distinct reals  $x_1, \dots, x_n$ , let  $L[f; x_1, \dots, x_n] : \mathbb{R} \rightarrow \mathbb{R}$  denote the unique polynomial of degree  $n - 1$  passing through  $(x_1, f(x_1)), \dots, (x_n, f(x_n))$ . By comparison of the Lagrange form of this polynomial to (2),

$$K(x_1, \dots, x_n) = -\frac{L[t \mapsto K_0(t)(t-1)^n; x_1, \dots, x_n](1)}{\prod_{i=1}^n (1-x_i)}, \quad (31)$$

That is,  $K(x_1, \dots, x_n)$  is the interpolating polynomial of  $t \mapsto K_0(t)(t-1)^n$  at nodes  $x_1, \dots, x_n$ , evaluated at 1, after dividing by  $-\prod_{i=1}^n (1-x_i)$ .

Next, let  $[x_1, \dots, x_n; f]$  denote the divided difference of order  $n-1$  of  $f$  at nodes  $x_1, \dots, x_n$ , that is, the leading coefficient of the Newton form of the unique polynomial of degree  $n - 1$  through  $(x_1, f(x_1)), \dots, (x_n, f(x_n))$  (de Boor, 2005). Then

$$K(x_1, \dots, x_n) = [x_1, \dots, x_n; t \mapsto K_0(t)(1-t)^{n-1}]. \quad (32)$$

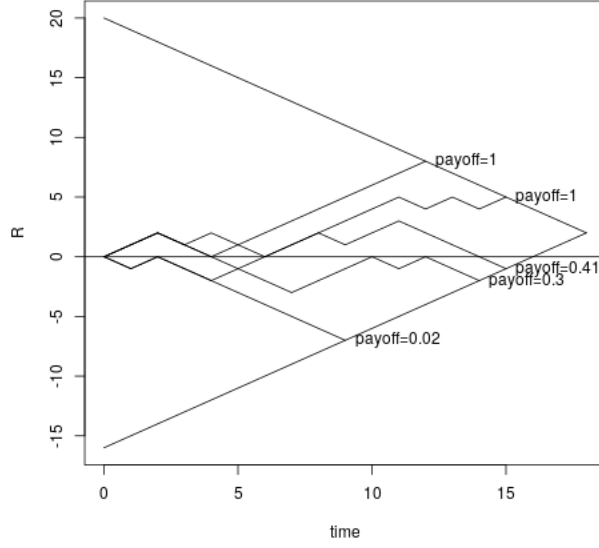


Figure 3: Interpretation of  $K(\mathbf{a}, \mathbf{b})$  as the expected payoff in a game. Five games are depicted, where player  $A$  begins with the 8 chips  $\mathbf{a} = (0.59, 0.01, 0.29, 0.28, 0.81, 0.26, 0.72, 0.91)$  and  $B$  with 10 chips  $\mathbf{b} = (1.05, 1.84, 3.68, 1.29, 1.4, 1.43, 1.34, 2.05, 1.06, 1.13)$ .

The interpretation of  $K$  using interpolating polynomials opens up many results, including an integral representation, the derivative of  $K$  with respect to a node, and confluent formulas (de Boor, 2005). See also the proof of Theorem 5 where the relation to Lagrange polynomials is applied. However, many of the results for interpolating polynomials do not carry over. The reason is that in the interpretations (31) and (32) the function to be interpolated,  $t \mapsto K_0(t)(t-1)^n$  or  $t \mapsto K_0(t)(1-t)^{n-1}$ , depends on the number  $n$  of nodes used for interpolation. As a consequence results for  $K$  resemble but still differ from the corresponding results for interpolating polynomials. For example, compare the explicit formula for  $K(x_1, \dots, x_n)$  given by (2),

$$\sum_{i=1}^n K_0(x_i) \prod_{j:j \neq i} \frac{x_i - 1}{x_i - x_j}.$$

with the formula for the Lagrange interpolant through  $(x_i, K_0(x_i)), i = 1, \dots, n$ ,

$$\sum_{i=1}^n K_0(x_i) \prod_{j:j \neq i} \frac{x_j - 1}{x_j - x_i}.$$

Similarly, given distinct  $i, j$ ,  $1 \leq i \leq n, 1 \leq j \leq n$ , compare the recursion formula (7) for  $K$ ,

