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# Random variate generation for the truncated negative gamma distribution<sup>\*</sup>

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#### Abstract

We provide a uniformly efficient and simple random variate generator for the truncated negative gamma distribution restricted to any interval.

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# 1. Introduction

In this note, we derive a uniformly fast random variate generator for the family of densities that are proportional to

 $f(x) = x^{-\lambda} \exp(-x), \ x \in [s, t),$ 

where  $0 < s < t \le \infty$  and  $\lambda \ge 1$  are the parameters. For  $\lambda < 1$ , we obtain the standard gamma  $(1 - \lambda)$  distribution, for which many good algorithms are available (see [2], [6] and [4]). For this reason we will call this the <u>negative gamma</u> family. Since it must be a density, we cannot have s = 0.

This distribution appears in the astrophysics literature where it is known as the power law with cut-off, or the power law with exponential cut-off. Our nomenclature stresses the tight connection with the gamma distribution.

Deriving uniformly fast algorithms for multi-parameter families of distributions becomes harder as the number of parameters grows. With three parameters,  $\lambda$ , *s* and *t*, one must be very careful. Our method is based on the fact that after an exponential transformation, the distribution is log-concave on its support.

The algorithms here are designed for situations in which one or more of the parameters change on each call. If they are static, then there are various other methods that should be considered, including table methods and adaptive rejection sampling [5].

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#### 2. A transformed negative gamma distribution

The following "trick" helps in a large number of examples. If X is negative gamma, then  $Y = \log(X/s)$  has a log-concave density proportional to

$$\exp\left(-(\lambda-1)(y+\log s)-se^y\right), y \in [0,\log(t/s)).$$

It is understood that when  $t = \infty$ , then the support of this density is  $[0, \infty)$ . This density has a unique mode at the origin, is monotonically decreasing on the positive halfline, and is log-concave. It is convenient to normalize so that the value of the function we will be dealing with is 1 at the origin. So, Y has density proportional to  $\exp(h(y))$ , where

$$h(y) = -(\lambda - 1)y - s(e^y - 1), y \in [0, \log(t/s)).$$

We recall that all log-concave densities for which the density is available in black box format, and for which the location of the mode (or a mode) is known, one can generate random variates by the rejection method thanks to a universal inequality given in [1]. That method breaks down when one only knows the density up to a normalization constant. In this case, our normalization constant involves the incomplete gamma integral, for which only approximations are known. One can get around the unknown normalization constant quite easily—the path to that was sketched in section 7.2.6 of Devroye [2], and in particular in Theorem 2.6 (page 299) and the algorithm on page 301, but indirectly also in the work of Hörmann et al. [6], and Leydold and Hörmann [7,8]), some automated methods worked out in the more recent papers of Devroye [3,4]). However, universal algorithms are never as efficient as specific designs.

Let z > 0 be fixed. We will only use the following two inequalities in the rejection method:

$$h(y) \le \begin{cases} 0 & \text{for all } y \ge 0, \\ h(z) + (y - z)h'(z) = h(z) - (y - z)((\lambda - 1) + se^z) & \text{if } y \ge z. \end{cases}$$

For general log-concave densities, Leydold and Hörmann [7,8] and indirectly Devroye [3,4] establish that the exponential tail should start when  $h(y) \approx -1$ . Doing so leads quite easily to the correct recipe for a uniformly fast algorithm. A useful choice of the threshold z is obtained as the minimum of three values. Define

$$z_0 = \log(t/s),$$
  

$$z_1 = \log\left(1 + \frac{1}{2s}\right)$$
  

$$z_2 = \frac{1}{2(\lambda - 1)} \text{ (which is } \infty \text{ if } \lambda = 1\text{)}$$

Then set

$$z = \min(z_0, z_1, z_2), w = \operatorname{argmin}(z_0, z_1, z_2).$$

Rejection will be based on

$$e^{h(y)} \le e^{g(y)} \stackrel{\text{def}}{=} \begin{cases} 1 & 0 \le y \le z, \\ \exp(h(z) - a(y - z)) & \text{if } z \le y. \end{cases}$$

where we define

$$a \stackrel{\text{def}}{=} (\lambda - 1) + se^{z}$$
.

