

Transformation of Random Variables

ES 114

Shreyans Jain & Guntas Singh Saran

IIT Gandhinagar

April 5, 2025

Outline

- 1 Random Variables Recap
- 2 Transformation of Random Variables
- 3 Warm-Up: PDF vs. CDF (Friendly Reminders)
- 4 Transformation: The Big Question
- 5 General Method: The CDF Trick
- 6 Example 1: Linear Transformation
- 7 Example 2: Squaring a Variable
- 8 Example 3: Trigonometric (Cosine)
- 9 Example 4: Exponential of a Funny PDF
- 10 Method Recap
- 11 Why Transform Random Variables?

What is a Random Variable?

Definition: A random variable (RV) is a function that maps outcomes in the sample space to real numbers.

Notation: $X : \Omega \rightarrow \mathbb{R}$

- Ω is the sample space (set of all possible outcomes).
- $X(\omega)$ assigns a number to each outcome ω .

What is a Random Variable?

Definition: A random variable (RV) is a function that maps outcomes in the sample space to real numbers.

Notation: $X : \Omega \rightarrow \mathbb{R}$

- Ω is the sample space (set of all possible outcomes).
- $X(\omega)$ assigns a number to each outcome ω .

(This mapping lets us use tools like algebra, calculus, and probability theory on uncertain events.)

Example: Tossing a fair die

- Sample space: $\Omega = \{1, 2, 3, 4, 5, 6\}$
- Define X : number shown on the die $\Rightarrow X : \Omega \rightarrow \{1, 2, 3, 4, 5, 6\}$
- PMF (Probability Mass Function): $p_X(k) = P(X = k)$

Example: Tossing a fair die

- Sample space: $\Omega = \{1, 2, 3, 4, 5, 6\}$
- Define X : number shown on the die $\Rightarrow X : \Omega \rightarrow \{1, 2, 3, 4, 5, 6\}$
- PMF (Probability Mass Function): $p_X(k) = P(X = k)$

For example:

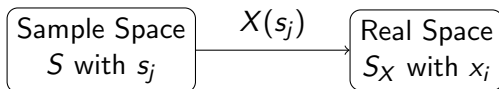
$$P(X = 4) = \frac{1}{6}$$

(This is a pointwise probability: probability is assigned to each outcome. All probabilities add up to 1.)

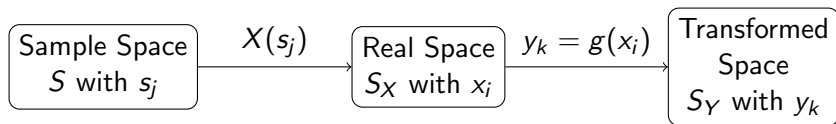
Transformation Diagram

Sample Space
 S with s_j

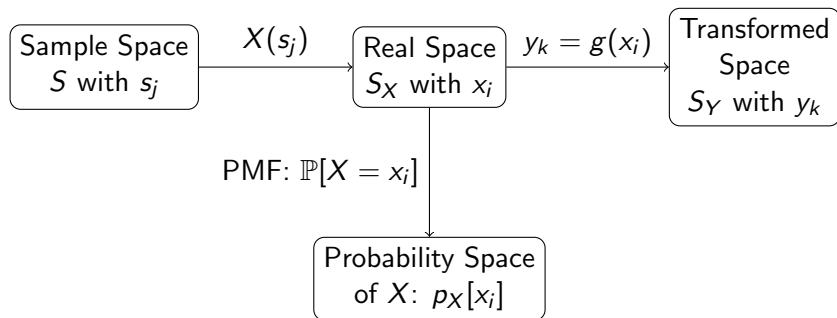
Transformation Diagram



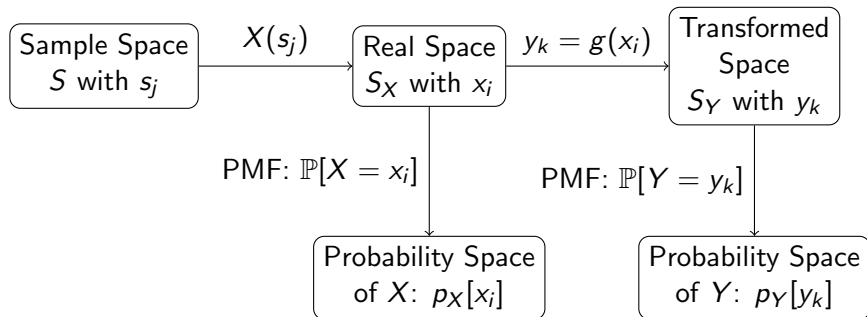
Transformation Diagram



Transformation Diagram



Transformation Diagram



Example: Squaring a Discrete Random Variable

Given: A discrete random variable X :