$$K(\mathbf{x}) = \frac{x_i - 1}{x_i - x_j} K(\mathbf{x}_{-j}) + \frac{x_j - 1}{x_j - x_i} K(\mathbf{x}_{-i})$$

with the corresponding formula given by Neville's algorithm for computing the value at 1 of the polynomial interpolating  $(x_k, K_0(x_k)), k = 1, \dots, n$ ,

$$K(\mathbf{x}) = \frac{x_i - 1}{x_i - x_j} K(\mathbf{x}_{-i}) + \frac{x_j - 1}{x_j - x_i} K(\mathbf{x}_{-j})$$

or the divided differences recursion formula,

$$[\mathbf{x}; K] = \frac{1}{x_i - x_j} [\mathbf{x}_{-j}; K] + \frac{1}{x_j - x_i} [\mathbf{x}_{-i}; K].$$

## 4 Extensions

Let  $\Theta_0$  denote the set of all finite products of nonnegative two-point distributions with mean 1, and let  $\Theta_1$  denote the set of all finite products of nonnegative two-point distributions at least one of which has mean strictly greater than 1.

We first consider generalizations of  $K$  via Theorem 6 allowing the values on leaf nodes to be arbitrary. The resulting functions need not be symmetric so in the following definition we use one example of a choice function on the indices of the function arguments.

**Definition 38.** *Given a function  $f : [0, 1]^{(\mathbb{N})} \cup [1, \infty)^{(\mathbb{N})} \rightarrow \mathbb{R}$ . extend its domain to  $\mathbb{R}_+^{(\mathbb{N})}$  by recursion 7. That is, for  $\mathbf{x} \in [0, \infty)^{(\mathbb{N})}$ ,  $|\mathbf{x}| \geq 2$ ,  $\mathbf{x} \notin [0, 1]^{(\mathbb{N})} \cup [1, \infty)^{(\mathbb{N})}$ , let  $i_0 = \min\{i : x_i \leq 1\}$ ,  $j_0 = \min\{j : x_j \geq 1\}$ , and*

$$f(\mathbf{x}) = p(x_{i_0}, x_{j_0}) f(\mathbf{x}_{-i_0}) + p(x_{j_0}, x_{i_0}) f(\mathbf{x}_{-j_0}).$$

Let  $\mathbb{K}$  denote the class of all functions so defined, as the values on the leaf nodes vary.

The function  $K$  is admissible in  $\mathbb{K}$  in the following sense.

**Theorem 39.** *Given  $f \in \mathbb{K}$ ,*

1. *If  $f(\mathbf{x}) < K(\mathbf{x})$  for a leaf node  $\mathbf{x}$ , then for some  $\alpha \in [0, 1]$  there exists  $\theta_0 \in \Theta_0$  such that  $\mathbb{P}_{\theta_0}(f(\mathbf{x}) \leq \alpha) > \mathbb{P}_{\theta_0}(K(\mathbf{x}) \leq \alpha)$ .*
2. *If  $f(\mathbf{x}) > K(\mathbf{x})$  for a leaf node  $\mathbf{x}$ , then for some  $\alpha \in [0, 1]$  there exists  $\theta_1 \in \Theta_1$  such that  $\mathbb{P}_{\theta_1}(f(\mathbf{x}) \leq \alpha) < \mathbb{P}_{\theta_1}(K(\mathbf{x}) \leq \alpha)$ .*

*Proof.* 1. (a) Suppose there is  $\mathbf{a} \in [0, 1]^n$  such that  $f(\mathbf{a}) < K(\mathbf{a}) = 1$ . Let  $\mathbf{X} \sim TP(\mathbf{a}, b\mathbf{1}, \mathbf{1})$ , with  $b$  to be specified. For  $\alpha \in [f(\mathbf{a}), 1)$ ,  $\mathbb{P}(f(\mathbf{X}) \leq \alpha) \geq \prod_{i=1}^n \mathbb{P}(X_i = a_i) = \prod_{i=1}^n p(a_i, b, 1)$  and  $\prod_{i=1}^n p(a_i, b, 1) \rightarrow 1$  as  $b \rightarrow \infty$ . So for large enough  $b$ ,  $\mathbb{P}(f(\mathbf{X}) \leq \alpha) > \alpha$ .

