## Moment Generating Functions

Let $X$ be a simple random variable asssuming the distinct values $x_{1}, \ldots, x_{l}$ with respective probabilities $p_{1}, \ldots, p_{l}$. Its moment generating function is

$$
\begin{equation*}
M(t)=E\left[e^{t X}\right]=\sum_{i=1}^{l} p_{i} e^{t x_{i}} \tag{9.1}
\end{equation*}
$$

(See (5.19) for expected values of functions of random variables.) This function, defined for all real $t$, can be regarded as associated with $X$ itself or as associated with its distribution-that is, with the measure on the line having mass $p_{i}$ at $x_{i}$ (see (5.12)).

If $c=\max _{i}\left|x_{i}\right|$, the partial sums of the series $e^{t X}=\sum_{k=0}^{\infty} t^{k} X^{k} / k$ ! are bounded by $e^{i t c c}$, and so the corollary to Theorem 5.4 applies:

$$
\begin{equation*}
M(t)=\sum_{k=0}^{\infty} \frac{t^{k}}{k!} E\left[X^{k}\right] \tag{9.2}
\end{equation*}
$$

Thus $M(t)$ has a Taylor expansion, and as follows from the general theory [A29], the coefficient of $t^{k}$ must be $M^{(k)}(0) / k$ ! Thus

$$
\begin{equation*}
E\left[X^{k}\right]=M^{(k)}(0) \tag{9.3}
\end{equation*}
$$

Furthermore, term-by-term differentiation in (9.1) gives

$$
M^{(k)}(t)=\sum_{i=1}^{l} p_{i} x_{i}^{k} e^{t x}=E\left[X^{k} e^{t X}\right]
$$

taking $t=0$ here gives (9.3) again. Thus the moments of $X$ can be calculated by successive differentiation, whence $M(t)$ gets its name. Note that $M(0)=1$.

Example 9.1. If $X$ assumes the values 1 and 0 with probabilities $p$ and $q=1-p$, as in Bernoulli trials, its moment generating function is $M(t)=$ $p e^{t}+q$. The first two moments are $M^{\prime}(0)=p$ and $M^{\prime \prime}(0)=p$, and the variance is $p-p^{2}=p q$.

If $X_{1}, \ldots, X_{n}$ are independent, then for each $t$ (see the argument follow$\operatorname{ing}(5.10)), e^{t X_{1}}, \ldots, e^{t X_{n}}$ are also independent. Let $M$ and $M_{1}, \ldots, M_{n}$ be the respective moment generating functions of $S=X_{1}+\cdots+X_{n}$ and of $X_{1}, \ldots, X_{n}$; of course, $e^{t S}=\Pi_{i} e^{t X_{i}}$. Since by (5.25) expected values multiply for independent random variables, there results the fundamental relation

$$
\begin{equation*}
M(t)=M_{1}(t) \cdots M_{n}(t) \tag{9.4}
\end{equation*}
$$

This is an effective way the sum $S$. The real intere so it is important to know from their moment generat

Consider along with ( 9.1 and suppose that $M(t)=N$ $M(t) \sim p_{i_{0}} e^{i x_{i_{0}}}$ and $N(t) \sim c_{c}$ same argument now applies tively that with appropriat the function (9.1) does uniql

Example 9.2. If $X_{1}, \ldots$, 0 with probabilities $p$ anc successes in $n$ Bernoulli tri generating function

$$
E\left[e^{t S}\right]=(
$$

The right-hand form shows distribution with mass $\binom{n}{k} p^{k}$ just established therefore yis

The cumulant generating
$C(t)$
(Note that $M(t)$ is strictly $\left.\left(M^{\prime}\right)^{2}\right) / M^{2}$, and since $M(0)$

$$
\begin{equation*}
C(0)=0, \quad C \tag{9.6}
\end{equation*}
$$

Let $m_{k}=E\left[X^{k}\right]$. The lead expansion of the logarithm i

$$
\begin{equation*}
C(t)= \tag{9.7}
\end{equation*}
$$

Since $M(t) \rightarrow 1$ as $t \rightarrow 0$, thi of 0 . By the theory of series

This is an effective way of calculating the moment generating function of the sum $S$. The real interest, however, centers on the distribution of $S$, and so it is important to know that distributions can in principle be recovered from their moment generating functions.

Consider along with (9.1) another finite exponential sum $N(t)=\sum_{j} q_{j} e^{t y_{j}}$, and suppose that $M(t)=N(t)$ for all $t$. If $x_{i_{0}}=\max x_{i}$ and $y_{j_{0}}=\max y_{j}$, then $M(t) \sim p_{i_{0}} e^{i x_{i_{0}}}$ and $N(t) \sim q_{j_{0}} e^{t y_{j_{0}}}$ as $t \rightarrow \infty$, and so $x_{i_{0}}=y_{j_{0}}$ and $p_{i_{0}}=q_{i_{0}}$. The same argument now applies to $\sum_{i \neq i_{0}} p_{i} e^{t x_{i}}=\sum_{j \neq j_{0}} q_{j} e^{t y_{j}}$, and it follows inductively that with appropriate relabeling, $x_{i}=y_{i}$ and $p_{i}=q_{i}$ for each $i$. Thus the function (9.1) does uniquely determine the $x_{i}$ and $p_{i}$.

Example 9.2. If $X_{1}, \ldots, X_{n}$ are independent, each assuming values 1 and 0 with probabilities $p$ and $q$, then $S=X_{1}+\cdots+X_{n}$ is the number of successes in $n$ Bernoulli trials. By (9.4) and Example 9.1, $S$ has the moment generating function

$$
E\left[e^{t S}\right]=\left(p e^{t}+q\right)^{n}=\sum_{k=0}^{n}\binom{n}{k} p^{k} q^{n-k} e^{t k}
$$

The right-hand form shows this to be the moment generating function of a distribution with mass $\binom{n}{k} p^{k} q^{n-k}$ at the integer $k, 0 \leq k \leq n$. The uniqueness just established therefore yields the standard fact that $P[S=k]=\binom{n}{k} p^{k} q^{n-k}$.

The cumulant generating function of $X$ (or of its distribution) is

$$
\begin{equation*}
C(t)=\log M(t)=\log E\left[e^{t X}\right] \tag{9.5}
\end{equation*}
$$

(Note that $M(t)$ is strictly positive.) Since $C^{\prime}=M^{\prime} / M$ and $C^{\prime \prime}=\left(M M^{\prime \prime}-\right.$ $\left.\left(M^{\prime}\right)^{2}\right) / M^{2}$, and since $M(0)=1$,

$$
\begin{equation*}
C(0)=0, \quad C^{\prime}(0)=E[X], \quad C^{\prime \prime}(0)=\operatorname{Var}[X] \tag{9.6}
\end{equation*}
$$

Let $m_{k}=E\left[X^{k}\right]$. The leading term in (9.2) is $m_{0}=1$, and so a formal expansion of the logarithm in (9.5) gives

$$
\begin{equation*}
C(t)=\sum_{v=1}^{\infty} \frac{(-1)^{v+1}}{v}\left(\sum_{k=1}^{\infty} \frac{m_{k}}{k!} t^{k}\right)^{v} \tag{9.7}
\end{equation*}
$$

Since $M(t) \rightarrow 1$ as $t \rightarrow 0$, this expression is valid for $t$ in some neighborhood of 0 . By the theory of series, the powers on the right can be expanded and

