RandLib documentation

Aleksandr Samarin

November 1, 2018

Contents

Part I
General information

1 Calculation of sample moments

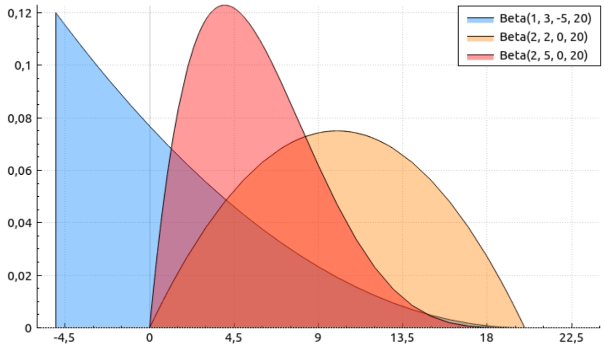
We use extension of Welford's method from Knuth. For every n-th element x we have

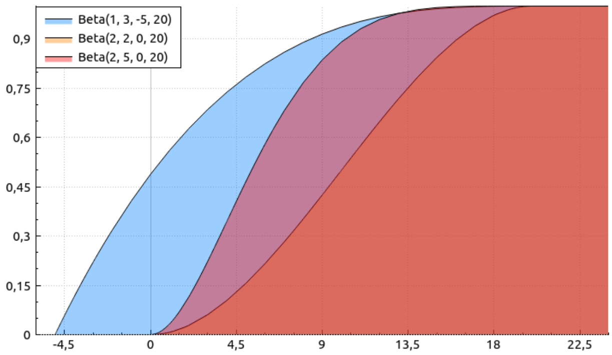
$$\begin{aligned}
\delta &= x - m_1,\\
m_1' &= m_1 + \frac{\delta}{n},\\
m_2' &= m_2 + \delta^2\frac{n-1}{n},\\
m_3' &= m_3 + \delta^3\frac{(n-1)(n-2)}{n^2} - 3\delta\frac{m_2}{n},\\
m_4' &= m_4 + \delta^4\frac{(n-1)(n^2-3n+3)}{n^3} + 6\delta^2\frac{m_2}{n^2} - 4\delta\frac{m_3}{n}.
\end{aligned}$$

Then m_1', $\frac{m_2}{n}$, $\mathrm{Skew}(X) = \frac{\sqrt{n}m_3'}{m_2'^{3/2}}$ and $\mathrm{Kurt}(X) = \frac{nm_4'}{m_2'^2}$ (we return excess kurtosis).

Part II
Continuous univariate distributions

2 Beta distribution





Notation	$X \sim \mathcal{B}(\alpha, \beta, a, b)$ $X \sim \mathcal{B}(\alpha, \beta)$ with $a = 0, b = 1$
Parameters	$\alpha, \beta > 0,\ a, b \in \mathbb{R}$
Domain	$x \in [a, b]$
$f(x)$	$\frac{y^{\alpha-1}(1-y)^{\beta-1}}{(b-a)B(\alpha,\beta)}$ with $y = \frac{x-a}{b-a}$
$F(x)$	$I_y(\alpha, \beta)$ for $y = \frac{x-a}{b-a}$
$\mathbb{E}[X]$	$a + (b-a)\frac{\alpha}{\alpha+\beta}$
$\mathrm{Var}(X)$	$(b-a)^2 \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$
Median	Searched numerically
Mode	$a + (b-a)\frac{\alpha-1}{\alpha+\beta-2}$ for $\alpha, \beta > 1$.
$\phi(t)$	Calculated numerically

Search of the median. In general, the value of median is unkwnown and searched numerically with initial value:

$$m \approx a + (b-a)\frac{\alpha - \frac{1}{3}}{\alpha + \beta - \frac{2}{3}}$$

for $\alpha, \beta \geq 1$. However, there are analytical solutions for some particular values:

- $m = \frac{a+b}{2}$, for $\alpha = \beta$,
- $m = a + (b-a)(1 - 2^{-\frac{1}{\beta}})$, for $\alpha = 1$,
- $m = a + (b-a)2^{-\frac{1}{\alpha}}$, for $\beta = 1$.

Calculation of characteristic function. For $\alpha, \beta \geq 1$ we use numerical integration by definition

$$\phi(t) = \int_a^b \cos(tx) f(x) dx + i \int_a^b \sin(tx) f(x) dx.$$

For shape parameters < 1, $f(x)$ has singularity points at 0 or 1 or both of them, and numerical integration is impossible. Then we use the following technique: firstly, we can show that

$$\phi(t|a, b) = \mathbb{E}[e^{it(a+(b-a)X)}] = e^{ita}\phi(z|0, 1)$$

with $z = (b - a)t$. Hence, w.l.o.g. we can consider standard case $a = 0$, $b = 1$. Then

$$\begin{aligned}
\Re(\phi(z)) &= \frac{1}{B(\alpha,\beta)} \int_0^1 \cos(zx) x^{\alpha-1}(1-x)^{\beta-1} dx \\
&= \frac{1}{B(\alpha,\beta)} \int_0^1 (\cos(zx) - 1) x^{\alpha-1}(1-x)^{\beta-1} dx + 1 \\
&= \frac{1}{B(\alpha,\beta)} \int_0^1 \frac{(\cos(zx) - 1)x^{\alpha-1} - (\cos(z) - 1)}{(1-x)^{1-\beta}} dx + 1 + \frac{\cos(z) - 1}{bB(\alpha,\beta)}.
\end{aligned}$$

The integrand now doesn't have any singularities, neither for $\alpha < 1$, nor for $\beta < 1$. Analogously we transform the imaginary part:

$$\begin{aligned}
\Im(\phi(z)) &= \frac{1}{B(\alpha,\beta)} \int_0^1 \sin(zx) x^{\alpha-1}(1-x)^{\beta-1} dx \\
&= \frac{1}{B(\alpha,\beta)} \int_0^1 \frac{\sin(zx)x^{\alpha-1} - \sin(z)}{(1-x)^{1-\beta}} dx + \frac{\sin(z)}{bB(\alpha,\beta)}.
\end{aligned}$$