(b) Suppose there is  $\mathbf{b} \in [1, \infty)^n$  such that  $f(\mathbf{b}) < K(\mathbf{b}) = 1/\prod_{i=1}^n b_i$ . Let  $\mathbf{X} \sim TP(\mathbf{0}, \mathbf{b}, \mathbf{1})$ . For  $\alpha \in [f(\mathbf{b}), 1/\prod_{i=1}^n b_i)$ ,  $\mathbb{P}(f(\mathbf{X}) \leq \alpha) \geq \prod_{i=1}^n p(b_i, 0, 1) = 1/\prod_{i=1}^n b_i$ , where  $1/\prod_{i=1}^n b_i$  is  $> \alpha = f(\mathbf{b})$ .

2. (a) Suppose there is  $\mathbf{a} \in [0, 1]^n$  such that  $f(\mathbf{a}) > K(\mathbf{a}) = 1$ . Then  $\mathbb{P}(f(\mathbf{X}) \leq 1) \leq 1 - \prod_{i=1}^n \mathbb{P}(X_i = a_i) < 1 = \mathbb{P}(K(\mathbf{X}) \leq 1)$  holds for any non-degenerate  $X_i \in \Theta_0 \cup \Theta_1, i = 1, \dots, n$ . Therefore 2. holds with  $\alpha = 1$ .

- (b) Suppose there is  $\mathbf{b} \in [1, \infty)^n$  such that  $f(\mathbf{b}) > K(\mathbf{b}) = 1/\prod_{i=1}^n b_i$ . Let  $\mathbf{X} \sim TP(\mathbf{0}, \mathbf{b}, \boldsymbol{\mu})$  with  $\boldsymbol{\mu} \in (1, \infty)^n$  variable. Then as  $\boldsymbol{\mu} \uparrow \mathbf{b}$  element-wise,  $\mathbb{P}(f(\mathbf{X}) \leq 1/\prod_{i=1}^n b_i) < 1 - \prod_{i=1}^n \mathbb{P}(X_i = b_i) \rightarrow 0$  whereas  $\mathbb{P}(K(\mathbf{X}) \leq 1/\prod_{i=1}^n b_i) = \prod_{i=1}^n \mathbb{P}(X_i = b_i) \rightarrow 1$ . Therefore 2. holds with  $\alpha = 1/\prod_{i=1}^n b_i$ .  $\square$

We next focus on a sub-class of symmetric functions, namely, those elements of  $\mathbb{K}$  that, like  $K$ , are multiplicative on leaf nodes.

**Theorem 40.** *As in Theorem 6, given a function  $f_0 : [0, \infty) \rightarrow \mathbb{R}$ , define*

$$f : [0, \infty)^{(\mathbb{N})} \rightarrow \mathbb{R} : (x_1, \dots, x_n) \rightarrow \sum_{i=1}^n f_0(x_i) \prod_{j:j \neq i} \frac{x_i - 1}{x_i - x_j}. \quad (33)$$

*Then  $f(\mathbf{x}) = \prod_{i=1}^n f(x_i)$  for all  $\mathbf{x} \in [0, 1]^n \cup [1, \infty)^n$  and  $n \geq 1$ , if and only if for all pairs of real numbers  $x, y$ ,*

$$f(x)f(y) = \frac{(y-1)f(y) - (x-1)f(x)}{y-x}. \quad (34)$$

*Then either  $f \equiv 0$  or there exists a pair of reals  $(q_1, q_2)$  such that*

$$f_0(x) = \begin{cases} \frac{1}{q_1 + (1-q_1)x} & x \in [0, 1) \\ \frac{1}{q_2 + (1-q_2)x} & x \geq 1. \end{cases} \quad (35)$$

*Proof.* The necessity of the functional equation follows from (7) applied to (33), since  $f(x, y) = p(x, y)f(y) + p(y, x)f(x)$  is the Newton quotient (34). Conversely, suppose by way of induction the result holds for some  $n \geq 1$ , and let  $\mathbf{x} = (x_1, \dots, x_{n+1})$  be a leaf node.

