



Bayesian Analysis of Shape Parameter of Frechet distribution using Non-Informative Prior

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ABSTRACT

In this paper we work on Frechet distribution with Bayesian paradigm. Posterior distribution is obtained by using Uniform, Jeffreys and generalization of non-informative priors. We use the quadrature numerical integration to solve the posterior distribution. Bayes estimator and their risk have been obtaining four loss functions. The performances of Bayes estimators are compared by using Monte Carlo simulation study.

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Introduction

Extreme value distribution are creating their importance in modeling extreme events such as floods, stock exchange, wind speed etc. There are three types of extreme value distribution and Frechet distribution is of second type of extreme value distribution. Gumbel (1965) estimates the parameters of Frechet distribution having three parameters by using method of moments and maximum likelihood estimation. Hood et al (1990) has estimates parameters for Frechet distribution by using maximum likelihood estimation for doubly censored data. Engelund and Rackwitz (1992) has determined the predictive distribution functions of extreme value distribution by using non-informative priors. Hood et al (1993) has estimated m-th maxima for Frechet distribution under different sampling techniques. Parameters of Frechet distribution has been estimated by maximum likelihood estimation under type-II censored data by Abbas and Tang (2013). Nasir and Aslam (2015) has estimated shape parameter of Frechet distribution by using informative priors via different loss functions.

The probability density function of Frechet distribution is

$$f(x; \alpha, \beta) = \frac{\alpha}{\beta} \left(\frac{\beta}{x}\right)^{\alpha+1} e^{-\left(\frac{\beta}{x}\right)^{\alpha}}, \text{ where } \alpha, \beta > 0$$

Where α is shape parameter and β is scale parameter.

We will work on the case for estimation of shape parameter by using non-informative priors.

Posterior distribution

Posterior distribution is derived by using Uniform, Jeffreys and generalization of non-informative priors.

The uniform prior for shape parameter α is

$$p(\alpha) \propto 1, \text{ where } \alpha > 0$$

The posterior distribution under uniform prior for parameter α for the data x_1, x_2, \dots, x_n is

$$p(\alpha|x) = \frac{1}{k_1} \alpha^n \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^{\alpha}}$$

Where

$$k_1 = \int_0^{\infty} \alpha^n \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^{\alpha}} d\alpha$$

We will solve it numerically because it is not in close form. The Jeffreys Prior for shape parameter is

$$p(\alpha) \propto \frac{1}{\alpha}, \text{ where } \alpha > 0$$

The posterior distribution under Jeffreys prior for parameter α for the data x_1, x_2, \dots, x_n is

$$p(\alpha|x) = \frac{1}{k_2} \alpha^{n-1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^{\alpha}}$$

$$k_2 = \int_0^{\infty} \alpha^{n-1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^{\alpha}} d\alpha$$

We will solve it numerically because it is not in close form. The generalization of non-informative prior (GNIP) for shape parameter α is

$$p(\alpha) \propto \frac{1}{\alpha^a}, \text{ where } \alpha > 0$$

The posterior distribution under generalization of non-informative prior for parameter α for the data x_1, x_2, \dots, x_n is

$$p(\alpha|x) = \frac{1}{k_3} \alpha^{n-a} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha}$$

Where

$$k_3 = \int_0^\infty \alpha^{n-a} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha$$

We will solve it numerically assuming a=2 because it is not in close form.

Bayesian Estimation under different loss functions

We have used four loss functions for estimation. The Bayes estimators (BEs) and their Bayes posterior risks (PRs) are as follow

Square error Loss function (SELF)

The Bayes estimator and their cross ponding risks under SELF using uniform prior is

$$\alpha^* = \int_0^\infty \frac{1}{k_1} \alpha^{n+1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha$$

$$\rho(\alpha^*) = \int_0^\infty \frac{1}{k_1} \alpha^{n+2} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha - \left(\int_0^\infty \frac{1}{k_1} \alpha^{n+1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha \right)^2$$

The BEs and PRs under Jeffreys prior for SELF is

$$\alpha^* = \int_0^\infty \frac{1}{k_2} \alpha^n \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha$$

$$\rho(\alpha^*) = \int_0^\infty \frac{1}{k_2} \alpha^{n+1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha - \left(\int_0^\infty \frac{1}{k_2} \alpha^n \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha \right)^2$$

The BEs and PRs under GNIP under SELF is

$$\alpha^* = \int_0^\infty \frac{1}{k_3} \alpha^{n-1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha$$

$$\rho(\alpha^*) = \int_0^\infty \frac{1}{k_1} \alpha^n \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha - \left(\int_0^\infty \frac{1}{k_1} \alpha^{n-1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha \right)^2$$