Estimation of shapes with known support. Assume that $a = 0$, $b = 1$ and we have a sample $X = (X_1, \ldots, X_n)$. Then a log-likelihood function is

$$\begin{aligned}
\ln \mathcal{L}(\alpha, \beta|X) &= \sum_{i=1}^n \ln f(X_i; \alpha, \beta) \\
&= (\alpha - 1) \sum_{i=1}^n \ln X_i + (\beta - 1) \sum_{i=1}^n \ln(1 - X_i) - n \ln B(\alpha, \beta).
\end{aligned} \tag{1}$$

Differentiating with respect to the shapes, we obtain

$$\frac{\partial \ln \mathcal{L}(\alpha, \beta|X)}{\partial \alpha} = \sum_{i=1}^n \ln X_i + n(\psi(\alpha + \beta) - \psi(\alpha)),$$

$$\frac{\partial \ln \mathcal{L}(\alpha, \beta|X)}{\partial \beta} = \sum_{i=1}^n \ln(1 - X_i) + n(\psi(\alpha + \beta) - \psi(\beta)).$$

Differentiating again we get the Hessian matrix:

$$\mathrm{H}(\ln \mathcal{L}(\alpha, \beta|X)) = n \cdot \begin{pmatrix} \psi_1(\alpha+\beta) - \psi_1(\alpha) & \psi_1(\alpha+\beta) \\ \psi_1(\alpha+\beta) & \psi_1(\alpha+\beta) - \psi_1(\beta) \end{pmatrix}.$$

Then we can find the estimators numerically, using Newton's procedure. The initial values of estimators are found via method of moments:

$$\hat{\alpha}_0 = \overline{X}_n \left(\frac{\overline{X}_n(1-\overline{X}_n)}{\hat{s}_n^2} - 1 \right),$$

$$\hat{\beta}_0 = (1-\overline{X}_n) \left(\frac{\overline{X}_n(1-\overline{X}_n)}{\hat{s}_n^2} - 1 \right).$$

These values are applicable only if $\hat{s}_n^2 < \overline{X}_n(1-\overline{X}_n)$. If this condition is not satisfied, we set $\hat{\alpha}_0 = \hat{\beta}_0 = 0.001$.
In the general case, when $a \neq 0$ or $b \neq 1$, we use the following transformation:

$$Y_i = \frac{X_i - a}{b - a}$$

and estimate parameters, using sample Y.

2.1 Arcsine distribution

Notation:

$$X \sim \text{Arcsine}(\alpha).$$

Relation to Beta distribution:

$$X \sim \mathcal{B}(1-\alpha, \alpha, a, b).$$

Estimation of shape. For Arcsine distribution log-likelihood function (1) turns into

$$\ln \mathcal{L}(\alpha|X) = -\alpha \sum_{i=1}^{n} \ln X_i + (\alpha - 1) \sum_{i=1}^{n} \ln(1 - X_i) - n \ln B(1-\alpha, \alpha).$$

Taking the derivative with respect to α we get

$$\frac{\partial \ln \mathcal{L}(\alpha|X)}{\partial \alpha} = \sum_{i=1}^{n} \ln \frac{1 - X_i}{X_i} + n\pi \cot(\pi\alpha).$$

Therefore, maximum-likelihood function is

$$\hat{\alpha} = -\frac{1}{\pi} \operatorname{atan} \left(\frac{n\pi}{\sum_{i=1}^{n} \ln \frac{1-X_i}{X_i}} \right).$$

If $\hat{\alpha}$ is negative, we add 1, because $\frac{\operatorname{atan}}{\pi} \in (-0.5, 0.5)$, while $\alpha \in (0, 1)$.

2.2 Balding-Nichols distribution

Notation:

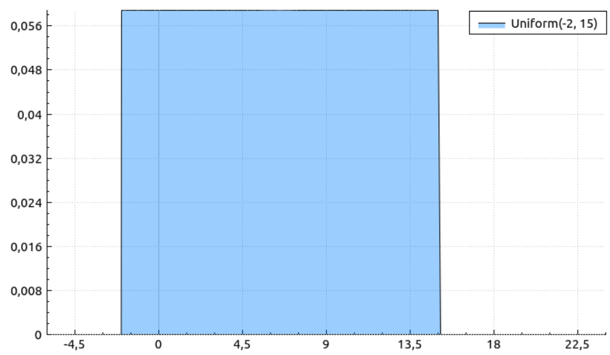
$$X \sim \text{Balding-Nichols}(p, F)$$

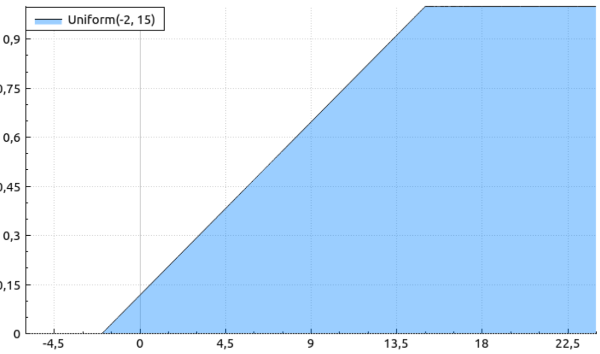
with $p, F \in (0, 1)$. Relation to Beta distribution:

$$X \sim \mathcal{B}(pF', (1-p)F')$$

with $F' = (1-F)/F$.

