<table>
<thead>
<tr>
<th>FIELD</th>
<th>GROUP</th>
<th>SUB.GR.</th>
</tr>
</thead>
</table>

11. TITLE (Include Security Classification)
A multivariate extension of Hoeffding's Lemma

12. PERSONAL AUTHOR(S):
Henry W. Block and Zhaoben Fang

13. TYPE OF REPORT
Technical

14. DATE OF REPORT (yr., mo., day)
November 1985

15. PAGE COUNT

16. SOURCE OF FUNDING NO.

<table>
<thead>
<tr>
<th>PROGRAM ELEMENT NO.</th>
<th>PROJECT NO.</th>
<th>TASK NO.</th>
<th>WORK UNIT NO.</th>
</tr>
</thead>
<tbody>
<tr>
<td>U102F</td>
<td>2304</td>
<td>A5</td>
<td></td>
</tr>
</tbody>
</table>

17. COSATI CODES

18. SUBJECT TERMS (Continue on reverse if necessary and identify by block number)
A MULTIVARIATE EXTENSION
OF Hoeffding's Lemma

by

Henry W. Block$^{1,2,3}$ and Zhaoben Fang$^{1,3}$

SERIES IN RELIABILITY AND STATISTICS
Department of Mathematics and Statistics
University of Pittsburgh
Pittsburgh, PA 15260

Technical Report No. 85-10
November 1985

$^1$Department of Mathematics and Statistics, University of Pittsburgh, Pittsburgh, PA 15260.

$^2$Supported by ONR Contract N00014-84-K-0084.

$^3$Supported by AFOSR Grant AFOSR-84-0113.
ABSTRACT

Hoeffding's Lemma gives an integral representation of the covariance of two random variables in terms of difference between their joint and marginal probability functions, i.e.,

\[ \text{Cov}(X,Y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \{P(X > x, Y > y) - P(X > x)P(Y > y)\} \, dx \, dy. \]

This identity has been found to be a useful tool in studying the dependence structure of various random vectors.

A generalization of this result for more than 2 random variables is given. This involves an integral representation of the multivariate joint cumulant. Applications of this result include characterizations of independence. Relationships with various types of dependence are also given.

AMS 1970 Subject Classification: Primary 62H05; Secondary 62N05.

Key Words: Hoeffding's Lemma, joint cumulant, characterization of independence, inequalities for characteristic functions, positive dependence, association.
1. Introduction

It is well known that if a random variable (rv) X has distribution function (df) $F(x)$ with finite expectation then

$$EX = \int_{-\infty}^{0} (1 - F(x)) dx - \int_{0}^{\infty} F(x) dx \quad (1)$$

The extension to high order moments is straightforward. That is, if $E|X|^n < \infty$

$$EX^n = n[\int_{-\infty}^{\infty} x^{n-1} (1 - F(x)) dx - \int_{-\infty}^{0} x^{n-1} F(x) dx] \quad (2)$$

W. Hoeffding (1940) gave a bivariate version of identity (1), which is mentioned in Lehmann (1966). Let $F_{X,Y}(x,y), F_X(x), F_Y(y)$ denote the joint and marginal distributions of random vector $(X,Y)$, where $E[XY], E[X], E[Y]$ are assumed finite. Hoeffding's Lemma is

$$EXY - EXEY = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \{F_{X,Y}(x,y) - F_X(x)F_Y(y)\} dx dy. \quad (3)$$

Lehmann (1966) used this result to characterize independence, among other things, and Jogdeo (1968) extended Lehmann's bivariate characterization of independence. Jogdeo obtained an extension of formula (3) which we now give. Let $(Y_1, Y_2, Y_3)$ be a triplet independent of $(X_1, X_2, X_3)$ and having the same distribution as $(-X_1, X_2, X_3)$ then

$$E(X_1 - Y_1)(X_2 - Y_2)(X_3 - Y_3)$$

$$= \iiint K(u_1, u_2, u_3) du_1 du_2 du_3 \quad (4)$$

where $K(u_1, u_2, u_3) = (P(B_1 A_2 A_3) + P(B_1)P(A_2 A_3) - P(A_2)P(B_1 A_3) - P(A_3)P(B_1 A_2)) - (P(A_1 A_2 A_3) + P(A_1)P(A_2 A_3) - P(A_2)P(A_1 A_3) - P(A_3)P(A_1 A_2))$, and $A_i = \{X_i < u_i\}$ for $i = 1, 2, 3$. $B_1 = \{X_1 < -u_1\}$. Jogdeo mentioned that a similar result holds for $n \geq 3$. 
We give a different generalization of Hoeffding's Lemma. Notice that expression (3) can be rewritten as

\[
\text{Cov}(X,Y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \text{Cov}(X_X(x),X_Y(y))dx\,dy
\]  

where \( X_X(x) = 1 \) if \( X > x \), 0 otherwise and that the covariance is the second order joint cumulant for the random vector \((X, Y)\). In the following we extend the results to the \( r \)-th order joint cumulant where \( r \geq 3 \).

2. Main results

Consider a random vector \((X_1, \ldots, X_r)\) where \( E|X_i|^r < \infty \), \( i = 1, \ldots, r \).

**Definition 1.** The \( r \)-th order joint cumulant of \((X_1, \ldots, X_r)\) denoted by \( \text{cum}(X_1, \ldots, X_r) \) is defined by

\[
\text{cum}(X_1, \ldots, X_r) = \sum (-1)^{p-1}(p-1)! (\mathbb{E} \prod_{j \in \nu_1} X_j) \cdots (\mathbb{E} \prod_{j \in \nu_p} X_j)
\]

where summation extends over all partitions \((\nu_1, \ldots, \nu_p), p = 1, 2, \ldots, r \), of \( \{1, \ldots, r\} \).

It can be shown (see Brillinger 1975) that \( \text{cum}(X_1, \ldots, X_r) \) is the coefficient of the term \((1)^{r_1} \cdots t_r \) in the Taylor series expansion of \( \log \mathbb{E}(\exp \sum_{j=1}^r t_j X_j) \).

