Concept of Sub-Independence

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https://epublications.marquette.edu/mscs_fac/398
Chapter 10

Concept of Sub-Independence

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ABSTRACT: Limit theorems as well as other well-known results in probability and statistics are often based on the distributions of the sums of independent random variables. The concept of sub-independence, which is weaker than that of independence, is shown to be sufficient to yield the conclusions of these theorems and results. It also provides a measure of dissociation between two random variables which is stronger than uncorrelatedness.

10.1 INTRODUCTION

Limit theorems as well as other well-known results in probability and statistics are often based on the distributions of the sums of independent (and often identically distributed) random variables rather than the joint distribution of the summands. Therefore, the full force of independence of the summands will not be required. In other words, it is the convolution of the marginal distributions which is needed, rather than the joint distribution of the summands which, in the case of independence, is the product of the marginal distributions. This is precisely the reason for the statement: “why assume independence when you can get by with sub-independence”.

A comprehensive treatment of the concept of sub-independence from its beginning 1979 to 2011 will appear as an Expository Article elsewhere which will include the content of this article.
The concept of sub-independence can help to provide solution for some modeling problems where the variable of interest is the sum of a few components. Examples include household income, the total profit of major firms in an industry, and a regression model \( Y = g(X) + \varepsilon \) where \( g(X) \) and \( \varepsilon \) are uncorrelated, however, they may not be independent. For example, in Bazargan et al. (2007), the return value of significant wave height \( Y \) is modeled by the sum of a cyclic function of random delay \( D, \hat{g}(D) \), and a residual term \( \hat{\varepsilon} \). They found that the two components are at least uncorrelated but not independent and used sub-independence to compute the distribution of the return value. For the detailed application of the concept of sub-independence in this direction we refer the reader to Bazargan et al. (2007).

For the sake of completeness we restate some well-known definitions. Let \( X \) and \( Y \) be two random variables (rv's) with joint and marginal cdf's (cumulative distribution functions) \( F_{X,Y}, F_X \) and \( F_Y \) respectively. Then \( X \) and \( Y \) are said to be independent if and only if

\[
F_{X,Y}(x,y) = F_X(x)F_Y(y), \quad \text{for all } (x,y) \in \mathbb{R}^2, \tag{10.1}
\]

or equivalently, if and only if

\[
\varphi_{X,Y}(s,t) = \varphi_X(s) \varphi_Y(t), \quad \text{for all } (s,t) \in \mathbb{R}^2, \tag{10.2}
\]

where \( \varphi_{X,Y}(s,t), \varphi_X(s) \) and \( \varphi_Y(t) \), respectively, are the corresponding joint and marginal cf's (characteristic functions). Note that (10.1) and (10.2) are also equivalent to

\[
P(X \in A \text{ and } Y \in B) = P(X \in A)P(Y \in B), \quad \text{for all Borel sets } A, B. \tag{10.3}
\]

The concept of sub-independence, as far as we have gathered, was formally introduced by Durairajan (1979), stated as follows: The rv's \( X \) and \( Y \) with cdf's \( F_X \) and \( F_Y \) are s.i. (sub-independent) if the cdf of \( X + Y \) is given by

\[
F_{X+Y}(z) = (F_X \ast F_Y)(z) = \int_{\mathbb{R}} F_X(z-y) \, dF_Y(y), \quad z \in \mathbb{R}, \tag{10.4}
\]

or equivalently if and only if

\[
\varphi_{X+Y}(t) = \varphi_{X,Y}(t,t) = \varphi_X(t) \varphi_Y(t), \quad \text{for all } t \in \mathbb{R}. \tag{10.5}
\]

The drawback of the concept of sub-independence in comparison with that of independence has been that the former does not have an equivalent definition in the sense of (10.3), which some believe, to be the natural definition of independence. We believe to have found such a definition now, which is stated below. We shall give two separate definitions, one for the discrete case (Definition 10.1) and the other for the continuous case (Definition 10.2).
CONCEPT OF SUB-INDEPENDENCE

Let \((X, Y) : \Omega \to \mathbb{R}^2\) be a discrete random vector with range \(\mathcal{R}(X, Y) = \{(x_i, y_j) : i, j = 1, 2, \ldots\}\) (finitely or infinitely countable). Consider the events

\[ A_i = \{\omega \in \Omega : X(\omega) = x_i\}, \quad B_j = \{\omega \in \Omega : Y(\omega) = y_j\} \]

and

\[ A^2 = \{\omega \in \Omega : X(\omega) + Y(\omega) = z\}, \quad z \in \mathcal{R}(X + Y). \]