2.3 Uniform distribution





Notation	$X \sim \mathcal{U}(a, b)$
Parameters	$a, b \in \mathbb{R}$
Domain	$x \in [a, b]$
$f(x)$	$\frac{1}{b-a}$
$F(x)$	$\frac{x-a}{b-a}$
$\mathbb{E}[X]$	$\frac{a+b}{2}$
$\text{Var}(X)$	$\frac{(b-a)^2}{12}$
Median	$\frac{a+b}{2}$
Mode	doesn't exist
$\phi(t)$	$\frac{e^{itb}-e^{ita}}{it(b-a)}$

Relation to Beta distribution:

$$X \sim \mathcal{B}(1, 1, a, b).$$

Estimation of support.

Frequentist inference. Likelihood function is

$$\mathcal{L}(a, b|X) = \frac{1}{(b-a)^n} \mathbf{1}_{\{X_i \in [a,b]\ \forall i=1,\dots,n\}}.$$

Therefore, $\mathcal{L}(a,b|X)$ is the largest for $\hat{b} = X_{(n)}$ and $\hat{a} = X_{(1)}$. However, using the fact that $X_{(k)} \sim B(k, n+1-k, a, b)$, these are biased estimators:

$$\mathbb{E}[X_{(1)}] = \frac{an+b}{n+1} \quad \text{and} \quad \mathbb{E}[X_{(n)}] = \frac{a+bn}{n+1}.$$

To get unbiased estimators we make the transformations:

$$\tilde{a} = \frac{nX_{(1)} - X_{(n)}}{n-1} \quad \text{and} \quad \tilde{b} = \frac{nX_{(n)} - X_{(1)}}{n-1}.$$

Then we get

$$\mathbb{E}[\tilde{a}] = \frac{n\mathbb{E}[X_{(1)}] - \mathbb{E}[X_{(n)}]}{n-1} = \frac{n(an+b) - (a+bn)}{n^2-1} = a.$$

Analogously, $\mathbb{E}[\tilde{b}] = b$.

Bayesian inference. Let us say, we try to estimate $\theta = b - a$ with known a. We set the prior distribution $\theta \sim \text{Pareto}(\alpha, \sigma)$:

$$h(\theta|\alpha,\sigma) = \frac{\alpha\sigma^\alpha}{\theta^{\alpha+1}} \mathbf{1}_{\{\theta \geq \sigma\}}.$$

The density of posterior distribution is

$$f(\theta|X) \propto \frac{\alpha\sigma^\alpha}{\theta^{\alpha+n+1}} \mathbf{1}_{\{\theta \geq \max(\sigma, X_{(n)} - a)\}} \sim \text{Pareto}(\alpha + n, \max(\sigma, X_{(n)} - a)).$$

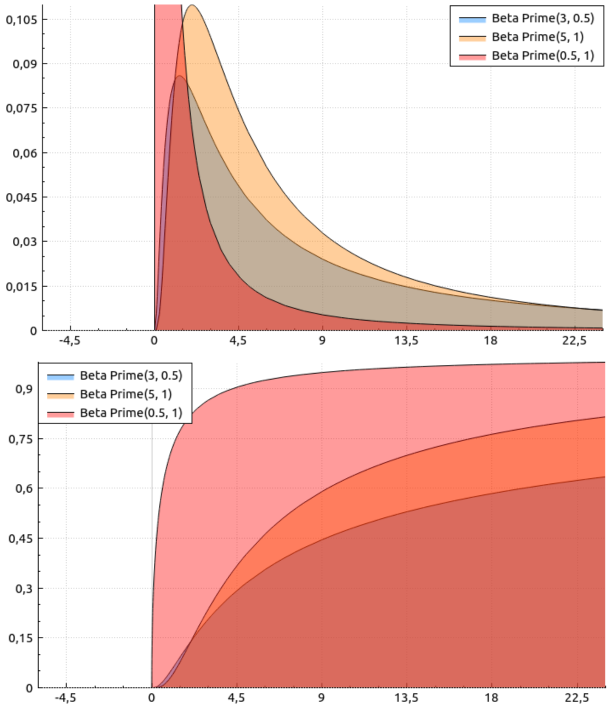
Hence, Bayesian estimator is

$$\mathbb{E}[\theta|X] = \frac{\alpha+n}{\alpha+n-1} \max(\sigma, X_{(n)} - a)$$

and MAP estimator is

$$\theta_{MAP} = \max(\sigma, X_{(n)} - a).$$

3 Beta-prime distribution



Notation	$X \sim \mathcal{B}'(\alpha, \beta)$
Parameters	$\alpha, \beta > 0$
Domain	$x \in \mathbb{R}^+$
$f(x)$	$\frac{x^{\alpha-1}(1+x)^{-\alpha-\beta}}{B(\alpha,\beta)}$
$F(x)$	$I_{\frac{x}{1+x}}(\alpha, \beta)$
$\mathbb{E}[X]$	$\frac{\alpha}{\beta-1}\mathbf{1}_{\{\beta>1\}} + \infty\mathbf{1}_{\{\beta\leq 1\}}$
$\mathrm{Var}(X)$	$\frac{\alpha(\alpha+\beta-1)}{(\beta-2)(\beta-1)^2}$, if $\beta > 1$
Median	Searched numerically
Mode	$\max\left(\frac{\alpha-1}{\beta+1}, 0\right)$.
$\phi(t)$	Calculated numerically

Relation to other distributions:

$$\frac{X}{1+X} \sim \mathcal{B}(\alpha, \beta),$$

$$\frac{\beta}{\alpha}X \sim F(2\alpha, 2\beta).$$

Search of the median. For $\alpha = \beta$ we have $m = 1$. Otherwise, we use the relation $m = \frac{m'}{1-m'}$, where m' is the median of beta-distribution $\mathcal{B}(\alpha, \beta)$.