$$\begin{aligned} f(x_1, \dots, x_{n+1}) &= p(x_1, x_{n+1})f(\mathbf{x}_{-1}) + p(x_{n+1}, x_1)f(\mathbf{x}_{-(n+1)}) \\ &= p(x_1, x_{n+1}) \prod_{i=2}^{n+1} f(x_i) + p(x_{n+1}, x_1) \prod_{i=1}^n f(x_i) \\ &= (p(x_1, x_{n+1})f(x_{n+1}) + p(x_{n+1}, x_1)f(x_1)) \prod_{i=2}^n f(x_i) \\ &= f(x_1, x_{n+1}) \prod_{i=2}^n f(x_i) \\ &= \prod_{i=1}^{n+1} f(x_i). \end{aligned}$$

To find the solutions to the functional equation (34) we show more generally that if a function  $f : D \rightarrow \mathbb{R}$  satisfies

$$f(x)f(y) = \frac{(y-1)f(y) - (x-1)f(x)}{y-x}, \quad x \neq y \quad (36)$$

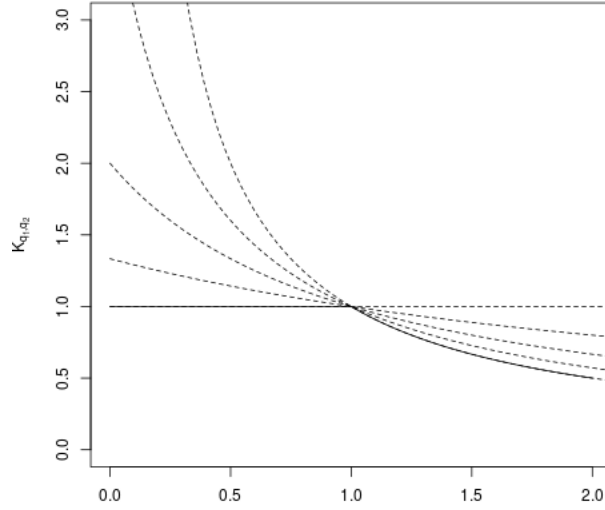


Figure 4: The functions  $K_{q_1, q_2}$  for some values  $(q_1, q_2) \in [0, 1]^2$ , and the lower envelope given by  $K = K_{1,0}$ .

on a domain  $D \subset \mathbb{R}$  with at least 3 points including a point  $y \in D$  satisfying  $y \neq 1, f(y) \neq 0, f(y) \neq 1$ , then for some  $q \in \mathbb{R}$ ,

$$f(x) = \frac{1}{q + (1 - q)x}.$$

Equation (35) follows by taking  $D = (0, 1)$  and  $D = [1, \infty)$ . Suppose  $f$  isn't the 0 function on  $D$ . Let  $x, y \in D$  be distinct,  $(y - 1)f(y) \neq 0$ , and  $y(f(y) - 1 + (1 - f(y))x) \neq 0$ , which can be found under our assumptions. Then the functional equation (36) may be re-written as

$$f(x) = \frac{(y - 1)f(y)}{(yf(y) - 1) + x(1 - f(y))} = \frac{1}{c_1 + c_2x}$$

$$c_1 = \frac{yf(y) - 1}{(y - 1)f(y)}, c_2 = \frac{1 - f(y)}{(y - 1)f(y)}.$$

Substituting this expression for  $f$  into the functional equation, for  $x \neq y$ , yields

$$\frac{1}{c_1 + c_2x} \frac{1}{c_1 + c_2y} = \frac{(c_1 + c_2)(y - x)}{(c_1 + c_2x)(c_1 + c_2y)},$$

implying  $c_1 + c_2 = 1$ . □

**Definition 41.** For a pair of reals  $q_1, q_2$ ,

$$K_{q_1, q_2} : [0, \infty)^{(\mathbb{N})} \rightarrow \mathbb{R} : (x_1, \dots, x_n) \rightarrow \sum_{i=1}^n f_0(x_i) \prod_{j: j \neq i} \frac{x_i - 1}{x_i - x_j}.$$

with  $f_0$  as in (35).

Several of the basic properties of  $K$  carry over to  $K_{q_1, q_2}$  when  $(q_1, q_2)$  belongs to the unit square.