Furthermore the following properties are easy to check:

(i) \( \text{cum}(a_1 X_1, \ldots, a_r X_r) = a_1 \cdots a_r \text{cum}(X_1, \ldots, X_r) \);

(ii) \( \text{cum}(X_1, \ldots, X_r) \) is symmetric in its arguments;

(iii) if any group of the \( X \)'s are independent of the remaining \( X \)'s then \( \text{cum}(X_1, \ldots, X_r) = 0 \);

(iv) for the random variable \((Y_1, X_1, \ldots, X_r)\), \( \text{cum}(X_1 + Y_1, X_2, \ldots, X_r) = \text{cum}(X_1, \ldots, X_r) + \text{cum}(Y_1, X_2, \ldots, X_r) \);

(v) for \( \mu \) constant, \( r \geq 2 \), \( \text{cum}(X_1 + \mu, X_2, \ldots, X_r) = \text{cum}(X_1, \ldots, X_r) \).
(vi) for \((X_1, \ldots, X_r), (Y_1, \ldots, Y_r)\) independent
\[
\text{cum}(X_1+Y_1, \ldots, X_r+Y_r) = \text{cum}(X_1, \ldots, X_r) + \text{cum}(Y_1, \ldots, Y_r);
\]
(vii) \(\text{cum}_X = \text{EX}_j, \text{cum}(X_j, X_j) = \text{Var} X_j\) and \(\text{cum}(X_i, X_j) = \text{cov}(X_i, X_j)\).

To represent certain moments by cumulants, we have the following useful identity.

**Lemma 1.** If \(E|X_1|^m < \infty\)
\[
\text{EX}_1 \ldots X_m - \text{EX}_1 \ldots \text{EX}_m
\]
\[
= \sum \text{cum}(X_k, k \in \mathcal{V}_1) \ldots \text{cum}(X_k, k \in \mathcal{V}_p) \tag{7}
\]

where \(\Sigma\) extends over all partitions \((\mathcal{V}_1, \ldots, \mathcal{V}_p), p = 1, \ldots, m-1,\) of \(\{1, \ldots, m\}\).

**Proof:** In the case of \(m = 2\), \(p = m-1 = 1\) and (7) reduces to the well known
\[
\text{EX}_1 X_2 - \text{EX}_1 \text{EX}_2 = \text{cum}(X_k, k \in \mathcal{V}_1) = \text{cov}(X_1, X_2)
\]

Notice that
\[
\text{EX}_1 \ldots X_n - \text{EX}_1 \ldots \text{EX}_m
\]
\[
= \text{EX}_1 \ldots \text{X}_{m-2} \text{X}_{m-1} \text{X}_m - \text{EX}_1 \ldots \text{EX}_{m-2} \text{EX}_{m-1} \text{X}_m
\]
\[
+ \text{EX}_1 \ldots \text{EX}_{m-2} \text{cov}(X_{m-1}, X_m).
\tag{8}
\]

Introduce the new notation \(Y_i = X_i, i = 1, \ldots, m-2, Y_{m-1} = X_{m-1} \cdot X_m\). By Theorem 2.3.2 in Brillinger (1975, p. 21) and induction we get (7).

Our main result is the following.

**Theorem 1.** For the random vector \((X_1, \ldots, X_r)\) \(r > 1\), if \(E|X_i|^r < \infty i = 1, 2, \ldots, r\), then
\[
\text{cum}(X_1, \ldots, X_r) = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} \text{cum}(x_1^{X_{1}}, \ldots, x_r^{X_{r}}) \, dx_1 \ldots dx_r \tag{9}
\]

where \(x^{X_{1}}(x_i) = 1\), if \(X_i > x_i\), 0 otherwise.
To prove the theorem we need a lemma which is of some independent interest.

**Lemma 2.** If \( E|X_1 \ldots X_r| < \infty \), we have

\[
E X_1 \ldots X_r = (-1)^r \int_{-\infty}^{\infty} \int_{-\infty}^{x_1} \ldots \int_{-\infty}^{x_{r-1}} \left( F(x) - \sum_{j=1}^{r} \epsilon(x_j)F(x) \right) \prod_{j=1}^{r} dx_j \ldots dx_r \\
+ \sum_{i<j} \epsilon(x_i)\epsilon(x_j)F(x_{(i,j)}) \ldots (-1)^r \prod_{j=1}^{r} \epsilon(x_j)dx_1, \ldots, dx_r
\]

(10)

where \( \epsilon(x_i) = 1 \) if \( x_i > 0 \), 0 otherwise. Here \( x^{(i_1, \ldots, i_k)} \) represents \((x_1, \ldots, x_{i_1-1}, x_{i_1+1}, \ldots, x_{i_2-1}, x_{i_2+1}, \ldots, x_{i_k-1}, x_{i_k+1}, \ldots, x_r)\). Also \( F(x^{(i_1, \ldots, i_k)}) \) is the marginal df of \( X^{(i_1, \ldots, i_k)} \). We omit the subscripts for \( F \) for simplicity when there is no ambiguity, e.g. \( F(x^{(1)}) \) is the marginal of \((X_2, \ldots, X_r)\).

**Proof:** First, we have the identity

\[
X_1 \equiv \int_{-\infty}^{\infty} (\epsilon(x_1) - I_{(-\infty,x_1)}(X_1))dx_1
\]

(11)

where \( I_{(-\infty,x_1)}(X_1) = 1 \) if \( X_1 < x_1 \), 0 otherwise. Then, by Fubini's theorem

\[
E X_1 \ldots X_r = E \left\{ \prod_{i=1}^{r} \int_{-\infty}^{\infty} (\epsilon(x_i) - I_{(-\infty,x_i)}(X_i))dx_i \right\}
\]

\[
= E \left\{ \prod_{i=1}^{r} \left[ \int_{-\infty}^{\infty} (\epsilon(x_i) - I_{(-\infty,x_i)}(X_i))dx_i \ldots dx_r \right] \right\}
\]

\[
= \int_{-\infty}^{\infty} E \left\{ \prod_{i=1}^{r} (\epsilon(x_i) - I_{(-\infty,x_i)}(X_i)) \right\} dx_1 \ldots dx_r
\]

\[
= \int_{-\infty}^{\infty} \left( \prod_{i=1}^{r} \epsilon(x_i) - \sum_{j=1}^{r} \prod_{k \neq j} \epsilon(x_k)F(x_j) + \sum_{i \neq j} \prod_{k \neq i,j} \epsilon(x_k)F(x_i,x_j) \right) \ldots + (-1)^r F(x)dx_1 \ldots dx_r
\]

which is just the right side of (10).