Calculation of characteristic function. For $\alpha \geq 1$ one can use numerical integration from section For $\alpha < 1$ we have $\lim_{x\to 0} f(x) \to \infty$ and $\int_0^\infty \cos(tx)f(x)dx$ is impossible to compute directly. Then we split the integral:

$$\int_0^\infty \cos(tx)f(x)dx = \int_0^\infty (\cos(tx) - 1)f(x)dx + 1.$$

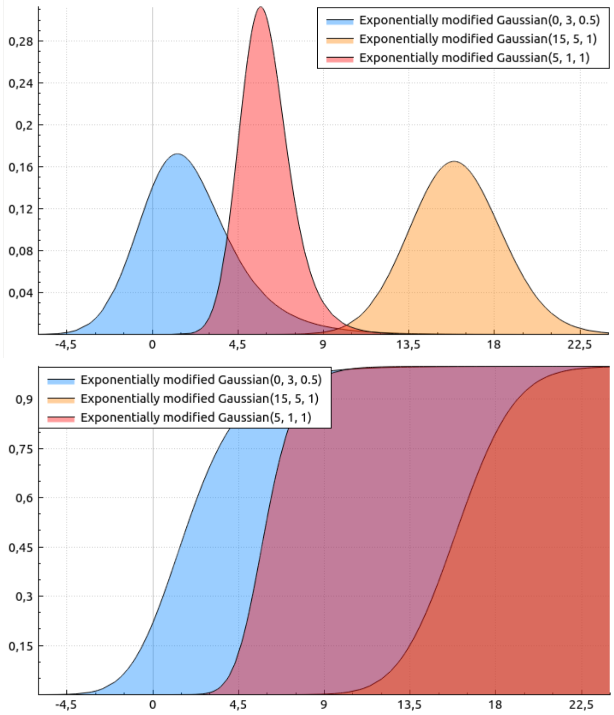
The limit of the integrand for $x \to 0$ is 0 now, regardless of the value of the shape α.

Estimation of shapes. Using relationship with Beta distribution we transform the sample:

$$Y_i = \frac{X_i}{1 + X_i}, \quad 1 \leq i \leq N,$$

and run estimation for beta-distributed Y.

4 Exponentially-modified Gaussian distribution



Notation	$X \sim \text{EMG}(\mu, \sigma, \lambda)$
Parameters	$\mu \in \mathbb{R}, \sigma > 0, \lambda > 0$
Domain	$x \in \mathbb{R}$
$f(x)$	$\frac{\lambda}{2} e^{\frac{\lambda}{2}(2\mu+\lambda\sigma^2-2x)} \operatorname{erfc}\left(\frac{\mu+\lambda\sigma^2-x}{\sqrt{2\sigma^2}}\right)$
$F(x)$	$\Phi(u, 0, v) - e^{-u+\frac{v^2}{2}+\log\Phi(u, v^2, v)}$, where $\Phi(x, \mu, \sigma)$ is Gaussian CDF, $u = \lambda(x-\mu)$, $v = \lambda\sigma$.
$\mathbb{E}[X]$	$\mu + 1/\lambda$
$\text{Var}(X)$	$\sigma^2 + 1/\lambda^2$
Median	Searched numerically
Mode	Searched numerically
$\phi(t)$	$\left(1 - \frac{it}{\lambda}\right)^{-1} \exp\left(i\mu t - \frac{1}{2}\sigma^2 t^2\right)$

Relation to other distribution: if $X \sim \mathcal{N}(\mu, \sigma^2)$ and $Y \sim \text{Exp}(\lambda)$, then $X + Y \sim \text{EMG}(\mu, \sigma, \lambda)$.

5 F-distribution

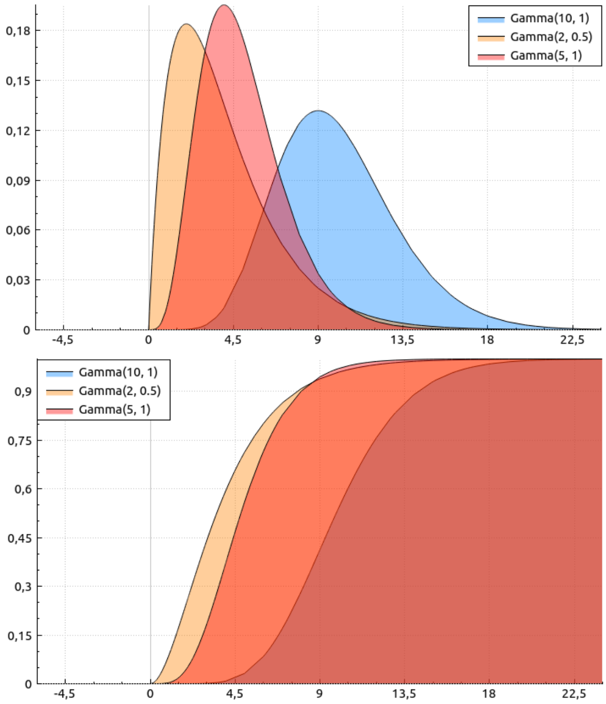
Notation	$X \sim \mathrm{F}(d_1, d_2)$
Parameters	$d_1, d_2 > 0$
Domain	$x \in \mathbb{R}^+$
$f(x)$	$\frac{\sqrt{\frac{(d_1 x)^{d_1} {d_2}^{d_2}}{(d_1 x + d_2)^{d_1 + d_2}}}}{x B\left(\frac{d_1}{2}, \frac{d_2}{2}\right)}$
$F(x)$	$I_{\frac{d_1 x}{d_1 x + d_2}}\left(\frac{d_1}{2}, \frac{d_2}{2}\right)$
$\mathbb{E}[X]$	$\frac{d_2}{d_2 - 2}$ for $d_2 > 2$
$\mathrm{Var}(X)$	$\frac{2 d_2^2 (d_1 + d_2 - 2)}{d_1 (d_2 - 2)^2 (d_2 - 4)}$ for $d_2 > 4$
Median	Searched numerically
Mode	$\max\left(\frac{d_2(d_1 - 2)}{d_1(d_1 + 2)}, 0\right)$
$\phi(t)$	Calculated numerically