Precautionary Loss Function (PLF)

The BEs and PRs under PLF using uniform prior is

$$\alpha^* = \sqrt{\int_0^\infty \frac{1}{k_3} \alpha^{n+2} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha}$$

$$\rho(\alpha^*) = 2^* \left[\sqrt{\int_0^\infty \frac{1}{k_1} \alpha^{n+2} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha} - \left(\int_0^\infty \frac{1}{k_1} \alpha^{n+1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha \right)^2 \right]$$

The BEs and PRs under PLF using Jeffreys prior is

$$\alpha^* = \sqrt{\int_0^\infty \frac{1}{k_2} \alpha^{n+1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha}$$

$$\rho(\alpha^*) = 2^* \left[\sqrt{\int_0^\infty \frac{1}{k_2} \alpha^{n+1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha} - \left(\int_0^\infty \frac{1}{k_2} \alpha^n \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha \right)^2 \right]$$

The BEs and PRs under PLF using GNIP prior is

$$\alpha^* = \sqrt{\int_0^\infty \frac{1}{k_3} \alpha^n \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha}$$

$$\rho(\alpha^*) = 2^* \left[\sqrt{\int_0^\infty \frac{1}{k_3} \alpha^n \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha} - \left(\int_0^\infty \frac{1}{k_3} \alpha^{n-1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha \right)^2 \right]$$

Simple Precautionary Loss Function (SPLF)

The BEs and PRs under SPLF using uniform prior is

$$\alpha^* = \sqrt{\frac{\int_0^\infty \frac{\alpha^{n+1}}{k_1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha}{\int_0^\infty \frac{\alpha^{n-1}}{k_1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha}}$$

$$\rho(\alpha^*) = 2^* \left[\sqrt{\frac{\int_0^\infty \frac{1}{k_1} \alpha^{n-1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha}{\int_0^\infty \frac{1}{k_1} \alpha^{n+1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha - 1}} \right]$$

The BEs and PRs under SPLF using Jeffreys prior is

$$\alpha^* = \sqrt{\frac{\int_0^\infty \frac{1}{k_2} \alpha^n \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha}{\int_0^\infty \frac{1}{k_1} \alpha^{n-2} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha}}$$

$$\rho(\alpha^*) = 2 * \frac{\int_0^\infty \frac{1}{k_2} \alpha^{n-2} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha}{\int_0^\infty \frac{1}{k_2} \alpha^n \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha - 1}$$

The BEs and PRs under SPLF using GNIP prior is

$$\alpha^* = \frac{\int_0^\infty \frac{1}{k_3} \alpha^{n-1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha}{\int_0^\infty \frac{1}{k_3} \alpha^{n-3} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha}$$

$$\rho(\alpha^*) = 2 * \frac{\int_0^\infty \frac{1}{k_2} \alpha^{n-1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha}{\int_0^\infty \frac{1}{k_2} \alpha^{n-3} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha - 1}$$

DeGroot Loss Function (1970) (DeLF)

The BEs and PRs under DeLF using uniform prior is

$$\alpha^* = \frac{\int_0^\infty \frac{\alpha^{n+2}}{k_1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha}{\int_0^\infty \frac{\alpha^{n+1}}{k_1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha}$$

$$\rho(\alpha^*) = \frac{\int_0^\infty \frac{1}{k_1} \alpha^{n+2} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha - \left(\int_0^\infty \frac{1}{k_1} \alpha^{n+1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha\right)^2}{\int_0^\infty \frac{1}{k_1} \alpha^{n+2} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha}$$

The BEs and PRs under DeLF using Jeffreys prior is

$$\alpha^* = \frac{\int_0^\infty \frac{\alpha^{n+1}}{k_1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha}{\int_0^\infty \frac{\alpha^n}{k_1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha}$$

$$\rho(\alpha^*) = \frac{\int_0^\infty \frac{1}{k_1} \alpha^{n+1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha - \left(\int_0^\infty \frac{1}{k_1} \alpha^n \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha\right)^2}{\int_0^\infty \frac{1}{k_1} \alpha^{n+1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha}$$