**Remark 1.** It is easy to see that (1) can be written as \( E X = \int_{-\infty}^{\infty} (\epsilon(x) - F(x))dx \), which is a special case of (10). Thus lemma 2 is an extension of (1).
Remark 2. Using the identity \( X_i = \int_{-\infty}^{\infty} x_i \cdot \epsilon(x_i) \cdot I_{(-\infty, x_i)}(x_i) \, dx_i \)
we can also obtain an extension of (2) i.e.

\[
\begin{align*}
\mathbb{E}[X_1 \cdots X_k] &= (-1)^k n_1 \cdots n_k \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} x_1 \cdots x_k \\
&\times \{ F(x_1 \cdots x_k) - \sum_{j=1}^{k} \epsilon(x_j) F(x^{(j)}) + \sum_{i<j} \epsilon(x_i) \epsilon(x_j) F(x^{(i,j)}) \} \\
&+ (-1)^k \prod_{i=1}^{k} \epsilon(x_i) \, dx_1 \cdots dx_k \\
\end{align*}
\]

(12)

where \( n_i \geq 1, n_1 + \cdots + n_k < r \).

Remark 3. When the \( X_i \)'s are nonnegative (12) reduces to

\[
\begin{align*}
\mathbb{E}[X_1 \cdots X_k] &= \int_{0}^{\infty} \cdots \int_{0}^{\infty} x_1 \cdots x_k \cdot \overline{F}(x_1, \ldots, x_k) \, dx_1 \cdots dx_k \\
\end{align*}
\]

(13)

where \( \overline{F}(x_1 \cdots x_k) \) is the survival function \( P(X_i > x_i, i = 1, \ldots, k) \). The bivariate case of (13) was mentioned by Barlow and Proschan (1981, p. 135).

The proof of the theorem 1 involves routine algebra and the use of Fubini's theorem and lemma 2. We have
\[ \begin{align*}
+ & (-1)^{r-r} \int_{-\infty}^{\infty} \left( \sum_{i=1}^{r} \prod_{j} F(x_j) \right) \, dx_1 \ldots dx_r \\
& + \sum_{i=1}^{r} \int_{-\infty}^{\infty} \left( \sum_{j} F(x_j) \right) \, dx_1 \ldots dx_r
\end{align*} \]

where \( n_{v_i} \) is the number of indices in \( v_i \), \( F(x_j, j \in v_i) \) is the marginal of rv's in \( v_i \), and \( F_i(x) \) is the marginal of \( X_i \). All terms with \( \varepsilon(x_i) \) factors cancel and the quantities \( \sum_{i=1}^{r} n_{v_i} j = 2, \ldots, p \) are all equal to \( r \).

Thus,
\[ \text{cum}(X_1 \ldots X_r) = (-1)^r \int_{-\infty}^{\infty} \left( \sum_{i=1}^{r} \prod_{j} F(x_j) - \sum_{j} F(x_j) \right) \, dx_1 \ldots dx_r \]

The last equality follows upon using properties (i), (iii) and (iv) of the cumulant. This completes the proof.

Remark 4. The result of Theorem 1 gives that
\[ \text{cum}(X_1, \ldots, X_r) = \int_{-\infty}^{\infty} \left( \sum_{i=1}^{r} \int_{-\infty}^{\infty} \text{cum}(\chi_{X_i}(x_1), \ldots, \chi_{X_i}(x_r)) \, dx_1 \ldots dx_r \right) \, dx_i. \]

The integral can then be expressed in a variety of ways. A general form is
where $A \cup B = \{1, 2, \ldots, r\}$. We then have various combinations of the distribution and/or survival function in the integrand. Some examples:

i) for $A = \emptyset$, card $B = r$ the integrand is

$$(-1)^r \sum_{j \in \mathcal{V}_1} F(x_j, i \in \mathcal{V}_2) + \ldots + (-1)^{r-1} \prod_{i=1}^{r} F_i(x_i);$$

ii) for $B = \emptyset$ the integrand is

$$\bar{F}(x) = \sum_{j \in \mathcal{V}_1} \bar{F}(x_j, i \in \mathcal{V}_2) \bar{F}(x_i) + \ldots + (-1)^{r-1} \prod_{i=1}^{r} \bar{F}_i(x_i).$$

3. Applications

In some sense, the cumulant is a measure of the independence of certain class of rv's.

The following result was shown by Jogdeo (1968). Let $F_{X_1, X_2, X_3}(x_1, x_2, x_3)$ belong to the family $M(3)$ where $M(3)$ denotes the class of trivariate distributions such that there exists a choice of $\Delta$ and $\Delta_i$, $i = 1, 2, 3$ such that

$$P(X_1 \Delta_1 = 1, X_2 \Delta_2 = 2, X_3 \Delta_3 = 3) \Delta \prod_{i=1}^{3} P(X_i \Delta_i = 1)$$

(14)

for all $x_1, x_2, x_3$ where the $\Delta$, $\Delta_i$ each denote one of the inequalities $\geq$ or $\leq$.

Then $X_i, X_j$ for all $i \neq j$ are uncorrelated and $\text{EX}_1 X_2 X_3 = \text{EX}_1 \text{EX}_2 \text{EX}_3$ if and only if the $X_i$'s are mutually independent.

Using Theorem 1 we get this conclusion directly. The "if" part is trivial.

Conversely since $F \in M(3)$ we know $F_{X_i X_j}(x_i, x_j) \in M(2)$ ($M(n)$ can be defined similarly). Since $X_i$ and $X_j$ are uncorrelated this implies the $X_i$'s are pairwise independent.
by Hoeffding's Lemma. Thus using Remark 4, (9) becomes

$$EX_1X_2X_3 - EX_1EX_2EX_3 =$$

$$\pm \int \int \int \{P(X_1 \Delta x_1, X_2 \Delta x_2, X_3 \Delta x_3) - P(X_1 \Delta x_1)P(X_2 \Delta x_2)P(X_3 \Delta x_3)\}dx_1dx_2dx_3.$$

Now since $F \in M(3)$ the integrand will not change sign, so that $EX_1X_2X_3 = EX_1EX_2EX_3$ implies

$$P(X_1 \Delta x_1, X_2 \Delta x_2, X_3 \Delta x_3) = P(X_1 \Delta x_1)P(X_2 \Delta x_2)P(X_3 \Delta x_3)$$

for all $x_1, x_2, x_3$ which means that the $X_i$'s are independent.