Relation to other distributions:

$$\frac{d_1 X}{d_2 + d_1 X} \sim \mathcal{B}\left(\frac{d_1}{2}, \frac{d_2}{2}\right),$$

$$\frac{d_1}{d_2} X \sim \mathcal{B}'\left(\frac{d_1}{2}, \frac{d_2}{2}\right).$$

6 Gamma distribution



Notation	$X \sim \Gamma(\alpha, \beta)$
Parameters	$\alpha > 0, \beta > 0$
Domain	$x \in \mathbb{R}^+$
$f(x)$	$\frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x}$
$F(x)$	$P(\alpha, \beta x)$
$\mathbb{E}[X]$	$\frac{\alpha}{\beta}$
$\mathrm{Var}(X)$	$\frac{\alpha}{\beta^2}$
Median	Searched numerically
Mode	$\max\left(\frac{\alpha-1}{\beta}, 0\right)$
$\phi(t)$	$\left(1 - \frac{it}{\beta}\right)^{-\alpha}$

More properties.

- $\mathbb{E}[\ln X] = \psi(\alpha) - \ln(\beta)$, $\mathrm{Var}(\ln X) = \psi^{(1)}(\alpha)$.
- $\mathbb{E}\left[\frac{1}{X}\right] = \frac{\beta}{\alpha-1}$.
- Let $X_i \sim \Gamma(\alpha_i, \beta)$ for $i = 1, \ldots, n$. Then
$$\sum_{i=1}^{n} X_i \sim \Gamma\left(\sum_{i=1}^{n} \alpha_i, \beta\right).$$

Estimation of parameters.

Frequentist inference. Log-likelihood function:

$$\ln \mathcal{L}(\alpha, \beta | X) = n\alpha \ln \beta - n \ln \Gamma(\alpha) + (\alpha - 1) \sum_{i=1}^{n} \ln X_i - \beta \sum_{i=1}^{n} X_i.$$

Derivatives:

$$\frac{\partial \ln \mathcal{L}(\alpha, \beta | X)}{\partial \alpha} = n \ln \beta - n\psi(\alpha) + \sum_{i=1}^{n} \ln X_i,$$

$$\frac{\partial \ln \mathcal{L}(\alpha, \beta|X)}{\partial \beta} = \frac{n\alpha}{\beta} - \sum_{i=1}^{n} X_i.$$

While the solution for the second equation is analytic:

$$\hat{\beta} = \frac{\alpha}{\overline{X}_n},$$

the first equation is solved numerically, using second derivative:

$$\frac{\partial^2 \ln \mathcal{L}(\alpha, \beta|X)}{\partial \alpha^2} = -n\psi_1(\alpha),$$

or if β is unknown:

$$\frac{\partial^2 \ln \mathcal{L}(\alpha, \beta|X)}{\partial \alpha^2} = -n\psi_1(\alpha) + \frac{n}{\alpha},$$

Moreover, the maximum-likelihood estimation of rate β is biased:

$$\begin{aligned}\mathbb{E}[\hat{\beta}] &= \mathbb{E}\left[\frac{\alpha n}{\sum_{i=1}^{n} X_i}\right] \\ &= \frac{\alpha n \beta}{\alpha n - 1}.\end{aligned}$$

Unbiased estimator will be

$$\tilde{\beta} = \frac{\alpha}{\overline{X}_n}\Big(1 - \frac{1}{n}\Big).$$

Bayesian inference. We suppose that prior distribution of rate β is $\Gamma(\kappa, \gamma)$:

$$h(\beta) = \frac{\gamma^{\kappa}}{\Gamma(\kappa)} \beta^{\kappa - 1} e^{-\gamma\beta}.$$

Then

$$f(\beta|X) \propto \beta^{\alpha n} e^{-\beta \sum_{i=1}^{n} X_i} \cdot \beta^{\kappa-1} e^{-\gamma\beta} \sim \Gamma\left(\alpha n + \kappa, \gamma + \sum_{i=1}^{n} X_i\right).$$

Therefore, Bayesian estimator is

$$\mathbb{E}[\beta|X] = \frac{\alpha n + \kappa}{\gamma + \sum_{i=1}^{n} X_i},$$

and MAP estimator is

$$\beta_{MAP} = \frac{\alpha n + \kappa - 1}{\gamma + \sum_{i=1}^{n} X_i}.$$

Exponential family parameterization Logarithm of probability mass function:

$$\log \mathbb{P}(X = x) = \alpha \log \beta - \log \Gamma(\alpha) + (\alpha - 1)\log x - \beta x.$$

Therefore, sufficient statistics $T(x) = (\log x, x)^T$, natural parameters $\theta = (\alpha - 1, -\beta)$, log-normalizer $F(\theta) = \log \Gamma(\theta_1 + 1) - (\theta_1 + 1)\log(-\theta_2)$, carrier measure $k(x) = 0$. Gradient of log-normalizer is $\nabla F(\theta) = \left(\psi(\theta_1 + 1) - \log(-\theta_2), -\frac{\theta_1+1}{\theta_2}\right)^T$ We conclude that adjusted cross-entropy is

$$\begin{aligned} H_F(\theta_q \| \theta_p) &= F(\theta_q) - \langle \theta_q, \nabla F(\theta_p) \rangle \\ &= \log \Gamma(\theta_{q1} + 1) - (\theta_{q1} + 1)\log(-\theta_{q2}) - \theta_{q1}(\psi(\theta_{p1} + 1) - \log(-\theta_{p2})) + \frac{\theta_{q2}(\theta_{p1} + 1)}{\theta_{p2}}. \end{aligned}$$

