## PRELIMINARIES



The purpose of this chapter is to summarize necessary background on probability theory needed in this work.

### 2.1 Definitions and Well-Known Results

By a probability apace we mean a measure space ( $\Omega, \mathcal{F}, \mathrm{P}$ ) in which $P(\Omega)=1$. Here $\Omega$ is a set known as a sample space , Te is a Borel field of subsets of $\Omega$, sets in $\mathcal{T}_{\star}$ will be refered to as events and the measure p is call a probability measure.

By an m-dimensional random vector we mean a measurable function X from $\Omega$ into $\mathrm{R}^{\mathrm{m}}$. A 1-dimensional random vector is aleo called a random variable. If $X$ is an m-dimensional random vector , then for any $w \in \Omega$, we have $x(w)=\left(x^{1}(w), \ldots, x^{m}(w)\right)$, where $x^{1}, \ldots, x^{m}$ are the components of $x$. For any Borel measurable function $g: R^{m} \longrightarrow R$, the composition goX of $g$ with an m-dimensional random vector X is always a random variable. If the integral
$\int_{\Omega}$ goXdP exists, we call it the expectation of goX, and will be denoted by $E[g(x)]$. Let $g_{j}\left(x^{1}, \ldots, x^{m}\right)=x^{j}$. If the expectation $E\left\{\left\{g_{j}(x)-E\left[g_{j}(x)\right]\right\}\left\{g_{k}(x)-E\left\{g_{k}(x)\right\}\right\}\right\}$ exists, it will be called the covariance of $x^{j}$ and $x^{k}$, written $\operatorname{cov}\left(x^{j}, x^{k}\right)$ 。In general, 1, if $E\left[\prod_{j=1}^{m}\left(g_{j}(x)\right)^{r} j\right\}$ exists, we call it a product moment of $x$ of order $r_{1}+\ldots+r_{m}$, and will be denoted by

$$
M_{r_{1}, \ldots, r_{m}}^{\prime}(x)
$$

Theorem 2.1.1 Let $X$ be a random vector, and put

$$
\lambda_{k}=M_{k, 0, \ldots, 0}^{\prime}(\mathrm{x})+M_{0, k, 0, \ldots, 0}^{\prime}(\mathrm{x})+\ldots+\mathcal{M}_{0, \ldots, 0, \mathrm{k}}^{\prime}(\mathrm{x}) .
$$

Then, if the series $\sum_{k=1}^{\infty} \lambda_{2 k}^{-\frac{1}{2 k}}$ is divergent, the distribution $P$ of $X$ is uniquely determined by its moments.

A proof of this theorem can be found in [1].
Por any random variable $x$, let $x^{[r]}=x(x-1) \ldots(x-r+1)$ and $x^{[0]}=1$. If $E\left[\prod_{j=1}^{m}\left(g_{j}(x)\right)\left[r_{j}\right]\right]$ exists, it will be called a product factorial moment of $X$ of order $r_{1}+\ldots+r_{m}$, and will be denoted by $M_{\left[r_{1}\right] \ldots\left[r_{m}\right](x) \text {. It is well known that we can express }}^{\prime}$ (2.1.1) $M_{r_{1}, \ldots, r_{m}}^{\prime}(x)=\sum_{i_{1=1}^{n} \ldots}^{r_{1}} \sum_{i_{m}=1}^{r} a_{i_{1} \ldots i_{m}}^{\left.\mu_{\left[i_{1}\right.}^{\prime}\right] \ldots\left[i_{m}\right]}{ }^{\prime}(x)$, where $a_{i_{1}} \ldots i_{m}$ depend only on $r_{1}, \ldots, r_{m}$.

