# Recurrence Relations for the Moments of Discrete Order Statistics

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이산순서 통계의 적률에 관한 점화식

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# I. Introduction

Suppose X<sub>1</sub>, X<sub>2</sub>,..., X<sub>n</sub> are n independent variables, each discrete cumulative distribution function P(x) over x=0,1,2.... Let X<sub>r:n</sub> (r=1, 2, ..., n) be the rth orerder statistic for these variates and let F<sub>r:n</sub>(x) be the c.d.f of X<sub>r:n</sub>. Then the c.d.f F<sub>r:n</sub>(x) is given by

(1.1) 
$$F_{r:n}(x) = \sum_{i=r}^{n} {n \choose i} p^{i}(x) [1-p(x)]^{n-1}$$

From the relation between binomial sums and the incomplite beta function, we write (1.1) as

(1.2) 
$$F_{r:n}(x) = I_{P(x)}(n, n-r+1)$$

Where  $I_{p}(a,b) = \frac{1}{B(a,b)} \int_{0}^{p} t^{a-1} (1-t)^{b-1} dt$ 

The bivariate joint c.d.f of  $X_{r:n}$  and  $X_{s:n}$  $(l \le r < s \le n)$  is conveniently denoted by F rs:n (x. y). Then  $F_{rs:n}(x, y)$  is obtained by a direct argument, we have for x < y

(1.3) 
$$F_{rs:n}(x,y) = \sum_{j=s}^{n} \sum_{i=r}^{j} \frac{n!}{i!(j-i)!(n-j)!}$$

 $P^{i}(x)[P(y)-P(x)]^{j-i}[1-P(y)]^{n-j}$ 

Also for  $x \ge y$  the inequality  $X_{s:n} \le y$  implies  $X_{r:n} \le x$ , so that

(1.4) 
$$F_{rs:n}(x,y) = F_{s:n}(y)$$
.

Generally we may remark that a similar argument leads to the multivariate joint c.d.f of the

$$X_{n_1:n_1}, X_{n_2:n_1}, \dots, X_{n_k:n}(1 \le n_1 \le n_2 \le \dots \le n_k \le n)$$
. We have for  $x_1 \le x_2 \le \dots \le x_k$ 

(1.5) 
$$F_{n_1 n_2 \cdots n_k : n}(x_1, x_2, \cdots, x_k)$$

$$= n! \sum_{\substack{s_{k}=n_{k}}}^{n} \sum_{\substack{s_{k-1}=n_{k-1}}}^{s_{k}} \cdots \sum_{\substack{s_{1}=n_{1}}}^{s_{2}} \frac{P^{s_{1}}(x_{1})}{s!}$$

$$\cdot \{\frac{k-1}{\pi} \frac{[P(x_{i+1})-P(x_{i})]^{s_{i+1}-s_{i}}}{(s_{i+1}-s_{i})!}\}$$

$$\cdot \frac{(1-P(x_{k}))^{n-s_{k}}}{(n-s_{k})!}$$

if  $X_i \ge x_j (1 \le i \le j \le k)$ , then we obtain

(1.6) 
$$F_{n_1n_2} \cdots n_k : n(x_1, x_2, \dots, x_k)$$
  
=  $F_{n_1} \cdots n_{i-1}n_{i+1} \cdot n_k : n(x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_k)$ 

## **∏**. Probability Functions

Suppose that p(x) is the probability function corresponding to the c.d.f P(x) over  $x = 0,1,2,\cdots$ . Let  $f_{r:n}(x)$  be the p.f of  $X_{r:n}$ . Then from (1.2) we have the expressions

(2.1) 
$$f_{r:n}(x) = F_{r:n}(x) - F_{r:n}(x-1)$$
  
=  $I_{P(x)}(r, n-r+1) - I_{P(x-1)}(r, n-r+1)$ 

the bivariate p.f  $f_{rs:n}(x,y)$  and the multivariate p.f  $fn_1n_2\cdots n_k:n(x_1,x_2,\cdots,x_k)$  follow from (1.4)~(1.6). For  $x_1 \langle x_2 \rangle \cdots \langle x_k$ , since

$$fn_{1}n_{2} \cdots n_{k}:n^{(x_{1}x_{2}, \dots, x_{k})}$$

$$= \sum_{\substack{s_{i}=0.1\\1 \leq i \leq k}} (-1) \sum_{i=1}^{n} s_{i}$$

$$\cdot F_{n_{1}n_{2}} \cdots n_{k}:n(x_{1}-s_{1}, x_{2}-s_{2}, \dots, x_{k}-s_{k}),$$