The n-dimension extension is straightforward and is given below.

**Theorem 2**

If $F_{X_1, \ldots, X_n}(x_1, \ldots, x_n) \in M(n)$, then $EX_1 \ldots X_n = \Pi_{i=1}^n EX_i$ for all subsets $\{i_1, \ldots, i_k\}$ of $\{1, \ldots, n\}$ if and only if $X_1, \ldots, X_n$ are independent.

**Proof:** $F_{X_1, \ldots, X_n}(x_1, \ldots, x_n) \in M(n)$ means $F_{X_{i_1}, \ldots, X_{i_k}}(x_{i_1}, \ldots, x_{i_k}) \in M(k)$ for any subset $\{i_1, \ldots, i_k\}$. By induction on $n$, using Theorem 1, we obtain

$$EX_1 \ldots X_n = \Pi_{j=1}^n EX_j = \pm \int \int \ldots \int \{P(X_1 \Delta x_1, \ldots, X_n \Delta x_n) - \Pi_{i=1}^n P(X_i \Delta x_i)\}dx_1 \ldots dx_n.$$

The integrand will not change sign, so $EX_1 \ldots X_n = \Pi_{j=1}^n EX_j$ implies that the $X_i$ are mutually independent.

Several authors have discussed dependence structures in which uncorrelatedness implies independence. Among them are Lehmann (1966), Jogdeo (1968), Joag-dev (1983) and Chhetry, D. et al (1985).

We now give a definition from Joag-dev (1983). Let $X = (X_1, \ldots, X_n)$ be a random vector, $A$ be a subset of $\{1, \ldots, n\}$ and $x = (x_1, \ldots, x_n)$ a vector of constants.

**Definition 2** Random vectors are said to be **PUOD** (positive upper orthant dependence) if a) below holds, **PLOD** (positive lower orthant dependence) if b) below holds and
POD\(^{+}\) (positive orthant dependent) if a) and b) below hold, where
\[
\text{a) } P(X > x) > \prod_{i=1}^{n} P(X_i > x_i), \\
\text{b) } P(X < x) > \prod_{i=1}^{n} P(X_i < x_i).
\]

If the reverse inequalities between the probabilities in a) and b) hold the three concepts are called NUOD, NLOD and NOD respectively.

**Definition 3.** A vector \(X\) is said to be SPOD (strongly positively orthant dependent) if for every set of indices \(A\) and for all \(x\) the following three conditions hold:
\[
\text{c) } P(X > x) > P(X_i > x_i, i \in A)P(X_j > x_j, j \in A^C), \\
\text{d) } P(X < x) > P(X_i < x_i, i \in A)P(X_j < x_j, j \in A^C), \\
\text{e) } P(X_i > x_i, i \in A, X_j < x_j, j \in A^C) < P(X_i > x_i, i \in A)P(X_j < x_j, j \in A^C).
\]

The relationships among these definitions are as follows:

\[
\text{Association} \Rightarrow \text{SPOD} \Rightarrow \text{POD} \Rightarrow \text{PLOD} \Rightarrow \text{PUOD} \Rightarrow \text{M(n)}. \tag{15}
\]

Since association, SPOD, POD, PLOD, PUOD are all subclasses of \(M(n)\), Theorem 2 generalizes some results in Lehmann (1966) and it gives us another proof of Theorem 2 in Joag-Dev (1983) as well as some new characterizations of independence for POD random variables. Corollary 1 is the result of Joag-Dev.

**Corollary 1.** Let \(X_1, \ldots, X_n\) be SPOD and assume \(\text{cov}(X_i, X_j) = 0\) for all \(i \neq j\). Then \(X_1, \ldots, X_n\) are mutually independent.

**Proof:** Since \(X_1, \ldots, X_n\) SPOD implies \((X_1 \ldots X_n) \in M(n)\) by Theorem 2 we need only check \(E X_{i_1} \ldots X_{i_k} = \prod_{j=1}^{k} E X_{i_j}\) for all subsets \(\{i_1, \ldots, i_k\}\) of \(\{1, \ldots, n\}\). When \(n = 2\)

\(\text{In Definition 2 in Block et al (1981), POD is used for what is called PUOD in this paper.}\)
SPOD is equivalent to PQD and uncorrelatedness implies \( X_1, X_2 \) independent. By induction on \( n \) we may assume all subsets with \((n-1)\) rv's are mutually independent and thus \( \text{EX}_1 \ldots \text{EX}_k = \prod \text{EX}_{j} \) for all \( 1 \leq k \leq n-1 \). Hence \( \text{cum}(X_i, k \in \nu) = 0 \) whenever \( \text{card}(\nu) \leq n-1 \). So we only need to check \( \text{EX}_1 \ldots \text{EX}_n = \prod \text{EX}_j \). By Lemma 1, Theorem 1 and because of the independence of any \((n-1)\) rv's

\[
\text{EX}_1 \ldots \text{EX}_n = \prod_{j=1}^{n} \text{EX}_j
\]

\[
= \sum \text{cum}(X_k, k \in \nu_1) \ldots \text{cum}(X_k, k \in \nu_p)
\]

\[
= \text{cum}(X_1, \ldots, X_n)
\]

\[
= \int_{-\infty}^{\infty} \ldots \int_{-\infty}^{\infty} \left( \text{P}(X > x) - \prod_{j=1}^{n} \text{P}(X_j > x_j) \right) dx_1 \ldots dx_n > 0. \quad (16)
\]