**Theorem 42.** *Suppose  $(q_1, q_2) \in [0, 1]^2$ . Then*

1.  $0 \leq k(x_1, \dots, x_n) \leq 1$ .
2.  $K(x_1, \dots, x_n)$  is symmetric in  $x_1, \dots, x_n$ .
3.  $K(x_1, \dots, x_n)$  is non-increasing in each  $x_i$ , and strictly decreasing if  $x_i > 1$  for some  $i$ .
4.  $K(x_1, \dots, x_n, y) \underset{\leq}{\overset{\geq}{\equiv}} K(x_1, \dots, x_n)$  according as  $y \underset{\geq}{\leq} 1$ .

The function  $K = K_{1,0}$  corresponds to  $(q_1, q_2) = (1, 0)$  and is a lower envelope for  $\{K_{q_1, q_2} : (q_1, q_2) \in [0, 1]^2\}$ . See Fig. 4. The likelihood ratio statistic (42) of Wang and Zhao (2003) can be situated in this family, which clarifies the result of Gaffke (2005) that  $K \leq R$ . The likelihood ratio  $R$  is obtained by minimizing over the diagonal in  $[0, 1] \times [0, 1]$  whereas  $K$  is obtained by minimizing over the unit square.

**Corollary 43** (Gaffke (2005, Theorem 2.1)). *For all  $\mathbf{x} \in [0, \infty)^{(\mathbb{N})}$ ,  $K(\mathbf{x}) \leq R(\mathbf{x})$ .*

*Proof.* For any  $(q_1, q_2) \in [0, 1]^2$

$$K_{1,0}(\mathbf{x}) \leq K_{q_1, q_2}(\mathbf{x})$$

holds whenever  $\mathbf{x} = x$  is a nonnegative real number, and so by the multiplicative property the inequality also holds whenever  $\mathbf{x}$  is any leaf node, and so by Theorem 12 the inequality also holds for any  $\mathbf{x} \in \mathbb{R}_+^{(\mathbb{N})}$ . Therefore, for any  $\mathbf{x} \in \mathbb{R}_+^{(\mathbb{N})}$ ,

$$\begin{aligned} R &= \inf_{q \in [0, 1]} \prod_{i=1}^n \frac{1}{q + (1 - q)x_i} \\ &= \inf_{q \in [0, 1]} K_{q, q}(\mathbf{x}) \\ &\geq \inf_{(q_1, q_2) \in [0, 1]^2} K_{q_1, q_2}(\mathbf{x}) \\ &= K_{1,0}(\mathbf{x}) = K(\mathbf{x}). \end{aligned}$$

□

**Theorem 44.** 1. *If  $q_1 \notin [0, 1]$  or  $q_2 \notin [0, 1]$ , there is  $\alpha \in [0, 1]$  and  $\mathbb{P}_0 \in \Theta_0$  such that for any  $n$ ,  $|\mathbf{X}| = n$ ,  $\mathbb{P}_0(K_{q_1, q_2}(\mathbf{X}) \leq \alpha) > \alpha$ .*

2. *If  $q_1 \in [0, 1]$  and  $q_2 \in [0, 1]$ , then for any  $\alpha \in (0, 1)$ ,*

$$\sup_{\mathbb{P}_1 \in \Theta_1} (\mathbb{P}_1(K(\mathbf{X}) \leq \alpha) - \mathbb{P}_1(K_{q_1, q_2}(\mathbf{X}) \leq \alpha)) \geq 0. \quad (37)$$

3. *If  $n = 1$ , there is  $\alpha \in [0, 1]$  such that the inequality is strict.*

4. If  $n \geq 2$ , the inequality (37) is strict.

*Proof.* 1. If  $q_1 \notin [0, 1]$  then there is some  $x \in [0, 1)$  such that  $K_{q_1, q_2}(x) < K(x)$ . Then with  $X \sim TP(x, b, 1)$ ,  $\mathbb{P}(K_{q_1, q_2}(X) \leq \alpha) \geq p(x, b) = \frac{b-1}{b-x}$  is  $> \alpha$  iff  $b > \frac{1-\alpha x}{1-\alpha}$ . If  $q_2 \notin [0, 1]$  then there is some  $x \in [1, \infty)$  such that  $K_{q_1, q_2}(x) < K(x)$ . Then with  $X \sim TP(0, x, 1)$ ,  $\alpha = \max(K_{q_1, q_2}(x), 0)$ ,  $\mathbb{P}(K_{q_1, q_2}(X) \leq \alpha) \geq p(x, 0) = 1/x$  which is  $> \alpha$ . Since  $K_{q_1, q_2}(\mathbf{x}, 1) = K_{q_1, q_2}(\mathbf{x})$  for all  $(q_1, q_2) \in [0, 1]^2$  and  $\mathbf{x} \in \mathbb{R}_+^{(\mathbb{N})}$ , the  $n = 1$  case can be extended to  $n > 1$  by taking  $X_i, i = 2, \dots, n$ , to be point masses at 1.

