## DISTRIBUTIONS OF KAC-STATISTICS

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1. Let  $N=N_{\lambda}$ ,  $X_1$ ,  $X_2$ , ...,  $X_N$  be independent random variables, N having a Poisson distribution with mean  $\lambda$  and each  $X_i$  having the same continuous distribution function F and being independent of N. Furthermore the modified empirical distribution function is defined by

$$F_{\lambda}^*(x) = \frac{1}{\lambda} \sum_{i=1}^N \Delta(X_i, x)$$
,

where  $\Delta(y, x)$  equals 0 or 1 according as y>x or  $y\leq x$  respectively.

The purpose of this note is to give a systematic computational method of the probability

(1) 
$$\alpha_{\lambda}^{*}(\beta, \gamma) = \Pr \left\{ \beta[F(x)] \leq F_{\lambda}^{*}(x) \leq \gamma[F(x)], \text{ for all } x \right\}.$$

Here  $\beta$  and  $\gamma$  are monotone non-decreasing functions on [0, 1] with  $\beta$  continuous to the left and  $\gamma$  continuous to the right. When  $\beta$  and  $\gamma$  are the linear functions

$$\beta(t) = t - \xi$$
,  $\gamma(t) = t + \xi$ ,

 $\alpha_i^*(\beta, \gamma)$  represents the probability distribution of the Kac-statistic

(2) 
$$K(\lambda) = \sup_{-\infty < x < \infty} \left| F_{\lambda}^{*}(x) - F(x) \right|.$$

2. Let  $U_1, U_2, \cdots$  be the independent random variables having the uniform distribution on [0, 1]. Since

$$\begin{split} \Pr\left\{\beta[F(x)] &\leq F_{i}^{*}(x) \leq \gamma[F(x)], \quad -\infty < x < \infty \mid N = n\right\} \\ &= \Pr\left\{\beta[F(x)] \leq \frac{1}{\lambda} \sum_{i=1}^{n} \Delta(X_{i}, x) \leq \gamma[F(x)], \quad -\infty < x < \infty\right\} \\ &= \Pr\left\{\beta[F(x)] \leq \frac{1}{\lambda} \sum_{i=1}^{n} \Delta(F(X_{i}), F(x)) \leq \gamma[F(x)], \quad -\infty < x < \infty\right\} \\ &= \Pr\left\{\beta(t) \leq \frac{1}{\lambda} \sum_{i=1}^{n} \Delta(U_{i}, t) \leq \gamma(t), \quad 0 < t < 1\right\} \equiv \alpha_{n}^{(\lambda)}(\beta, \gamma) , \end{split}$$

then we can express the probability (1) as

$$\alpha_{\lambda}^{*}(\beta, \gamma) = \sum_{n=0}^{\infty} \Pr \{N = n\} \alpha_{n}^{(\lambda)}(\beta, \gamma)$$
$$= \sum_{n=0}^{\infty} \frac{\lambda^{n} e^{-\lambda}}{n!} \alpha_{n}^{(\lambda)}(\beta, \gamma) .$$

It is easily seen that  $\alpha_n^{(\lambda)}(\beta, \gamma) = 0$  for  $n < \lambda \beta(1)$  or  $n > \lambda \gamma(1)$ . Then we have

(3) 
$$\alpha_{\lambda}^{*}(\beta, \gamma) = \sum_{n=m_{1}}^{m_{2}} \frac{\lambda^{n} e^{-\lambda}}{n!} \alpha_{n}^{\langle \lambda \rangle}(\beta, \gamma) ,$$

where  $m_1 = m_1(\beta)$  is the smallest integer not smaller than  $\lambda\beta(1)$  and  $m_2 = m_2(\gamma)$  is the largest integer smaller than  $\lambda\gamma(1)$ . From the assumptions on  $\beta$  and  $\gamma$  we can define

$$(4) \qquad \nu_k^{\langle 1 \rangle} = \nu_k^{\langle 1 \rangle}(\beta) = \sup_{0 \le t \le 1} \left\{ t : \beta(t) \le \frac{k-1}{1} \right\}, \qquad k = 1, 2, \cdots, m_1$$