**Definition 10.1** The discrete rv’s \(X\) and \(Y\) are s.i. if for every \(z \in \mathcal{R}(X + Y)\)

\[
P(A^2) = \sum_{i,j} P(A_i) P(B_j). \tag{10.6}
\]

To see that (10.6) is equivalent to (10.5), suppose \(X\) and \(Y\) are s.i. via (10.5), then

\[
\sum_{i,j} e^{i\pi(x_i+y_j)} f(x_i, y_j) = \sum_{i,j} e^{i\pi(x_i+y_j)} f_X(x_i) f_Y(y_j),
\]

where \(f, f_X\) and \(f_Y\) are probability functions of \((X, Y), X\) and \(Y\) respectively. Let \(z \in \mathcal{R}(X + Y)\), then

\[
e^{iz} \sum_{i,j, x_i+y_j = z} f(x_i, y_j) = e^{iz} \sum_{i,j, x_i+y_j = z} f_X(x_i) f_Y(y_j),
\]

which implies (10.6).

For the continuous case, we observe that the half-plane \(H = \{(x, y) : x + y < 0\}\) can be written as a countable disjoint union of rectangles:

\[ H = \bigcup_{i=1}^{\infty} E_i \times F_i, \]

where \(E_i\) and \(F_i\) are intervals. Now, let \((X, Y) : \Omega \to \mathbb{R}^2\) be a continuous random vector and for \(c \in \mathbb{R}\), let

\[ A_c = \{\omega \in \Omega : X(\omega) + Y(\omega) < c\} \]

and

\[ A_i^{(c)} = \left\{ \omega \in \Omega : X(\omega) - \frac{c}{2} \in E_i \right\}, \quad B_i^{(c)} = \left\{ \omega \in \Omega : Y(\omega) - \frac{c}{2} \in F_i \right\}. \]
DEFINITION 10.2. The continuous rv's $X$ and $Y$ are s.i. if for every $c \in \mathbb{R}$

$$P(A_c) = \sum_{i=1}^{\infty} P(A_i^{(c)}) P(B_i^{(c)}). \quad (10.7)$$

To see that (10.7) is equivalent to (10.4), observe that (LHS of (10.7))

$$P(A_c) = P(X + Y < c) = P((X, Y) \in H_c), \quad (10.8)$$

where $H_c = \{(x, y) : x + y < c\}$. Now, if $X$ and $Y$ are s.i. then

$$P(A_c) = (P_X \times P_Y)(H_c)$$

where $P_X, P_Y$ are probability measures on $\mathbb{R}$ defined by

$$P_X(B) = P(X \in B) \quad \text{and} \quad P_Y(B) = P(Y \in B),$$

and $P_X \times P_Y$ is the product measure.

We also observe that (RHS of (10.7))

$$\sum_{i=1}^{\infty} P(A_i^{(c)}) P(B_i^{(c)}) = \sum_{i=1}^{\infty} P\left(\frac{X - c}{2} \in E_i\right) P\left(\frac{Y - c}{2} \in F_i\right)$$

$$= \sum_{i=1}^{\infty} P\left(X \in E_i + \frac{c}{2}\right) P\left(Y \in F_i + \frac{c}{2}\right)$$

$$= \sum_{i=1}^{\infty} P_X \times P_Y\left(E_i + \frac{c}{2}\right) \times \left(F_i + \frac{c}{2}\right). \quad (10.9)$$

Now, (10.8) and (10.9) will be equal if $H_c = \bigcup_{i=1}^{\infty} \left[\left(E_i + \frac{c}{2}\right) \times \left(F_i + \frac{c}{2}\right)\right]$, which is true since the points in $H_c$ are obtained by shifting each point in $H$ over to the right by $\frac{c}{2}$ units and then up by $\frac{c}{2}$ units.

REMARKS 10.1.

(i) Note that $H$ can be written as a union of squares and triangles. The triangles are congruent to $0 \leq y < x, \ 0 \leq x < 1$ which in turn can be written as a disjoint union of squares. For example, take $[0, 1/2) \times [0, 1/2)$ then $[1/2, 3/4) \times [0, 1/4)$ and so on.

(ii) The discrete rv's $X$, $Y$ and $Z$ are s.i. if (10.6) holds for any pair and

$$P(A^d) = \sum_{i,j,k} \sum_{x+y+z} P(A_i) P(B_j) P(C_k). \quad (10.10)$$

For p variate case we need $2^p - p - 1$ equations of the above form.