it has been definded that  $x_o = -1$ ,  $X_{k+1} = \infty$  $n_0 = o$  and  $n_{k+1} = n+1$  we have

$$f_{n_{1}n_{2}}\cdots_{n_{k}}:n(x_{1},x_{2},\cdots,x_{k})$$

$$= n! \sum \{\frac{k}{\pi} \frac{(p(x_{i}))^{s_{i}+t_{i}+1}}{(s_{i}+t_{i}+1)!}\}$$

$$\cdot \{\frac{k}{\pi} \frac{(p(x_{j+1}-1)-p(x_{i}))^{n_{j+1}-n_{j}-s_{j+1}-t_{j}-1}}{(n_{i+1}-n_{i}-s_{i+1}-t_{i}-1)!}\}$$

where  $\Sigma$  denotes the sumation over nonnegative integral values of  $s_1$ ,  $t_1$ ,  $s_2$ ,  $t_2$ , ...,  $s_k$ ,  $t_k$  subject to  $s_i + t_i \le n_{i+1} - n_i - 1(i=1,2,$ ..., k), and it is that  $t_o=0$  and  $s_{k+1}=0$ . Setting

$$C_{n_{1}n_{2}\cdots n_{k}}^{n} = \frac{n!}{\frac{\pi}{1}} \frac{\pi}{(n_{i+1}-n_{i}-1)!}$$

we may write

$$\begin{aligned} & \text{fn}_{1}n_{2}\cdots n_{k}:n(x_{1},x_{2},\cdots,x_{k}) \\ &= C_{n_{1}n_{2}}^{n}\cdots n_{k}:s_{1}=0:t_{k}=0:s_{i}:t_{s_{1}}^{n-1}) \\ & \cdot (\sum_{t=1}^{n-n_{k}}) \frac{\sum_{i=1}^{k-1} (n_{i+1}-n_{i}-1)!}{\sum_{i=1}^{k-1} (n_{i+1}-n_{i}-1)!:s_{i+1}!t_{i}!} \\ & \cdot \{\sum_{i=0}^{k} (P(x_{i}-1)-P(x_{i}))^{n_{i}+1}-n_{i}-s_{i+1}-t_{i}-1\} \\ & \cdot \{\sum_{i=0}^{k} (p(x_{i}))^{s_{i}+t_{i}+1}\} \\ & \cdot \int_{0}^{1} \int_{0}^{1} \cdots \int_{0}^{1} z_{1}^{s_{1}(1-z_{1})}^{t_{1}} (\sum_{i=2}^{k} z_{i}^{t_{i}(1-z_{i})^{s_{i}}}) \\ & \cdot dz_{1}dz_{2}\cdots dz_{k} \end{aligned}$$
where the sumation  $\Sigma$  subject to  $t_{i}=m_{i+1} \\ & -n_{i}-1(i=1,2\cdots,k-1) \text{ and } s_{i}=n_{i}-n_{i-1}-t_{i-1} \\ & -1(i=2,3,\cdots,k). \text{ Interchanging the sumation and integral signs, we simplify this equation repeatedly. Putting  $v_{i} = P(x_{i}) - z_{i} \\ & p(x_{i})(x_{i}=k,k-1,\cdots,2), \text{ and } v_{1} = P(x_{i}-1) \\ & + z_{1}p(x_{i}), we have \\ \int_{0}^{1} \frac{n_{i+1}-n_{i}-1}{t_{i}} \frac{n_{i}-n_{i}-1}{s_{i}} \\ & \cdot (n_{i}-n_{i-1}-s_{i}-t_{i-1}-1)!s_{i}! (v_{i+1}-P(x_{i}))^{n_{i+1}-n_{i}-t_{i}-1} \\ & \cdot (p(x_{i}-1)-P(x_{i-1}))^{n_{i+1}-n_{i}-t_{i}-1} \\ & \cdot (p(x_{i}-1)-P(x_{i-1}))^{n_{i+1}-n_{i}-t_{i}-1} \\ & (v_{i}-P(x_{i-1}))^{n_{i}-n_{i}-1}-t_{i-1}-1} \\ & (v_{i}-P(x_{i-1}))^{n_{i}-n_{i}-1}-t_{i-1}-1} \\ & \text{for } i=k, k-1, \cdots, 2 \text{ and} \\ & \int_{0}^{1} \sum_{n_{1}=0}^{n_{1}-1} \frac{n_{i}-n_{i}-1}{s_{i}} \\ & \text{for } i=k, k-1, \cdots, 2 \text{ and} \\ & \int_{0}^{n_{1}-1} \frac{n_{2}-n_{1}-1}{s_{1}-1} \\ & (n_{i}-n_{i}-1)^{n_{i}-1} \\ & (n_{i}-n_$$ 