The characteristic function of a random vector $x$ is defined as $\varphi\left(t_{1}, \ldots, t_{m}\right)=E\left(e^{i t_{0} x}\right)$, where $t \in R^{m}, t_{0} x=t_{1} x^{1}+\ldots+t_{m} x^{m}$. Since $\left|e^{i t \cdot x}\right|=1$ for all $t \in R^{m}$, it follows that the characteristic function can be defined for every random vector. The generating function $G\left(t_{1}, \ldots, t_{m}\right)$, if it exists, is defined by $G\left(t_{1}, \ldots, t_{m}\right)=\varphi\left(\frac{\log t}{i} 1, \ldots, \frac{\log t}{i} m^{i}\right)$. It can be shown that, if $\mu_{\left[r_{1}\right] \ldots\left[r_{m}\right]}^{\prime}(X)$ exists, then for any non-negative integers $r_{1}, \ldots, r_{m}$


### 2.2 Convergence of Distributions of Random Vectors

A sequence $\left\{P_{n}\right\}$ is said to converge to the distribution $P$, and write $P \longrightarrow P$, if $\int_{n} f d P_{n} \Longrightarrow \int_{\Omega} f d P$ for every bounded, continuous real function $f$ on $\Omega$. Let $\left\{x_{n}\right\}$ be a sequence of random vectors, we say that $\left\{x_{n}\right\}$ converges in distribution to the random vector $X$, and write $X_{n} \xrightarrow{d}$, if the distribution $P_{n}$ of $X_{n}$ converges to the distribution $p$ of $X$.

Theorem 2.2.1 Let $\left\{x_{n}\right\}$ be a sequence of random vectors such that for any non-negative integers $r_{1}, \ldots, r_{m}$
(a)
 $r_{1}, \ldots, r_{m}\left(X_{n}\right)$, exist for all $n$;
(b) $\left|M_{r_{1}, \ldots, r_{m}}^{\prime}\left(x_{n}\right)\right| \leq k\left(r_{1}, \ldots, r_{m}\right)$ for all $n$;
(c) $\lim _{\mathrm{n} \rightarrow \infty} \mathcal{M}_{r_{1}, \ldots, r_{m}^{\prime}}^{\prime}\left(x_{n}\right)=M_{r_{1}, \ldots, r_{m}}^{\prime}$ exists ;
(d )there exists a random vector X with distribution P such that $M_{r_{1}, \ldots, r_{m}}^{\prime}(x)=M_{r_{1}, \ldots, r_{m}}^{\prime}$ and $P$ is uniquely determined by $\mu_{r_{1}, \ldots, r_{m}}^{\prime}$.

Then $\left\{x_{n}\right\}$ converges to $X$.
A proof of this theorem can be found in [5].

### 2.3 Multivariate Poisson Distribution

In this section we give a definition of multivariate Poisson distributions and some results about them .

First we introduce some notations . For any positive integer
m , let
(2.3.1) $\quad P_{m}=\{s / P \neq s \subseteq\{1,2, \ldots, m\}\}$

Throughout our discussion, we shall use $P_{m}$ as the index set of our parameters .

Definition 2.3.1 If a random vector X has the characteristic function
(2.3.2)

$$
\varphi\left(t_{1}, \ldots, t_{m}\right)=\exp \left[\sum_{s \in p_{m}}\left(a(s) \prod_{i \in s} z_{i}\right)-\sum_{s \in P_{m}} a(s)\right]
$$

where $a(s)$ are non-negative real numbers and $z_{\mathbf{j}}=\exp \left(i t_{j}\right)$, we say that it has a multivariate Poisson with parameters ass) 。

This definition is the same as that used by Carol E. Fuchs and H.T. David [2] . From (2.3.2), we have
(2.3.3) $G\left(t_{1}, \ldots, t_{m}\right)=\exp \left[\sum_{s \xi P_{m}}\left(a(s) \prod_{i \in s} t_{i}\right)-\sum_{s \in P_{m}} a(s)\right]$
from which the joint probability functions of $x^{1}, \ldots, x^{m}$ can be derived . We have
(2.3.4) $P\left(x^{1}=k_{1}, \ldots, x^{m}=k_{m}\right)=e^{-A m} \sum_{\substack{\sum_{j \in S} \alpha(s)=k_{j} \text { for all } j \\ \alpha(s) \geqq 0}} \frac{\left(a(s) P_{m}^{\alpha(s)}\right.}{\alpha(s)!}$,
where $A_{m}=\sum_{s \in P_{m}} a(s)$.
It can be shown that the distribution of a multivariate Poisson is uniquely determined by its moments $M_{r_{1}, \ldots, r_{m}}^{\prime}$. A proof of this fact can be found in [2].