Similarly

\[
\text{EX}_1 \ldots \text{EX}_n = \prod_{j=1}^{n} \text{EX}_j
\]

\[
= \text{E}(-X_1)(-X_2)X_3 \ldots X_n - \text{E}(-X_1)\text{E}(-X_2)\text{EX}_3 \ldots \text{EX}_n
\]

\[
= \text{cum}(-X_1, -X_2, X_3 \ldots X_n)
\]

\[
= \int_{-\infty}^{\infty} \ldots \int_{-\infty}^{\infty} \left( \text{P}(-X_1 > x_1, -X_2 > x_2, X_3 > x_3 \ldots X_n > x_n) - \text{P}(-X_1 > x_1)\text{P}(-X_2 > x_2)\text{P}(X_3 > x_3)\ldots\text{P}(X_n > x_n) \right) dx_1 \ldots dx_n
\]

\[
= \int_{-\infty}^{\infty} \ldots \int_{-\infty}^{\infty} \left( \text{P}(X_1 < -x_1, X_2 < -x_2, X_i > x_i, i = 3, \ldots, n) - \text{P}(X_1 < -x_1)\text{P}(X_2 < -x_2) \prod_{i=3}^{n} \text{P}(X_i > x_i) \right) dx_1 \ldots dx_n
\]

\[
= \int_{-\infty}^{\infty} \ldots \int_{-\infty}^{\infty} \left( \text{P}(X_j < -x_j, j = 1, 2, X_i > x_i, i = 3, \ldots, n) - \text{P}(X_j < -x_j, j = 1, 2)\text{P}(X_i > x_i, i = 3 \ldots n) \right) dx_1 \ldots dx_n
\]

\[
< 0. \quad (17)
\]
The last equality holds by the induction assumption of mutual independence and the last inequality is due to SPOD. Combining (16) and (17) completes the proof.

**Theorem 3.** Let \( X_1, X_2, X_3 \) be POD and assume \( X_i, X_j \) for all \( i \neq j \) are uncorrelated. Then \( X_1, X_2, X_3 \) are mutually independent.

**Proof:** The following two summands are nonnegative since \( X_1, X_2, X_3 \) are POD. By Lemma 1 we then have

\[
3 \sum_{i=1}^{3} [P(X_i > x_i, X_2 > x_2, X_3 > x_3) - \prod_{i=1}^{3} P(X_i > x_i)]
+ [P(X_1 \leq x_1, X_2 \leq x_2, X_3 \leq x_3) - \prod_{i=1}^{3} P(X_i \leq x_i)]
= \text{cum}(\chi_{X_1}(x_1), \chi_{X_2}(x_2), \chi_{X_3}(x_3)) + \sum_{i\neq j\neq k} P(X_i > x_i) \text{cov}(\chi_{X_j}(x_j), \chi_{X_k}(x_k))
+ \text{cum}(1 - \chi_{X_1}(x_1), 1 - \chi_{X_2}(x_2), 1 - \chi_{X_3}(x_3)) + \sum_{i\neq j\neq k} P(X_i \leq x_i) \text{cov}(\chi_{X_j}(x_j), \chi_{X_k}(x_k))
= \sum_{i\neq j} \text{cov}(\chi_{X_i}(x_i), \chi_{X_j}(x_j)).
\]

Since \( X_i, X_j \) POD and \( \text{cov}(X_i, X_j) = 0 \) we obtain \( \text{cov}(\chi_{X_i}(x_i), \chi_{X_j}(x_j)) = 0 \). Thus \( P(X_i > x_i, i=1,2,3) - \prod_{i=1}^{3} P(X_i > x_i) = 0 \), i.e. \( X_1, X_2, X_3 \) are mutually independent.

**Remark 5.** For three rv's \( X_1, X_2, X_3 \) the mixed positive dependence defined in Chhetry, et. al (1985) implies POD but the converse is not true as shown by an example in Joag-dev (1983). Notice that since the mixed positive dependence implies POD in Corollary 1, the SPOD can be relaxed to this mixed condition.

**Theorem 4.** Assume \( n = 2\ell+1 \) is an odd positive integer and \( X_1, \ldots, X_n \) are POD. Then if \( E(X_i, \ldots, X_k) = \prod_{i=1}^{\ell} E_{i_{\ell+1}} \ldots E_{i_k} \) for any subset \( \{i_1, \ldots, i_k\} \) of \( \{1, \ldots, 2\ell+1\} \) it follows that \( X_1, \ldots, X_n \) are mutually independent.
Proof: By Theorem 2, we need only check $EX_1 \ldots X_n = EX_1 \ldots EX_n$. On the one hand

$$EX_1 \ldots X_n - EX_1 \ldots EX_n = \text{cum}(X_1 \ldots X_n) = \int \ldots \int \left\{ P(X_i > x_i, i=1,\ldots,n) - \prod_{j=1}^{n} P(X_j > x_j) \right\} dx_1 \ldots dx_n \geq 0.$$ 

On the other hand

$$EX_1 \ldots X_n - EX_1 \ldots EX_n = (-1)^{2i+1} \left\{ E(-X_1) \ldots (-X_n) - E(-X_1) \ldots E(-X_n) \right\}$$

$$= (-1)^{2i+1} \text{cum}(-X_1, \ldots, -X_n)$$

$$= (-1)^{2i+1} \int \ldots \int \left\{ P(X_i < -x_i, i=1,\ldots,n) - \prod_{j=1}^{n} P(X_j < -x_j) \right\} dx_1 \ldots dx_n < 0.$$ 

Remark 6. For $n=4$ we construct, in Example 1 below, POD rv's such that any three of $X_i$'s are independent but the $X_i$'s are not mutually independent. This shows that the conditions of Theorem 4 are reasonable. In Example 2, we show that for POD rv's $\text{cov}(X_i, X_j) = 0$ is not enough to give mutual independence when $2i+1 > 3$.

Example 1. Let $X_1, \ldots, X_4$ have the distribution given below. It's easy to check that for $i \neq j \neq k$, $X_i, X_j, X_k$ are mutually independent and that $X_1 \ldots X_4$ are POD.

<table>
<thead>
<tr>
<th>$X_1$</th>
<th>$X_2$</th>
<th>$X_3$</th>
<th>$X_4$</th>
<th>Pr</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1/8</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1/8</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1/8</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1/8</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1/8</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1/8</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1/8</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1/8</td>
</tr>
</tbody>
</table>
Since \( P(X_i > \frac{1}{2}, i = 1, \ldots, 4) - \prod_{i=1}^{4} P(X_i > \frac{1}{2}) = \frac{1}{16} \geq 0 \), \( X_1 \ldots X_4 \) are not mutually independent.

