

Functions of Random Variables

Lecture 4

Spring 2002

Function of a Random Variable

Let U be an random variable and $V = g(U)$. Then V is also a rv since, for any outcome e , $V(e) = g(U(e))$.

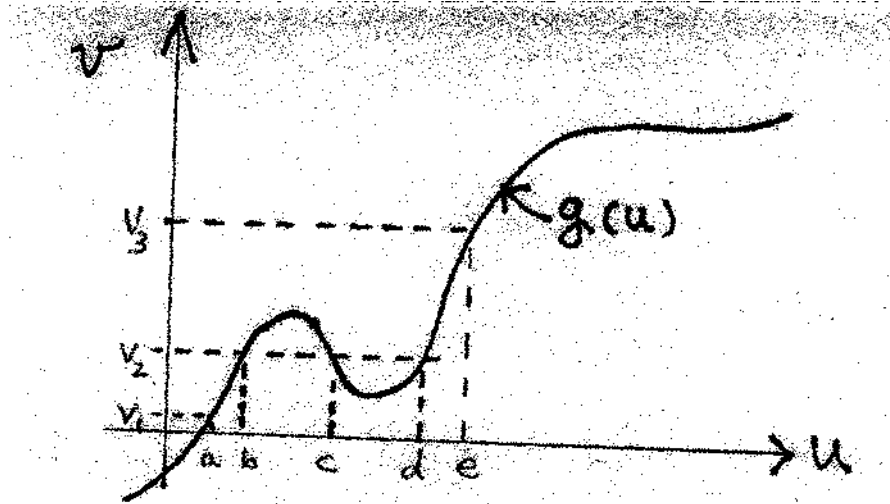
There are many applications in which we know $F_U(u)$ and we wish to calculate $F_V(v)$ and $f_V(v)$.

The distribution function must satisfy

$$F_V(v) = P[V \leq v] = P[g(U) \leq v]$$

To calculate this probability from $F_U(u)$ we need to find all of the intervals on the u axis such that $g(u) \leq v$.

Function of a Random Variable



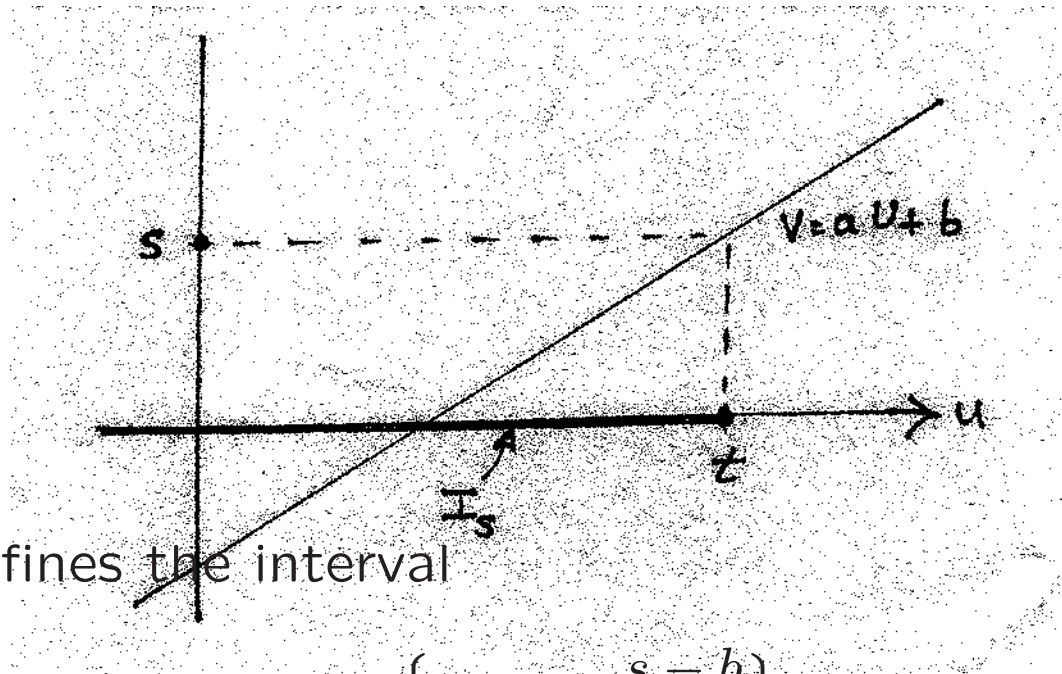
$$v \leq v_1 \quad \text{if} \quad u \leq a$$

$$v \leq v_2 \quad \text{if} \quad u \leq b \quad \text{or} \quad c \leq u \leq d$$

$$v \leq v_3 \quad \text{if} \quad u \leq e$$

For any number s , values of u such that $g(u) \leq s$ fall in a set of intervals \mathcal{I}_s .