Adjusted entropy is

$$\begin{aligned} H_F(\theta) &= \log \Gamma(\theta_1 + 1) - \log(-\theta_2) - \theta_1 \psi(\theta_1 + 1) + \theta_1 + 1 \\ &= \log \Gamma(\alpha) - \log \beta - (\alpha - 1) \cdot \psi(\alpha) + \alpha. \end{aligned}$$

And Kullback-Leibler divergence:

$$\begin{aligned} \mathrm{KL}(p\|q) &= H_F(\theta_q \| \theta_p) - H_F(\theta_p) \\ &= \log \frac{\Gamma(\alpha_q)}{\Gamma(\alpha_p)} + \alpha_q \log \frac{\beta_p}{\beta_q} + (\alpha_p - \alpha_q)\psi(\alpha_p) + \alpha_p\left(\frac{\beta_q}{\beta_p} - 1\right) \end{aligned}$$

6.1 Chi-squared distribution

Notation:

$$X \sim \chi^2_k.$$

Relation to Gamma distribution:

$$X \sim \Gamma\left(\frac{k}{2}, \frac{1}{2}\right).$$

Kullback-Leibler divergence:

$$\mathrm{KL}(p\|q) = \log \frac{\Gamma(k_q/2)}{\Gamma(k_p/2)} + \frac{1}{2}(k_p - k_q)\psi(k_p/2).$$

Relation to other distributions: if $X_1, \ldots, X_k \sim \mathcal{N}(0, 1)$, then $\sum_{i=1}^k X_i \sim \chi^2_k$.

6.2 Erlang distribution

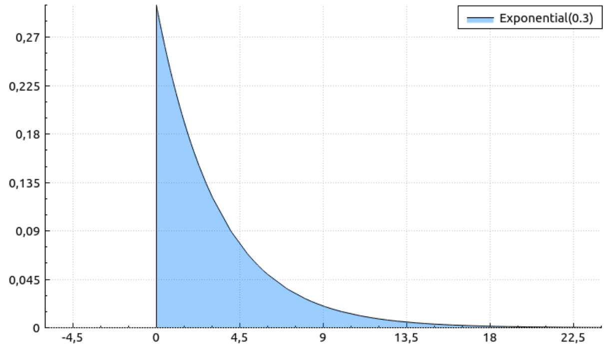
Notation:

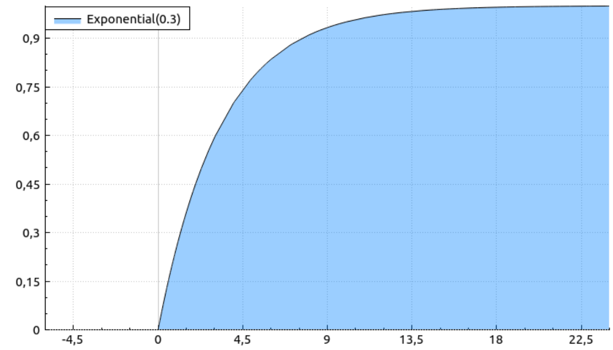
$$X \sim \mathrm{Erlang}(k, \beta).$$

The only difference between Gamma and Erlang distributions is that latter takes an integer number k as a shape parameter. Relation to other distributions: if $X \sim \mathrm{Erlang}(k, \beta)$ and $Y \sim \mathrm{Po}(\beta x)$, then

$$\mathbb{P}(X < x) = P(k, \beta x) = \mathbb{P}(Y > k).$$

6.3 Exponential distribution





Notation	$X \sim \mathrm{Exp}(\lambda)$
Parameters	$\lambda > 0$
Domain	$x \in \mathbb{R}^+$
$f(x)$	$\lambda e^{-\lambda x}$
$F(x)$	$1 - e^{-\lambda x}$
$\mathbb{E}[X]$	$\frac{1}{\lambda}$
$\mathrm{Var}(X)$	$\frac{1}{\lambda^2}$
Median	$\frac{\ln(2)}{\lambda}$
Mode	0
$\phi(t)$	$\frac{\lambda}{\lambda - it}$

Relation to Gamma distribution:

$$X \sim \Gamma(1, \lambda).$$

Hence, estimation of parameter λ is the particular case of estimation of rate β for Gamma distribution.
Adjusted cross-entropy:

$$H_F(\lambda_q \| \lambda_p) = \frac{\lambda_q}{\lambda_p} - \log \lambda_q.$$

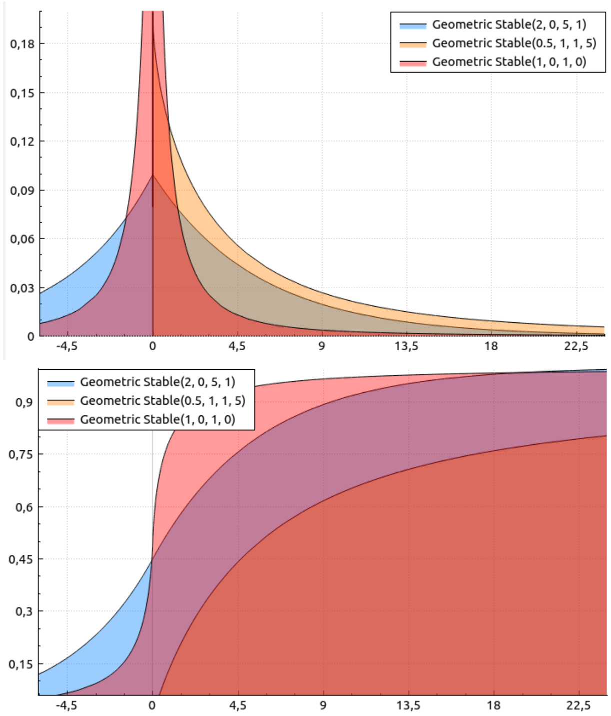
Thus adjusted entropy is

$$H_F(\lambda) = 1 - \log \lambda$$

and Kullback-Leibler divergence:

$$\mathrm{KL}(p\|q) = \log \frac{\lambda_p}{\lambda_q} + \frac{\lambda_q}{\lambda_p} - 1.$$