We first establish that this is uniformly fast. We did not attempt to optimize the rejection constant. Slightly moving z can improve the bound of Theorem 1:

**Theorem 1.** Let N be the number of loops in the rejection method based on the above inequality. Then

$$\sup_{\substack{0 < s \le t \le \infty \\ \lambda \ge 1}} \mathbb{E}\{N\} \le e + 2.$$

**Proof.** Observe that the integral under the dominating curve  $e^g$  is

$$z + \frac{e^{h(z)}}{a} \mathbb{1}_{[w>0]}.$$

The integral of  $e^h$  over [0, z] is at least  $z \exp(h(z))$ . Thus,

$$\mathbb{E}\{N\} \le \frac{z + \frac{e^{h(z)}}{a} \mathbb{1}_{[w>0]}}{z \exp(h(z))} = \exp\left(-h(z)\right) + \frac{1}{az} \mathbb{1}_{[w>0]} \stackrel{\text{def}}{=} I + II.$$

If  $z = z_1$ , then  $az \ge sz_1e^{z_1} = (s + 1/2)\log(1 + \frac{1}{2s}) \ge \frac{1}{2}$ . If  $z = z_2$ , then  $az \ge (\lambda - 1)z_2 = 1/2$ . So,  $II \le 2$ . Now, we always have

$$-h(z) = (\lambda - 1)z + s(e^{z} - 1) \le (\lambda - 1)z_2 + s(e^{z_1} - 1) = 1.$$

Therefore,  $\mathbb{E}\{N\} \leq e+2$ .  $\Box$ 

#### 3. The rejection algorithm for our example

To apply the rejection method, we need the integrals of  $e^g$  over [0, z] and  $[z, \infty)$ , respectively. The former is z. The latter is given by

$$b \stackrel{\text{def}}{=} \frac{1}{a} e^{h(z)} = \frac{1}{a} \exp\left(-(\lambda - 1)z - s\left(e^z - 1\right)\right).$$

Furthermore, we note that a random variate with density proportional to  $e^g$  on  $[z, \infty)$  is simply generated as z+E/a, where *E* is a standard exponential random variable. Finally, in the algorithm below, if *W* is a candidate point generated from  $e^h$ , and *V* is a uniform [0, 1] random variable, then we replace the rejection step  $Ve^{h(W)} \le e^{g(W)}$  by the condition  $E^* > h(W) - g(W)$ , where we used the fact that *V* is distributed as  $e^{-E^*}$ , where  $E^*$  is exponentially distributed (see the various lines that involve  $E^*$ ). This leads to the following rejection algorithm.

[Algorithm for the negative gamma density on [s,t] of parameter  $\lambda \geq 1.$ ]

```
[Set-up]
  z_0 \leftarrow \log(t/s)
  z_1 \leftarrow \log(1 + 1/(2s))
  z_2 \leftarrow rac{1}{2(\lambda-1)} (\infty if \lambda=1)
  z \leftarrow \min(z_0, z_1, z_2)
  w \leftarrow \arg\min(z_0, z_1, z_2)
  a \leftarrow (\lambda - 1) + se^z
  b \leftarrow \frac{1}{a} \exp\left(-(\lambda - 1)z - s\left(e^z - 1\right)\right)
[Generation]
if w = 0 then repeat
                    W \leftarrow zU, where U is uniform [0,1]
                    generate an exponential random variable E^*
                    Accept \leftarrow [E^* > (\lambda - 1)W + s(e^W - 1)]
                    until Accept
             else repeat
                    if V < z/(z+b) (where V is uniform on [0,1])
                       then W \leftarrow zU, where U is uniform [0,1]
                              generate an exponential random variable E^*
                              Accept \leftarrow [E^* > (\lambda - 1)W + s(e^W - 1)]
                       else W \leftarrow z + E/a, where E is exponential
                              generate an exponential random variable E^*
                              Accept \leftarrow [W \le \log(t/s)]
                                    and [E^* > se^{z} \left( e^{W-z} - 1 - (W-z) \right)]
                    until Accept
\texttt{return} \ X \leftarrow se^W
```

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#### 4. A special case: $\lambda = 1$

For the one parameter density proportional to

$$f(x) = \frac{1}{x}e^{-x}, x \ge s > 0,$$

the algorithm becomes much simpler:

In the algorithm above, we tacitly replaced  $z_1$  by the choice of z given in the first line of the algorithm. One can verify that the bounding method used in Theorem 1 gives the better estimate  $\mathbb{E}\{N\} \le e + 1$ .