(iii) The represent “sub-independence” which is weaker than independence.

We may think of such relations as a “sub-independence” relation. For example, the usual assumption in the Central Limit Theorem is that the sequence of sample means is independent in nature. This implies the law of large numbers, which states that the joint distribution of the random variables becomes more and more concentrated around the true mean as the number of variables increases.

(iv) For the case of two random variables, we have

$$\sum_{i,j=1}^{\infty} P(A_i) P(B_j) = \sum_{i,j} P(A_i \cap B_j).$$

This limit theorem states that the joint distribution of two random variables converges to the product distribution of their marginal distributions.

EXAMPLE 10.1

$$\varphi_{X,Y}(t, s) = \lim_{n \to \infty} \frac{1}{n} \sum_{i=1}^{n} X_i Y_i$$

where $\beta$ is a constant and

$$X + Y \text{ is normal},$$

$$X - Y \text{ is not normal}.$$
(iii) The representation (10.7) can be extended to the multivariate case as well.
(iv) For the sake of simplicity of the computations, (10.5) and its extension to the multivariate case will be taken as definition of sub-independence.

We may in some occasions have asked ourselves if there is a concept between "uncorrelatedness" and "independence" of two random variables. It seems that the concept of "sub-independence" is the one: it is much stronger than uncorrelatedness and much weaker than independence. The notion of sub-independence seems important in the sense that under usual assumptions, Khintchine's Law of Large Numbers and Lindeberg-Levy's Central Limit Theorem as well as other important theorems in probability and statistics hold for a sequence of s.i. random variables. While sub-independence can be substituted for independence in many cases, it is difficult, in general, to find conditions under which the former implies the latter. Even in the case of two discrete identically distributed rv's $X$ and $Y$, the joint distribution can assume many forms consistent with sub-independence. In order for two random variables $X$ and $Y$ to be s.i., the probabilities

$$ p_i = P(X = x_i), \quad i = 1, 2, ..., n $$

and

$$ q_{ij} = P(X = x_i, Y = y_j), \quad i, j = 1, 2, ..., n, $$

must satisfy the following conditions:

1. $\sum(q_{ij} - p_i p_j) = 0$, where the sum extends for all values of $i$ and $j$ for which $x_i + x_j = z$ and $z$ takes all the values in the set $\{\min(x_i + x_j), ..., \max(x_i + x_j)\}$;

2. $p_i = \sum_{j} q_{ij} = \sum_{j} q_{ji}, \quad i = 1, 2, ..., n$.

This linear system in $n^2$ variables $q_{ij}$ is considerably underdetermined for all but the smallest value of $n$ specially if a large number of points $(x, y)$ lie on the line $x + y = z$. On the other hand, the only $q_{ij}$ consistent with independence is $q_{ij} = p_i p_j$.

If $X$ and $Y$ are s.i., then unlike independence, $X$ and $\alpha Y$ are not necessarily s.i. for any real $\alpha \neq 1$ as the following simple example shows.

**Example 10.1.** Let $X$ and $Y$ have the joint cf given by

$$ \Phi_{X,i}(t_1, t_2) = \exp\{-\left[\frac{t_1^2 + t_2^2}{2}\right]\left[1 + \beta t_1 t_2 (t_1 - t_2)^2 \times \exp\{\frac{(t_1^2 + t_2^2)}{4}\}\right]\}, (t_1, t_2) \in \mathbb{R}^2, $$

where $\beta$ is an appropriate constant. Then $X$ and $Y$ are s.i. standard normal rv's, and hence $X + Y$ is normal with mean 0 and variance 2, but $X$ and $-Y$ are not s.i. and consequently $X - Y$ does not have a normal distribution.

The concept of sub-independence defined earlier can be extended to $n$ ($> 2$) rv's as follows.
**Definition 10.3.** The rv's $X_1, X_2, ..., X_n$ are s.i. if for each subset $\{X_{a_1}, X_{a_2}, ..., X_{a_r}\}$ of $\{X_1, X_2, ..., X_n\}$

$$
\varphi_{X_{a_1}, ..., X_{a_r}}(t, ..., t) = \prod_{i=1}^r \varphi_{X_{a_i}}(t), \text{ for all } t \in \mathbb{R}.
$$

(10.11)

To see how weak the concept of sub-independence is in comparison with that of independence, even in the case involving normal distribution, Hamedani (1983) gave the following example.