2. If  $(q_1, q_2) \in [0, 1]^2$ , then for any  $\mathbf{x} \in \mathbb{R}_+^{(\mathbb{N})}$ ,  $K_{1,0}(\mathbf{x}) \leq K_{q_1, q_2}(\mathbf{x})$ , so  $\mathbb{P}(K_{1,0}(\mathbf{X}) \leq \alpha) \geq \mathbb{P}(K_{q_1, q_2}(\mathbf{X}) \leq \alpha)$  for any  $\mathbb{P}$ .

3. As above, if  $q_1 \notin [0, 1]$  or  $q_2 \notin [0, 1]$  there is  $x \in [0, 1)$  or  $x \in [1, \infty)$ , respectively, such that  $K_{q_1, q_2}(x) < K(x)$ , and so this result follows from Theorem 39.

4. Suppose first that  $q_1 \in (0, 1]$ , so that  $K(x) < K_{q_1, 0}(x)$  for all  $x \in (0, 1)$ . For  $a \in (0, 1), b \in (1, \infty), \alpha \in (0, 1), \mu > 1$ , consider the inequalities

$$K(a, b) \leq \alpha < K_{q_1, 0}(a, b) \quad (38)$$

which may be re-written as

$$1 \leq \frac{\alpha - p(a, b)/b}{1 - p(a, b)} < K_{q_1, 0}(a, b).$$

The middle term is  $\alpha$  at  $b = 1$  and  $\rightarrow \infty$  as  $b \rightarrow \infty$ , and so by continuity there is some  $b = b^* \in [1, \infty)$  for which (38) holds. Then with  $X_1, X_2$  both  $\sim TP(a, b^*, \mu)$  for any  $0 \leq a \leq 1 < \mu < b^*$ ,

$$\begin{aligned} \mathbb{P}(K(X_1, X_2) \leq \alpha) &= \mathbb{P}((X_1, X_2) = (a, b^*)) + \mathbb{P}((X_1, X_2) = (b^*, a)) + \mathbb{P}((X_1, X_2) = (b^*, b^*)) \\ &> \mathbb{P}((X_1, X_2) = (b^*, b^*)) \\ &= \mathbb{P}(K_{q_1, 0}(X_1, X_2) \leq \alpha). \end{aligned}$$

Since  $K_{q_1, 0}(x) \geq K_{q_1, q_2}(x)$  for all  $q_2 \in [0, 1]$  and  $x \geq 0$ ,  $\mathbb{P}(K_{q_1, q_2}(X) \leq \alpha) \leq \mathbb{P}(K_{q_1, 0}(X) \leq \alpha) \leq \mathbb{P}(K(X) \leq \alpha)$  with  $\mathbb{P} \in \Theta_1$ .

Next suppose that  $q_2 \in [0, 1)$ , so that  $K(x) < K_{1, q_2}(x)$  for all  $x > 1$ . Let  $b = 1/\alpha$ ,  $a < 1 < \mu \leq b$ , and  $X \sim TP(a, b, \mu)$ . Then  $\mathbb{P}(K(X) \leq \alpha) = \mathbb{P}(X = b) = p(b, a, \mu) > 0$  whereas  $\mathbb{P}(K_{1, q_2}(X) \leq \alpha) = 0$ , since  $K_{1, q_2}(b) > K(b) = \alpha$  and  $K_{1, q_2}(a) \geq K_{1, q_2}(b)$  by anti-monotonicity (Theorem 42). Since  $K_{1, q_2}(x) \leq K_{q_1, q_2}(x)$  for all  $q_1 \in [0, 1]$  and  $x \geq 0$ ,  $\mathbb{P}(K_{q_1, q_2}(X) \leq \alpha) \leq \mathbb{P}(K_{1, q_2}(X) \leq \alpha) \leq \mathbb{P}(K(X) \leq \alpha)$  with  $\mathbb{P} \in \Theta_1$ .

