The pdf of the Sum of Two Continuous Random Variables
Suppose $X_{1}$ and $X_{2}$ are irvs (independent random variables) with pfds $f_{1}\left(\mathrm{X}_{1}\right)$ and $f_{2}\left(\mathrm{X}_{2}\right)$ so that the joint pdf of of the vector $\left[\begin{array}{ll}\mathrm{X}_{1} & \mathrm{X}_{2}\end{array}\right]$ is given by $\mathrm{f}\left(\mathrm{x}_{1}, \mathrm{x}_{2}\right)=$ $f_{1}\left(x_{1}\right) f_{2}\left(x_{2}\right)$. The objective is to find the pdf of $Y=X_{1}+X_{2}$ given that $f_{1}\left(x_{1}\right)$ and $f_{2}\left(X_{2}\right)$ are known. First, let $\mathrm{g}(\mathrm{y})$ denote the pdf of Y ; then $\mathrm{g}(\mathrm{y})$, which is the function we are seeking to find, is called the convolution of $\mathrm{f}_{1}\left(\mathrm{x}_{1}\right)$ with $\mathrm{f}_{2}\left(\mathrm{x}_{2}\right)$. In statistical literature this is written as $\mathrm{g}(\mathrm{y})=\mathrm{f}_{1}\left(\mathrm{x}_{1}\right)^{*} \mathrm{f}_{2}\left(\mathrm{x}_{2}\right)$.

To this end, make the transformations $\mathrm{Y}=\mathrm{X}_{1}+\mathrm{X}_{2}$ and $\mathrm{W}=\mathrm{X}_{2}$; thus, the inverse transformations are $\mathrm{X}_{1}=\mathrm{Y}-\mathrm{W}$ and $\mathrm{X}_{2}=\mathrm{W}$. Letting $\mathrm{h}(\mathrm{y}, \mathrm{w})$ denote the joint pdf of Y and W , then

$$
\iint_{R} f\left(x_{1}, x_{2}\right) d x_{1} d x_{2}=\iint_{R^{*}} f(y-w, w)|J| d y d w=\iint_{R^{*}} h(y, w) d y d w
$$

The reason behind the above equality is the fact that in general the differential of area dA $=\mathrm{dx}_{1} \mathrm{dx}_{2}$ in $\mathrm{x}_{1}-\mathrm{x}_{2}$ plane does not transform to $\mathrm{dA}^{*}=\mathrm{dy} \mathrm{dw}$ in the $\mathrm{y}-\mathrm{w}$ coordinate system, but dx1 dx2 $\rightarrow|\mathrm{J}|$ dy dw, where

$$
|J|=\left|\begin{array}{ll}
\frac{\partial x_{1}}{\partial y} & \frac{\partial x_{1}}{\partial w} \\
\frac{\partial x_{2}}{\partial y} & \frac{\partial x_{2}}{\partial w}
\end{array}\right|
$$

is called the Jacobian determinant of the transformation. For our example, $|\mathbf{J}|=$

$$
\left|\begin{array}{rr}
\mathbf{1} & \mathbf{1} \\
\mathbf{0} & \mathbf{1}
\end{array}\right|=1 \text {, and hence the } \mathbf{h}(\mathbf{y}, \mathbf{w})=\mathbf{f}\left(\mathbf{x}_{\mathbf{1}}, \mathbf{x}_{\mathbf{2}}\right)|\mathrm{J}|=\mathbf{f}(\mathbf{y}-\mathbf{w}, \mathbf{w})|\mathbf{J}|=\mathrm{f}(\mathrm{y}-\mathrm{w}, \mathrm{w}) \text {. }
$$

Therefore, the marginal density of y is given by $\mathrm{g}(\mathrm{y})=\int_{-\infty}^{\infty} \mathbf{h}(\mathrm{y}, \mathrm{w}) \mathbf{d w}=$

$$
\int_{-\infty}^{\infty} f(y-w, w) d w=\int_{-\infty}^{\infty} f_{1}\left(y-x_{2}\right) f_{2}\left(x_{2}\right) d x_{2}=\int_{-\infty}^{\infty} f_{1}\left(x_{1}\right) f_{2}\left(y-x_{1}\right) d x_{1}
$$



The above Figure was drawn by Luke Miller, a Ph.D. Student in ISE Department of AU, where $\mathrm{y}=\mathrm{x}_{1}+\mathrm{x}_{2}$.