**Example 10.2.** Given $\{(a_k, b_k) : k = 1, 2, ..., N\}$ a finite set in $\mathbb{R}^2$. Consider the joint cf

$$
\varphi_{X,Y}(t_1, t_2) = \exp\left\{-\frac{1}{2}(c_1 - c_2)(t_1^2 + t_2^2)\right\} \prod_{k=1}^N \left(\varphi_{X_k}(t_1 t_2 - a_k^2 b_k^2), (t_1, t_2) \in \mathbb{R}^2, \right.
$$

where $c_1$ and $c_2$ are suitable constants. Then $X$ and $Y$ are standard normal rv's, $X$ and $Y$, as well as, $X$ and $-Y$ are s.i. and more

$$
\varphi_{X,Y}(a_k t, b_k t) = \varphi_X(a_k t) \varphi_Y(b_k t), \text{ for all } t \in \mathbb{R}, \ k = 1, 2, ..., N,
$$

i.e., $a_k X$ and $b_k Y, \ k = 1, 2, ..., N$ are s.i. of course $a_k X + b_k Y, \ k = 1, 2, ..., N$ are all normally distributed, but $X$ and $Y$ are not independent.

**Remark 10.2.** The set $\{(a_k, b_k) : k = 1, 2, ..., N\}$ in Example 10.2 cannot be taken to be infinitely countable. Hamedani and Tata (1975) showed that two normally distributed rv's $X$ and $Y$ are independent only if they are uncorrelated and $a_k X$ and $b_k Y, \ k = 1, 2, ..., N$ are all normally distributed, but $X$ and $Y$ are not independent.

$$
\varphi_{X,Y}(a_k t, b_k t) = \varphi_X(a_k t) \varphi_Y(b_k t), \text{ for all } t \in \mathbb{R}, \ k = 1, 2, ..., \right.
$$

where, $\{(a_k, b_k) : k = 1, 2, ...\}$ is a distinct sequence in $\mathbb{R}^2$.

### 10.2 Some Applications of the Concept of Sub-independence

We mention below a few results in which the assumption of independence is replaced by that of sub-independence, starting with the s.i. version of Cramér's famous theorem (Theorem 1, 1936) which appeared in Hamedani and Walter (1984b).

**Theorem 10.1.** (Cramér). If the sum $X + Y$ of the rv's $X$ and $Y$ is normally distributed and these rv's are s.i., then each of $X$ and $Y$ is normally distributed.

**Proposition 10.1.** (Chung). Let $X$ and $Y$ be s.i.i.d. (sub-independent and identically distributed) rv's with mean 0 and variance 1 such that

(i) $X$ and $-Y$ are s.i.,

(ii) $X + Y$ and $X - Y$ are s.i.

Then, both $X$ and $Y$ have standard normal distributions.
PROPOSITION 10.2. (Chung). Let $X$ and $Y$ as well as $X$ and $-Y$ be s.i. normally distributed rv's with the same variance. Then $X + Y$ and $X - Y$ are s.i.

THEOREM 10.2. Let $X$ and $Y$ be s.i.i.d. nondegenerate rv's. If $X^2$ and $\frac{1}{2}(X + Y)^2$ are i.d. chi-square with one degree of freedom, then the common distribution of $X$ and $Y$ is standard normal.

THEOREM 10.3. Let $X_1, X_2, \ldots, X_n$ be s.i.i.d. nondegenerate rv's. If $k X_k$ (for $k = 1, 2, \ldots, n$) are chi-square with one degree of freedom for two positive integers $m_1$ and $m_2$, then $X_i$'s are normally distributed.

A rv $X$ (or its pdf $f_X$) is called reciprocal if its cf is a multiple of a pdf. It is called self-reciprocal if there exist constants $A$ and $\alpha$ such that $Af_X(\alpha t)$ is the cf of $X$. It is strictly self-reciprocal if $(2\pi)^{-\frac{1}{2}} f_X(t)$ is the cf of $X$. Using the concepts of reciprocal, self-reciprocal, strictly self-reciprocal and sub-independence, Hamedani and Walter (1985) reported the following observations (Propositions 10.3, 10.4 and Theorem 10.7 below).

PROPOSITION 10.3. Let $X$ be the standard normal rv, $Y$ be an infinitely divisible rv s.i. of $X$. Then $X + Y$ is self-reciprocal if and only if $Y$ is normally distributed.

THEOREM 10.4. Let $X$ be the standard normal rv and $Y$ be strictly self-reciprocal and s.i. of $X$. Then $X + Y$ is self-reciprocal if and only if $Y$ is normally distributed.

