

# Estimation and Inference

## 1.1 Setting

Consider data of the form  $(U_i, \delta_i)$ , where  $U_i$  is the observation time, and  $\delta_i$  indicates that an event occurred prior to censoring:

$$\delta_i = \mathbb{I}(T_i \leq C_i).$$

Suppose the event times  $(T_i)$  follow a generalized Gamma distribution with *shape parameters*  $\alpha$  and  $\beta$ , and *rate parameter*  $\lambda$ . The survival function is:

$$S(t) = \frac{1}{\Gamma(\alpha)} \Gamma\{\alpha, (\lambda t)^\beta\}, \quad t > 0.$$

The density of the generalized gamma distribution is:

$$f(t) = \frac{\beta\lambda}{\Gamma(\alpha)} (\lambda t)^{\alpha\beta-1} e^{-(\lambda t)^\beta}, \quad t > 0.$$

where  $\Gamma(\cdot)$  is the standard gamma function, and  $\Gamma(\cdot, \cdot)$  is the upper incomplete gamma function:

$$\Gamma(\alpha, t) = \int_t^\infty s^{\alpha-1} e^{-s} ds.$$

The hazard function for the generalized gamma distribution is:

$$h(t) = \frac{(\lambda t)^{\alpha\beta-1} e^{-(\lambda t)^\beta}}{\Gamma\{\alpha, (\lambda t)^\beta\}}, \quad t > 0.$$

## 1.2 Likelihood

The density contribution of the  $i$ th subject is:

$$f_i = \frac{\beta\lambda}{\Gamma(\alpha)} (\lambda u_i)^{\alpha\beta-1} e^{-(\lambda u_i)^\beta}.$$

taking the logarithm:

$$\ln f_i = \ln \beta + \ln \lambda - \ln \Gamma(\alpha) + (\alpha\beta - 1) \ln(\lambda u_i) - (\lambda u_i)^\beta.$$

The survival contribution of the  $i$ th subject is:

$$S_i = \frac{1}{\Gamma(\alpha)} \Gamma\{\alpha, (\lambda u_i)^\beta\}.$$

The log survival contribution is:

$$\ln S_i = \ln \Gamma\{\alpha, (\lambda u_i)^\beta\} - \ln \Gamma(\alpha).$$

The right censored likelihood is:

$$L(\boldsymbol{\theta}) = \prod_{i=1}^n f_i^{\delta_i} S_i^{1-\delta_i}.$$

The right censored log likelihood is:

$$\begin{aligned} \ell(\boldsymbol{\theta}) \propto & \sum_{i=1}^n \delta_i \left( \ln \beta + \ln \lambda - \ln \Gamma(\alpha) + \alpha \beta \ln \lambda + \alpha \beta \ln u_i - \ln \lambda - \lambda^\beta u_i^\beta \right) \\ & + \sum_{i=1}^n (1 - \delta_i) \left( \ln \Gamma\{\alpha, (\lambda u_i)^\beta\} - \ln \Gamma(\alpha) \right). \end{aligned}$$

Let  $\Delta_n = \sum_{i=1}^n \delta_i$  denote the number of observed failures. The log likelihood becomes:

$$\begin{aligned} \ell(\boldsymbol{\theta}) \propto & \Delta_n \ln \beta - n \ln \Gamma(\alpha) + \Delta_n \alpha \beta \ln \lambda \\ & + \alpha \beta \sum_{i=1}^n \delta_i \ln u_i - \lambda^\beta \sum_{i=1}^n \delta_i u_i^\beta + \sum_{i=1}^n (1 - \delta_i) \ln \Gamma\{\alpha, (\lambda u_i)^\beta\}. \end{aligned}$$

When  $\beta = 1$ , the gamma log likelihood is recovered:

$$\begin{aligned} \ell(\alpha, \beta = 1, \lambda) = & -n \ln \Gamma(\alpha) + \Delta_n \alpha \ln \lambda \\ & + \alpha \sum_{i=1}^n \delta_i \ln u_i - \lambda \sum_{i=1}^n \delta_i u_i + \sum_{i=1}^n (1 - \delta_i) \ln \Gamma\{\alpha, \lambda u_i\}. \end{aligned}$$

