

MTH 511a - 2020: Lecture 6

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1 Generating continuous random variables

We will discuss three methods for generating continuous random variables:

1. Inverse transform
2. The accept-reject method
3. Ratio of uniforms

1.1 Inverse transform

The principles of the inverse transform method for discrete distributions, apply similarly to continuous random variables.

Consider a random variable X with probability density function $f(x)$ so that $f(x) \geq 0$, $\int_{-\infty}^{\infty} f(x) = 1$ and distribution function is

$$F(x) = \int_{-\infty}^x f(x) dx .$$

The following theorem will be the foundation for the inverse transform method.

Theorem 1. *Let $U \sim U[0, 1]$. For any continuous distribution F , a random variable $X = F^{-1}(U)$ has distribution F .*

Proof. Let F_X be the distribution function of $X = F^{-1}(U)$. Then,

$$\begin{aligned} F_X(x) &= \Pr(X \leq x) \\ &= \Pr(F^{-1}(U) \leq x) \\ &= \Pr(F(F^{-1}(U)) \leq F(x)) \\ &= \Pr(U \leq F(x)) \\ &= F(x). \end{aligned}$$

□

Example 1. Exponential(1): For the Exponential(1) distribution, the cdf is $F(x) = 1 - e^{-x}$. Thus,

$$F^{-1}(u) = -\log(1 - u).$$

To generate $X \sim \text{Exp}(1)$ we can thus use the following algorithm:

Algorithm 1 Exponential(1) Inverse transform

- 1: Generate $U \sim U[0, 1]$
 - 2: Set $X = -\log(1 - U) \sim \text{Exp}(1)$
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Example 2. Cauchy distribution: Cauchy distribution has pdf

$$f(x) = \frac{1}{\pi} \frac{1}{(1 + x^2)},$$

and

$$u = F(x) = \int_{-\infty}^x f(y) dy = \frac{1}{\pi} \arctan(x) + \frac{1}{2}.$$

So, $F^{-1}(u) = \tan(\pi(u - .5))$.

Algorithm 2 Cauchy distribution

- 1: Generate $U \sim U[0, 1]$
 - 2: Set $X = \tan(\pi(U - .5)) \sim \text{Cauchy}$
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Example 3. Gamma distribution: The CDF of a Gamma(n, λ) distribution is

$$F(x) = \int_0^x \frac{\lambda e^{-\lambda y} (\lambda y)^{n-1}}{\Gamma(n)} dy.$$

Thus, we don't know the CDF in closed form and cannot find the inverse. This is an example where the inverse transform method cannot work.

1.2 Accept-reject method

Suppose we cannot generate from distribution function $F(x)$ with pdf $f(x)$, like the Gamma distribution example. We can use accept-reject in a similar way as the discrete case.

Draw samples from a distribution with density $g(x)$, and accept or reject it based on certain probabilities.

Let the support of F be \mathcal{X} and choose a proposal distribution G with density $g(x)$ whose support is larger or the same as the support of F . That is, if \mathcal{Y} is the support of G then, $\mathcal{X} \subseteq \mathcal{Y}$. If we can find c such that

$$\sup_{x \in \mathcal{X}} \frac{f(x)}{g(x)} \leq c,$$

then an accept-reject sampler can be implemented.

Algorithm 3 Accept-reject for continuous random variables

- 1: Draw $U \sim U[0, 1]$
 - 2: Draw proposal $Y \sim G$
 - 3: **if** $U \leq \frac{f(Y)}{c g(Y)}$ **then**
 - 4: Return $X = Y$
 - 5: **else**
 - 6: Go to Step 1.
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Theorem 2. *Algorithm 3 returns $X \sim F$.*

Proof. Consider any set B in \mathcal{X} . We will show that

$$\Pr(X \in B) = F(B).$$

First, we consider the probability of acceptance:

$$\begin{aligned} \Pr(\text{accept}) &= \Pr\left(U \leq \frac{f(Y)}{c g(Y)}\right) \\ &= \mathbb{E}\left[I\left(U \leq \frac{f(Y)}{c g(Y)}\right)\right] \\ &= \mathbb{E}\left[\mathbb{E}\left[I\left(U \leq \frac{f(Y)}{c g(Y)}\right) \mid Y\right]\right] \\ &= \mathbb{E}\left[\Pr\left(U \leq \frac{f(Y)}{c g(Y)} \mid Y\right)\right] \end{aligned}$$

$$\begin{aligned}
&= \mathbb{E} \left[\frac{f(Y)}{cg(Y)} \right] \\
&= \int_{\mathcal{Y}} \frac{f(y)}{cg(y)} g(y) dy \\
&= \frac{1}{c} \int_{\mathcal{Y}} f(y) dy \\
&= \frac{1}{c} \int_{\mathcal{X}} f(y) dy + \frac{1}{c} \int_{\mathcal{Y}/\mathcal{X}} f(y) dy \\
&= \frac{1}{c}.
\end{aligned}$$

Now that we have this established, consider

$$\begin{aligned}
\Pr(X \in B) &= \Pr(Y \in B \mid \text{accept}) \\
&= \frac{\Pr \left(Y \in B, U < \frac{f(Y)}{cg(Y)} \right)}{\Pr(\text{accept})} \\
&= c \cdot \mathbb{E} \left[\mathbb{E} \left[I \left(Y \in B, U < \frac{f(Y)}{cg(Y)} \right) \mid Y \right] \right] \\
&= c \cdot \mathbb{E} \left[I(Y \in B) \mathbb{E} \left[I \left(U < \frac{f(Y)}{cg(Y)} \right) \mid Y \right] \right] \\
&= c \cdot \mathbb{E} \left[I(Y \in B) \frac{f(Y)}{cg(Y)} \right] \\
&= c \cdot \int_B \frac{f(y)}{cg(y)} g(y) dy \\
&= \int_B f(y) \\
&= F(B).
\end{aligned}$$

□

From the proof, we know that $\Pr(\text{accept}) = 1/c$, and just like the discrete example, the number of attempts it takes to generate an acceptance is distributed Geometric($1/c$). Thus

Mean number of loops for an acceptance is $= c$.

1.3 Questions to think about

- Can we use the inverse transform method to generate sample from a normal distribution?
- In A-R, do we want c to be large or small?
- Can we always find such a c ?