# Lecture Note 5 * Random Variable/Vector Transformation 

MIT 14.30 Spring 2006
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## 13 Function of a Random Variable (Univariate Model)

### 13.1 Discrete Model

Let $X$ be a discrete random variable with $\operatorname{pmf} f_{X}(x)$. Define a new random variable $Y$ as a function of $X, Y=r(X)$. The pmf of $Y, f_{Y}(y)$, is derived as follows:

$$
\begin{equation*}
f_{Y}(y)=P(Y=y)=P[r(X)=y]=\sum_{x: r(x)=y} f_{X}(x) \tag{31}
\end{equation*}
$$

Example 13.1. Find $f_{Y}(y)$, where $Y=X^{2}$ and $P(X=x)=0.2$ for $x=-2,-1,0,1,2,0$ if otherwise.

[^0]
### 13.2 Continuous Model

### 13.2.1 2-Step Method

Let $X$ be a random variable with pdf $f_{X}(x)$. Define a new random variable $Y$ as a function of $X, Y=r(X)$. The pdf of $Y, f_{Y}(y)$, is derived as follows:

$$
\begin{align*}
& 1^{\text {st }} \text { step : } F_{Y}(y)=P(Y \leq y)=P[r(X) \leq y]=\int_{x: r(x) \leq y} f_{X}(x) d x \\
& 2^{\text {nd }} \text { step : } f_{Y}(y)=\frac{d F_{Y}(y)}{d y} \quad \text { (at every point } F_{Y}(y) \text { is differentiable). } \tag{32}
\end{align*}
$$

Example 13.2. Find $f_{Y}(y)$, where $Y=X^{2}$ and $X \sim U[-1,1]$.

### 13.2.2 1-Step Method

Let $X$ be a random variable with pdf $f_{X}(x)$. Define the set $\mathcal{X}$ as all possible values of $X$ such that $f_{X}(x)>0\left[\mathcal{X}=\left\{x: f_{X}(x)>0\right\}\right.$; for example: $\left.a<X<b\right]$.

Define a new random variable $Y$, such that $Y=r(X)$, where $r()$ is a strictly monotone function (increasing or decreasing) and a differentiable (and thus continuous) function of $X$. Then, the pdf of $Y, f_{Y}(y)$, is derived as follows:

$$
f_{Y}(y)= \begin{cases}f_{X}\left(r^{-1}(y)\right)\left|\frac{\partial r^{-1}(y)}{\partial y}\right|, & \text { for } y \in \mathcal{Y} \subseteq R  \tag{33}\\ 0, & \text { otherwise }\end{cases}
$$

Where the set $\mathcal{Y}$ is defined as: $\mathcal{Y}=\{y: y=r(x)$ for all $x \in \mathcal{X}\}$. For example: $a<X<b \Longleftrightarrow \alpha<Y<\beta$.

- If $r(x)$ is not monotonic, find a partition of $X$ such that each segment is monotonic. Then, apply the method to each segment and aggregate.
- Where does formula (33) come from?

Example 13.3. Find $f_{Y}(y)$, where $Y=4 X+3$ and $f(x)=7 e^{-7 x}$ if $0<x<\infty, 0$ if otherwise.

Example 13.4. Do Example 13.2 using the 1-step method.

## 14 Function of a Random Vector (Multivariate Model)

### 14.1 Discrete Model

Let $\mathbf{X} \equiv\left(X_{1}, X_{2}, \ldots, X_{n}\right)$ be a random vector with joint $\operatorname{pmf} f_{\mathbf{X}}\left(x_{1}, \ldots, x_{n}\right)$.
Define a new random vector $\mathbf{Y} \equiv\left(Y_{1}, Y_{2}, \ldots, Y_{m}\right)$ as a function of the random vector $\mathbf{X}$, such that $Y_{i}=r_{i}\left(X_{1}, X_{2}, \ldots, X_{n}\right)$ for $i=1 \ldots m$. The joint $\operatorname{pmf}$ of $\mathbf{Y}, f_{\mathbf{Y}}\left(y_{1}, y_{2}, \ldots, y_{m}\right)$, is derived as follows:

$$
\begin{equation*}
\left.f_{\mathbf{Y}}\left(y_{1}, y_{2}, \ldots, y_{m}\right)=\sum_{\substack{\left(x_{1}, \ldots, x_{n}\right) \\ \vdots i=1 . m}} f_{\mathbf{X}}\left(x_{1}, \ldots, x_{n}\right)=y_{i}\right)\left(x_{1}, \ldots, x_{n}\right) \tag{34}
\end{equation*}
$$

- This is a direct generalization of section 13.1 , where (34) is the generalization of (31).

Example 14.1. (Convolution) Let $(X, Y)$ be a random vector, such that $X$ and $Y$ are independent and discrete RVs with pmf $f_{X}(x)$ and $f_{Y}(y)$. Find $P(Z=z)$, where $Z=Y+X$.