Notice also that
\[
P(X_1 < x_1, X_2 < x_2, X_3 > x_3, X_4 > x_4)
- P(X_1 < x_1 P(X_2 < x_2) P(X_3 > x_3, X_4 > x_4)
= \text{cum}(1 - x_{X_1}(x_1), 1 - x_{X_2}(x_2), x_{X_1}(x_1), x_{X_2}(x_2))
= \text{cum}(x_{X_i}(x_i), i = 1, \ldots, 4)
= P(X_i > x_i, i = 1, \ldots, 4) - \prod_{i=1}^{4} P(X_i > x_i)
\geq 0,
\]
so these rv's are not SPOD.

**Example 2.** Let \( X_1, \ldots, X_5 \) have the distribution given below.

<table>
<thead>
<tr>
<th>( X_1 )</th>
<th>( X_2 )</th>
<th>( X_3 )</th>
<th>( X_4 )</th>
<th>( X_5 )</th>
<th>Pr</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1/16</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1/16</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1/16</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1/16</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1/16</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1/16</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1/16</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1/16</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1/16</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1/16</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1/16</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1/16</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1/16</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1/16</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1/16</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1/16</td>
</tr>
</tbody>
</table>

It is easy to check that this is PUOD and PLOD, thus it is POD. However \( EX_i X_j = 4/16 \) and \( EX_i = \frac{1}{2} \) for all \( i,j \).

In this example we can use Theorem 3 to prove that any \( X_i, X_j, X_k \) are mutually independent since subsets of POD rv's are still POD.
Newmann and Wright (1981), using an inequality for the ch.f.'s of rv's $X_1, \ldots, X_m$, provided another proof for the characterization of the independence of associated rv's. This is Theorem 1 of Newmann et al (1981). These authors proved that if $X_1, \ldots, X_m$ are associated with finite variance, joint and marginal ch.f.'s $\phi(r_1, \ldots, r_m)$ and $\phi_j(r_j)$ then

$$|\phi(r_1, \ldots, r_m) - \prod_{j=1}^{m} \phi_j(r_j)| \leq \frac{1}{2} \sum_{j \neq k} |r_j||r_k| \text{cov}(X_j, X_k),$$

(18)

To extend this inequality we need the following lemma.

**Lemma 3.** For the rv $(X_1, \ldots, X_m)$ with $E|X_1|^m < \infty$,

$$\text{cum}(\exp(ir_1X_1), \ldots, \exp(ir_mX_m))$$

$$= \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} r_1 \cdots r_m \exp(i \sum_{j=1}^{m} r_j x_j \text{cum}(X_{x_1}^{x_1}, \ldots, X_{x_m}^{x_m})dx_1 \cdots dx_m$$

(19)

where $r_1, \ldots, r_m$ are real numbers and $\chi_{X_j}(x_j) = 1$ when $X_j > x_j$ and 0 otherwise.

**Proof:** This proof of result is similar to Lemma 2. Use the identity

$$\exp(ir_k X_k) - 1 = i \int_{-\infty}^{\infty} r_k \exp(ir_k X_k)(\varepsilon(x_k) - I_{(-\infty, x_k]}(X_k))dx_k.$$

We obtain

$$\text{cum}(\exp(ir_k X_k), k = 1, \ldots, m)$$

$$= \text{cum}(\exp(ir_k X_k) - 1, k = 1, \ldots, m)$$

$$= \sum_{l=1}^{p} \prod_{k \in E} \left( \frac{1}{2} \sum_{j \neq k} |r_j||r_k| \text{cov}(X_j, X_k) \right)$$

$$= \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} r_1 \cdots r_m \exp(i \sum_{j=1}^{m} r_j x_j \text{cum}(X_{x_1}^{x_1}, \ldots, X_{x_m}^{x_m})dx_1 \cdots dx_m.$$
Using Lemma 3 we can obtain a result parallel to (18) for certain classes of rv's.

Theorem 4. If $X_1, \ldots, X_m$ are rv's such that $E|X_j|^m < \infty$, $j = 1, \ldots, m$ and $\text{cum}(X_{j_1} \ldots X_{j_k})$ has the same sign for all subsets $\{j_1, \ldots, j_k\}$ of $\{1, \ldots, m\}$ and all $x_1, \ldots, x_k$. Then

$$|\phi(r_1, \ldots, r_m) - \prod_{j=1}^{m} \phi_j(r_j)| \leq \prod_{j=1}^{m} |r_j| \cdot |E X_1 \ldots X_m - EX_1 \ldots EX_m|.$$  \hspace{1cm} (20)

Here $\phi(r_1, \ldots, r_m)$ and $\phi_j(r_j)$ are the joint and marginal ch.f's of $(X_1, \ldots, X_m)$.

**Proof:** From the fact that the $\text{cum}(X_{j_1} \ldots X_{j_k})$ have the same sign, and from Lemma 1, Lemma 3 and Theorem 1 we have

$$|\phi(r_1, \ldots, r_m) - \prod_{j=1}^{m} \phi_j(r_j)| = |E \prod_{k=1}^{m} \exp(ir_k X_k) - \prod_{k=1}^{m} E \exp(ir_k X_k)|$$

$$= |\sum \text{cum}(\exp ir X_j, j \in V_1) \ldots \text{cum}(\exp ir X_j, j \in V_p)|$$

$$= \left| \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} \prod_{j=1}^{m} \text{cum}(X_{j_1}, j \in V_1) \ldots \text{cum}(X_{j_n}, j \in V_p) \ dx_{j_1} \ldots dx_{j_n} \right|$$

$$\leq |r_1| \ldots |r_m| \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} |\sum \text{cum}(X_{j_1}, j \in V_1) \ldots \text{cum}(X_{j_n}, j \in V_p)| \ dx_{j_1} \ldots dx_{j_n}$$

$$= \prod_{k=1}^{m} |r_k| \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} \prod_{j=1}^{m} \text{cum}(X_{j_1}, j \in V_1) \ldots \text{cum}(X_{j_n}, j \in V_p) \ dx_{j_1} \ldots dx_{j_n}$$

$$= |r_1| \ldots |r_m| |E X_1 \ldots X_m - EX_1 \ldots EX_m|.$$  \hspace{1cm} (20)

**Remark 7.** In Example 3 below we define rv's which are uncorrelated but not mutually independent. By Corollary 1 they cannot be associated so that Theorem 1 of Newman and Wright (1981) does not apply. However Theorem 4 gives an upper
bound for the difference of ch.f's, since it is easy to check $\text{cum}(x_{x_1}(x_1), x_{x_2}(x_2), x_{x_3}(x_3)) = 0$, 
$i \neq j$, and $\text{cum}(x_{x_1}(x_1), x_{x_2}(x_2), x_{x_3}(x_3)) > 0$ for all $x_1, x_2, x_3$.