(5) 
$$\mu_k^{\langle \lambda \rangle} = \mu_k^{\langle \lambda \rangle}(\gamma) = \inf_{0 \le t \le 1} \left\{ t : \gamma(t) \ge \frac{k}{\lambda} \right\}, \qquad k = 1, 2, \dots, m_2$$

and for each  $n \ (m_1 \leq n \leq m_2)$ ,

$$(6) \qquad \alpha_{n}^{\langle \lambda \rangle}(\beta, \gamma) = \Pr \left\{ \mu_{1}^{\langle \lambda \rangle} \leq U_{1}^{(n)} \leq \nu_{1}^{\langle \lambda \rangle}, \cdots, \mu_{m_{1}}^{\langle \lambda \rangle} \leq U_{m_{1}}^{(n)} \leq \nu_{m_{1}}^{\langle \lambda \rangle}, \\ \mu_{m_{1}+1}^{\langle \lambda \rangle} \leq U_{m_{1}+1}^{(n)}, \cdots, \mu_{n}^{\langle \lambda \rangle} \leq U_{n}^{(n)} \right\} \\ \equiv g_{n}^{\langle \lambda \rangle}(\nu_{1}^{\langle \lambda \rangle}, \cdots, \nu_{m_{1}}^{\langle \lambda \rangle}; \mu_{1}^{\langle \lambda \rangle}, \cdots, \mu_{n}^{\langle \lambda \rangle}),$$

where  $U_1^{(n)}, \dots, U_n^{(n)}$  are the order statistics from a sample of n independent uniform random variables. Thus we have

THEOREM 1. The probability (1) can be calculated by (3) and (6), where the values of  $g_n^{(1)}$  are obtained by Theorem 4 of Suzuki [7] or Theorem of Steck [6].

# 3. Next we proceed to the one-sided case

(7) 
$$\alpha_{\lambda}^{*}(\beta, \infty) = \Pr \left\{ \beta[F(x)] \leq F_{\lambda}^{*}(x), \text{ for all } x \right\},$$

(8) 
$$\alpha_i^*(0,\gamma) = \Pr\left\{F_i^*(x) \leq \gamma [F(x)], \text{ for all } x\right\},$$

which are the generalized forms of the one-sided Kac-statistics

$$(9) K^+(\lambda) = \sup \left[ F(x) - F_{\lambda}^*(x) \right],$$

(10) 
$$K^{-}(\lambda) = \sup [F_{\lambda}^{*}(x) - F(x)].$$

when  $\gamma = \infty$  we have  $m_2 = m_2(\gamma) = \infty$  and

(11) 
$$\alpha_{i}^{*}(\beta, \infty) = \frac{\lambda^{m_{1}}e^{-\lambda}}{m_{1}!} \sum_{j=0}^{\infty} \lambda^{j} \alpha_{i,j},$$

where

$$lpha_{{\scriptscriptstyle \lambda},j} \! = \! rac{m_1!}{(m_1\! + \! j)!} lpha_{m_1\! + j}^{\langle \lambda 
angle}(eta,\, \infty) \! = \! rac{m_1!}{(m_1\! + \! j)!} \Pr \left\{ U_1^{(m_1+j)} \! <\! 
u_1^{\langle \lambda 
angle}, \cdots, \, U_{m_1}^{(m_1+j)} \! <\! 
u_{m_1}^{\langle \lambda 
angle} 
ight\} \, .$$

We shall now define the following polynomials for any  $n \ge 1$  and  $\mu_1, \dots, \mu_n$   $(0 \le \mu_1 \le \dots \le \mu_n \le 1)$ ,

$$Q_0 = 1$$

$$Q_k = Q_k(\mu_1, \dots, \mu_k) = -\sum_{i=0}^{k-1} {k \choose i} \mu_k^{k-i} Q_i$$
,  $k = 1, 2, \dots, n$ .