The BEs and PRs under DeLF using GNIP prior is

$$\alpha^* = \frac{\int_0^\infty \frac{\alpha^n}{k_1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha}{\int_0^\infty \frac{\alpha^{n-1}}{k_1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha}$$

$$\rho(\alpha^*) = \frac{\int_0^\infty \frac{1}{k_1} \alpha^n \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha - \left(\int_0^\infty \frac{1}{k_1} \alpha^{n-1} \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha\right)^2}{\int_0^\infty \frac{1}{k_1} \alpha^n \beta^{n\alpha} \prod_{i=1}^n \left(\frac{1}{x_i}\right)^{\alpha+1} e^{-\sum_{i=1}^n \left(\frac{\beta}{x_i}\right)^\alpha} d\alpha}$$

Simulation Study

Simulation has many properties that whether the data are discrete or continuous. By simulation, Bayesian problems of updating estimates can be handled easily. By this process the results tend to be very clear. When the analysis solution of the problems may be difficult or impossible, simulation can provide an effective way to handle. So by taking different values of parameters along different sample size the properties of posterior distribution are verified through simulation study. Also take different values of parameter $\alpha = \{2, 4, 6\}$ for three cases the properties of posterior distribution are verified. This section presents simulation study of Bayes estimators and posterior risks.

Table 1. Simulation result for PLF Assuming $\beta=3$

n	Prior	$\alpha=2$	$\alpha=6$
UP	30	2.0831 (0.0372)	6.2852 (0.1128)
	50	2.0612 (0.0222)	6.1781 (0.0666)
	70	2.0315 (0.0157)	6.1253 (0.0477)
	100	2.0346 (0.0111)	6.1240 (0.0334)
JP	30	2.0599 (0.0382)	6.1657 (0.1149)
	50	2.0320 (0.0226)	6.0972 (0.0673)
	70	2.0221 (0.0159)	6.0606 (0.0481)
	100	2.0079 (0.0110)	6.0339 (0.0331)
GNIP	30	2.0027 (0.0796)	6.0094 (0.7228)
	50	1.9991 (0.0459)	5.9753 (0.4143)
	70	2.0006 (0.0326)	6.0078 (0.2932)
	100	1.9954 (0.0224)	6.0878 (0.0054)

Table 2. Simulation Result for PLF Assuming $\beta=5$

n	Prior	$\alpha=2$	$\alpha=6$
UP	30	2.0848 (0.0376)	6.2770 (0.1130)
	50	2.0650 (0.0224)	6.1507 (0.0667)
	70	2.0382 (0.0158)	6.1004 (0.0475)
	100	2.0273 (0.0110)	6.0794 (0.0330)
JP	30	2.0505 (0.0383)	6.1500 (0.1138)
	50	2.0305 (0.0224)	6.1092 (0.0675)
	70	2.0291 (0.0160)	6.0484 (0.0478)
	100	2.0142 (0.0111)	6.0460 (0.0333)
GNIP	30	2.1001 (0.0381)	6.2587 (0.0380)
	50	2.0578 (0.0209)	6.1849 (0.0208)
	70	2.0493 (0.0178)	6.1513 (0.0178)
	100	2.0317 (0.0154)	6.0342 (0.0333)

Table 3. Simulation Result for SELF Assuming $\beta = 3$

n	Prior	$\alpha = 2$	$\alpha = 6$
UP	30	2.0908 (0.0373)	6.2273 (0.1111)
	50	2.0608 (0.0224)	6.1642 (0.0672)
	70	2.0455 (0.0158)	6.1093 (0.0473)
	100	2.0253 (0.0110)	6.0899 (0.0331)
JP	30	2.0502 (0.0816)	6.0963 (0.7144)
	50	2.0253 (0.0462)	6.1064 (0.4245)
	70	2.0215 (0.0326)	6.0687 (0.2946)
	100	2.0148 (0.0225)	6.0331 (0.2024)
GNIP	30	1.9930 (0.0796)	6.0094 (0.7228)
	50	2.0014 (0.0464)	5.9753 (0.4143)
	70	2.0064 (0.0328)	6.0078 (0.2932)
	100	1.9976 (0.0224)	5.9999 (0.2028)

Table 5. Simulation Result for DeLF Assuming $\beta = 3$

n	Prior	$\alpha = 2$	$\alpha = 6$
UP	30	2.1156 (0.0177)	6.3414 (0.0177)
	50	2.0687 (0.0108)	6.2304 (0.0108)
	70	2.0454 (0.0076)	6.1351 (0.0077)
	100	2.0314 (0.0054)	6.1045 (0.0054)
JP	30	2.0869 (0.0185)	6.2685 (0.0186)
	50	2.0419 (0.0110)	6.0853 (0.0111)
	70	2.0289 (0.0079)	6.1223 (0.0078)
	100	2.0195 (0.0054)	6.0662 (0.0055)
GNIP	30	2.0027 (0.0803)	6.0094 (0.7228)
	50	1.9991 (0.0459)	5.9753 (0.4143)
	70	2.0006 (0.0326)	6.0078 (0.2932)
	100	1.9954 (0.0224)	6.0508 (0.0334)