X	$p_X(x)$
-2	1/4
-1	1/4
0	1/8
1	1/8
2	1/4

Example: Squaring a Discrete Random Variable

Given: A discrete random variable X :

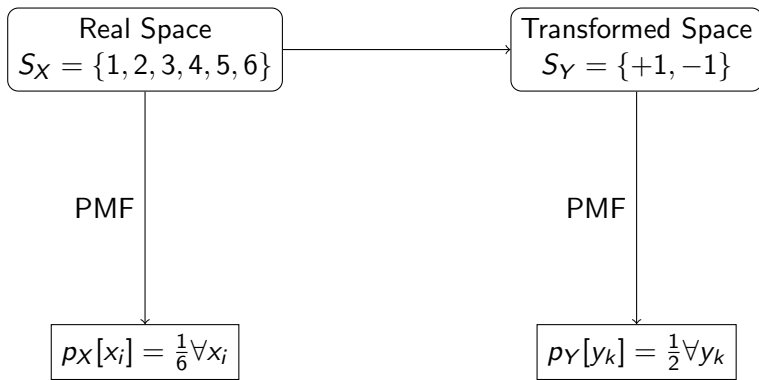
X	$p_X(x)$
-2	1/4
-1	1/4
0	1/8
1	1/8
2	1/4

Transformed Variable: $Y = X^2$:

Y	$p_Y(y)$
0	1/8
1	3/8
4	4/8

Die Toss Transformation

$$y_k = g(x_i) = \begin{cases} +1, & x_i \text{ even} \\ -1, & x_i \text{ odd} \end{cases}$$



Reminder 1: PDF (Probability Density Function)

- Denoted $f_X(x)$ for a random variable X .
- Tells you how "dense" the probability is near each point x .
- The area under $f_X(x)$ from $-\infty$ to some point a gives the probability of $X \leq a$.

Reminder 1: PDF (Probability Density Function)

- Denoted $f_X(x)$ for a random variable X .
- Tells you how "dense" the probability is near each point x .
- The area under $f_X(x)$ from $-\infty$ to some point a gives the probability of $X \leq a$.

Reminder 2: CDF (Cumulative Distribution Function)

- Denoted $F_X(x) = P(X \leq x)$.
- Always non-decreasing, starts at 0, goes up to 1.
- We often say $F_X(x) = \int_{-\infty}^x f_X(t) dt$.

(CDF is "Cumulative," PDF is "Point density." Think of PDF as the "speed," and CDF as the "distance traveled so far.")

Motivation: Transforming X into $Y = g(X)$

Given:

- A random variable X with known PDF $f_X(x)$ and CDF $F_X(x)$.
- A function $g(\cdot)$ (could be linear, quadratic, cosine, etc.).
- We define a new random variable: $Y = g(X)$.

Motivation: Transforming X into $Y = g(X)$

Given:

- A random variable X with known PDF $f_X(x)$ and CDF $F_X(x)$.
- A function $g(\cdot)$ (could be linear, quadratic, cosine, etc.).
- We define a new random variable: $Y = g(X)$.

Wanted:

- The PDF of Y , $f_Y(y)$.
- The CDF of Y , $F_Y(y)$.

The CDF Trick: Step-by-Step

Step 1: Express $F_Y(y)$ in terms of X .

$$F_Y(y) = P(Y \leq y) = P(g(X) \leq y).$$

- Rewrite $g(X) \leq y$ in terms of conditions on X .
- Then you can use $F_X(x)$ or integrals of $f_X(x)$ to evaluate that probability.

The CDF Trick: Step-by-Step

Step 1: Express $F_Y(y)$ in terms of X .

$$F_Y(y) = P(Y \leq y) = P(g(X) \leq y).$$

- Rewrite $g(X) \leq y$ in terms of conditions on X .
- Then you can use $F_X(x)$ or integrals of $f_X(x)$ to evaluate that probability.

Step 2: Differentiate to find $f_Y(y)$.

$$f_Y(y) = \frac{d}{dy} F_Y(y).$$

Example 1: $Y = 2X + 3$

Given: $Y = 2X + 3$.