 $\cdot (v_2 - P(x_1))^{n_2 - n_1 - t_1 - 1} (P(x_1 - 1))^{n_1 - s_1 - 1}$ 

$$\int_{P(x_1)}^{P(x_1+t_1+t_1)} z_1^{s_1(1-z_1)} z_1^{t_1} dz_1$$

$$= \int_{P(x_1-t_1)}^{P(x_1)} v_1^{n_1-t_1} (v_2-v_1)^{n_2-n_1-t_1} dv_1.$$

therefore, we obtain

$$(2.2) \quad f_{n_{1}n_{2}\cdots n_{k}}:n^{(x_{1},x_{2},\cdots,x_{k})} \\ = C_{n_{1}n_{2}}^{n} \cdots n_{k} \int_{P(x_{k}-1)}^{P(x_{k})} f^{p(x_{k-1})} \cdots \\ \int_{P(x_{1}-1)}^{P(x_{1})} v_{1}^{n_{1}-1} \{ \frac{k^{-1}}{\pi} (v_{i+1}-v_{i})^{n_{i+1}-n_{i}-1} \} \\ \cdot (1-v_{k})^{n-n_{k}} dv_{1} dv_{2} \cdots dv_{k}$$

the right hand side is the Dirichlet integral. this probability function may be extended as follows. For  $x_1 \le x_2 \le \dots \le x_k$ ,

(2.3) 
$$f_{n_{1}n_{2}\cdots n_{k}}(x_{1}, x_{2}, \cdots, x_{k}) = c_{n_{1}n_{2}}^{n} \cdots n_{k}$$
$$\int_{P(x_{k})}^{P(x_{k})} \int_{P(x_{k-1}-1)}^{Q_{k-1}} \int_{P(x_{1}-1)}^{Q_{1}} v_{1}^{n_{1}-1}$$
$$\cdot \{ \frac{k^{-1}}{\pi} (v_{i+1}-v_{i})^{n_{i+1}-n_{i}-1} \} (1-v_{k})^{n-n_{k}}$$
$$\cdot dv_{1} dv_{2} \cdots dv_{k}$$

where  $Q_1 = \min \{v_{i+1}, P(x_j)\}$   $(i=1,2, \cdots, K-1)$ . We derive the relationship of the bivariate p.f  $f_{rs}(x,y)$  for x = y in particular  $f_{rs}(x,x)$ 

$$=\sum_{i=0}^{r-1}\sum_{j=0}^{n-s}\frac{n!}{(r-i-1)!(s-r+i+j+1)!(n-s-j)}$$
  

$$\cdot [P(x-1)]^{r-i-1}[p(x)]^{s-v+i+j+1}[1-j^{2}(x)]^{n-s-j}$$
  

$$=C_{rs}^{n}\sum_{i=0}^{r-1}\sum_{j=0}^{n-s}{(r-1) \choose i}(P(x-1)^{r-i-1}$$
  

$$\cdot [p(x)]^{s-r+i+j+1}[1-P(x)]^{n-s-j}$$
  

$$\cdot \int_{0}^{1}\sum_{j=0}^{1}{(1-z_{1})}^{s-r-1}z_{2}^{j}(1-z_{2})^{s-r+i}dz_{2}dz_{1}$$

$$= C_{rs_{i}=0}^{n} \sum_{i=0}^{r-1} {r-1 \choose i} (P(x-1))^{r-i-1} \int_{0}^{1} [1-P(x) + z_{2}p(x)]^{n-s} (P(x) - z_{2}p(x))^{s-r+i} p(x) dz_{2}$$
$$\cdot \int_{0}^{1} z_{1}^{i} (1-z_{1}) dz_{1}.$$