Table 4. Simulation Result for SELF Assuming $\beta = 5$

n	prior	$\alpha = 2$	$\alpha = 6$
UP	30	2.0997 (0.0376)	6.2672 (0.1122)
	50	2.0512 (0.0222)	6.1762 (0.0669)
	70	2.0467 (0.0159)	6.1127 (0.0473)
	100	2.0277 (0.0111)	6.0840 (0.0330)
JP	30	2.0509 (0.0811)	6.1154 (0.7223)
	50	2.0185 (0.0460)	6.0523 (0.4106)
	70	2.0113 (0.0323)	6.0320 (0.2920)
	100	2.0179 (0.0226)	6.0291 (0.2017)
GNIP	30	1.9947 (0.0791)	5.972 (0.7167)
	50	2.0028 (0.0465)	5.9994 (0.4186)
	70	1.9944 (0.0323)	6.0135 (0.2962)
	100	2.0083 (0.0226)	6.0134 (0.2036)

Table 6. Simulation Result for DeLF Assuming $\beta = 5$

n	prior	$\alpha = 2$	$\alpha = 6$
UP	30	2.1277 (0.0178)	6.3937 (0.0077)
	50	2.0742 (0.0107)	6.2219 (0.0107)
	70	2.0506 (0.0077)	6.1400 (0.0077)
	100	2.0277 (0.0054)	6.0937 (0.0054)
JP	30	2.0868 (0.0184)	6.2555 (0.0186)
	50	2.0492 (0.0110)	6.1396 (0.0110)
	70	2.0353 (0.0079)	6.1163 (0.0078)
	100	2.0241 (0.0055)	6.0629 (0.0055)
GNIP	30	1.9987 (0.0799)	6.0038 (0.7201)
	50	2.0053 (0.0469)	5.9762 (0.4147)
	70	2.0045 (0.0326)	6.0112 (0.2943)
	100	1.9941 (0.0223)	5.9999 (0.2028)

Table 7. Simulation Result for SPLF Assuming $\beta = 3$

n	Prior	$\alpha = 2$	$\alpha = 6$
UP	30	2.0588 (0.0189)	6.2336 (0.0186)
	50	2.0330 (0.0111)	6.1150 (0.0111)
	70	2.0227 (0.0079)	6.0718 (0.0079)
	100	2.0103 (0.0054)	6.0643 (0.0055)
JP	30	2.0121 (0.0194)	6.1003 (0.0192)
	50	2.0059 (0.0114)	6.0236 (0.0114)
	70	2.0133 (0.0080)	5.9981 (0.0080)
	100	2.0047 (0.0056)	6.0336 (0.0056)
GNIP	30	1.9900 (0.0202)	6.1304 (0.1136)
	50	1.9955 (0.0117)	6.0727 (0.0677)
	70	1.9975 (0.0082)	6.0744 (0.0479)
	100	1.9974 (0.0056)	6.0348 (0.0332)

Table 8. Simulation Result For SPLF Assuming $\beta = 5$

n	prior	$\alpha = 2$	$\alpha = 6$
UP	30	2.0623 (0.0186)	6.2343 (0.0188)
	50	2.0403 0.0110	6.1024 (0.0111)
	70	2.0207 (0.0079)	6.0850 (0.0079)
	100	2.0214 (0.0055)	6.0454 (0.0055)
JP	30	2.0122 (0.0195)	6.0736 (0.0195)
	50	2.0105 (0.0114)	6.0264 (0.0114)
	70	2.0123 0.0080	6.0345 (0.0080)
	100	2.0023 (0.0055)	6.0288 (0.0056)
GNIP	30	2.0461 (0.0380)	6.1532 (0.1147)
	50	2.0346 (0.0225)	6.1271 (0.0682)
	70	2.0242 (0.0161)	6.0754 (0.0480)
	100	2.0144 (0.0110)	6.0559 (0.0333)

Conclusion

From the above simulation study we conclude that by increasing sample size Bayes estimators approaches to its true value and by increasing sample size Bayes posterior risks decreases. DeGroot loss function with uniform prior is performing better as Bayes posterior risks is minimum among all loss functions.

This study can be further extended by using other non-informative priors and other loss functions.

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