When evaluated at  $\alpha = 1$ , the upper incomplete gamma reduces to:

$$\ln \Gamma(\alpha = 1, s) = \ln \int_s^\infty e^{-u} du = \ln e^{-s} = -s.$$

Consequently, when  $\alpha = 1$ , the Weibull log likelihood is recovered:

$$\begin{aligned} \ell(\alpha = 1, \beta, \lambda) = & \Delta_n \ln \beta + \Delta_n \beta \ln \lambda + \beta \sum_{i=1}^n \delta_i \ln u_i - \lambda^\beta \sum_{i=1}^n \delta_i u_i^\beta - \sum_{i=1}^n (1 - \delta_i) \lambda^\beta u_i^\beta \\ = & \Delta_n \ln \beta + \Delta_n \beta \ln \lambda + \beta \sum_{i=1}^n \delta_i \ln u_i - \lambda^\beta \sum_{i=1}^n u_i^\beta. \end{aligned}$$

### 1.3 Score Equations

The score equation for  $\alpha$  is:

$$\mathcal{U}_\alpha = -n\psi(\alpha) + \Delta_n \beta \ln \lambda + \beta \sum_{i=1}^n \delta_i \ln u_i + \sum_{i=1}^n (1 - \delta_i) \frac{\partial \ln \Gamma\{\alpha, (\lambda u_i)^\beta\}}{\partial \alpha}$$

The score equation for  $\beta$  is:

$$\begin{aligned} \mathcal{U}_\beta = & \frac{\Delta_n}{\beta} + \Delta_n \alpha \ln \lambda + \alpha \sum_{i=1}^n \delta_i \ln u_i - \lambda^\beta \ln \lambda \sum_{i=1}^n \delta_i u_i^\beta \\ & - \lambda^\beta \sum_{i=1}^n \delta_i u_i^\beta \ln u_i + \sum_{i=1}^n (1 - \delta_i) \frac{\partial \ln \Gamma\{\alpha, (\lambda u_i)^\beta\}}{\partial (\lambda u_i)^\beta} \cdot \frac{\partial (\lambda u_i)^\beta}{\partial \beta}. \end{aligned}$$

The score equation for  $\lambda$  is:

$$\mathcal{U}_\lambda = \frac{\Delta_n \alpha \beta}{\lambda} - \beta \lambda^{\beta-1} \sum_{i=1}^n \delta_i u_i^\beta + \sum_{i=1}^n (1 - \delta_i) \frac{\partial \ln \Gamma\{\alpha, (\lambda u_i)^\beta\}}{\partial (\lambda u_i)^\beta} \cdot \frac{\partial (\lambda u_i)^\beta}{\partial \lambda}$$

The partials of the upper incomplete gamma were obtained in the derivations for the (standard) gamma distribution.

## 1.4 Observed Information

The Hessian for  $\alpha$  is:

$$\mathcal{H}_{\alpha\alpha} = -n\dot{\psi}(\alpha) + \sum_{i=1}^n (1 - \delta_i) \Psi_2\{\alpha, (\lambda u_i)^\beta\}.$$

The Hessian for  $\beta$  is:

$$\begin{aligned} \mathcal{H}_{\beta\beta} = & -\frac{\Delta_n}{\beta^2} - \lambda^\beta \ln^2 \lambda \sum_{i=1}^n \delta_i u_i^\beta - 2\lambda^\beta \ln \lambda \sum_{i=1}^n \delta_i u_i^\beta \ln u_i - \lambda^\beta \sum_{i=1}^n \delta_i u_i^\beta \ln^2 u_i \\ & + \sum_{i=1}^n (1 - \delta_i) \left( \frac{\partial^2 \ln \Gamma\{\alpha, (\lambda u_i)^\beta\}}{\partial \{(\lambda u_i)^\beta\}^2} \cdot \left\{ \frac{\partial (\lambda u_i)^\beta}{\partial \beta} \right\}^2 + \frac{\partial \ln \Gamma\{\alpha, (\lambda u_i)^\beta\}}{\partial (\lambda u_i)^\beta} \cdot \left\{ \frac{\partial^2 (\lambda u_i)^\beta}{\partial \beta^2} \right\} \right). \end{aligned}$$