PROPOSITION 10.4. Let $X$ be the standard normal rv, $Y$ a symmetric (about $0$) rv s.i. of $X$. Then $Y$ is strictly self-reciprocal if and only if the cf $\varphi$ of the rv $X + Y$ satisfies the functional equation

$$\varphi(t) = \frac{1}{\sqrt{2\pi}} \int_{\mathbb{R}} \exp\left\{\frac{(s + it)^2}{2}\right\} \varphi(s) ds, \text{ for all } t \in \mathbb{R}. $$

THEOREM 10.5. Let $X$ and $Y$ be s.i.i.d. rv's whose sum $X + Y$, is symmetric. Then $X$ and $Y$ are symmetric rv's.

THEOREM 10.6. Let $X$ and $Y$ be s.i. and $X + Y$ symmetric. If $X$ is symmetric with cf $\varphi_X(t) \neq 0$, for all $t$, then $Y$ must be symmetric.

THEOREM 10.7. (Raikov). If $X$ and $Y$ are non-negative integer-valued rv's such $X + Y$ has a Poisson distribution and $X$ and $Y$ are s.i., then each of $X$ and $Y$ has a Poisson distribution.

As we mentioned before, the well-known Khintchine's Law of Large Numbers and Lindeberg-Lévy's Central Limit Theorem as well as other important results can be stated in terms of s.i. rv's. Hamedani and Walter (1984a) reported several versions of the central limit theorems for s.i.i.d. rv's to which we refer the reader for details.
10.3. A DIFFERENT BUT EQUIVALENT INTERPRETATION OF SUB-INDEPENDENCE AND RELATED RESULTS

Ebrahimi et al. (2010) look at the concept of sub-independence in different but equivalent definition which provides a better understanding of this concept. Here we copy a portion of their paper since it treats this notion in completely different direction than we have dealt with so far. They present models for the joint distribution of uncorrelated variables that are not independent, but the distribution of their sum is given by the product of their marginal distributions. These models are referred to as the summable uncorrelated marginals distributions. They are developed utilizing the assumption of sub-independence, which has been employed in the present work in various directions, for the derivation of the distribution of the sum of random variables.

We shall now revisit the definition of sub-independence of the rv’s $X_1, X_2, \ldots, X_p$. We use $p$ in place of $n$ to be consistent with its use by Ebrahimi et al. (2010). Let $X = (X_1, X_2, \ldots, X_p)$ be a random vector with cdf $F$ and $c_f(t)$. Components of $X$ are said to be s.i. if

$$
\Psi(t) = \prod_{i=1}^{p} \psi_i(t), \quad \forall t = (t, t, \ldots, t) \in \mathbb{R}^p,
$$

(10.12)

where $\psi_i(t)$ is cf of $X_i$. We first consider the bivariate case $p = 2$ and let $F$ be the cdf of $X = (X_1, X_2)$, and $X' = (X'_1, X'_2)$ denote the random vector with cdf $F'(x_1, x_2) = F'_i(x_i)$ $F'_j(x_j)$, where $F'_i, i = 1, 2$ is the marginal cdf of $X_i$

**DEFINITION 10.4.** $F$ is said to be SUM (summable uncorrelated marginals) bivariate distribution if $X_1 + X_2 \sim X'_1 + X'_2$, where $\sim$ denotes the stochastic equality. Random variables with a SUM joint distribution are referred to as SUM random variables.

It is clear that the SUM and sub-independence are equivalent, so the two terminologies can be used interchangeably. It is also clear that the class of SUM rv’s are closed under scalar multiplication and addition under independence. That is, if $X = (X_1, X_2)$ is a SUM random vector, so is $a X$, and if $Y = (Y_1, Y_2)$ is another SUM random vector independent of $X$, then $X + Y$ is also SUM random vector. However, the SUM property is directional in that $X_1$ and $X_2$ being SUM rv’s does not imply that $X_1$ and $aX_2$ are SUM. Definition 10.4 can be generalized to any specific direction by $a_1X_1 + a_2X_2 \sim a_1X'_1 + a_2X'_2$.

We define a bivariate SUM copula to be a SUM distribution on the unit square $[0,1]^2$ with uniform marginals. We state the following lemma, due to Ebrahimi et al. (2010), which explains the construction of families of SUM models by linking the univariate pdf’s $f_i(x), i = 1, 2$. 