7 Geometric Stable distribution



Notation	$X \sim \mathrm{GS}_\alpha(\beta, \gamma, \mu)$
Parameters	$\alpha \in (0, 2], \beta \in [-1, 1],$ $\gamma > 0, \mu \in \mathbb{R}$
Domain	$x \in \ldots$
$f(x)$	Calculated numerically
$F(x)$	Calculated numerically
$\mathbb{E}[X]$	$k + \lambda$
$\mathrm{Var}(X)$	$2(k + 2\lambda)$
Median	Searched numerically
Mode	Searched numerically
$\phi(t)$	...

7.1 Asymmetric Laplace distribution

7.2 Laplace distribution

8 Kolmogorov-Smirnov distribution

9 Logistic distribution

10 Log-normal distribution

11 Marchenko-Pastur distribution

Notation	$X \sim \mathcal{MP}(\lambda, \sigma^2)$
Parameters	$\lambda, \sigma^2 > 0$
Domain	$x \in [\sigma^2 a, \sigma^2 b]$, if $\lambda < 1$, $x \in [\sigma^2 a, \sigma^2 b] \cup \{0\}$, otherwise, where $a = (1-\sqrt{\lambda})^2$ and $b = (1+\sqrt{\lambda})^2$
$f(x)$	...
$F(x)$	...
$\mathbb{E}[X]$	σ^2
$\mathrm{Var}(X)$	$\sigma^4 \lambda$
Median	0 if $\lambda > 2$, otherwise searched numerically
Mode	$\frac{\sigma^2(\lambda-1)^2}{\lambda+1}$, if $\lambda < 1$, 0, otherwise
$\phi(t)$	Calculated numerically

Calculation of characteristic function. For $\lambda > 1$ we use numerical integration by definition

$$\phi(t) = \int_{\sigma^2 a}^{\sigma^2 b} \cos(tx) f(x) dx + i \int_{\sigma^2 a}^{\sigma^2 b} \sin(tx) f(x) dx.$$

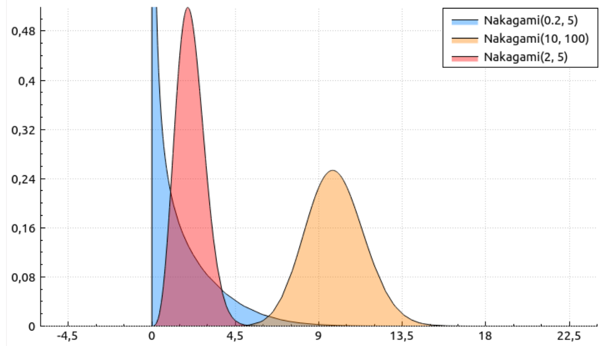
For $\lambda = 1$ we split the integrand for real part by $(\cos(tx) - 1) f(x)$ and $f(x)$:

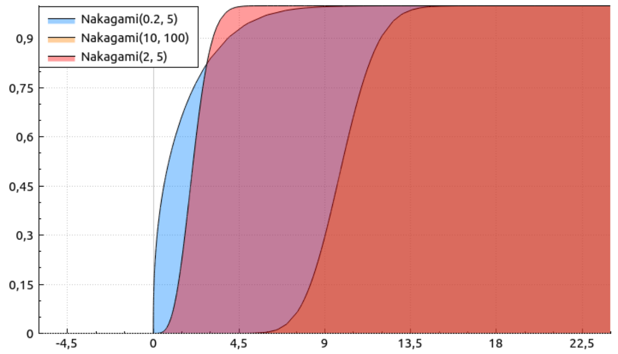
$$\Re(\phi(t)) = \int_{\sigma^2 a}^{\sigma^2 b} (\cos(tx) - 1) f(x) dx + 1.$$

And for $\lambda < 1$ we calculate integral at point 0 separately:

$$\begin{aligned}\phi(t) &= \int_{\{0\} \cup [\sigma^2 a, \sigma^2 b]} \cos(tx) f(x) dx + i \int_{\{0\} \cup [\sigma^2 a, \sigma^2 b]} \sin(tx) f(x) dx \\ &= 1 - \frac{1}{\lambda} + \int_{\sigma^2 a}^{\sigma^2 b} \cos(tx) f(x) dx + i \int_{\sigma^2 a}^{\sigma^2 b} \sin(tx) f(x) dx.\end{aligned}$$

12 Nakagami distribution





Notation	$X \sim \text{Nakagami}(\mu, \omega)$
Parameters	$\mu, \omega > 0$
Domain	$x \in \mathbb{R}^+$
$f(x)$	$\frac{2\mu^\mu}{\Gamma(\mu)\omega^\mu} x^{2\mu-1} e^{-\frac{\mu}{\omega}x^2}$
$F(x)$	$P(\mu, \mu x^2/\omega)$
$\mathbb{E}[X]$	$\frac{\Gamma(\mu+1/2)}{\Gamma(\mu)}\sqrt{\frac{\omega}{\mu}}$
$\text{Var}(X)$	$\omega - (\mathbb{E}[X])^2$
Median	Searched numerically
Mode	$\max\left(\sqrt{\frac{(2\mu-1)\omega}{2\mu}}, 0\right)$
$\phi(t)$	Calculated numerically

Calculation of characteristic function. For $\mu < 1$ $\lim_{x\to 0} f(x) \to \infty$. Then we use the following transformation for real part of characteristic function:

$$\begin{aligned}\Re(\phi(t)) &= \int_0^\infty \cos(tx) f(x) dx \\ &= \int_0^\infty (\cos(tx) - 1) f(x) + 1\end{aligned}$$