**Example 3.** Consider the rv's $X_1, X_2, X_3$ with distribution given below.

<table>
<thead>
<tr>
<th>$X_1$</th>
<th>$X_2$</th>
<th>$X_3$</th>
<th>Pr</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1/4</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1/4</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1/4</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1/4</td>
</tr>
</tbody>
</table>

These are PUOD but not POD.

For nonnegative rv's we can go further.

**Theorem 5.** If the rv's $X_1, \ldots, X_m$ are nonnegative (nonpositive) and PUOD (PLOD) with finite mth moments then

$$|\phi(r_1, \ldots, r_m) - \prod_{j=1}^{m} \phi_j(r_j)| \leq |r_1| \ldots |r_m| |\text{EX}_1 \ldots \text{EX}_m - \text{EX}_1 \ldots \text{EX}_m|.$$  \hspace{1cm} (22)

**Proof:** We prove the PUOD case only. Using Lemma 1, Lemma 3 and Remark 3

$$|\phi(r_1, \ldots, r_m) - \prod_{j=1}^{m} \phi_j(r_j)| = |E \exp \left( \sum_{j=1}^{m} r_j X_j \right) - \prod_{j=1}^{m} E \exp(\tau_j X_j)|$$

$$= \left| \int_{0}^{\infty} \int_{0}^{\infty} \cdots \int_{0}^{\infty} \left( \prod_{j=1}^{m} \phi_j(r_j) \right) \text{F}(x_1, \ldots, x_m) \text{dx}_1 \cdots \text{dx}_m \right|$$

$$\leq |r_1| \ldots |r_m| \left| \int_{0}^{\infty} \cdots \int_{0}^{\infty} \left( \prod_{j=1}^{m} \phi_j(r_j) \right) \text{dx}_1 \cdots \text{dx}_m \right|$$

$$= |r_1| \ldots |r_m| \left| \int_{0}^{\infty} \cdots \int_{0}^{\infty} \left( \prod_{j=1}^{m} \phi_j(r_j) \right) \text{F}(x_1, \ldots, x_m) \text{dx}_1 \cdots \text{dx}_m \right|$$

$$= |r_1| \ldots |r_m| |\text{EX}_1 \ldots \text{EX}_m - \text{EX}_1 \ldots \text{EX}_m|. \hspace{1cm} (23)$$

**Corollary 2.** Under the conditions of Theorem 5, if $\text{EX}_1 \ldots \text{X}_n = \text{EX}_1 \ldots \text{EX}_m$, then $X_1, \ldots, X_n$ are independent.
4. Cumulants and Dependence

Cumulants provide us with useful measures of the joint statistical dependence of random variables. However, the relationships with positive and negative dependence are not similar to those in the bivariate (covariance) case. We give some examples to illustrate the relationship between the sign of the cumulant and dependence in the trivariate case.

Remark 8. By property (iii) of cumulants if any group of X's is independent of the remaining X's then \( \text{cum}(X_1, \ldots, X_r) = 0 \). The converse is true for normal distributions when \( r = 2 \) but not for \( r > 2 \). For the trivariate normal, we can have \( \text{cum}(X_1, X_2, X_3) = 0 \) where \( X_1, X_2, X_3 \) are not necessarily independent.

Remark 9. Assume \( E X_i > 0 \) for \( i = 1, 2, 3 \) and \( \text{cov}(X_i, X_j) > 0 \) for \( i, j = 1, 2, 3 \) (or the even stronger conditions \( \text{cov}(X_i X_j (x_i) X_j (x_j)) > 0 \) and \( \text{cum}(X_1, X_2, X_3) > 0 \)). These do not imply PUOD as is shown in the following example.

Example 4. Let \( X_1, X_2, X_3 \) take the values 0, +1 with:
- \( P(X_1 = x_1, X_2 = x_2, X_3 = x_3, x_1 x_2 x_3 \neq 0) = 0; \)
- \( P(X_1 = x_2 = x_3 = 0) = 0; \)
- \( P(X_1 = 0, X_j = x_j, X_k = x_k, x_j x_k > 0) = \frac{1}{9}, \)
- \( 1, j, k = 1, 2, 3, x_j = x_k = 1 \) or \( x_j = x_k = -1; \) and \( P(X_1 = x_1, X_2 = x_2, X_3 = x_3) = \frac{1}{36} \) for the remaining cases. It is easy to check that \( E X_i = EX_1 X_2 X_3 = 0, EX_1 X_j > 0, \) and \( \text{cum}(X_1, X_2, X_3) = 0 \) but

\[
P(X_1 > 0, X_2 > 0, X_3 > 0) - P(X_1 > 0)P(X_2 > 0)P(X_3 > 0) = -\frac{11}{36} < 0.
\]

Remark 10. Let \( E X_i > 0 \) and assume \( (X_1, X_2, X_3) \) PUOD. This does not imply \( \text{cum}(X_1, X_2, X_3) > 0 \) as is shown in Example 5.

Example 5. Let \( (X_1, X_2, X_3) \) have distribution given below. It is easy to check that \( (X_1, X_2, X_3) \) is PUOD and that \( E X_i = 0 \), but \( \text{cum}(X_1, X_2, X_3) = -0.15 < 0. \)
Remark 11. Let \((X_1, X_2, X_3)\) be associated. It need not be true that \(\text{cum}(X_1, X_2, X_3) \geq 0\) as is shown in Example 6.