Finally, the  $n = 1$  and  $n = 2$  cases given here can be extended to greater values of  $n$  by taking additional  $X_i$  to be point masses, as mentioned above.

□

## 5 Asymptotic results

**Theorem 45.** Given  $X_i \sim TP(a_i, b_i, 1)$ ,  $i = 1, 2, \dots$ , assume as  $n \rightarrow \infty$ ,

1.  $\sum_{i=1}^{\infty} ((1 - a_i)(b_i - 1)(2 - a_i - b_i)^2)/i^2 < \infty$
2.  $\frac{1}{n} \sum_{i=1}^n (1 - a_i)(b_i - 1) \not\rightarrow 0$
3.  $\frac{\max_{1 \leq i \leq n} (1 - a_i)(b_i - 1)}{\sum_{i=1}^n (1 - a_i)(b_i - 1)} \rightarrow 0$ .

Then as  $n \rightarrow \infty$ ,  $K(X_1, \dots, X_n)$  converges in distribution to a standard uniform random variable.

*Proof.* We make only superficial changes to the proof of Gaffke (2005), which applied to the case of identically distributed  $X_i$ .

By Kolmogorov's SLLN,  $\sum_{i=1}^{\infty} \text{Var}((X_i - 1)^2)/i^2 < \infty$  implies

$$\frac{1}{n} \sum_{i=1}^n ((X_i - 1)^2 - \mathbb{E}((X_i - 1)^2)) \rightarrow 0 \text{ a.s.}$$

Since  $\text{Var}((X_i - 1)^2) = (1 - a_i)(b_i - 1)(2 - a_i - b_i)^2$ , Assumption 1 provides the required hypothesis.

We next show that  $\frac{1}{n} \max_{1 \leq i \leq n} (X_i - 1)^2 \rightarrow 0$  a.s. If  $(X_i - 1)^2$  is bounded on a sample path, the result follows, otherwise let  $n_k, k = 1, 2, \dots$ , denote the increasing sequence of record times. Then

$$\begin{aligned} & \frac{1}{n_k} (X_{n_k} - 1)^2 + \left( \frac{1}{n_k} - \frac{1}{n_k - 1} \sum_{i=1}^{n_k-1} ((X_i - 1)^2 - \mathbb{E}(X_i - 1)^2) \right) \\ &= \frac{1}{n_k} \sum_{i=1}^{n_k} ((X_i - 1)^2 - \mathbb{E}(X_i - 1)^2) - \frac{1}{n_k - 1} \sum_{i=1}^{n_k-1} ((X_i - 1)^2 - \mathbb{E}(X_i - 1)^2) \\ &\rightarrow 0 \text{ a.s.} \end{aligned}$$

implies  $\frac{1}{n_k} (X_{n_k} - 1)^2 \rightarrow 0$  a.s. Next,

$$\frac{\max_{1 \leq i \leq n} (X_i - 1)^2}{\sum_{i=1}^n (X_i - 1)^2} = \frac{\max_{1 \leq i \leq n} (X_i - 1)^2}{\sum_{i=1}^n \mathbb{E}(X_i - 1)^2} \frac{\sum_{i=1}^n \mathbb{E}(X_i - 1)^2}{\sum_{i=1}^n (X_i - 1)^2}$$

where Assumption 2 and the SLLN from the first step imply the second factor in the last line converges to 1 a.s. Another application implies

$$\frac{\max_{1 \leq i \leq n} (X_i - 1)^2}{\sum_{i=1}^n \mathbb{E}(X_i - 1)^2} = \frac{\frac{1}{n} \max_{1 \leq i \leq n} (X_i - 1)^2}{\frac{1}{n} \sum_{i=1}^n \mathbb{E}(X_i - 1)^2} \rightarrow 0 \text{ a.s.}$$

Therefore,

$$\frac{\max_{1 \leq i \leq n} (X_i - 1)^2}{\sum_{i=1}^n (X_i - 1)^2} \rightarrow 0 \text{ a.s.}$$