Example: $V = aU + b$



For any s , $t = \frac{s-b}{a}$ defines the interval

$$\mathcal{I}_s = \{u : u \leq t\} = \left\{u : u \leq \frac{s-b}{a}\right\}$$

For any probability distribution function $F_U(u)$ we then find

$$F_V(v) = P\left[U \leq \frac{v-b}{a}\right] = F_U\left[\frac{v-b}{a}\right]$$

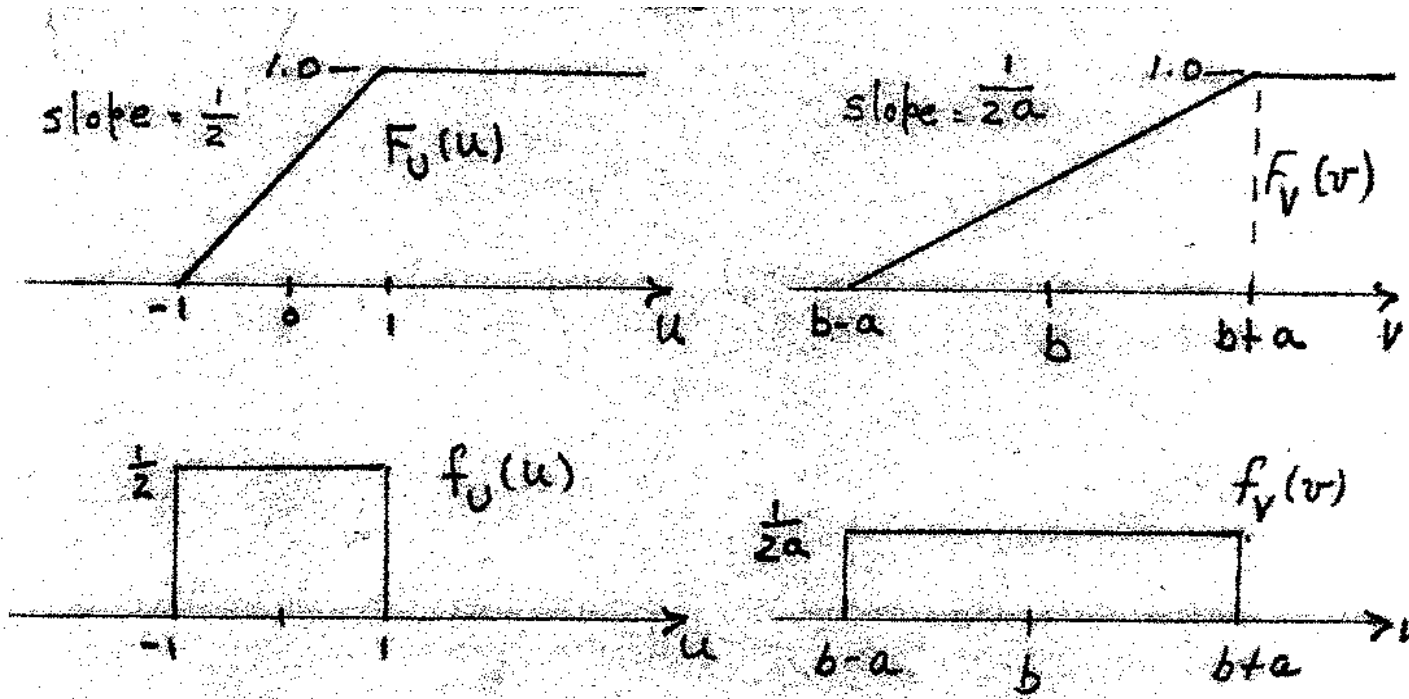
Example: $V = aU + b$

Suppose U has a uniform distribution on the interval $-1 \leq u \leq 1$.
Then

$$F_U(u) = \begin{cases} 0 & \text{for } u \leq -1 \\ \frac{1}{2} + \frac{u}{2} & \text{for } -1 \leq u \leq 1 \\ 1 & \text{for } u \geq 1 \end{cases}$$

$$F_V(v) = F_U\left[\frac{v-b}{a}\right] = \begin{cases} 0 & \text{for } v \leq b-a \\ \frac{1}{2} + \frac{v-b}{2a} & \text{for } b-a \leq v \leq b+a \\ 1 & \text{for } v \geq b+a \end{cases}$$

