## Functions of a Random Variable \& Moment Generating Functions - Prof. Richard B. Goldstein

## Discrete

$\mathrm{Y}=\mathrm{u}(\mathrm{X})$ is a one-to-one (1-1) transform
Let $\mathrm{y}=\mathrm{u}(\mathrm{x})$ and the inverse $\mathrm{x}=\mathrm{w}(\mathrm{y})$. Then $\mathrm{g}(\mathrm{y})=\mathrm{f}[\mathrm{w}(\mathrm{y})]$ is the probability distribution of Y
$\mathrm{Y}_{1}=\mathrm{u}_{1}\left(\mathrm{X}_{1}, \mathrm{X}_{2}\right)$ and $\mathrm{Y}_{2}=\mathrm{u}_{2}\left(\mathrm{X}_{1}, \mathrm{X}_{2}\right)$ are 1-1 transforms
Let $\mathrm{y}_{1}=\mathrm{u}_{1}\left(\mathrm{x}_{1}, \mathrm{x}_{2}\right)$ and $\mathrm{y}_{2}=\mathrm{u}_{2}\left(\mathrm{x}_{1}, \mathrm{x}_{2}\right)$ have inverse functions $\mathrm{x}_{1}=\mathrm{w}_{1}\left(\mathrm{y}_{1}, \mathrm{y}_{2}\right)$ and $\mathrm{x}_{2}=\mathrm{w}_{2}\left(\mathrm{y}_{1}, \mathrm{y}_{2}\right)$
Then $g\left(y_{1}, y_{2}\right)=f\left[w_{1}\left(y_{1}, y_{2}\right), w_{2}\left(y_{1}, y_{2}\right)\right]$

## Continuous

As above, but now $\mathrm{g}(\mathrm{y})=\mathrm{f}[\mathrm{w}(\mathrm{y})]|\mathrm{J}|$ where $\mathrm{J}=\mathrm{w}^{\prime}(\mathrm{y})$ is the Jacobian of the transform
Also as above, but now $\mathrm{g}\left(\mathrm{y}_{1}, \mathrm{y}_{2}\right)=\mathrm{f}\left[\mathrm{w}_{1}\left(\mathrm{y}_{1}, \mathrm{y}_{2}\right), \mathrm{w}_{2}\left(\mathrm{y}_{1}, \mathrm{y}_{2}\right)\right]|\mathrm{J}|$
where $J$ is given by the 2 by 2 determinant: $J=\left|\begin{array}{ll}\frac{\partial x_{1}}{\partial y_{1}} & \frac{\partial x_{1}}{\partial y_{2}} \\ \frac{\partial x_{2}}{\partial y_{1}} & \frac{\partial x_{2}}{\partial y_{2}}\end{array}\right|$
Note: These concepts basically follow the rules for integral substitution or transforms in two variables

## Moments

$r^{\text {th }}$ moment about the origin $\mu_{r}^{\prime}=E\left(X^{r}\right)=\left\{\begin{array}{l}\sum_{x} x^{r} f(x) \text { if } X \text { is discrete } \\ \int_{-\infty}^{\infty} x^{r} f(x) d x \text { if } X \text { is continuous }\end{array}\right.$
moments can also be taken about the mean - for example the variance is the $2^{\text {nd }}$ moment about the mean moment generating functions and their properties
$M_{X}(t)=E\left(e^{t x}\right)=\left\{\begin{array}{l}\sum_{x} e^{t x} f(x) \text { if } X \text { is discrete } \\ \int_{-\infty}^{\infty} e^{t x} f(x) d x \text { if } X \text { is continuous } \quad \frac{d^{r} M_{X}(t)}{d t^{r}}=\mu_{r}^{\prime},\end{array}\right.$
If two r.v.'s have the same moment generating functions, then they have the same probability dist.
$\mathrm{M}_{\mathrm{X}+\mathrm{a}}(\mathrm{t})=\mathrm{e}^{\mathrm{at}} \mathrm{M}_{\mathrm{X}}(\mathrm{t})$
If $S_{n}=\sum_{i=1}^{n} a_{i} X_{i}$ then $M_{S_{n}}(t)=M_{X_{1}}\left(a_{1} t\right) M_{X_{2}}\left(a_{2} t\right) \cdots M_{X_{n}}\left(a_{n} t\right)$

| Discrete Distribution | Probability Function | Moment Generating <br> Function |
| :---: | :---: | :---: |
| Binomial | $\mathrm{f}(\mathrm{x})=\binom{\mathrm{n}}{\mathrm{x}} \mathrm{p}^{\mathrm{x}}(1-\mathrm{p})^{\mathrm{n-x}}, \mathrm{x}=0,1, \ldots, \mathrm{n}$ | $\left[\mathrm{pe}^{\mathrm{t}}+(1-\mathrm{p})\right]^{\mathrm{n}}$ |
| Geometric | $\mathrm{f}(\mathrm{x})=\mathrm{p}(1-\mathrm{p})^{\mathrm{x}-1}, \mathrm{x}=1,2, \ldots$ | $\frac{\mathrm{pe}^{t}}{1-(1-\mathrm{p}) \mathrm{e}^{t}}$ |
| Poisson | $\mathrm{f}(\mathrm{x})=\frac{\lambda^{x} \mathrm{e}^{-\lambda}}{\mathrm{x}!}, \mathrm{x}=0,1, \ldots$ | $\exp \left[\lambda\left(\mathrm{e}^{\mathrm{t}}-1\right)\right]$ |


| Continuous <br> Distribution | Probability Function | Moment Generating <br> Function |
| :---: | :---: | :---: |
| Uniform | $\mathrm{f}(\mathrm{x})=\frac{1}{\mathrm{~b}-\mathrm{a}}, \mathrm{a} \leq \mathrm{x} \leq \mathrm{b}$ | $\frac{\mathrm{e}^{\mathrm{bt}}-\mathrm{e}^{\mathrm{at}}}{\mathrm{t}(\mathrm{b}-\mathrm{a})}$ |
| Normal | $\mathrm{f}(\mathrm{x})=\frac{1}{\sigma \sqrt{2 \pi}} \exp \left[-\frac{(\mathrm{x}-\mu)^{2}}{2 \sigma^{2}}\right],-\infty<\mathrm{x}<\infty$ | $\exp \left(\mu \mathrm{t}+\frac{\mathrm{t}^{2} \sigma^{2}}{2}\right)$ |
| Exponential | $\mathrm{f}(\mathrm{x})=\frac{1}{\beta} \mathrm{e}^{-\mathrm{x} / \beta}, \beta>0,0 \leq \mathrm{x}<\infty$ | $(1-\beta \mathrm{t})^{-1}$ |
| Gamma | $\mathrm{f}(\mathrm{x})=\frac{\mathrm{x}^{\alpha-1} \mathrm{e}^{-\mathrm{ex/} \mathrm{\beta}}}{\Gamma(\alpha) \beta^{\alpha}}, 0<\mathrm{x}<\infty$ | $(1-\beta \mathrm{t})^{-\alpha}$ |
| Chi-Square | $\mathrm{f}(\mathrm{x})=\frac{\mathrm{x}^{(v / 2)-1} \mathrm{e}^{-\mathrm{x} / 2}}{\Gamma(v / 2) 2^{v / 2}}, 0<\mathrm{x}<\infty$ | $(1-2 \mathrm{t})^{-\mathrm{v} / 2}$ |

The moment generating functions for hypergeometric, beta, and lognormal distributions either do not exist or are too complicated to express in closed form.