Example1. Suppose $X_{1} \sim U(0,1)$ and $X_{2} \sim U(0.50,2)$; then $f_{1}\left(x_{1}\right)=1$, $0 \leq x_{1} \leq 1$ and $f_{2}\left(x_{2}\right)=2 / 3,0.50 \leq x_{2} \leq 2.0$. The objective is to find the convolution of $f_{1}\left(x_{1}\right)$ with $f_{2}\left(x_{2}\right)$ denoted by $g(y)$, where $0.50 \leq y \leq 3$. I have shown, by drawing a figure similar to the above, that the pdf of $y$ will be given by

$$
g(y)=\int_{R_{2}}(2 / 3) \mathrm{dx}_{2}=\left\{\begin{array}{ll}
(2 y-1) / 3, & 0.50 \leq y \leq 1.5 \\
2 / 3, & 1.50 \leq y \leq 2.0, \\
2(1-y / 3), & 2.0 \leq y \leq 3.0 \\
0, \text { Elsewhere }
\end{array}=f_{1}\left(x_{1}\right)^{*} f_{2}\left(x_{2}\right)\right.
$$

where the integration is carried out over the range of x 2 . The analytic geometry involved in developing the above convolution is extremely difficult and will be discussed in class, if necessary, for the interested reader. I do believe that integration in the $\mathrm{x}_{1}$ direction is feasible but more difficult in order to obtain the marginal pdf of y from the joint $\mathrm{pdf} \mathrm{h}(\mathrm{y}$,
$\mathrm{x}_{1}$ ). For $0.50 \leq \mathrm{y} \leq 1.5$, $\mathrm{x}_{1}$ will range from 0 to $\mathrm{x}_{1}=\mathrm{y}-0.50$; for $1.50 \leq \mathrm{y} \leq 2.0$, $\mathrm{x}_{1}$ will range from 0 to 1 , and for $2.0 \leq y \leq 3$, $x_{1}$ will range from $y-2$ to 1 .

Example2. Suppose $X_{1}$ and $X_{2}$ are irvs (independent rvs) which are Exponentially distributed at rates $\lambda_{2} \geq \lambda_{1}$. As before, let $\mathrm{Y}=\mathrm{X}_{1}+\mathrm{X}_{2}$ and $\mathrm{g}(\mathrm{y})=$ $\left(\lambda_{1} e^{-\lambda_{1} x_{1}}\right)^{*}\left(\lambda_{2} e^{-\lambda_{2} x_{2}}\right)$. Then $g(y)=\int_{0}^{y} f_{2}\left(y-x_{1}\right) f_{1}\left(x_{1}\right) d x_{1}=$ $\int_{0}^{y} \lambda_{2} e^{-\lambda_{2}\left(y-x_{1}\right)}\left(\lambda_{1} e^{-\lambda_{1} x_{1}}\right) d x_{1}=$ $\lambda_{1} \lambda_{2} \mathbf{e}^{-\lambda_{2} \mathrm{y}} \int_{0}^{\mathrm{y}} \mathrm{e}^{-\left(\lambda_{1}-\lambda_{2}\right) \mathrm{x}_{1}} \mathbf{d x _ { 1 }}=\frac{\lambda_{1} \lambda_{2}}{\left(\lambda_{2}-\lambda_{1}\right)}\left[\mathrm{e}^{-\lambda_{1} \mathrm{y}}-\mathrm{e}^{-\lambda_{2} \mathrm{y}}\right], 0 \leq \mathrm{y}<\infty$

Exercise. Obtain the above convolution again by integrating wrt $\mathrm{x}_{2}$ and prove that the above convolution reduces to the Gamma pdf at the rate $\lambda$ and $\mathrm{n}=2$ as $\lambda_{1} \rightarrow \lambda_{2}=\lambda$.