Example: $V = aU + b$



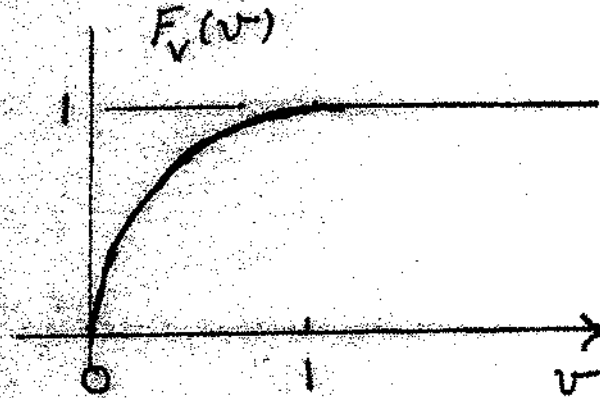
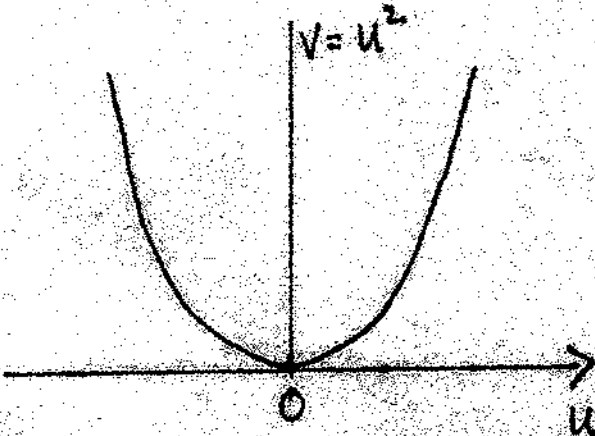
Example: $V = U^2$

$$\mathcal{I}_s = \{u : -\sqrt{s} \leq u \leq \sqrt{s} \text{ for } s \geq 0\}$$

$$P[V \leq v] = P[U \in \mathcal{I}_v] = P[\sqrt{v} \leq U \leq \sqrt{v}] \text{ for } v \geq 0$$

$$P[V \leq v] = \begin{cases} 0 & \text{for } v \leq 0 \\ \frac{2\sqrt{v}}{2} = \sqrt{v} & \text{for } 0 \leq v \leq 1 \\ 1 & \text{for } v \geq 1 \end{cases}$$

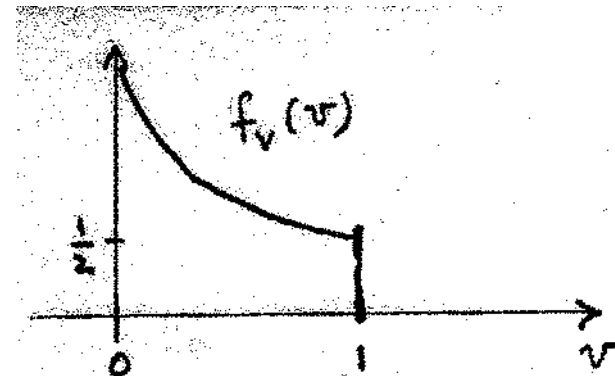
Example: $V = U^2$ with same $F_U(u)$



Probability density function

$$f_V(v) = \frac{dF_V}{dv} = \frac{1}{2\sqrt{v}}$$

for $0 < v \leq 1$



Probability Density Function

The probability density function can be computed by

$$f_V(v) = \frac{dF_V}{dv}$$

This requires first computing $F_V(v)$ as in the last example.

It is often convenient to compute $f_V(v)$ directly from $f_U(u)$ and the function $V = g(U)$.