The following theorem is an immediate consequence of
Theorem 2.2.1.
Theorem 2.3.1 Let X be a multivariate Poisson random vector . Let $\left\{x_{n}\right\}$ be a sequence of random vectors such that for any non-negative integers $r_{1}, \ldots, r_{m}$ (a) $\mathcal{Y}_{r_{1}, \ldots, r_{m}}^{\prime}\left(x_{n}\right)$, exist for all $n$;

(c') $\lim _{n \rightarrow \infty} \mu_{r_{1}}^{\prime}, \ldots, r_{m}\left(x_{n}\right)=\mu_{r_{1}, \ldots, r_{m}}^{\prime}(x)$.
Then $X_{n}$ converges to $x$.
By applying (2.1.1), we obtain a sufficient condition for convergence to a Poisson random vector in terms of factorial moments .

Theorem 2.3.2 Let $x$ be a multivariate Poisson random vector . Let $\left\{x_{n}\right\}$ be a sequence of random vectors such that for any non-negative integers $r_{1}, \ldots, r_{m}$

$$
\begin{aligned}
& \text { (a") } M_{\left(r_{1}\right] \ldots\left[r_{m}\right]}^{\prime}\left(x_{n}\right) \text {, exist for all } n ; \\
& \text { (b") }\left|M_{\left[r_{1}\right]}^{\prime} \ldots\left[r_{m}\right]\left(x_{n}\right)\right| \leqq K\left(r_{1}, \ldots, r_{m}\right) \text { for all } n \text {; }
\end{aligned}
$$

(c') $\lim _{n \rightarrow \infty} M^{\prime}\left(r_{1}\right] \ldots\left[r_{m}\right]_{n}^{\left(x_{n}\right)}=M_{\left[r_{1}\right]}^{\prime} \ldots\left[r_{m}\right]^{(x)} \cdot$
Then $X_{n}$ converges to $X$.
In order to apply the Theorem 2.3 .2 , we need to know the factorial moments of Poisson random vectors. . These are given in the following theorem.

Theorem 2.3.3 Let $x$ be an m-dimensional Poisson random vector with parameters $a(s), s \in P_{m}$. Then the factorial moments of $X$ are given by

where $r_{1}, \ldots, r_{m}$ are any nonnegative integers, and
$D=\left\{d / d: P_{m} \rightarrow\{0,1, \ldots 0\rangle \sum_{j \in s} d(s)=r_{j}\right\} \quad, \lambda(s)=\sum_{s \uparrow s^{i} \in P_{m}} a\left(s^{\prime}\right)$.
Proof Observe that

$$
\begin{aligned}
(2.3 .6) G\left(t_{1}, \ldots, t_{m}\right) & =\exp \left[\sum_{s \in P_{m E R S I}}\left(a(s) \prod_{i \in s_{i}}\right)-\sum_{s \in P_{m}} a(s)\right] \\
& =\exp \left[\sum_{s \in p_{m}} a(s)\left(\prod_{i \in s} t_{i}-1\right)\right]
\end{aligned}
$$

We shall show that for any $s \in P_{m}$
(2.3.7) $\prod_{i \in s} t_{i}-1=\sum_{\phi \neq s * s} \prod_{i \in s^{*}}\left(t_{i}-1\right)$.

We prove this by induction on the cardinality of $\mathrm{Se} \mathrm{P}_{\mathrm{m}}$. For $|s|=1$, it is clear that (2.3.7) holds . Assume that (2.3.7) holds for all $s \in P_{m}$ such that $|s|=k \geqslant 1$. Let $s^{\prime} \in P_{m}$ be such that $\left|s^{\prime}\right|=k+1$. We assume that $s^{\prime}=\left\{j_{1}, \ldots, j_{k+1}\right\}$ and let $s^{\prime \prime}=\left\{j_{1}, \ldots, j_{k}\right\}$.