Then we have from Theorem 3 of Suzuki [7]

$$\Pr \{U_1^{(n)} \ge \mu_1, \cdots, U_n^{(n)} \ge \mu_n\} = \sum_{k=0}^n \binom{n}{k} Q_k = f_n(\mu_1, \cdots, \mu_n).$$

Therefore putting  $\mu_1 = 1 - \nu_{m_1}^{\langle \lambda \rangle}, \dots, \mu_{m_1} = 1 - \nu_1^{\langle \lambda \rangle},$ 

$$egin{aligned} lpha_{1,j} &= rac{m_1!}{(m_1+j)!} \Pr\left\{ U_1^{(m_1+j)} \leq 
u_1^{\langle \lambda 
angle}, \cdots, U_{m_1}^{(m_1+j)} \leq 
u_{m_1}^{\langle \lambda 
angle} 
ight\} \ &= rac{m_1!}{(m_1+j)!} f_{m_1+j}(0, \dots, 0, \mu_1, \dots, \mu_{m_1}) \ &= rac{m_1!}{(m_1+j)!} \Big[ 1 + \sum\limits_{i=1}^{m_1} inom{m_1+j}{i+j} Q_{i+j}(0, \dots, 0, \mu_1, \dots, \mu_i) \Big] \ &= \sum\limits_{i=0}^{m_1} inom{m_1}{i} Q_i^{\langle j 
angle}, \end{aligned}$$

where

(12) 
$$Q_0^{(j)} = \frac{m_1!}{(m_1+j)!}$$

$$Q_i^{(j)} = Q_i^{(j)}(\mu_1, \dots, \mu_i) = \frac{i!}{(i+j)!} Q_{i+j}(0, \dots, 0, \mu_1, \dots, \mu_i) .$$

Consequently from (11)

(13) 
$$\alpha_{\lambda}^{*}(\beta, \infty) = \frac{\lambda^{m_1} e^{-\lambda}}{m_1!} \sum_{j=0}^{\infty} \lambda^{j} \sum_{i=0}^{m_1} {m_1 \choose i} Q_i^{(j)},$$

It is easily shown by induction that

(14) 
$$Q_{k} = \sum_{i=0}^{k-1} (-1)^{i} {k \choose i} f_{k-i} + (-1)^{k} Q_{0}.$$

Noting that  $f_k$  represents probability, we have

$$|Q_i^{(j)}| \leq \frac{i!}{(i+j)!} 2^{i+j}$$

and then  $\sum\limits_{i=0}^{\infty}\lambda^{j}|Q_{i}^{(j)}|\leq 2^{i}i!e^{2\lambda}$ . Thus we can express the relation (13) as

(15) 
$$\alpha_{\lambda}^{*}(\beta, \infty) = \frac{\lambda^{m_1} e^{-\lambda}}{m_!!} \sum_{i=0}^{m_1} {m_1 \choose i} Q_{i}^{\langle \lambda \rangle},$$

where

(16) 
$$Q_i^{(\lambda)} = \sum_{j=0}^{\infty} \lambda^j Q_i^{(j)}, \quad i = 0, 1, \dots, m_1$$

It should be more convenient that the relation (16) is expressed by some recurrence formula. From the definition of  $Q_h$ 

$$\sum_{h=0}^{k+j} {k+j \choose h} \mu_{k+j}^{k+j-h} Q_h(\mu_1', \dots, \mu_h') = 0.$$

Putting  $\mu'_1 = \cdots = \mu'_j = 0$ ,  $\mu'_{j+1} = \mu_1, \cdots, \mu'_{k+j} = \mu_k$ , we have  $\mu_k^{k+j} + \sum_{i=1}^k \binom{k+j}{i+i} \mu_k^{k-i} Q_{i+j} (0, \cdots, 0, \mu_1, \cdots, \mu_i) = 0$ ,

i.e.

$$\mu_k^{k+j} + \frac{(k+j)!}{k!} \sum_{i=1}^k \binom{k}{i} \mu_k^{k-i} Q_i^{(j)}(\mu_1, \dots, \mu_i) = 0$$
.