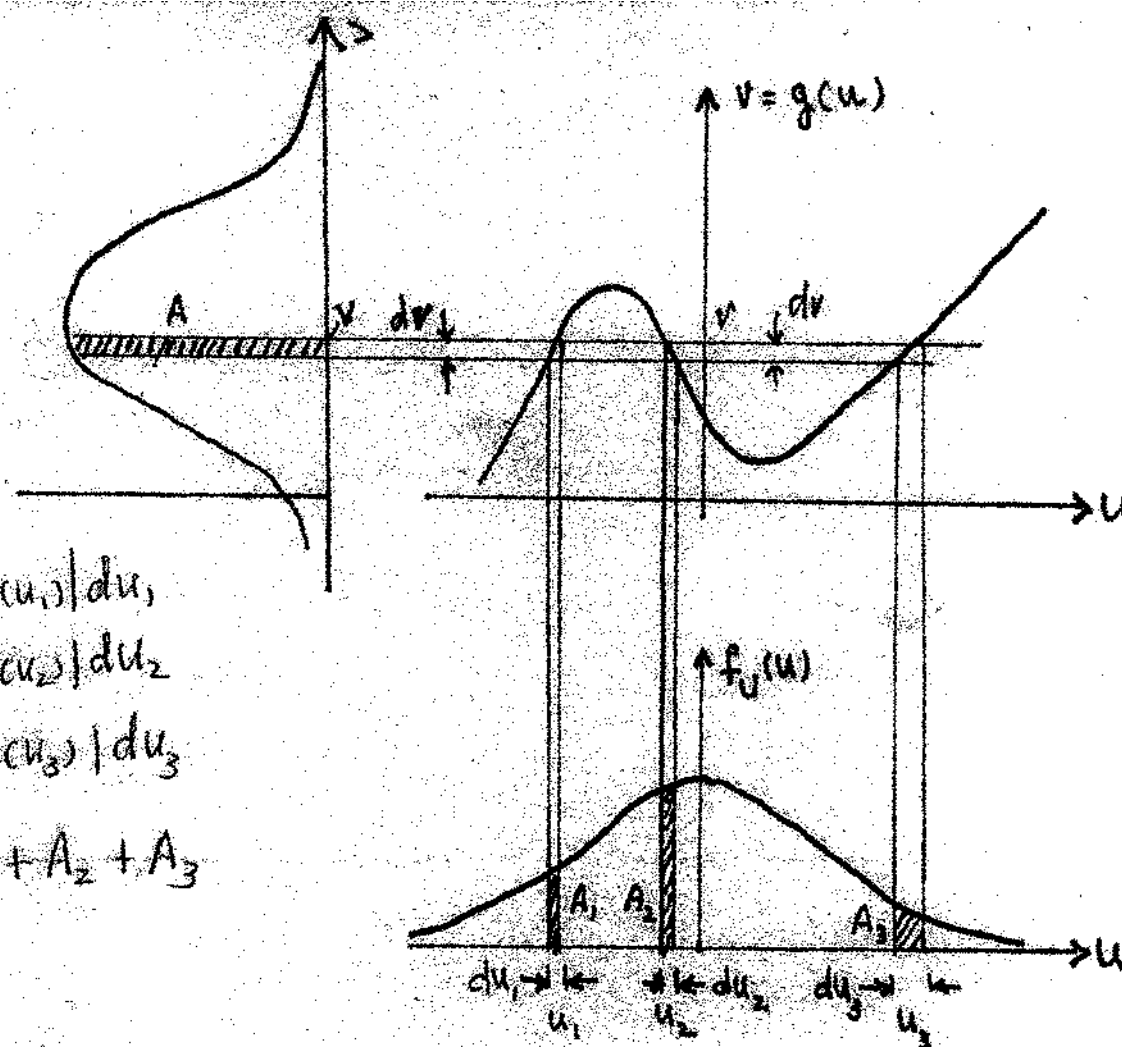
For any specific value of y find the solutions u_n such that

$$v = g(u_1) = \dots = g(u_n) = \dots$$

We will show that

$$f_V(v) = \frac{f_U(u_1)}{|g'(u_1)|} + \dots + \frac{f_U(u_n)}{|g'(u_n)|} + \dots$$

Probability Density Function



$$dv = |g'(u_1)| du_1$$

$$dv = |g'(u_2)| du_2$$

$$dv = |g'(u_3)| du_3$$

$$A = A_1 + A_2 + A_3$$

Probability Density Function

The areas under the curves must be equal.

$$A = A_1 + A_2 + A_3$$

$$f_V(v)dv = f_U(u_1)du_1 + f_U(u_2)du_2 + f_U(u_3)du_3$$

$$f_V(v)dv = f_U(u_1)\frac{dv}{|g'(u_1)|} + f_U(u_2)\frac{dv}{|g'(u_2)|} + f_U(u_3)\frac{dv}{|g'(u_3)|}$$

$$f_V(v) = \frac{f_U(u_1)}{|g'(u_1)|} + \frac{f_U(u_2)}{|g'(u_2)|} + \frac{f_U(u_3)}{|g'(u_3)|}$$

In general, the summation is over all the roots of $v = g(u)$ for any particular v . If there are no roots, then $f_V(v) = 0$ for that v .