putting  $v = P(x) - z_2 p(x)$ , we have

$$f_{rs}(x,x) = C_{rs}^{n} \sum_{i=0}^{r-1} {r-1 \choose i} (P(x-1))^{r-i-1}$$

$$\cdot \int_{P(x-1)}^{P(x)} (1-v)^{n-s} [v-P(x-1)]^{s-r+i} dv \int_{0}^{1} z_{1}^{i}$$

$$\cdot (1-z_{1})^{s-r-1} dz_{1}$$

$$= C_{rs}^{n} \int_{P(x-1)}^{P(x)} \{\int_{0}^{1} [P(x-1)+z_{1}v-z_{1}P(x-1)]^{r-1}$$

$$\cdot [v-P(x-1)-z_{1}v+z_{1}P(x-1)]^{s-r-1}$$

$$\cdot [v-P(x+1)] dz_{1} \{(1-v)^{n-s} dv.$$

Putting u=P(x-1)+zv-zP(x-1), we obtain the equation

(2.4) 
$$f_{rs}(x,x) = \int_{P(x-1)}^{P(x)} \int_{P(x-1)}^{v} f_{rs}(x,x) = \int_{P(x-1)}^{P(x-1)} \int_{P(x-1)}^{v} du dv.$$

Accordingly for  $x \le y$  the bivariate  $p \cdot f$  $f_{rs}(x,y)$  may be written as

(2.5) 
$$f_{rs}(x,y) = \int_{P(y-1)}^{P(y)} \int_{P(x-1)}^{Q} u^{r-1} \cdot (v-u)^{s-r-1} (1-v)^{n-s} du dv$$

where  $Q = \min |v, p(x)|$ .

using the equation (2,5), we may easily find the p.f  $fw_n(w)$  and c.d.f  $Fw_n(w)$  of the range  $W_n = X_n - X_1$ . when w > 0,

(2.6) 
$$fw_n(w) = n(n-1) \sum_{x=0}^{\infty} \int_{P(x-1)}^{P(x)} \int_{P(x+w+1)}^{P(x+w)} F(x+w+1)$$

$$(v-u)^{n-2} dv du$$
  
=  $\sum_{x=0}^{\infty} \{P(x+w)-P(x-1)\}^{n} - [P(x+w)-P(x)]^{n}$   
+  $[P(x+w-1)-P(x)]^{n} - [P(x+w-1)]^{n}$   
-  $P(x-1)]^{n} \}$ 

and when w = 0.

(2.7) 
$$fw_{n}(o) = n(n-1) \sum_{x=0}^{\infty} \int_{P(x-1)}^{P(x)} P(x-1) \int_{u}^{P(x)} (v-u)^{n-2} dv du = \sum_{x=0}^{\infty} [p(x)]^{n}$$

so that we have

(2.8) 
$$Fw_{n}(w)$$
  
=[P(w)]<sup>n</sup>+  $\sum_{x=0}^{\infty} \{ [P(x+w+1)-P(x)]^{n} - [P(x+w)-P(x)]^{n} \}$ 

for  $w \ge 0$ .

Also we may find the p.f  $fw_{r,r+1}(w)$  and c.d.f  $Fw_{r,r+1}(w)$  of  $W_{r,r+1} = X_{r+1} - X_r$  from the equation (2,5). Since for  $x \langle y \rangle$ 

$$fr, r+1:n^{(x,y)} = {\binom{n}{r}} (P^{r}(x) - P^{r}(x-1)) \{ [1 - P(y-1)]^{n-r} - (1 - P(y)]^{n-r} \},$$

$$(2.9) \quad fw_{r,r+1}(w) = {\binom{n}{r}} \sum_{x=0}^{\infty} (P^{r}(x) - P^{r}(x-1)) \{ [1 - P(x+w-1)]^{n-r} - [1 - P(x+w)]^{n-r} \}$$

for w > 0. From

 $f_{r,r+1}(x,x)$ 

$$= \frac{n!}{(r+1)!(n-r)!} \int_{P(x-1)}^{P(x)} u^{r-1} (1-u)^{n-r} du$$
  
- $\binom{n}{r} (P^{r}(x) - P^{r}(x-1)) (1-P(x))^{n-r},$   
(2.10) fw<sub>r,r+1</sub>(0) = 1- $\binom{n}{r}$   $\sum_{x=0}^{\infty} (P^{r}(x-1))$   
- $p^{r}(x-1) (1-P(x))^{n-r}$   
Therefroe we have  
(2.11) Fw<sub>r,r+1</sub>(w) = 1- $\binom{n}{r}$   $\sum_{x=0}^{\infty} (P^{r}(x))$ 

$$-p^{r}(x-1)$$
 [1-P(x+w)]<sup>n-r</sup>

for  $\mathbf{w} \ge 0$ .