The Hessian in  $\lambda$  is:

$$\begin{aligned} \mathcal{H}_{\lambda\lambda} = & -\frac{\Delta_n \alpha \beta}{\lambda^2} - \beta(\beta - 1) \lambda^{\beta-2} \sum_{i=1}^n \delta_i u_i^\beta \\ & + \sum_{i=1}^n (1 - \delta_i) \left( \frac{\partial^2 \ln \Gamma\{\alpha, (\lambda u_i)^\beta\}}{\partial \{(\lambda u_i)^\beta\}^2} \cdot \left\{ \frac{\partial (\lambda u_i)^\beta}{\partial \lambda} \right\}^2 + \frac{\partial \ln \Gamma\{\alpha, (\lambda u_i)^\beta\}}{\partial (\lambda u_i)^\beta} \cdot \left\{ \frac{\partial^2 (\lambda u_i)^\beta}{\partial \lambda^2} \right\} \right). \end{aligned}$$

The mixed partial w.r.t.  $\alpha$  and  $\beta$  is:

$$\mathcal{H}_{\alpha\beta} = \Delta_n \ln \lambda + \sum_{i=1}^n \delta_i \ln u_i + \sum_{i=1}^n (1 - \delta_i) \frac{\partial^2 \ln \Gamma\{\alpha, (\lambda u_i)^\beta\}}{\partial \alpha \partial (\lambda u_i)^\beta} \cdot \left\{ \frac{\partial (\lambda u_i)^\beta}{\partial \beta} \right\}.$$

The mixed partial w.r.t.  $\alpha$  and  $\lambda$  is:

$$\mathcal{H}_{\alpha\lambda} = \frac{\Delta_n \beta}{\lambda} + \sum_{i=1}^n (1 - \delta_i) \frac{\partial^2 \ln \Gamma\{\alpha, (\lambda u_i)^\beta\}}{\partial \alpha \partial (\lambda u_i)^\beta} \cdot \left\{ \frac{\partial (\lambda u_i)^\beta}{\partial \lambda} \right\}.$$

The mixed partial w.r.t.  $\beta$  and  $\lambda$  is:

$$\begin{aligned}\mathcal{H}_{\beta\lambda} = & \frac{\Delta_n \alpha}{\lambda} - \lambda^{\beta-1} \sum_{i=1}^n \delta_i u_i^\beta - \beta \lambda^{\beta-1} \ln \lambda \sum_{i=1}^n \delta_i u_i^\beta - \beta \lambda^{\beta-1} \sum_{i=1}^n \delta_i u_i^\beta \ln u_i \\ & + \sum_{i=1}^n (1 - \delta_i) \left( \frac{\partial^2 \ln \Gamma\{\alpha, (\lambda u_i)^\beta\}}{\partial \{(\lambda u_i)^\beta\}^2} \cdot \left\{ \frac{\partial (\lambda u_i)^\beta}{\partial \beta} \right\} \left\{ \frac{\partial (\lambda u_i)^\beta}{\partial \lambda} \right\} \right) \\ & + \sum_{i=1}^n (1 - \delta_i) \left( \frac{\partial \ln \Gamma\{\alpha, (\lambda u_i)^\beta\}}{\partial (\lambda u_i)^\beta} \cdot \left\{ \frac{\partial^2 (\lambda u_i)^\beta}{\partial \beta \partial \lambda} \right\} \right).\end{aligned}$$

## 1.5 Complete Data

### 1.5.1 Likelihood

Suppose all events are observed. The log likelihood reduces to:

$$\ell(\boldsymbol{\theta}) \propto n \ln \beta - n \ln \Gamma(\alpha) + n \alpha \beta \ln \lambda + \alpha \beta \sum_{i=1}^n \ln u_i - \lambda^\beta \sum_{i=1}^n u_i^\beta.$$