### 14.2 Continuous Model

### 14.2.1 2-Step Method

Let $\mathbf{X} \equiv\left(X_{1}, X_{2}, \ldots, X_{n}\right)$ be a random vector with joint pdf $f_{\mathbf{X}}\left(x_{1}, \ldots, x_{n}\right)$.
Define a new random vector $\mathbf{Y} \equiv\left(Y_{1}, \ldots, Y_{m}\right)$ as a function of the random vector $\mathbf{X}$, such that $Y_{i}=r_{i}\left(X_{1}, X_{2}, \ldots, X_{n}\right)$ for $i=1, \ldots, m$. The joint pdf of $\mathbf{Y}, f_{\mathbf{Y}}\left(y_{1}, \ldots, y_{m}\right)$, is derived as follows (for the case where $m=1$ ):

$$
\begin{align*}
& 1^{\text {st }} \text { step : } F_{Y}(y)=P(Y \leq y)=P\left[r\left(X_{1}, \ldots, X_{n}\right) \leq y\right]=\int \ldots \int_{(\mathbf{x}): r(\mathbf{x}) \leq y} f_{\mathbf{X}}\left(x_{1}, \ldots, x_{n}\right) d x_{1} \ldots d x_{n} \\
& 2^{\text {nd }} \text { step : } f_{Y}(y)=\frac{d F_{Y}(y)}{d y} \quad \text { (at every point } F_{Y}(y) \text { is differentiable.) } \tag{35}
\end{align*}
$$

- This is a direct generalization of section 13.2.1, where (35) is the generalization of (32) (for the case where $m=1$ ).
- The case where $m>1$ is analogous (but more messier).


### 14.2.2 1-Step Method

Let $\mathbf{X} \equiv\left(X_{1}, X_{2}, \ldots, X_{n}\right)$ be a random vector with joint $\operatorname{pdf} f_{\mathbf{X}}\left(x_{1}, \ldots, x_{n}\right)$.

Define a new random vector $\mathbf{Y} \equiv\left(Y_{1}, \ldots, Y_{n}\right)$ as a function of the random vector $\mathbf{X}$, such that $Y_{i}=r_{i}\left(X_{1}, X_{2}, \ldots, X_{n}\right)$ for $i=1, \ldots, n$, where condition (37) holds. The joint pdf of $\mathbf{Y}, f_{\mathbf{Y}}\left(y_{1}, \ldots, y_{n}\right)$, is derived as follows:

$$
f_{\mathbf{Y}}\left(y_{1}, y_{2}, \ldots, y_{n}\right)= \begin{cases}f_{\mathbf{X}}\left(s_{1}(), s_{2}(), \ldots, s_{n}()\right)|J|, & \text { for }\left(y_{1}, y_{2}, \ldots, y_{n}\right) \in \mathcal{Y} \subseteq R^{n}  \tag{36}\\ 0, & \text { otherwise }\end{cases}
$$

where

$$
\begin{array}{rll}
Y_{1}=r_{1}\left(X_{1}, \ldots X_{n}\right) & & X_{1}=s_{1}\left(Y_{1}, \ldots Y n\right) \\
Y_{2}=r_{2}\left(X_{1}, \ldots X_{n}\right) & \text { unique } & X_{2}=s_{2}\left(Y_{1}, \ldots Y n\right) \\
\vdots & \text { transformation } & \vdots  \tag{37}\\
Y_{n}=r_{n}\left(X_{1}, \ldots X_{n}\right) & \longrightarrow & X_{n}=s_{n}\left(Y_{1}, \ldots Y_{n}\right) ;
\end{array}
$$

and

$$
J=\operatorname{det}\left[\begin{array}{ccc}
\frac{\partial s_{1}}{\partial y_{1}} & \cdots & \frac{\partial s_{1}}{\partial y_{n}}  \tag{38}\\
\vdots & \ddots & \vdots \\
\frac{\partial s_{n}}{\partial y_{1}} & \cdots & \frac{\partial s_{n}}{\partial y_{n}}
\end{array}\right] \quad \text { (Jacobian); }
$$

and
$\mathcal{X}$ is the support of $X_{1}, \ldots X_{n}: \mathcal{X}=\left\{\mathbf{x}: f_{\mathbf{X}}(\mathbf{x})>0\right\}$.
$\mathcal{Y}$ is the induced support of $Y_{1}, \ldots Y_{n}: \mathcal{Y}=\{\mathbf{y}: \mathbf{y}=r(\mathbf{x})$ for all $\mathbf{x} \in \mathcal{X}\}$.

$$
\begin{equation*}
\left(x_{1}, \ldots x_{n}\right) \in \mathcal{X} \Longleftrightarrow\left(y_{1}, \ldots y_{n}\right) \in \mathcal{Y} \tag{39}
\end{equation*}
$$

- Note that for this method to work, $m$ has to be equal to $n(n=m)$.
- If condition (37) does not hold, find a partition such that it holds in each segment. Then, apply the method to each segment and aggregate.
- This is a direct generalization of 13.2 .2 , where (36) is the generalization of (33).
- Reminder: if $A=\left[\begin{array}{ll}a & b \\ c & d\end{array}\right]$, then $\operatorname{det}(A)=|A|=a d-c b$.

Example 14.2. Let $\left(X_{1}, X_{2}\right)$ be a random vector, such that $X_{1}$ and $X_{2}$ are continuous RVs with joint pdf $f\left(x_{1}, x_{2}\right)=e^{-x_{1}-x_{2}}$ if $0 \leq x_{i}$, and 0 if otherwise. Using the 1 -step method find $f_{Y}(y)$, where $Y=X_{1}+X_{2}$.

Example 14.3. Let $\left(X_{1}, X_{2}, \ldots, X_{n}\right)$ be a continuous random vector containing $n$ independent and identically distributed random variables, ${ }^{1}$ where $X_{i} \sim U[0,1]$. Compute the pdf of the following two transformations of the random vector $\mathbf{X}$ : i) $Y_{\max }=\max \left\{X_{1}, X_{2}, \ldots, X_{n}\right\}$ and ii) $Y_{\min }=\min \left\{X_{1}, X_{2}, \ldots, X_{n}\right\}$.

[^1]
[^0]:    *Caution: These notes are not necessarily self-explanatory notes. They are to be used as a complement to (and not as a substitute for) the lectures.

[^1]:    ${ }^{1}$ iid for short or also called "random sample." More on this in Lecture Note 7.