# III. Moments and recurrence Relations

We write the population mean, variance, *k*th raw moments and *k*th factorial moments as

(3.1) 
$$\mu = \varepsilon X$$
,  $\delta^2 = \operatorname{var} X$ ,  $\mu^{(k)} = \varepsilon(X^k)$ ,  
 $\mu_{(k)} = \varepsilon(X^{[k]})$ 

The moments of ordered stastics is defined

$$(3.2) \quad \mu_{r;n} = \varepsilon X_{r;n}, \mu^{(a)}_{r;n} = \varepsilon (X_{r;n}^{a}), \\\delta_{r;n}^{2} = \operatorname{var} X_{r;n}, \mu_{rs;n} = \varepsilon (X_{r;n}^{a} X_{s;n}), \\\mu_{rsin}^{(a)} = \varepsilon (X_{r;n}^{a} X_{s;n}^{a}), \mu_{rs;n}^{(a \ b)} \\= \varepsilon (X_{r;n}^{a} X_{r;n}^{b}), \delta_{rs;n}^{2} = \operatorname{cov}(X_{r;n}, X_{s;n}), \\\mu_{n_{1}n_{2}} \cdots n_{k} : n = \varepsilon (X_{n_{1}} : n X_{n_{2}} : n \cdots X_{n_{k}}; n), \\\mu_{n_{1}n_{2}}^{(a)} \cdots n_{k} : n = \varepsilon (X_{n_{1}}^{a} : n X_{n_{2}}^{a}: n \cdots X_{n_{k}}^{a}; n), \\\mu_{n_{1}n_{2}}^{(a)} \cdots n_{k} : n = \varepsilon (X_{n_{1}}^{a} : n X_{n_{2}}^{a}: n \cdots X_{n_{k}}^{a}; n), \\\mu_{n_{1}n_{2}}^{(a)} \cdots n_{k} : n = \varepsilon (X_{n_{1}}^{a}: n X_{n_{2}}^{a}: n \cdots X_{n_{k}}^{a}; n), \\\mu_{n_{1}n_{2}}^{(a)} \cdots n_{k} : n = \varepsilon (X_{n_{1}}^{a}: n X_{n_{2}}^{a}: n \cdots X_{n_{k}}^{a}; n), \\\mu_{n_{1}n_{2}}^{(a)} \cdots n_{k} : n = \varepsilon (X_{n_{1}}^{a}: n X_{n_{2}}^{a}: n \cdots X_{n_{k}}^{a}; n), \\\mu_{n_{1}n_{2}}^{(a)} \cdots n_{k} : n = \varepsilon (X_{n_{1}}^{a}: n X_{n_{2}}^{a}: n \cdots X_{n_{k}}^{a}; n), \\\mu_{n_{1}n_{2}}^{(a)} \cdots n_{k} : n = \varepsilon (X_{n_{1}}^{a}: n X_{n_{2}}^{a}: n \cdots X_{n_{k}}^{a}; n), \\\mu_{n_{1}n_{2}}^{(a)} \cdots n_{k} : n = \varepsilon (X_{n_{1}}^{a}: n X_{n_{2}}^{a}: n \cdots X_{n_{k}}^{a}; n), \\\mu_{n_{1}n_{2}}^{(a)} \cdots n_{k} : n = \varepsilon (X_{n_{1}}^{a}: n X_{n_{2}}^{a}: n \cdots X_{n_{k}}^{a}; n), \\\mu_{n_{1}n_{2}}^{(a)} \cdots n_{k} : n = \varepsilon (X_{n_{1}}^{a}: n X_{n_{2}}^{a}: n \cdots X_{n_{k}}^{a}; n), \\\mu_{n_{1}n_{2}}^{(a)} \cdots n_{k} : n = \varepsilon (X_{n_{1}}^{a}: n X_{n_{2}}^{a}: n \cdots X_{n_{k}}^{a}; n), \\\mu_{n_{1}n_{2}}^{(a)} \cdots n_{n_{k}} : n = \varepsilon (X_{n_{1}}^{a}: n X_{n_{2}}^{a}: n \cdots X_{n_{k}}^{a}; n), \\\mu_{n_{1}n_{2}}^{(a)} \cdots n_{n_{k}} : n = \varepsilon (X_{n_{1}}^{a}: n X_{n_{2}}^{a}: n \cdots X_{n_{k}}^{a}; n), \\\mu_{n_{1}n_{2}}^{(a)} \cdots n_{n_{k}} : n = \varepsilon (X_{n_{1}}^{a}: n X_{n_{2}}^{a}: n \cdots X_{n_{k}}^{a}; n), \\\mu_{n_{1}n_{2}}^{(a)} \cdots n_{n_{k}}^{a}: n = \varepsilon (X_{n_{1}}^{a}: n X_{n_{2}}^{a}: n \cdots X_{n_{k}}^{a}; n), \\\mu_{n_{1}n_{2}}^{(a)} \cdots n_{n_{k}}^{a}: n = \varepsilon (X_{n_{1}}^{a}: n X_{n_{2}}^{a}: n \cdots X_{n_{k}}^{a}; n), \\\mu_{n_{1}n_{2}}^{(a)} \cdots n_{n_{k}}^{a}: n = \varepsilon (X_{n_{1}}^{a}: n X_{n_{2}}^{a}: n \cdots X_{n_{k}}^{a}; n), \\\mu_{n_{1}n_{2}}^{(a)} \cdots n_{n_{k}}^{a}: n = \varepsilon (X_{n_{1}}^{a}: n X_$$