Step 1: Find $F_Y(y)$.

$$F_Y(y) = P(Y \leq y) = P(2X + 3 \leq y) = P\left(X \leq \frac{y-3}{2}\right) = F_X\left(\frac{y-3}{2}\right).$$

Example 1: $Y = 2X + 3$

Given: $Y = 2X + 3$.

Step 1: Find $F_Y(y)$.

$$F_Y(y) = P(Y \leq y) = P(2X + 3 \leq y) = P\left(X \leq \frac{y-3}{2}\right) = F_X\left(\frac{y-3}{2}\right).$$

Step 2: Find $f_Y(y)$.

$$f_Y(y) = \frac{d}{dy}F_Y(y) = \frac{1}{2}f_X\left(\frac{y-3}{2}\right).$$

Example 2: $Y = X^2$

Trickier, because squaring is not one-to-one:

$$Y = X^2 \implies X = \pm\sqrt{Y}.$$

Step 1: $F_Y(y)$.

$$F_Y(y) = P(X^2 \leq y) = P(-\sqrt{y} \leq X \leq \sqrt{y}) = F_X(\sqrt{y}) - F_X(-\sqrt{y}).$$

Example 2: $Y = X^2$

Trickier, because squaring is not one-to-one:

$$Y = X^2 \implies X = \pm\sqrt{Y}.$$

Step 1: $F_Y(y)$.

$$F_Y(y) = P(X^2 \leq y) = P(-\sqrt{y} \leq X \leq \sqrt{y}) = F_X(\sqrt{y}) - F_X(-\sqrt{y}).$$

Step 2: $f_Y(y)$.

$$f_Y(y) = \frac{d}{dy} F_Y(y) = \frac{1}{2\sqrt{y}} \left[f_X(\sqrt{y}) + f_X(-\sqrt{y}) \right].$$

Example 2: Uniform X in $[a, b]$ (with $a > 0$)

If $X \sim \text{Uniform}[a, b]$, then $Y = X^2 \in [a^2, b^2]$.

- CDF:

$$F_Y(y) = \frac{\sqrt{y} - a}{b - a}, \quad a^2 \leq y \leq b^2$$

(careful with sign if $a > 0$).

- PDF:

$$f_Y(y) = \frac{1}{\sqrt{y}(b - a)}, \quad a^2 \leq y \leq b^2.$$

Example 3: $Y = \cos X$, with $X \sim \text{Uniform}[0, 2\pi]$

Step 1: $F_Y(y) = P(\cos X \leq y)$.

- This might feel like a geometry/trig puzzle.
- For $\cos X \leq y$, we find the ranges of X in $[0, 2\pi]$ that satisfy $\cos X \leq y$.

Example 3: $Y = \cos X$, with $X \sim \text{Uniform}[0, 2\pi]$

Step 1: $F_Y(y) = P(\cos X \leq y)$.

- This might feel like a geometry/trig puzzle.
- For $\cos X \leq y$, we find the ranges of X in $[0, 2\pi]$ that satisfy $\cos X \leq y$.

Result (from standard trig):

$$F_Y(y) = 1 - \frac{\cos^{-1}(y)}{\pi}, \quad \text{for } -1 \leq y \leq 1.$$

Example 3: $Y = \cos X$, with $X \sim \text{Uniform}[0, 2\pi]$

Step 1: $F_Y(y) = P(\cos X \leq y)$.

- This might feel like a geometry/trig puzzle.
- For $\cos X \leq y$, we find the ranges of X in $[0, 2\pi]$ that satisfy $\cos X \leq y$.

Result (from standard trig):

$$F_Y(y) = 1 - \frac{\cos^{-1}(y)}{\pi}, \quad \text{for } -1 \leq y \leq 1.$$

Step 2: Differentiate to find $f_Y(y)$.

$$f_Y(y) = \frac{1}{\pi \sqrt{1 - y^2}}, \quad -1 \leq y \leq 1.$$

Example 4: $Y = e^X$ with $f_X(x) = a e^x e^{-ae^x}$

Step 1: $F_Y(y)$.

$$F_Y(y) = P(Y \leq y) = P(e^X \leq y) = P(X \leq \ln y).$$

$$F_Y(y) = \int_{-\infty}^{\ln y} a e^x e^{-ae^x} dx.$$

Example 4: $Y = e^X$ with $f_X(x) = a e^x e^{-ae^x}$

Step 1: $F_Y(y)$.

$$F_Y(y) = P(Y \leq y) = P(e^X \leq y) = P(X \leq \ln y).$$

$$F_Y(y) = \int_{-\infty}^{\ln y} a e^x e^{-ae^x} dx.$$

Step 2: $f_Y(y)$.