Multiplying  $k!\lambda^j/(k+j)!$  and summing over j, we have

**PROOF** OF (14). Since relation (14) holds for k=1, we suppose the relation (14) is true for  $k \le k_0$ . Then denoting  $f_0 \equiv 0$  we have

$$\begin{split} Q_{k_0+1} &= f_{k_0+1} - \sum_{j=0}^{k_0} \binom{k_0+1}{j} Q_i \\ &= f_{k_0+1} - \sum_{j=1}^{k_0} \binom{k_0+1}{j} \left[ \sum_{i=0}^{j-1} (-1)^{i} \binom{j}{i} f_{j-i} + (-1)^{j} Q_0 \right] - Q_0 \\ &= f_{k_0+1} - \sum_{h=1}^{k_0} \sum_{i=0}^{k_0-h} (-1)^{i} \binom{k_0+1}{i} \binom{k_0+1-i}{h} f_h + (-1)^{k_0+1} Q_0 \\ &= f_{k_0+1} - \sum_{h=1}^{k_0} \binom{k_0+1}{k_0+1-h} f_h \sum_{i=0}^{k_0-h} \binom{k_0+1-h}{i} (-1)^{i} + (-1)^{k_0+1} Q_0 \\ &= f_{k_0+1} + \sum_{h=0}^{k_0} (-1)^{k_0+1-h} \binom{k_0+1}{k_0+1-h} f_h + (-1)^{k_0+1} Q_0 \\ &= f_{k_0+1} + \sum_{i=1}^{k_0} (-1)^{i} \binom{k_0+1}{i} f_{k_0+1-i} + (-1)^{k_0+1} Q_0 \\ &= \sum_{i=0}^{k_0} (-1)^{i} \binom{k_0+1}{i} f_{k_0+1-i} + (-1)^{k_0+1} Q_0 \ . \end{split}$$

$$\sum_{j=0}^{\infty} \frac{k!}{(k+j)} \lambda^{j} \mu_{k}^{k+j} + \sum_{i=1}^{k} \binom{k}{i} \mu_{k}^{k-i} Q_{i}^{(1)}(\mu_{1}, \cdots, \mu_{i}) = 0.$$

Consequently

$$Q_0^{\langle \lambda \rangle} = \frac{m_1!}{\lambda^{m_1}} \sum_{i=m_1}^{\infty} \frac{\lambda^i}{i!}$$

$$(17) \qquad Q_1^{\langle \lambda \rangle} = Q_1^{\langle \lambda \rangle}(\mu_1) = -\frac{1}{\lambda} \sum_{i=1}^{\infty} \frac{(\lambda \mu_1)^i}{i!}$$

$$Q_k^{\langle \lambda \rangle} = Q_k^{\langle \lambda \rangle}(\mu_1, \dots, \mu_k) = -\frac{k!}{\lambda^k} \sum_{i=k}^{\infty} \frac{(\lambda \mu_k)^i}{i!} - \sum_{i=1}^{k-1} {k \choose i} \mu_k^{k-i} Q_i^{\langle \lambda \rangle},$$

$$k = 2, \dots, m_1, \dots$$

Summalizing these we have

THEOREM 2. The probability (7) can be calculated by (14) using the relation (17).

4. We finally propose the computational method for the probability (8).

THEOREM 3. The probability (8) can be calculated by

$$\alpha_{\lambda}^{*}(0, \gamma) = \sum_{k=0}^{m_2} c_k(\lambda) Q_k(\mu_1^{\langle \lambda \rangle}, \cdots, \mu_k^{\langle \lambda \rangle}),$$

where  $c_k(\lambda) = e^{-\lambda} \frac{\lambda^k}{k!} \sum_{l=0}^{m_2-k} \frac{\lambda^l}{l!}$ .

**PROOF.** When  $\beta=0$ ,  $m_1=0$  and we have

$$\alpha_{\lambda}^{*}(0,\gamma) = e^{-\lambda} + \sum_{n=1}^{m_{2}} \frac{\lambda^{n} e^{-\lambda}}{n!} \alpha_{n}^{\langle \lambda \rangle}(0,\gamma)$$

$$= e^{-\lambda} + \sum_{n=1}^{m_{2}} \frac{\lambda^{n} e^{-\lambda}}{n!} \Pr \{U_{1}^{(n)} \geq \mu_{1}^{\langle \lambda \rangle}, \cdots, U_{n}^{(n)} \geq \mu_{n}^{\langle \lambda \rangle}\}$$