Observe that

$$
\begin{aligned}
& \left(\prod_{j \in s,} t_{j}\right)-1=\left(\prod_{j \in s^{\prime}} t_{j}\right)-\left(\prod_{j \in s "} t_{j}\right)+\left(\prod_{j \in s^{\prime \prime}} t_{j}\right)-1 \\
& =\left(\prod_{j \in s^{\prime \prime}} t_{j}\right)\left(t_{j_{k+1}}-1\right)+\left(\prod_{j \in s^{\prime \prime}} t_{j}\right)-1 \\
& =\left(\prod_{j \in s^{\prime \prime}} t_{j}\right)\left(t_{j_{k+1}}-1\right)-\left(t_{j_{k+1}}-1\right)+\left(\prod_{j \in s^{\prime \prime}} t_{j}\right)-1+\left(t_{j_{j+1}}-1\right) \\
& =\left(t_{j_{k+1}}-1\right)\left(\Pi_{j \in s^{\prime \prime}} t_{j}-1\right)+\left(\prod_{j \in s^{\prime \prime}} t_{j}-1\right)+\left(t_{j_{k+1}}-1\right)
\end{aligned}
$$

$$
\begin{aligned}
& +\left(t j_{k+1}-1\right) \\
& =\sum_{\phi \neq s^{* s} s^{\prime} j \varepsilon s *} \prod_{j}\left(t_{j}-1\right) \text {. }
\end{aligned}
$$

Hence (2.3.7) holds for all $s \in P$.
By using (2.3.7) it follows from $(2.3 .6)$ that

$$
\begin{aligned}
& G\left(t_{1}, \ldots, t_{m}\right)=\exp \left[\sum_{s \in P_{m}} a(s)\left(\sum_{\hat{c} \neq s^{*} \subseteq \text { si } \in S^{*}}\left(t_{i}-1\right)\right)\right]
\end{aligned}
$$

$$
\begin{aligned}
& =\exp \left[\sum_{s^{*} \in P_{m}} \sum_{s^{*} \leq s \in P_{m}} a(s) \prod_{\text {i\& } s^{*}}\left(t_{i}-1\right)\right] \\
& =\exp \left[\sum_{s^{*} \notin P_{m}}\left(\sum_{s^{*} \subsetneq s \in P_{m}} a(s)\right) \prod_{i \in s^{*}}\left(t_{i}-1\right)\right] \\
& =\exp \left\{\sum_{s^{*} \in \mathrm{P}_{\mathrm{m}}} \lambda\left(s^{*}\right) \prod_{i \in s^{*}}\left(t_{i}-1\right)\right] \\
& =\sum_{n=0}^{\infty}\left[\sum_{s^{*} \in P_{m}} \lambda\left(s^{*}\right) \prod_{i \in s^{*}}\left(t_{i}-1\right)\right]^{n} / n!
\end{aligned}
$$

$$
\begin{aligned}
=\sum_{n=0}^{\infty}\left[\sum_{\sum_{s^{*} \in P_{m}}^{\alpha\left(s^{*}\right)=n}\{ }\left\{\prod_{\alpha^{*} s^{*} \in P_{m}}\left(\lambda\left(s^{*}\right) \prod_{i \in S^{*}}\left(t_{i}-1\right)\right)^{\alpha\left(s^{*}\right)} n!\right\} / \prod_{s^{*} \in P_{m}}\left(\alpha\left(s^{*}\right)!\right)|n!|\right.
\end{aligned}
$$

$$
=\sum_{n=0}^{\infty} \sum_{\substack{s^{*} \in P_{m} \\ \alpha\left(s^{*}\right) 刃 0}} \prod_{\left.\sum^{*}\right)=n} \frac{\left(\lambda\left(s^{*}\right)\right)^{\alpha(s *)}}{\alpha\left(s^{*}\right)!} \prod_{j=1}^{m}\left(t_{j}-1\right)^{\sum_{j k s^{*}} \alpha\left(s^{*}\right)}
$$