To obtain the mean and variance of an ordered statistic, we consider the following Lemma.

Lemma 1. Suppose that  $p(x)(i=0,1,2,\cdots)$  is the discrete parent of which c.d.f is P(x). Let q(x)=1-P(x) and define the generating functions

$$\boldsymbol{\Theta}(s) = \sum_{x=0}^{\infty} p(x) s^{x}$$
,  $\phi(s) = \sum_{x=0}^{\infty} q(x) s^{x}$ .

If the kth factorial moment  $\mu_{[k]}$  exists, then

(3.3) 
$$\mu_{[k]} = k \phi^{(k-1)}(1)$$

therefore the mean and variance are given by

$$(3.3)' \quad \mu = \mu_{1} = \sum_{x=0}^{\infty} [1 - P(x)]$$
$$\delta^{2} = \mu_{2} + \mu(1 - \mu)$$
$$= 2 \sum_{x=0}^{\infty} x [1 - P(x)].$$

Applying these results to the moments of  $X_{r \ge n}$ ,  $W_n$  and  $W_{rr+1}$ , from (1.2), (2.8) and (2.11) we obtain as

Theorem 2.

(3.4) 
$$\mu_{r;n} = \sum_{x=0}^{\infty} (1 - Ip_{(x)}(r, n - r + 1))$$
$$\delta_{r;n}^{2} = 2 \sum_{x=0}^{\infty} x [1 - Ip_{(x)}(r, n - r + 1)]$$
$$+ \mu_{r;n}(1 - \mu_{r;n})$$
(3.5) 
$$\varepsilon W_{n} = \sum_{x=0}^{\infty} \{1 - P^{n}(x) - (1 - P(x))^{n}$$
$$\operatorname{var} W_{n} = 2 \sum_{y=0}^{\infty} \sum_{x=0}^{y} \{1 - P^{n}(y) - (1 - P(x))^{n}$$
$$+ [P(y) - P(x)]^{n} \} - \varepsilon W_{n}(1 - \varepsilon W_{n})$$
(3.6) 
$$\varepsilon W_{r,r+1} = {n \choose r} \sum_{y=0}^{\infty} \sum_{x=0}^{y} [P^{r}(x)$$
$$- P^{r}(x-1)](1 - P(y)]^{n-r}$$

$$var W_{rr+1} = {n \choose r} \sum_{y=0}^{\infty} \sum_{x=0}^{y} (y-x)$$
$$[P^{r}(x)-P^{r}(x-1)][1-P(y)]^{n-r}$$
$$+ \varepsilon W_{rr+1} (1-\varepsilon W_{rr+1}),$$