Example: $V = U^2$ with rectangular $f_U(u)$

If $v < 0$ there are no roots $\Rightarrow f_V(v) = 0$.

If $v \geq 0 \Rightarrow u_1 = -\sqrt{v}, u_2 = \sqrt{v}$

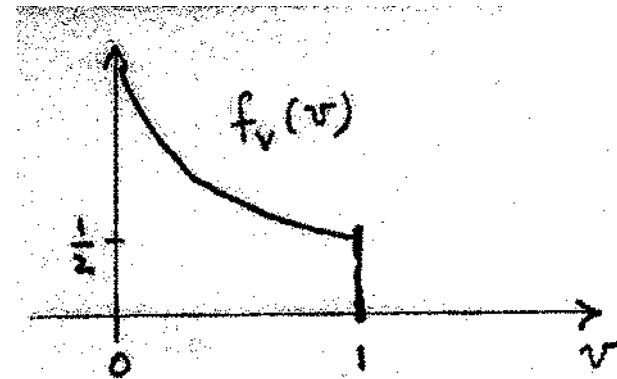
$g'(u) = 2u \Rightarrow g'(u_1) = -2\sqrt{v}$ and

$g'(u_2) = 2\sqrt{v}$

$$f_V(v) = \frac{f_U(-\sqrt{v})}{2\sqrt{v}} + \frac{f_U(\sqrt{v})}{2\sqrt{v}}$$

$$f_U(u) = \frac{1}{2} \text{Rect}(u/2)$$

$$f_V(v) = \frac{1}{2\sqrt{v}} \quad \text{for } 0 < v \leq 1$$



Sums of Random Variables

Let U and V be random variables, and let $W = U + V$.

Given $F_{U,V}(u, v)$ and the pdf $f_{U,V}(u, v)$ find $F_W(w)$ and $f_W(w)$.

$$F_W(w) = P[U + V \leq w]$$

$$F_W(w) = \int_{-\infty}^{\infty} \left[\int_{-\infty}^{w-u} f_{U,V}(u, v) dv \right] du$$

$$f_W(w) = \frac{dF_W}{dw}$$

Leibnitz' Rule

If $a(t)$, $b(t)$ and $r(s, t)$ are all differentiable with respect to t then

$$\frac{d}{dt} \int_{a(t)}^{b(t)} r(s, t) ds = r[b(t), t]b'(t) - r[a(t), t]a'(t) + \int_{a(t)}^{b(t)} \frac{\partial}{\partial t} r(s, t) ds$$

Sums of Random Variables

$$\begin{aligned}f_W(w) &= \frac{d}{dw} \int_{-\infty}^{\infty} \left[\int_{-\infty}^{w-u} f_{U,V}(u, v) dv \right] du \\ &= \int_{-\infty}^{\infty} \left[\frac{d}{dw} \int_{-\infty}^{w-u} f_{U,V}(u, v) dv \right] du \\ &= \int_{-\infty}^{\infty} f_{U,V}(u, w - u) du\end{aligned}$$

If U and V are statistically independent random variables then

$$f_W(w) = \int_{-\infty}^{\infty} f_U(u) f_V(w - u) du$$

Here we recognize an old friend, the convolution integral.

Averages of Random Variables

Suppose that a random variable U can take on any one of L random values, say u_1, u_2, \dots, u_L . Imagine that we make n independent observations of U and that the value u_k is observed n_k times, $k = 1, 2, \dots, L$. Of course, $n_1 + n_2 + \dots + n_L = n$. The empirical average can be computed by

$$\bar{u} = \frac{1}{n} \sum_{k=1}^L n_k u_k = \sum_{k=1}^L \frac{n_k}{n} u_k$$

The concept of statistical averages extends from this simple concept