**LEMMA 10.5.**

The conditions provided such that:

(a) $f_1(x) = \text{constant}$ for some $x_0 
(b) \int f_2(x) \, dx = \text{constant}
(c) f_1(x) f_2(x) = \text{constant}

The resulting distribution is SUM.
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**Lemma 10.1.** Let \( f_i(x) \), \( i = 1, 2 \) be pdf's and \( g(x_i, x_j) \) a measurable function. Set

\[
f_\beta(x_1, x_2) = f_1(x_1) f_2(x_2) + \beta g(x_1, x_2), \quad (x_1, x_2) \in \mathbb{R}^2.
\]

Then for some \( \beta \in \mathbb{R} \), \( f_\beta(x_1, x_2) \) is a SUM pdf with marginal pdf's \( f_i(x) \), \( i = 1, 2 \), provided that:

1. \( f_\beta(x_1, x_2) \geq 0 \)
2. \( \int_{\mathbb{R}} g(x_1, x_2) \, dx_1 = \int_{\mathbb{R}} g(x_1, x_2) \, dx_2 = 0 \) for all \( (x_1, x_2) \in \mathbb{R}^2 \)
3. \( \int_{\mathbb{R}} g(c-t, t) \, dt = 0 \) for all \( c \in \mathbb{R} \).

The next example illustrates Lemma 10.1.

**Example 10.3.** Let \( f_i(x) \), \( i = 1, 2 \) be two pdf's on \([0, 1]\) and set

\[
f_\beta(x_1, x_2) = f_1(x_1) f_2(x_2) + \beta \sin[2\pi(x_2 - x_1)], \quad (x_1, x_2) \in [0,1]^2,
\]

such that for some \( \beta \in \mathbb{R} \), \( f_\beta(x_1, x_2) \) is a pdf on \([0, 1]^2\).

We mention here examples in which \((X_1, X_2)\) has a SUM distribution and \(X_1\) and \(X_2\) are \(i.d.\) with symmetric pdf's other than \(N(0,1)\).

(i) Standard Cauchy: \( f(x) = \frac{1}{\pi(1 + x^2)} \), \( x \in \mathbb{R} \);

(ii) Laplace Double Exponential: \( f(x) = \frac{1}{2\sigma} e^{-|x-\mu|/\sigma} \), \( x \in \mathbb{R} \);

(iii) Hyperbolic Secant: \( f(x) = \frac{1}{2\gamma K_1(\gamma)} e^{-\gamma \sqrt{x^2 + (x-\mu)^2}} \), \( x \in \mathbb{R} \), where \( K_1 \) is a modified Bessel function of the second kind;

(iv) Logistic or Sech-Square(d): \( f(x) = \frac{e^{-(x-\mu)/s}}{s(1 + e^{-(x-\mu)/s})^2} \), \( x \in \mathbb{R} \) and \( \mu = \text{mean} \) and \( s \) is proportion to standard deviation;

(v) Raised Cosine: \( f(x) = \frac{1}{2s} \left[ 1 + \cos \left( \frac{\pi(x-\mu)}{s} \right) \right] \), \( \mu - s \leq x \leq \mu + s \).
(vi) Wigner Semicircle: \( f(x) = \frac{2}{\pi r^2} \sqrt{r^2 - x^2} \), \(-r < x < r\).

\[
f(x) = \frac{1}{2\pi} \frac{\sin^2 \left( \frac{x}{2} \right)}{\left( \frac{x}{2} \right)}; \quad f(x) = \frac{2(2 + x^2) \sin^2 \left( \frac{x}{4} \right) + x \left( x + \sin \left( \frac{x}{2} \right) \right)}{2\pi x^2 (1 + x^2)};
\]

\[
f(x) = \frac{4\sin^2 \left( \frac{x}{4} \right)}{\pi x^2}; \quad f(x) = \frac{4 \left( x - 2 \sin \left( \frac{x}{2} \right) \right)}{\pi x^3} \quad x \in \mathbb{R}.
\]

Note that the \( cf's \) corresponding to \( pdf's \) (vii) are respectively

\[
\varphi(t) = \begin{cases} 1 - |t| & \text{if } |t| \leq 1 \\ 0 & \text{if } |t| > 1 \end{cases}; \quad \varphi(t) = \begin{cases} 1 - |t| & \text{if } |t| \leq \frac{1}{2} \\ \frac{1}{2} e^{-|t|} & \text{if } |t| > \frac{1}{2} \end{cases};
\]

\[
\varphi_1(t) = \begin{cases} 1 - 2|t| & \text{if } |t| \leq \frac{1}{2} \\ 0 & \text{if } |t| > \frac{1}{2} \end{cases}; \quad \varphi_2(t) = \left| \varphi_1(t) \right|^2 \quad t \in \mathbb{R}.
\]

The graphs of the first two \( pdf's \) in (vii) are bell-shaped and can be used to approximate normal \( pdf \). Hamedani et al. (2011) have presented various examples of bivariate mixture SUM distributions based on the \( pdf's \) given in (vii).