Proof. For any c.d.f P(x) the existence e x implies

 $\lim_{x \to -\infty} x P(x) = \lim_{x \to \infty} x (1 - P(x)) = 0$ we use this result. From (2, 14)

$$\varepsilon W_{n}(W_{n}-1) = 2 \sum_{w=0}^{\infty} w\{1-F_{W_{n}}(w)\}$$
$$= 2 \sum_{x=0}^{\infty} x[1-P^{n}(x)] - 2 \sum_{x=0}^{\infty} \sum_{w=0}^{\infty} w$$
$$\cdot \{[P(x+w+1)-P(x)]^{n} - [P(x+w)-P(x)]^{n}\}.$$

But

$$\sum_{w=0}^{\infty} W\{ [P(x+w+1)-P(x)]^{n} - [P(x+w)-P(x)]^{n} \}$$

$$= \sum_{w=0}^{\infty} \{ w([1-P(x)]^{n} - [P(x+w)-p(x)]^{n}) - (w+1)([1-P(x)]^{n} - [P(x+w+1)-P(x)]^{n}) \}$$

$$+ \sum_{w=0}^{\infty} ([1-P(x)]^{n} - [P(x+w+1)-P(x)]^{n})$$

$$= \sum_{w=0}^{\infty} ([1-P(x)]^{n} - [P(x+w+1)-P(x)]^{n})$$

$$= \sum_{w=0}^{\infty} ([1-P(x)]^{n} - [P(x+w)-P(x)]^{n})$$

$$- (1-P(x)]^{n} = \sum_{y=0}^{\infty} \{ [1-P(x)]^{n} - [P(y) - P(x)]^{n} \}$$

Hence

$$\varepsilon W_{n}(W_{n}-1) = 2 \sum_{y=0}^{\infty} \{y[1-P^{n}(y)] + [1-P(y)]^{n} \} - 2 \sum_{y=0}^{\infty} \sum_{x=0}^{y} \{(1-P(x))^{n} - [P(y)-P(x)]^{n} \}$$

therefore

$$\begin{aligned} \operatorname{var} \mathbf{W}_{n} &= 2 \sum_{y=0}^{\infty} \sum_{x=0}^{y} \left\{ 1 - P^{n}(y) - [1 - P(x)]^{n} + [P(y) - P(x)]^{n} \right\} - \varepsilon W_{n}(1 + \varepsilon W_{n}). \end{aligned}$$

The basic relationship between ordered stastics and unordered statistics is

$$(3.7) \sum_{\substack{n_i \neq n_j \ n_1 : n}} X^{a_1} X^{a_2} \cdots X^{a_k} \\ = \sum_{\substack{n_i = n_j \ n_1 : n}} X^{a_1} \frac{X^{a_2} \cdots X^{a_k}}{n_1 \ n_2} \cdots X^{a_k}$$

Where the sign  $\sum_{n_j\neq n_j}$  is the sumation of all terms  $n_{i,j\neq n_j}$  corresponding to the permutations  $n_1, n_2, \dots, n_k$  which consists of different numbers of 1,2 ..., n. The lefthand side is only a rearrangement of the right hand side. Using this relation we have

#### Teeorem 3.

(3.8) 
$$\sum_{n_{k} \neq n_{j}} \mu_{n_{1}n_{2}}^{(a_{1}, a_{2} \cdots a_{k})} = \frac{n^{(k)} \mu^{(a_{1})} \mu^{(a_{2})} \cdots \mu^{(a_{k})}}{n^{(k)} \mu^{(a_{1})} \mu^{(a_{2})} \cdots \mu^{(a_{k})}}$$
  
(3.9) 
$$\sum_{n_{1}=1}^{n-k+1} \sum_{n_{2}=n_{1}+1}^{n} \sum_{n_{k}=n_{k-1}+1}^{n} \mu_{n_{1}n_{2}}^{(a)} \cdots n_{k} : n = \binom{n}{k} \{\mu^{(a)}\}^{k}$$

Corollary.

(3.10) 
$$\sum_{r=1}^{n} \mu_{r,n}^{(a)} = n \mu^{(a)}$$
  
(3.11)  $\sum_{r=1}^{n} \sum_{s=1}^{n} \delta_{rs,n} = n \delta^{2}$ 

We consider contraction for sample size.