$$
=\sum_{k=0}^{\infty} \cdots \sum_{k=0}^{\infty} \sum_{j \in s^{*}}^{\infty} \alpha\left(s^{*}\right)=k_{j}, \text { for } \text { all } \prod_{s^{*} \in P_{m}} \frac{\left(\lambda\left(s^{*}\right)\right)^{\alpha\left(s^{*}\right)}}{\alpha\left(s^{*}\right)!} \prod_{j=1}^{m}\left(t_{j}-1\right)^{j} .
$$

Hence

$$
\left|t_{j}\right|<1, j=1, \ldots, m .
$$

Therefore

$$
\begin{aligned}
& \lim _{t \rightarrow \overline{1}}^{j=1, \ldots, m} \frac{\partial r_{1}+\ldots+r_{m}}{\partial t_{m} \ldots \partial t_{1}}\left(G\left(t_{1}, \ldots, t_{m}\right)\right. \\
& =\sum_{\substack{j \in s \\
\alpha(s) \geqslant 0}} \alpha(s)=r_{j} \text { for all } j, \prod_{s \in P_{m} \frac{(\lambda(s))}{\alpha(s)!}}^{\prod_{j=1}^{m} r_{j}} r_{j}
\end{aligned}
$$

$$
\begin{aligned}
& \frac{\partial r_{1}+\ldots+r_{m}}{\partial t_{m}^{r_{m}} \ldots \partial t_{1}}\left(G\left(t_{1}, \ldots, t_{m}\right) \quad\right. \text { (b) }
\end{aligned}
$$

$$
\begin{aligned}
& =\sum_{\substack{j \in s \\
\alpha(s) \geq 0}} \prod_{j(s)=r_{j}} \text { for all } j, r_{j=1}^{m} \prod_{s \in P_{m}} \frac{(\lambda(s))}{\alpha(s)!} \\
& =\sum_{d \in D} \prod_{j=1}^{m}\left(r_{j}!\right) \prod_{s \in P_{m}} \frac{\Omega(s))}{d(s)!}
\end{aligned}
$$

By (2.1.2), we have (2.3.5)
2.4 Factorial Moments/of Zero-One Random Vectors

Our main theorem of chapter III, deals with random vectors whose components $X_{i}^{j}$ can take only the values 0 or 1 . For such random variables we always have $X_{i}^{j}\left(X_{i}^{j}-1\right)=0$ identically . This identity gives us a useful identity which will be needed in the computation of factorial moments of such random vectors .

Lemma 2.4.1 If $X_{i}^{j}=0$ or 1 for all $i=1, \ldots, n j=1, \ldots, m$, then for any non-negative integers $r_{1}, \ldots, r_{m}$ such that $r_{1}+\ldots+r_{m} \geqq 1$, we have
(2.4.1) $\prod_{j=1}^{m}\left[\sum_{i=1}^{n} x_{i}^{j}\right]^{\left[r_{j}\right]}$

$$
\begin{aligned}
& i_{j 1} \text { are distinct, } j=1, \ldots, m
\end{aligned}
$$

Proof First we prove that, if $r_{j} \geqslant 1$, then

$$
\text { (2.4.2) } \begin{aligned}
{\left[\sum_{i=1}^{n} x_{i}^{j}\right)^{\left(r_{j}\right)}=} & \sum_{i_{j=1}^{n} 1}^{n} \cdots \sum_{i_{j \bar{r}_{j}^{1}}^{n}}^{n} x_{i j}^{j} \ldots x_{i j r}^{j} . \\
& i_{j 1} \text { are distinct }
\end{aligned} .
$$