#### 5. The gamma density with parameter in (0, 1]

There are many methods for generating gamma random variables with arbitrary parameters. We are interested though in the case of gamma random variables with parameter  $b = 1 - \lambda \in (0, 1]$ , i.e., having density

 $\frac{x^{-\lambda}e^{-x}}{\Gamma(1-\lambda)},$ 

but restricted to the interval  $[s, t] \subseteq [0, \infty)$ . This is a three parameter family of distributions. The purpose is, once again, to derive a uniformly fast rejection method.

First we note that the transformed random variable

 $Y = X^b$ 

has density proportional to

 $\exp\left(-y^{1/b}\right), y \ge 0,$ 

when X is gamma (b). It is much simpler to deal with Y, as its density is monotonically decreasing and log-concave on the positive halfline. We note that this same transformation has also been suggested by Tanizaki [10]. We will restrict Y to  $[s^b, t^b]$ . Note that the density of Y is proportional to  $\exp(h(y))$  where

$$h(y) = s - y^{1/b}.$$

This normalized form has  $h(s^b) = 0$ , which facilitates the further development. Set

$$z_0 = t^b,$$
  
 $z_1 = (1 + s)^b,$   
 $z = \min(z_0, z_1).$ 

On  $[s^b, z]$ , we will apply rejection with as bounding curve 1. On  $[z, t^b]$ , if this interval is not empty, we use the bound

 $h(y) \le h(z) - a(y - z),$ 

with  $a = -h'(z) = (1/b)z^{(1/b)-1}$ . The algorithm is as follows:

```
[Algorithm for the negative gamma density on [s,t] of parameter \lambda \in [0,1).]
[Set-up]
  b \leftarrow 1 - \lambda
  z_0 \leftarrow t^b
  z_1 \leftarrow (1+s)^b
  z \leftarrow \min(z_0, z_1)
  w \leftarrow \arg\min(z_0, z_1)
  a \leftarrow (1/b) z^{(1/b)-1}
  \gamma \leftarrow \frac{1}{a} \exp\left(s - z^{1/b}\right)
[Generation]
if w = 0 then repeat
                   W \leftarrow s^b + (t^b - s^b)U, where U is uniform [0,1]
                   generate an exponential random variable E^*
                   Accept \leftarrow [E^* > W^{1/b} - s]
                   until Accept
            else repeat
                   if V < (z - s^b)/((z - s^b) + \gamma) (where V is uniform on [0, 1])
                      then W \leftarrow s^b + (z - s^b)U, where U is uniform [0,1]
                             generate an exponential random variable E^*
                             Accept \leftarrow [E^* > W^{1/b} - s]
                      else W \leftarrow z + E/a, where E is exponential
                             generate an exponential random variable E^*
                             Accept \leftarrow [W < t^b]
                                   and [E^* > W^{1/b} - z^{1/b} - a(W - z)]
                   until Accept
\texttt{return} \ X \leftarrow W^{1/b}
```

**Theorem 2.** Let N be the number of loops in the rejection method based on the above algorithm. Then

$$\sup_{\substack{0 \le s \le t \le \infty \\ \lambda \in [0,1)}} \mathbb{E}\{N\} \le \frac{e^2}{e-1}.$$

**Proof.** Observe that the integral under the dominating curve  $e^h$  is

$$z - s^b + \frac{e^{h(z)}}{a} \mathbb{1}_{[w>0]}.$$

The integral of  $e^h$  over  $[s^b, z]$  is at least  $(z - s^b) \exp(h(z))$ . Thus,

$$\mathbb{E}\{N\} \le \frac{z - s^b + \frac{e^{h(z)}}{a} \mathbb{1}_{[w>0]}}{(z - s^b) \exp(h(z))} = \exp\left(-h(z)\right) + \frac{1}{a(z - s^b)} \mathbb{1}_{[w>0]} \stackrel{\text{def}}{=} I + II.$$

If  $z = z_1$ , then

$$a(z - s^{b}) = \frac{z_{1}^{1/b - 1}(z_{1} - s^{b})}{b}$$
  
=  $\frac{(s + 1)((1 + s)^{b} - s^{b})}{b(s + 1)^{b}}$   
=  $\frac{s + 1}{b} \left(1 - \frac{1}{(1 + 1/s)^{b}}\right)$   
 $\geq \frac{s + 1}{b} (1 - \exp(-b/(s + 1))).$ 

Since  $s + 1 \ge b$ , the expression is at least (e - 1)/e. So,  $II \le e/(e - 1)$ . Now, we always have

$$-h(z) = z^{1/b} - s \le z_1^{1/b} - s = 1.$$

So,  $I \leq e$ .  $\Box$ 

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