## Theorem 4.

(3.12) 
$$\begin{array}{c} n-k+1 & n-k+2 & n \\ \Sigma & \Sigma & \cdots & \Sigma \\ n_1=1 & n_2=n_1+1 & n_k=n_{k-1}+1 \end{array} \\ \mu \begin{pmatrix} (a_1, a_2, \cdots a_k) \\ n_1n_2 \cdots n_k : n \end{pmatrix} = \begin{pmatrix} n \\ k \end{pmatrix} \mu \begin{pmatrix} (a_1, a_2, \cdots a_k) \\ 1, 2, \cdots k : k \end{pmatrix}$$

Proof. Since

$$C_{n_{1}n_{2}\cdots n_{k}}^{n} = n^{\lfloor k \rfloor} \frac{\pi}{\pi} (n_{i+1}-i-1 - 1) ,$$
  

$$C_{1,2, \cdots, k}^{k} = k!$$

where  $n_{k+1} = n+1$ , and in (2,3)

$$\sum_{\substack{n_{i}=i\\n_{i}=i}}^{n_{i+1}-1} {n_{i+1}-i-1 \choose n_{i}-i} v_{i}^{n_{i}-i} (v_{i+1}-v_{i})^{n_{i+1}-n_{i}-1}$$

$$= v_{i+1}^{n_{i+1}-i-1} (i=1,2,\cdots,k)$$

where  $v_{k+1} = 1$ , Theorem 4 follows.

We have the following recurrecne relations between the moments of order statistics.

#### Theorem 5.

(3.13) 
$$\sum_{i=0}^{k} (n_{i+1} - n_i) \mu \frac{(a_{1}, \cdots a_{i}, a_{i+1} \cdots a_{k})}{n_{1}' \cdots n_{i}' n_{i+1} \cdots n_{k} \cdot n_{k}}$$
$$= n \mu \frac{(a_{1}, a_{2} \cdots a_{k})}{n_{1} n_{2}' \cdots n_{k}' \cdot n - 1}$$

where  $n_0=1$ ,  $n_{k+1}=n+1$  and  $n_i^1=n_i-1$ 

$$(i=0,1,2,\cdots k)$$

Proof. Since

$${}_{nC_{1_{2}}'n'_{1_{2}}'\cdots n'_{k}}^{n-1} = (n_{i+1}-n_{i})C_{n'_{i}}^{n}\cdots n'_{i}.n_{i+1}\cdots n_{k}}^{n}$$

and in(2,9)

$$\sum_{i=0}^{k} (\mathbf{v}_{i+1} - \mathbf{v}_i) = 1$$

where  $V_o=0$  and  $V_{k+1}=1$ , Theorem 5 follows. Applying Theorem 5 we have

# Corolary.

(3.14) 
$$(n-r)\mu_{r:n}^{(a)} + r \mu_{r+1:n}^{(a)} = n\mu_{r:n-1}^{(a)}$$
  
(3.15)  $\mu_{r:n}^{(a)} = \sum_{i=n+r+1}^{n} {\binom{i-1}{n-r}} {\binom{n}{i}} {\binom{i-1}{i}} {\binom{n}{i}} {\binom{-1}{i}}^{r+i-n-1} u_{1:i}^{(a)}$ 

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(3.16) 
$$(n-r)^{[n]}\mu_{r:n}^{(a)} = \sum_{i=0}^{m} (-r)^{[i]}n^{[m-i]}$$

$$\cdot \binom{m}{i} \mu_{r+1:n-m+i}^{(a)}$$

(3.17) 
$$\mu_{r:n}^{(a)} = \sum_{i=r}^{n} {\binom{i-1}{r-1} \binom{n}{i} (-1)^{i-r} \mu_{i:i}^{(a)}}$$
  
(3.18)  ${\binom{n}{m}} \mu_{r:m} = \sum_{i=0}^{n-m} {\binom{n-r-i}{m-r} \binom{r+i-1}{i}} \mu_{r+i:m}$ 

(3.19) 
$$\sum_{i=1}^{n} \frac{1}{i} \mu_{i:n}^{(a)} = \sum_{i=1}^{n} \frac{1}{i} \mu_{1:i}^{(a)}$$

(3.20) 
$$\sum_{i=1}^{n} \frac{1}{n-i+1} \mu_{i:n}^{(a)} = \sum_{i=1}^{n} \frac{1}{i} \mu_{i:i}^{(a)}$$

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# 國文抄錄

이산 순서 확률 변수들의 결합 확률 함수는 디리클레 적분으로 표시할 수 있다. 본 논문에서는 이를 이용하여 이산 순서통계량들의 적률에 관한 몇가지 관계식을 규명하였다.