- Use the substitution $u = e^x$. Then $x = \ln u$ and $dx = \frac{du}{u}$.
- After the dust settles, you'll get $f_Y(y) = a e^{-ay}$, an exponential(a) distribution.

(“This wild PDF for X was cleverly chosen so that $Y = e^X$ becomes a plain old exponential distribution. Magic!”)

Method Recap & Final Thoughts

General Recipe

- 1 Always start with CDF: $F_Y(y) = P(g(X) \leq y)$.
- 2 Translate that event: rewrite in terms of X .
- 3 Use known PDFs or CDFs of X : for uniform, normal, or any distribution you have.
- 4 Differentiate to get $f_Y(y)$.

Big Hints

- If $g(\cdot)$ is invertible and monotonic, a direct formula (chain rule) is straightforward.
- If $g(\cdot)$ is not one-to-one (like squaring), break it into the relevant pieces (e.g. $+\sqrt{y}$ and $-\sqrt{y}$).
- *Draw pictures*: helps see “compression” or “expansion” of probability mass.

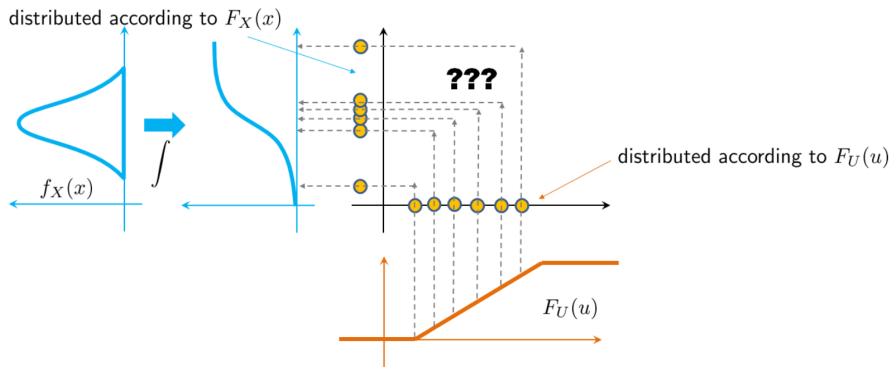
Problem Statement: Sampling from a Given Distribution

- Suppose we want to sample from a random variable X with a known cumulative distribution function (CDF) $F_X(x)$.
- Direct sampling may not be possible for arbitrary distributions.
- Can we use a simple random number generator (like uniform $U \sim \mathcal{U}(0, 1)$) to generate samples of X ?
- Yes! The **Inverse Transform Method** allows this by using the transformation:

$$X = F_X^{-1}(U).$$

Remember that $F_Y(y) = F_X(g^{-1}(y))$

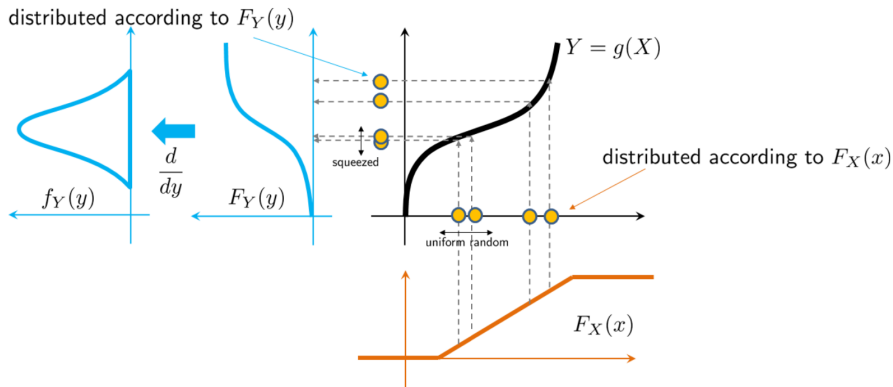
What are we looking for?



The inverse problem is: By using what transformation g , such that $X = g(U)$, can we make sure that X is distributed according to $f_X(x)$ (or $F_X(x)$)?

Looking at Y , the samples are traveling with g^{-1} in order to go back to F_X . Therefore, we need g^{-1} in the formula.

Why Does This Work?: Visualizing the Process



The transformation g that can turn a **uniform random variable** into a random variable following a distribution $F_X(x)$ is given by

$$g(u) = F^{-1}(u)$$

Use: $F_X(u) = u$, for $X \sim \mathcal{U}(0,1)$

Questions?

“Because the best way to make sense of a transformation is to ask what can go wrong!”