### 1.5.2 Score

The score for  $\alpha$  is:

$$\mathcal{U}_\alpha = -n\psi(\alpha) + n\beta \ln \lambda + \beta \sum_{i=1}^n \ln u_i.$$

The score for  $\beta$  is:

$$\mathcal{U}_\beta = \frac{n}{\beta} + n\alpha \ln \lambda + \alpha \sum_{i=1}^n \ln u_i - \lambda^\beta \ln \lambda \sum_{i=1}^n u_i^\beta - \lambda^\beta \sum_{i=1}^n u_i^\beta \ln u_i.$$

The score for  $\lambda$  is:

$$\mathcal{U}_\lambda = \frac{n\alpha\beta}{\lambda} - \beta \lambda^{\beta-1} \sum_{i=1}^n u_i^\beta.$$

Solving  $\mathcal{U}_\lambda \stackrel{\text{Set}}{=} 0$  for  $\lambda$ :

$$\hat{\lambda}(\alpha, \beta) = \left( \frac{1}{n\alpha} \sum_{i=1}^n u_i^\beta \right)^{-1/\beta}.$$

### 1.5.3 Hessian

The Hessian for  $\alpha$  is:

$$\mathcal{H}_{\alpha\alpha} = -n\dot{\psi}(\alpha).$$

The Hessian for  $\beta$  is:

$$\mathcal{H}_{\beta\beta} = -\frac{n}{\beta^2} - \lambda^\beta \ln^2 \lambda \sum_{i=1}^n u_i^\beta - 2\lambda^\beta \ln \lambda \sum_{i=1}^n u_i^\beta \ln u_i - \lambda^\beta \sum_{i=1}^n u_i^\beta \ln^2 u_i.$$

The Hessian for  $\lambda$  is:

$$\mathcal{H}_{\lambda\lambda} = -\frac{n\alpha\beta}{\lambda^2} - \beta(\beta-1)\lambda^{\beta-2} \sum_{i=1}^n u_i^\beta.$$

The mixed partials are:

$$\begin{aligned} \mathcal{H}_{\alpha\beta} &= n \ln \lambda + \sum_{i=1}^n \ln u_i, \\ \mathcal{H}_{\alpha\lambda} &= \frac{n\beta}{\lambda}, \\ \mathcal{H}_{\beta\lambda} &= \frac{n\alpha}{\lambda} - \beta\lambda^{\beta-1} \ln \lambda \sum_{i=1}^n u_i^\beta - \lambda^{\beta-1} \sum_{i=1}^n u_i^\beta - \beta\lambda^{\beta-1} \sum_{i=1}^n u_i^\beta \ln u_i. \end{aligned}$$

#### 1.5.4 Profiling

The profile log likelihood of  $(\alpha, \beta)$  is:

$$\ell(\alpha, \beta) \propto n \ln \beta - n \ln \Gamma(\alpha) + n\alpha \ln(n\alpha) - n\alpha \ln \left( \sum_{i=1}^n u_i^\beta \right) + \alpha\beta \sum_{i=1}^n \ln u_i - n\alpha.$$

Taking the partial with respect to  $\beta$ :

$$\mathcal{U}_\beta^\dagger = \frac{n}{\beta} - n\alpha \frac{\sum_{i=1}^n u_i^\beta \ln u_i}{\sum_{i=1}^n u_i^\beta} + \alpha \sum_{i=1}^n \ln u_i.$$

This equation admits a solution in  $\alpha$ :

$$\hat{\alpha}(\beta) = \frac{1}{\beta} \left( \frac{\sum_{i=1}^n u_i^\beta \ln u_i}{\sum_{i=1}^n u_i^\beta} - \frac{1}{n} \sum_{i=1}^n \ln u_i \right)^{-1}.$$

Substituting the MLE for  $\alpha$  into the profile log likelihood of  $(\alpha, \beta)$  gives a profile log likelihood for  $\beta$  alone.