We can consider multivariate SUM random variables. Let \( F \) be the \( cdf \) of \( X = (X_1, X_2, ..., X_p)' \) and \( X^* = (X^*_1, X^*_2, ..., X^*_p)' \) denote the random vector with \( cdf \) \( F^* = \prod_{i=1}^p F_i \), where \( F_i \) is the \( cdf \) of \( X_i \).

**DEFINITION 10.5.** \( F \) is said to be a SUM\( p \) (SUM distribution of order \( p \)) if

\[
\sum_{i=1}^p X_i = \sum_{i=1}^p X^*_i.
\]

The following example, due to Ebrahimi et al. (2010), shows a trivariate SUM distribution.

**EXAMPLE 10.4.** Let \( X = (X_1, X_2, X_3)' \) and consider the distribution with \( pdf \)

\[
f_\beta(x) = \frac{1}{(2\pi)^{3/2}} e^{-\frac{1}{2} x' x} \left( 1 + \beta (x_1 - x_2) (x_1 - x_3) (x_2 - x_3) e^{-\frac{1}{2} x' x} \right), \quad x \in \mathbb{R}^3,
\]

where \( \beta = 1 \).

The \( cf \)

\[
\Psi_\beta(t) = \left( 1 + \beta t_1 (t_2 - t_3) e^{-\frac{1}{2} t' t} \right), \quad t_j \in \mathbb{R}, j = 2, 3, ...
\]

where \( t = (t_1, t_2, t_3)' \) are SUM2 univariate \( N(0, n) \), \( n \geq 2 \).

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The \( cf \)

\[
\Psi_\beta(t) = \left( 1 + \beta t_1 (t_2 - t_3) e^{-\frac{1}{2} t' t} \right), \quad t_j \in \mathbb{R}, j = 2, 3, ...
\]
where \( \beta = B^{-1} \) and

\[
\left| (x_1 - x_2)(x_1 - x_3)(x_2 - x_3) e^{-\frac{1}{2} \| x \|^2} \right| \leq B. \tag{10.15}
\]

The corresponding cdf is

\[
\psi_\beta(t) = e^{-\frac{1}{2} \| t \|^2} - \frac{1}{2\sqrt{2}} \beta_i (t_1 - t_2)(t_1 - t_3)(t_2 - t_3) e^{-\frac{1}{4\sqrt{2}} \| t \|^2}, \quad t \in \mathbb{R}^3,
\]

where \( t = (t_1, t_2, t_3)' \). Clearly \( f_\beta(x) \) is SUM3. It can be shown that \( f_\beta(x, x_j), \; i \neq j = 1, 2, 3 \) are SUM2 for all \( \beta \) satisfying (10.15). So, \( f_\beta(x) \) is a trivariate SUM distribution. The univariate marginals are \( N(0, 1) \), so the distributions of \( a'X \) where \( \sum_{k=1}^3 \rho_k = n \leq 3 \) are \( N(0, n) \), \( n = 2, 3 \), given by the independent trivariate normal model.

The following example is quite interesting in the sense that any subset of size \( r < n \) is s.i. but not independent.

**Example 10.5.** Let \( (X_1, X_2, \ldots, X_n) \) have pdf given by

\[
f_\beta(x) = \frac{1}{(2\pi)^{n/2} \sigma^n} e^{-\frac{1}{2} \| x \|^2} \left[ 1 + \frac{1}{(2c)^{n/2}} \left( x_2^2 - x_3^2 \right) \left[ 12c^2 - 2c \left( x_3^2 + x_1^2 \right) + x_1^2 x_2^2 \right] \right]
\]

where \( 0 < c < \frac{1}{2} \), \( \beta = B^{-1} \) and

\[
\left| \frac{1}{(2c)^{n/2}} \left( x_2^2 - x_3^2 \right) \left[ 12c^2 - 2c \left( x_3^2 + x_1^2 \right) + x_1^2 x_2^2 \right] \right| \leq B.
\]

The cdf for \( f_\beta \) is

\[
\psi_\beta(t_1, t_2, \ldots, t_n) = e^{-\frac{1}{2} \sum_{j=1}^n \| t_j \|^2} + \beta \sum_{j=1}^n \left( \sum_{k=1}^n \Pi_{i=1}^k (t_i - t_j) \right) e^{-\frac{1}{4c} \| t_j \|^2}, \quad (t_1, t_2, \ldots, t_n) \in \mathbb{R}^n.
\]

Then \( X_j's \) are s.i.i.d. \( N(0, 1) \). The same is also true for random vector \( (X_1, X_2, \ldots, X_j) \), \( j = 2, 3, \ldots, n - 1 \). So, \( X_1, X_2, \ldots, X_n \) indeed form a sequence of s.i.i.d rv's.
We conclude this section with a characterization of the multivariate SUM distribution.