Let  $Z_1, Z_2, \dots$  be independent standard exponential random variables. Along almost any sample path  $x_1, x_2, \dots$ , of  $X_1, X_2, \dots$ , the assumptions of the Lindeberg-Feller CLT for the sequence  $(x_1 - 1)Z_1, (x_2 - 1)Z_2, \dots$ , are satisfied, so that

$$\frac{\sum_{i=1}^n (x_i - 1)Z_i - \sum_{i=1}^n (x_i - 1)}{(\sum_{i=1}^n (x_i - 1)^2)^{1/2}}$$

converges in distribution to a standard normal random variable. Using Definition 1,

$$|K(x_1, \dots, x_n) - \Phi(-\frac{\sum_{i=1}^n (x_i - 1)}{(\sum_{i=1}^n (x_i - 1)^2)^{1/2}})| \rightarrow 0.$$

Finally, Assumptions 2, implying  $\sum \sigma_i^2 \rightarrow \infty$ , and 3 are the Lindeberg-Feller conditions for the sequence  $X_1 - 1, X_2 - 1, \dots$ , so

$$\frac{\sum_{i=1}^n (X_i - 1)}{(\sum_{i=1}^n (X_i - 1)^2)^{1/2}}$$

converges in distribution to a standard normal random variable. Since its negation must also then converge to a standard normal,

$$\Phi(-\frac{\sum_{i=1}^n (X_i - 1)}{(\sum_{i=1}^n (X_i - 1)^2)^{1/2}})$$

converges in distribution to a standard uniform random variable, and so also must  $K(X_1, \dots, X_n)$ .  $\square$

## 6 Background

Suppose  $X_1, \dots, X_n$ , are independent random variables with known lower bounds  $l_1, \dots, l_n$ . Given  $\mu_0 > \max_i l_i$ , consider the problem of testing

$$H_0 : \max_i \mathbb{E}X_i \leq \mu_0 \text{ vs. } H_a : \max_i \mathbb{E}X_i > \mu_0. \quad (39)$$

Shifting the data by  $\min l_i$ , and then scaling by  $\max l_i - \min l_i$ , linearity of expectation implies that (39) is the same as testing, based on nonnegative, independent  $X_1, \dots, X_n$ ,

$$H_0 : \max_i \mathbb{E}X_i \leq 1 \text{ vs. } H_a : \max_i \mathbb{E}X_i > 1. \quad (40)$$

Gaffke (2005) proposes to use  $K(X_1, \dots, X_n)$  as a test statistic for (40), rejecting  $H_0$  iff  $K(X_1, \dots, X_n) \leq \alpha$ . This test controls the false positive rate at level  $\alpha$  iff, for all nonnegative, independent  $X_1, \dots, X_n$ , with means in  $[0, 1]$ ,

$$\mathbb{P}(K(X_1, \dots, X_n) \leq \alpha) < \alpha. \quad (41)$$

Since  $K$  is non-increasing in each argument (Theorem 2), another shift of the data reduces the problem to showing (41) holds for all non-negative, independent  $X_1, \dots, X_n$ , with mean

1. As a final reduction, Gaffke (2005), citing Theorem 2.4 and Lemma 2.5 of Gaffke (2004), notes that it is enough to consider nonnegative, independent  $X_1, \dots, X_n$ , with mean 1, with each  $X_i$  supported on two points. This reduction also follows directly from Theorem 1 of Dubins (1962). In this form, Gaffke’s strong conjecture (41) asserts that  $K$  provides a valid test statistic for the hypothesis testing problem (39). A weaker conjecture of Gaffke (2005) is that (41) holds under the further requirement that the  $X_i$  be identically distributed.

Another test for (39) is the likelihood ratio test of Wang and Zhao (2003). The test statistic is given by

$$R : \mathbb{R}_+^{(\mathbb{N})} \rightarrow \mathbb{R} : (x_1, \dots, x_n) \mapsto \inf_{q \in [0,1]} \prod_{i=1}^n \frac{1}{q + (1-q)x_i}, \quad (42)$$

and the decision rule at level  $\alpha$  is to reject the null based on a sample  $X_1, \dots, X_n$ , when  $R(X_1, \dots, X_n) \leq \alpha$ . Gaffke (2005) establishes that  $K(x_1, \dots, x_n) \leq R(x_1, \dots, x_n)$  (see also Section 4), so that establishing (41) for  $K$  implies that it also holds for  $R$ , and so the validity of the likelihood ratio test follows from that of the test based on  $K$ .

For motivation underlying the form of the statistic  $K$ , as well as equivalent formulations using uniformly distributed random variables, see Gaffke (2005).

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