## 1 Moment generating functions - supplement to chap 1

The moment generating function (mgf) of a random variable $X$ is

$$
\begin{equation*}
M_{X}(t)=E\left[e^{t X}\right] \tag{1}
\end{equation*}
$$

For most random variables this will exist at least for $t$ in some interval containing the origin. The mgf is a computational tool. By taking derivatives and evaluating them at $t=0$ you can compute moments:

$$
\begin{equation*}
M^{\prime}(0)=E[X], \quad M^{\prime \prime}(0)=E\left[X^{2}\right], \quad M^{(k)}(0)=E\left[X^{k}\right] \tag{2}
\end{equation*}
$$

If $Y=a X+b$ for constants $a$ and $b$, then

$$
\begin{equation*}
M_{Y}(t)=e^{b t} M_{X}(a t) \tag{3}
\end{equation*}
$$

If $X_{1}, X_{2}, \cdots X_{n}$ are independent and $Y=X_{1}+\cdots X_{n}$, then

$$
\begin{equation*}
M_{Y}(t)=M_{X_{1}}(t) M_{X_{2}}(t) \cdots M_{X_{n}}(t) \tag{4}
\end{equation*}
$$

### 1.1 Discrete distributions

Bernouilli distribution: This is a random variable $X$ that only equals 0 and 1. The parameter $p$ is $P(X=1)$.

$$
\begin{equation*}
E[X]=p, \quad \operatorname{Var}(X)=p(1-p), \quad M(t)=(1-p)+p e^{t} \tag{5}
\end{equation*}
$$

Binomial distribution: Flip a coin $n$ times, $X$ is the number of heads, $p$ is the probability of heads.

$$
\begin{gather*}
f(x \mid n, p)=\binom{n}{x} p^{x}(1-p)^{n-x}, \quad x=0,1,2, \cdots, n  \tag{6}\\
E[X]=n p, \quad \operatorname{Var}(X)=n p(1-p), \quad M(t)=\left[(1-p)+p e^{t}\right]^{n} \tag{7}
\end{gather*}
$$

Note that the binomial random variable is the sum of $n$ independent Bernoulli random variables with the same $p$.

Poisson: For $\lambda>0$,

$$
\begin{gather*}
f(x \mid \lambda)=\frac{e^{-\lambda} \lambda^{x}}{x!}, \quad x=0,1,2, \cdots  \tag{8}\\
E[X]=\lambda, \quad \operatorname{Var}(X)=\lambda, \quad M(t)=\exp \left(\lambda\left(e^{t}-1\right)\right) \tag{9}
\end{gather*}
$$

Geometric: Flip a coin until we get heads for the first time. $X$ is the number of tails we get before this first heads.

$$
\begin{gather*}
f(x \mid p)=p(1-p)^{x}, \quad x=0,1,2, \cdots  \tag{10}\\
E[X]=\frac{1-p}{p}, \quad \operatorname{Var}(X)=\frac{1-p}{p^{2}}, \quad M(t)=\frac{p}{1-(1-p) e^{t}} \tag{11}
\end{gather*}
$$

Warning: some people define $X$ to be the total number of flips including the one that gave you the first head.
Negative binomial: Flip a coin until we get heads for the $k$ th time. $X$ is the number of flips including the flip on which the $k$ th head happened.

$$
\begin{equation*}
E[X]=\frac{k(1-p)}{p}, \quad \operatorname{Var}(X)=\frac{k(1-p)}{p^{2}}, \quad M(t)=\left(\frac{p}{1-(1-p) e^{t}}\right)^{k} \tag{12}
\end{equation*}
$$

Warning: some people define $X$ to be the total number of flips including the ones that gave you the first $k$ heads.

### 1.2 Continuous distributions

Normal: For $\sigma>0$ and any $\mu$,

$$
\begin{align*}
& f(x \mid \mu, \sigma)=\frac{1}{\sigma \sqrt{2 \pi}} \exp \left(\frac{-(x-\mu)^{2}}{2 \sigma^{2}}\right), \quad-\infty<x<\infty  \tag{13}\\
& E[X]=\mu, \quad \operatorname{Var}(X)=\sigma^{2}, \quad M(t)=\exp \left(\mu t+\frac{1}{2} \sigma^{2} t^{2}\right) \tag{14}
\end{align*}
$$

Exponential: For $\lambda>0$,

$$
\begin{gather*}
f(x \mid \lambda)=\lambda e^{-\lambda x}, \quad x \geq 0  \tag{15}\\
E[X]=\frac{1}{\lambda}, \quad \operatorname{Var}(X)=\frac{1}{\lambda^{2}}, \quad M(t)=\frac{\lambda}{\lambda-t} \tag{16}
\end{gather*}
$$

Gamma: For $\alpha, \beta>0$,

$$
\begin{equation*}
f(x \mid \alpha, \beta)=\frac{\beta^{\alpha}}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x}, \quad x \geq 0 \tag{17}
\end{equation*}
$$

If $\alpha$ is an integer, $\Gamma(\alpha)=(\alpha-1)$ !.

$$
\begin{equation*}
E[X]=\frac{\alpha}{\beta}, \quad \operatorname{Var}(X)=\frac{\alpha}{\beta^{2}}, \quad M(t)=\left(\frac{\beta}{\beta-t}\right)^{\alpha} \tag{18}
\end{equation*}
$$

This shows that the sum of $k$ independent exponential random variables with parameter $\lambda$ has a gamma distribution with $\alpha=k$ and $\beta=\lambda$.
Warning: Some people parameterize the gamma distribution differently. Their $\beta$ is my $1 / \beta$.
Chi-squared or $\chi^{2}$ : Let $Z_{1}, Z_{2}, \cdots, Z_{n}$ be independent standard normal RV's. Let

$$
\begin{equation*}
X=\sum_{i=1}^{n} Z_{i}^{2} \tag{19}
\end{equation*}
$$

Then $X$ has the chi-squared distribution with $n$ degrees of freedom. It can be shown that this is the gamma distribution with $\alpha=n / 2$ and $\beta=1 / 2$. So the pdf is

$$
\begin{gather*}
f(x \mid n)=\frac{1}{2^{n / 2} \Gamma(n / 2)} x^{n / 2-1} e^{-x / 2}, \quad x \geq 0  \tag{20}\\
E[X]=n, \quad \operatorname{Var}(X)=2 n, \quad M(t)=\left(\frac{1}{1-2 t}\right)^{n / 2} \tag{21}
\end{gather*}
$$

Note that the sum of independent chi-squared is again with chi-squared with the number of degree of freedom adding.
Student's t: Let $U$ and $V$ be independent random variables. $U$ has a standard normal distribution, and $V$ has a chi-square distribution with $n$ degrees of freedom. Let

$$
\begin{equation*}
T=\frac{U}{\sqrt{V / n}} \tag{22}
\end{equation*}
$$

The distribution of $T$ is called Student's $t$ distribution (or just the $t$ distribution) with $n$ degrees of freedom. The pdf is

$$
\begin{equation*}
f(x \mid n)=\frac{\Gamma\left(\frac{n+1}{2}\right)}{(n \pi)^{1 / 2} \Gamma\left(\frac{n}{2}\right)}\left(1+\frac{x^{2}}{n}\right)^{-(n+1) / 2}, \quad-\infty<x<\infty \tag{23}
\end{equation*}
$$

The mgf is not defined.