## Properties

**Result 2.0.1.** The  $k$ th moment of the generalized gamma distribution is:

$$\mathbb{E}(T^k) = \frac{\Gamma(\alpha + k/\beta)}{\lambda^k \Gamma(\alpha)}.$$



**Proof.** Writing out the  $k$ th moment:

$$\mathbb{E}(T^k) = \frac{1}{\Gamma(\alpha)} \int_0^\infty t^k \{(\lambda t)^\beta\}^\alpha e^{-(\lambda t)^\beta} (\beta \lambda) (\lambda t)^{-1} dt.$$

Make the change of variables:

$$u = (\lambda t)^\beta, \quad du = \beta \lambda (\lambda t)^{\beta-1} dt.$$

The inverse transformation is:

$$t = u^{1/\beta} / \lambda.$$

Expressing the change of measure as:

$$u^{-1} du = (\beta \lambda) (\lambda t)^{-1} dt,$$

the integral becomes:

$$\mathbb{E}(T^k) = \frac{1}{\Gamma(\alpha)} \int_0^\infty \frac{u^{k/\beta}}{\lambda^k} u^\alpha e^{-u} u^{-1} du = \frac{\Gamma(\alpha + k/\beta)}{\lambda^k \Gamma(\alpha)}.$$



**Corollary 2.0.1.** The mean of the generalized gamma distribution is:

$$\mathbb{E}(T) = \frac{\Gamma(\alpha + 1/\beta)}{\lambda \Gamma(\alpha)}.$$

The variance of the generalized gamma distribution is:

$$\mathbb{V}(T) = \frac{1}{\lambda^2 \Gamma(\alpha)} \left\{ \Gamma(\alpha + 2/\beta) + \frac{\Gamma^2(\alpha + 1/\beta)}{\Gamma(\alpha)} \right\}.$$



## 2.1 First Arrival

Suppose that  $T$  follows a generalized gamma  $(\alpha, \beta, \lambda)$  distribution, and that  $C$  follows a Weibull  $(\beta, \delta)$  distribution. The probability that  $T$  is censored by  $C$  is:

$$\mathbb{P}(T > C) = \mathbb{E}\mathbb{P}(T > C|T) = \mathbb{E}_T\left\{1 - e^{-(\delta T)^\beta}\right\} = \frac{\beta\lambda}{\Gamma(\alpha)} \int_0^\infty (\lambda t)^{\alpha\beta-1} e^{-(\lambda t)^\beta} \left(1 - e^{-(\delta t)^\beta}\right) dt.$$

Rearranging the integrand:

$$\mathbb{P}(T > C) = 1 - \frac{\lambda^{\alpha\beta}}{\Gamma(\alpha)} \int_0^\infty t^{\alpha\beta} e^{-(\lambda^\beta + \delta^\beta)t^\beta} \cdot \beta t^{-1} dt.$$

Let  $\theta = (\lambda^\beta + \delta^\beta)$ , and make the change of variables:

$$u = \theta t^\beta, \quad du = \beta \theta t^{\beta-1} dt.$$

The inverse transformation is:

$$t = (u/\theta)^{1/\beta},$$

and the change of measure is expressible as:

$$\beta t^{-1} dt = u^{-1} du.$$

The probability of first arrival becomes:

$$\mathbb{P}(T > C) = 1 - \frac{\lambda^{\alpha\beta}}{\Gamma(\alpha)} \int_0^\infty \frac{u^\alpha}{\theta^\alpha} e^{-u} \cdot u^{-1} du = 1 - \frac{\lambda^{\alpha\beta}}{\theta^\alpha} = 1 - \frac{(\lambda^\beta)^\alpha}{(\lambda^\beta + \delta^\beta)^\alpha}.$$

Suppose we desire to generate independent exponential censoring times  $C$  such that the probability of censoring is  $\pi_C$ . The required rate for the censoring distribution is:

$$\delta = \lambda \left\{ \frac{1 - (1 - \pi_C)^{1/\alpha}}{(1 - \pi_C)^{1/\alpha}} \right\}^{1/\beta}.$$