

Definition. Let $h : \mathbb{R} \rightarrow \mathbb{R}$. For any set $A \subset \mathbb{R}$ the **inverse image** of A by h is

$$h^{-1}(A) = \{x : h(x) \in A\}.$$

In particular, for $y \in \mathbb{R}$, $h^{-1}((-\infty, y]) = \{x : h(x) \leq y\}$.

Theorem. Let X be a r.v. and h a real-valued function. The cdf for $Y = h(X)$ is then

$$F_Y(y) = P(X \in h^{-1}((-\infty, y])).$$

Proof. $F_Y(y) = P(Y \leq y) = P\{h(X) \in (-\infty, y]\} = P(X \in h^{-1}((-\infty, y])).$ \square

Example. Let $Y = \#$ successes in n independent Bernoulli(p) trials, $W = n - Y$ ($\#$ failures).

What is the distribution of W ?

Short answer: $W = \#$ negative ‘successes’ in n independent Bernoulli($1 - p$) trials
 $\Rightarrow W \sim \text{binomial}(n, 1 - p)$.

Slowly: Let $w \in \{0, 1, \dots, n\}$. Then $f_W(w) = P(n - Y = w) = P(Y = n - w) = \binom{n}{n-w} p^{n-w} (1-p)^w = \frac{n!}{(n-w)!(n-n+w)!} p^{n-w} (1-p)^w = \binom{n}{w} (1-p)^w (1 - (1-p))^{n-w}$; now introduce $\tilde{p} = 1 - p$.

Corollary. Assume, additionally, that Y is discrete.

- (i) The pmf for Y is $f_Y(y) = P(X \in h^{-1}\{y\})$.
- (ii) If X is also discrete with pmf f_X then $f_Y(y) = \sum_{x \in h^{-1}\{y\}} f_X(x)$.
- (iii) If h is 1-1 with inverse h^{-1} then X must also be discrete and $f_Y(y) = f_X(h^{-1}\{y\})$.

Proof. (i) holds since $f_Y(y) = P(h(X) \in \{y\}) = P(X \in h^{-1}\{y\})$, (ii) since P is additive, and (iii) since h is 1-1 and therefore $h^{-1}\{y\}$ is *one* value. \square

Corollary. Consider X and $Y = h(X)$ as before; let Y be (absolutely) continuous.

- (i) The pdf for Y is $f_Y(y) = \frac{d}{dy} P(X \in h^{-1}((-\infty, y]))$.
- (ii) If h is 1-1 with inverse h^{-1} and differentiable then X is (absolutely) continuous and

$$f_Y(y) = \frac{1}{|h'\{h^{-1}(y)\}|} f_X\{h^{-1}(y)\}.$$

Proof. (i) Y is absolutely continuous, i.e. for those y at which F' exists, $f_Y(y) = \frac{d}{dy} F_Y(y) = \frac{d}{dy} P(X \in h^{-1}((-\infty, y]))$ by the previous theorem.

(ii) Assume h *strictly increasing*. Then, applying the chain rule,

$$\begin{aligned} f_Y(y) &= \frac{d}{dy} P\{h(X) \leq y\} = \frac{d}{dy} P\{X \leq h^{-1}(y)\} = \frac{d}{dy} F_X\{h^{-1}(y)\} \\ &= \frac{d}{dy} h^{-1}(y) f_X\{h^{-1}(y)\} = \frac{1}{h'\{h^{-1}(y)\}} f_X\{h^{-1}(y)\} \end{aligned}$$

with $h' > 0$. We can therefore write $\frac{1}{|h'\{h^{-1}(y)\}|} f_X\{h^{-1}(y)\}$.

Assume h *decreasing*. Then, similarly, $f_Y(y) = \frac{d}{dy} P\{h(X) \leq y\} = \frac{d}{dy} P\{X \geq h^{-1}(y)\} = \frac{d}{dy} [1 - F_X\{h^{-1}(y)\}] = -\frac{1}{h'\{h^{-1}(y)\}} f_X\{h^{-1}(y)\}$ with $h' < 0$. Again we can write $\frac{1}{|h'\{h^{-1}(y)\}|} f_X\{h^{-1}(y)\}$. \square

It is easier to recall the previous density transformation formula if one writes

$$f_Y(y) = \left| \frac{dx}{dy} \right| f_X(x).$$