**Theorem 10.8** Let \( \Phi_j, j = 1, 2, \ldots, n \) be cf's and let

\[
\Psi_\beta(t_1, t_2, \ldots, t_n) = \Pi_{j=1}^n \Phi_j(t_j) + \beta \cdot q(t_1, t_2, \ldots, t_n),
\]

where \( q(t), t \in \mathbb{R}^n \) is non-negative definite, continuous at the origin and \( q(t, t, \ldots, t) = 0 \) for \( t \in \mathbb{R} \). Then for some constant \( \beta \), \( \Psi_\beta \) is cf of a SUM distribution if \( |\Psi_\beta(t)| \leq 1 \) for all \( t \in \mathbb{R}^n \).

**Proof.** \( \Psi_\beta \) is non-negative definite, continuous at the origin and \( \Psi_\beta(0) = 1 \). Then by Bochner’s Theorem \( \Psi_\beta \) is a cf.

### 10.4 Equivalence of Sub-independence and Independence in a Special Case

The interesting question is that under what conditions sub-independence implies independence. It is possible to have an answer for this question if the underlying joint distribution has a specific form. The following result (Lemma 10.2), due to Ebrahimi et al. (2010), relates the SUM distributions to the well-known notions of POD (Positive Orthant Dependence) and NOD (Negative Orthant Dependence) defined below.

**Definition 10.6.** A multivariate distribution \( F \) is said to be POD (NOD) if

\[
\overline{F}(x_1, x_2, \ldots, x_p) \geq (\leq) \Pi_{i=1}^p \overline{F}_i(x_i),
\]

where \( \overline{F}(x_1, x_2, \ldots, x_p) = P(X_1 > x_1, X_2 > x_2, \ldots, X_p > x_p) \) and \( \overline{F}_i(x_i) = P(X_i > x_i) \).

It is known that under POD (NOD), if \( \rho(X_i, X_j) = 0 \) (correlation coefficient), then \( X_i \) and \( X_j \) are pairwise independent, without implying any higher order dependency among \( X_i \)'s. For details about POD (NOD) and other notions of dependence see Barlow and Proschan (1981).

**Lemma 10.2.** Let \( X = (X_1, X_2, \ldots, X_p)' \) be a nonnegative random vector with a POD (NOD) distribution \( F \). Then \( F \) is a SUM distribution if and only if \( F(x) = \Pi_{i=1}^p F_i(x_i) \), where \( F_i \) is cdf of \( X_i \).

### 10.5 Dissociation and Sub-independence

De Paula (2008), presented a bivariate distribution for which

\[
E(Y^n | X) = E(Y^n) \quad \text{and} \quad E(X^n | Y) = E(X^n), \quad n = 1, 2, \ldots
\]

**References**

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i.e., $X^*$ and $Y^*$ are uncorrelated for all positive integers $m$ and $n$, but $X$ and $Y$ are not independent. De Paula’s goal was to show a measure of dissociation between two dependent $rv$’s $X$ and $Y$ beyond the concept of uncorrelatedness of $X$ and $Y$. Hamedani and Volkmer (2009a, 2009b) showed that the $rv$’s considered in De Paula (2008) are not s.i. Then, they presented a bivariate distribution for which (10.16) holds, $X$ and $Y$ are s.i., but not independent. This provides a stronger measure of dissociation between $X$ and $Y$ (see Hamedani and Volkmer (2009b)).

ACKNOWLEDGEMENTS

The author is grateful to Barry Arnold and Hans Volkmer for their invaluable suggestion concerning the definition of sub-independent continuous random variables in terms of events.

REFERENCES


11.1 Introduction

Multi-array is a very versatile class of objects. It is in the state of a very active development and is expected to undergo a rapid development in the future. There are many other applications in areas such as image analysis, computer vision, information retrieval, and multi-channel signal processing. In algebraic terms, a tensor is a multi-linear object.