



Programming for AI

Sampling Techniques, Inverse Transform Technique

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Sampling from a Given Distribution

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- Instead of the CDF F , we may be given a target PMF or PDF from which to sample

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Inverse Transform Technique (ITT)

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- **Claim:** The CDF of X is exactly equal to F , i.e., $F_X = F$

Example

- Let X be a discrete random variable with the following PMF:

$$p_X(x) = \begin{cases} 0.1, & x = 10, \\ 0.2, & x = 20, \\ 0.3, & x = 30, \\ 0.4, & x = 40, \\ 0, & \text{otherwise.} \end{cases}$$

Use the inverse transform method to generate a sample from the above distribution.

Example

- **[Generating a Sample from Rayleigh Distribution]**

The PDF of the Rayleigh distribution is given by

$$f(r) = r e^{-r^2/2}, \quad r > 0.$$

Use the inverse transform method to generate a sample from the above distribution.

Gaussian Samples on Python via ITT

- Python's built-in module

```
numpy.random.normal(loc, scale, size)
```

generates n independent samples from $\mathcal{N}(\mu, \sigma^2)$, where

$$n = \text{size}, \quad \mu = \text{loc}, \quad \sigma = \text{scale}.$$

- In principle, the above module uses the inverse transform technique

Gaussian Samples on Python via ITT

1. Let $U_1, U_2 \stackrel{\text{i.i.d.}}{\sim} \text{Unif}(0, 1)$
2. Let R and Θ be two random variables defined via

$$R = F_1^{-1}(U_1), \quad \Theta = 2\pi U_2,$$

where F_1 is the CDF of the Rayleigh distribution

3. Let Y_1 and Y_2 be defined as

$$Y_1 = R \cos(\Theta), \quad Y_2 = R \sin(\Theta).$$

4. Then, $Y_1, Y_2 \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(0, 1)$
5. To get $X \sim \mathcal{N}(\mu, \sigma^2)$, simply **discard Y_2 , and**

$$X = \sigma Y_1 + \mu.$$

6. Repeat steps 1-5 a total of n times to get $X_1, X_2, \dots, X_n \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(\mu, \sigma^2)$