Since $\left[\sum_{1=1}^{n} x_{i}^{j}\right]^{[1]}=\sum_{i=1}^{n} x_{i}^{j}$, hence (2.4.2) holds for $r_{j}=1$.
Assume that (2.4.2) holds for $r_{j}=k \geqq 1$ 。
Observe that

$$
+\cdots+\sum_{i_{j} \bar{i}^{1}}^{n} \cdots \sum_{i_{j=1}}^{n} x_{i}^{n} \ldots x_{i 1}^{j}\left(x_{i j k}^{j}-1\right) .
$$

$$
i_{j l} \text { are distinct }
$$

$$
\begin{aligned}
& {\left[\sum_{i=1}^{n} x_{i}^{j}\right]^{\{k+1]}=\left[\sum_{i=1}^{n} x_{i}^{j}\right\}[k]\left[\left\{\sum_{i=1}^{n} x_{i}^{j}-k\right\}\right.} \\
& \begin{aligned}
= & \left\{\sum_{i_{j=1}^{n}}^{n} \cdots \sum_{i_{j k}^{1}}^{n} x_{i j 1} \ldots x_{i j k}^{j}\right\}\left\{\sum_{i=1}^{n} x_{i}^{j}-k\right\} \\
& i_{j 1} \text { are distinct }
\end{aligned}
\end{aligned}
$$

$$
\begin{aligned}
& =\sum_{i_{j}=1}^{n} \cdots \sum_{i_{j \bar{k}}^{1}}^{n}\left\{\left(x_{i_{j 1}^{j}}^{j} \ldots x_{i}^{j}\right)\left(\sum_{i_{j k} \bar{\tau} \bar{k}+1}^{n} x_{i}^{j}+\left(x_{i}^{j}-1\right)+\ldots+\left(x_{i}^{j}-1\right)\right\}\right. \\
& i_{j 1} \text { are distinct } \quad i_{j(k+1)} \neq i_{j 1}, \ldots, i_{j k}
\end{aligned}
$$

$$
\begin{aligned}
& i_{j l} \text { are distinct } \quad i_{j l} \text { are distinct }
\end{aligned}
$$

$$
\begin{aligned}
&= \sum_{i_{j=1}=1}^{n} \cdots \sum_{i_{j(k+1)}}^{n} x_{i_{j 1}^{j}}^{j} \ldots x_{i_{j(k+1)}^{j}} \\
& i_{j 1} \text { are distinct }
\end{aligned}
$$

The last equality follows from the fact that $x_{i}^{j}\left(x_{i}^{j}-1\right)=0$. Hence (2.4.2) holds for any positive integer $r_{j}$. Observe that for any non-negative integers $r_{1}, \ldots, r_{m}$ such that $r_{1}+\ldots+r_{m} \geqq 1$

i $_{j 1}$ are distinct $j=1, \ldots, m$
Theorem 2.4.1 Let $x_{i}=\left(x_{i}^{1}, \ldots, x_{i}^{m}\right), i=1, \ldots, n$ be m-dimensional random vectors where the components can take only the values 0 or 1 . Let $S_{n}=X_{1}+\ldots+X_{n}$. Then for any nonnegative integers $r_{1}, \ldots, r_{m}$ such that $r_{1}+\ldots+r_{m} \geqq 1$, we have

 $i_{j l}$ are distinct $j=1, \ldots, m$

Proof For any non-negative integers $r_{1}, \ldots, r_{m}$
$(2.4 .4) M_{\left[r_{1}\right] \ldots\left[r_{m}\right]}^{\prime}\left(s_{n}\right)=E\left(\prod_{j=1}^{m}\left[\sum_{i=1}^{n} x_{i}^{j}\right]^{\left[r_{j}\right]}\right)$.
Applying the Lemma 2.4.1 to (2.4.4) , we have
$(2.4 .5) \mathcal{M}^{\prime}{ }_{\left[r_{1}\right] \ldots\left[r_{m}\right]^{\left(S_{n}\right)}, ~}$
 $i_{j 1}$ are distinct $j=1, \ldots, m$
 $i_{j 1}$ are distinct $j=1, \ldots, m$

$1_{j l}$ are distinct $j=1, \ldots, m$