Example 6. Assume \((X_1, X_2, X_3)\) are binary rv's with distribution

\[
P(X_1 = X_2 = X_3 = 0) = 0.3; \quad P(X_1 = x_1, X_2 = x_2, X_3 = x_3) = 0.1 \text{ for all other } \{x_1, x_2, x_3\} \in \{0,1\}^3
\]

Checking all binary nondecreasing functions \(\Gamma(X_1, X_2, X_3)\) and \(\Delta(X_1, X_2, X_3)\) we have \(\text{cov}(\Gamma, \Delta) \geq 0\). Thus \((X_1, X_2, X_3)\) are associated but \(\text{cum}(X_1, X_2, X_3) = -0.012 < 0\).

Remark 12. If \((X, Y)\) are binary and \(\text{cov}(X, Y) \geq 0\) then \((X, Y)\) is associated as was shown in Barlow and Proschan (1981). However if \((X_1, X_2, X_3)\) are binary, then \(\text{cov}(X_i, X_j) \geq 0, i, j = 1, 2, 3\) and \(\text{cum}(X_1, X_2, X_3) \geq 0\) do not imply \((X_1, X_2, X_3)\) associated as is seen in Example 7.

Example 7. Assume \((X_1, X_2, X_3)\) are binary rv's with the distribution below. Then

\[
\text{cov}(X_i, X_j) = \frac{1}{180} > 0 \text{ and } \text{cum}(X_1, X_2, X_3) = \frac{-1}{135} > 0.
\]

However for the increasing functions \(\max(X_1, X_2)\) and \(\max(X_1, X_3)\)

\[
\text{cov}(\max(X_1, X_2), \max(X_1, X_3)) = -\frac{1}{900} < 0,
\]

so \((X_1, X_2, X_3)\) are not associated.
If we add some restrictions, some results can be obtained. We give these below and omit the easy proofs.

**Proposition 1.** If \( \text{cov}(X_i, X_j) = 0 \), for \( i, j = 1, 2, 3 \) then \((X_1, X_2, X_3)\) PUOD implies \( \text{cum}(X_1, X_2, X_3) \geq 0 \) and \((X_1, X_2, X_3)\) PLOD implies \( \text{cum}(X_1, X_2, X_3) \leq 0 \).

**Remark 13.** Notice that under the above assumptions we have the peculiar situation that PUOD \( \Leftrightarrow \) NLOD and PLOD \( \Leftrightarrow \) NUOD.

**Proposition 2.** Let \((X_1, X_2, X_3)\) be a binary trivariate rv. If \( \text{cov}(X_i, X_j) > 0, \text{cum}(X_1, X_2, X_3) > 0\), and additionally condition (M) below holds, then \((X_1, X_2, X_3)\) is associated for \( i, j, k = 1, 2, 3 \).

\[
\begin{align*}
\text{cov}(X_i \uparrow X_j \downarrow X_k, X_j \uparrow X_k) & > 0 \\
\text{cov}(X_i \uparrow X_j, X_i \uparrow X_k) & > 0 \\
\end{align*}
\]

\((M)\)

where

\[
X_i \uparrow X_j = 1 - (1-X_i)(1-X_j) = \max(X_i, X_j) .
\]

To prove Proposition 2 we need to check for all binary increasing functions \( \Gamma \) and \( \Delta \) that \( \text{cov}(\Gamma(X_1, X_2, X_3), \Delta(X_1, X_2, X_3)) > 0 \). We leave this to the reader.

Although \( \text{cum}(X_1, X_2, X_3) \geq 0 \) does not imply PUOD we introduce a new condition which does imply positive dependence.
Definition 4. The r.v. \((X_1, X_2, X_3)\) is said to be positive upper indicator cumulant dependence (PUCD) if for all \(x_1, x_2, x_3\)

\[
\tilde{F}(x_1, x_2, x_3) - \tilde{F}_1(x_1)\tilde{F}_2(x_2)\tilde{F}_3(x_3) \geq \sum_{i \neq j \neq k} \tilde{F}_1(x_i)\text{cov}(X_j(x_j), X_k(x_k)) > 0.
\]

It is easy to see that PUCD is equivalent to

\[
\text{cov}(X_i(x_i), X_j(x_j)) \geq 0 \text{ for all } i, j \text{ and } \text{cum}(X_i(x_i), X_j(x_j), X_k(x_k)) > 0.
\]

The relationships between PUCD and other positive dependence concepts are as follows:

\[
PUCD \Rightarrow \text{cum}(X_1, X_2, X_3) \geq 0
\]

\[
POD \Rightarrow \text{PuOD} \Rightarrow \text{cov}(X_i(x_i)) > 0
\]

(24)

and no other implications hold. Example 5 shows that PUOD \(\not\Rightarrow\) PUCD, Example 6 shows that POD \(\not\Rightarrow\) PUCD, Example 3 shows that PUCD \(\not\Rightarrow\) POD and Example 8 below shows that \(\text{cum}(X_1, X_2, X_3) > 0 \not\Rightarrow\) PUCD.

Example 8. Let \((X_1, X_2, X_3)\) be the r.v. with survival function

\[
\tilde{F}(x_1, x_2, x_3) = e^{-\lambda \max(x_1, x_2, x_3)}, \quad x_i \geq 0, \quad \lambda > 0.
\]

Then \(\text{cum}(X_1, X_2, X_3) = \frac{2}{\lambda^3} > 0\) but \(X_1, X_2, X_3\) are not PUCD. Let \(x_1 = x_2 = x_3 = \frac{1}{\lambda} \ln 4/3\), then

\[
\tilde{F}(x_1, x_2, x_3) - \tilde{F}_1(x_1)\tilde{F}_2(x_2)\tilde{F}_3(x_3) = \frac{21}{64},
\]

but

\[
\sum \tilde{F}_1(x_i)\text{cov}(X_j(x_j), X_k(x_k)) = \frac{27}{64}.
\]

By Theorem 4 if \((X_1, \ldots, X_n)\) is PUCD, then \(\text{EX}_1 \cdots X_m = \prod_{j=1}^{m} \text{EX}_j\) implies mutually independence. The definition of PUCD can be generalized to lower positive and negative dependence concepts also.
REFERENCES


END
DTC
9-86