$$= e^{-\lambda} \left\{ 1 + \sum_{n=1}^{m_{2}} \frac{\lambda^{n}}{n!} f_{n}(\mu_{1}^{\langle \lambda \rangle}, \cdots, \mu_{n}^{\langle \lambda \rangle}) \right\}$$

$$= e^{-\lambda} \left\{ 1 + \sum_{n=1}^{m_{2}} \frac{\lambda^{n}}{n!} \sum_{k=0}^{n} {n \choose k} Q_{k} \right\}$$

$$= e^{-\lambda} \sum_{k=0}^{m_{2}} Q_{k} \sum_{n=k}^{m_{2}} \frac{\lambda^{n}}{k!(n-k)!}$$

$$= e^{-\lambda} \sum_{k=0}^{m_{2}} Q_{k} \frac{\lambda^{k}}{k!} \sum_{n=0}^{m_{2}-k} \frac{\lambda^{n}}{k!}$$

$$= \sum_{k=0}^{m_{2}} c_{k}(\lambda) Q_{k}(\mu_{1}, \cdots, \mu_{k}) .$$

5. Finally we shall briefly sketch some historical results on distribution of Kac-statistics. We define the following functions:

$$\beta_{1}(t; \varepsilon, a, b) = \begin{cases} \min(t-\varepsilon, 0) & 0 \leq t \leq a \\ \max(t-\varepsilon, 0) & a \leq t \leq b \\ b-\varepsilon & b \leq t \leq 1 \end{cases}$$

$$(0 \leq a < b \leq 1)$$

$$\beta_{2}(t; \varepsilon, b) = \begin{cases} 0 & 0 \leq t \leq \varepsilon/(1+\varepsilon) \\ (1+\varepsilon)t-\varepsilon & \varepsilon/(1+\varepsilon) \leq t \leq b \\ (1+\varepsilon)b-\varepsilon & b \leq t \leq 1 \\ (0 < \varepsilon/(1+\varepsilon) \leq b \leq 1) \end{cases}$$

$$\gamma_{1}(t; \varepsilon, a, b) = \begin{cases} a+\varepsilon & 0 \leq t \leq a \\ t+\varepsilon & a \leq t \leq b \\ \infty & b \leq t \leq 1 \\ (0 \leq a < b \leq 1) \end{cases}$$

Then we can summarize various results on Kac-statistics as follows.

Type of statistics	Finite form	Limit form $(\lambda \rightarrow \infty)$
One-sided Kolmogorov type		
$\beta_1(\cdot; \varepsilon, a, b)$		Csörgő [3], Theorem 2
$\gamma = \infty$	Coorgo and Alva [4]	Coëraë [2] Theorem 1
a=0	Csörgő and Alvo [4], Theorem 1	Csörgő [3], Theorem 1
$ \begin{cases} \varepsilon = 0 \\ a = 0, b = 1 \end{cases} $		Csörgő [3], Corollary 2
a=0, b=1	Takács [8], Theorem 5 Allen and Beekman [1], Theorem 1	Allen and Beekman [1], Theorem 2
Adjoint form		
$\beta = 0$	Takács [8], Theorem 4	
$\gamma_1=(\cdot;\varepsilon,0,1)$		
One-sided Reny type		
$\beta_2(\cdot;arepsilon,b)$	Csörgő and Alvo [4],	
γ=∞	Theorem 2	
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### (Continued)

Type of statistics	Finite form	Limit form $(\lambda \to \infty)$
Two-sided Kolmogorov type		
$\beta_1(\cdot; \varepsilon, a, b)$		
$\gamma_1(\cdot;\varepsilon,a,b)$		
a=a'=0		Csörgő [3], Theorem 5
a=a', b=b'		Csörgő [3], Theorem 4
$\begin{cases} a=a'=0 \\ a=a', b=b' \\ a=a'=0, b=b' \\ a=a'=0, b=b'=1 \end{cases}$		Csörgő [3], Theorem 3
a=a'=0, b=b'=1	Allen and Beekman [2], Theorem 1	Kac [5]

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