Relation to other distributions: if $Y \sim \Gamma\big(\mu, \mu/\omega\big)$, then

$$X \sim \text{Nakagami}(\mu, \omega).$$

12.1 Chi distribution

Notation:

$$X \sim \chi_k$$

Relation to Nakagami distribution:

$$X \sim \text{Nakagami}\left(k/2, k\right).$$

12.2 Maxwell-Bolzmann distribution

Notation:

$$X \sim \mathrm{MB}(\sigma)$$

Relation to Nakagami distribution:

$$X \sim \text{Nakagami}\left(3/2, \sigma^2\right).$$

12.3 Rayleigh distribution

Notation:

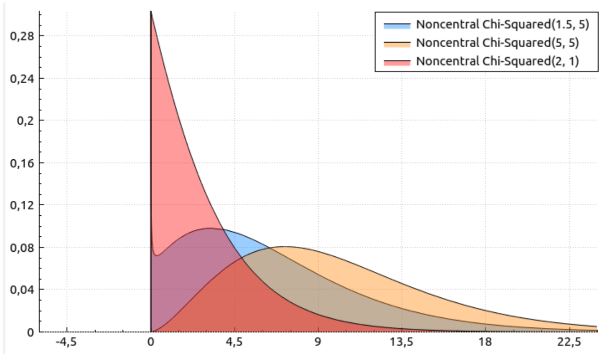
$$X \sim \text{Rayleigh}(\sigma)$$

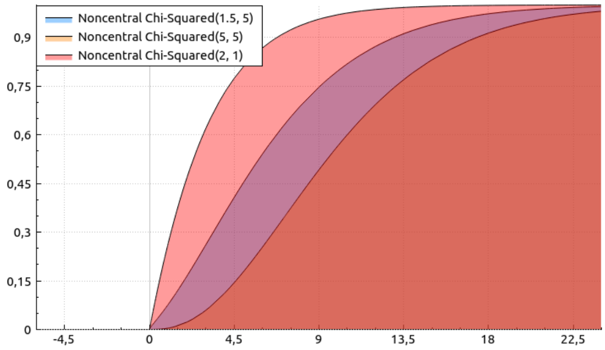
Relation to Nakagami distribution:

$$X \sim \text{Nakagami}\left(1, 2\sigma^2\right).$$

Estimation of scale. ...

13 Noncentral Chi-Squared distribution





Notation	$X \sim \chi_k'^2(\lambda)$
Parameters	$k > 0, \lambda > 0$
Domain	$x \in \mathbb{R}^+$
$f(x)$	$\frac{1}{2} e^{-\frac{x+\lambda}{2}} \left(\frac{x}{\lambda}\right)^{\frac{k-2}{4}} I_{\frac{k}{2}-1}(\sqrt{\lambda x})$
$F(x)$	$\mathrm{MarcumP}_{\frac{k}{2}}(\frac{\lambda}{2}, \frac{x}{2})$
$\mathbb{E}[X]$	$k + \lambda$
$\mathrm{Var}(X)$	$2(k + 2\lambda)$
Median	Searched numerically
Mode	Searched numerically for $k > 2$, 0, otherwise
$\phi(t)$	$\frac{\exp \frac{it\lambda}{1-2it}}{(1-2it)^{k/2}}$

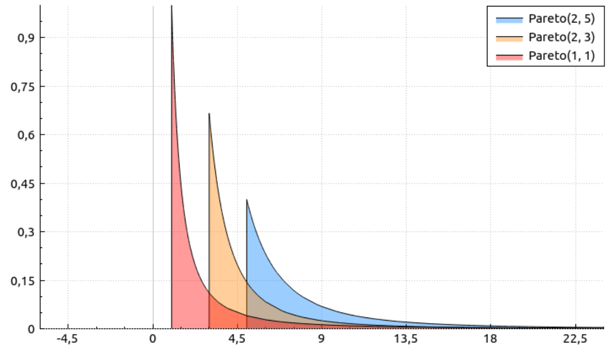
Relation to other distributions:

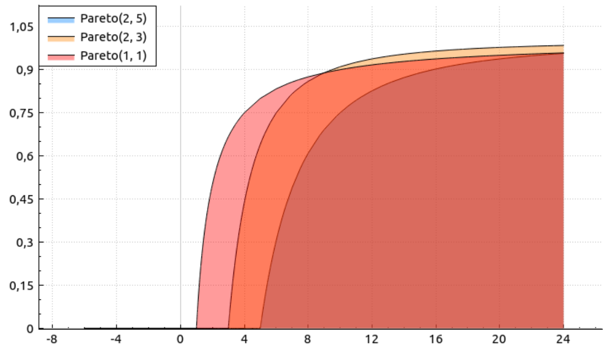
- Let $X_1, \ldots, X_k$ be independent with $X_i \sim \mathcal{N}(\mu_i, 1)$, $i = 1, \ldots, k$. Then

$$\sum_{i=1}^{k} X_i^2 \sim \chi_k'^2 \Big(\sum_{i=1}^{k} \mu_i^2 \Big).$$

- If $\lambda = 0$, then $X \sim \chi_k^2$.
- If $J \sim \mathrm{Po}(\lambda)$, then $\chi_{k+2J}^2 \sim \chi_k'^2(\lambda)$.

14 Pareto distribution





Notation	$X \sim \text{Pareto}(\alpha, \sigma)$
Parameters	$\alpha, \sigma > 0$
Domain	$x \geq \sigma$
$f(x)$	$\frac{\alpha\sigma^\alpha}{x^{\alpha+1}}$
$F(x)$	$1 - \left(\frac{\sigma}{x}\right)^\alpha$
$\mathbb{E}[X]$	$\frac{\alpha\sigma}{\alpha-1}$ for $\alpha > 1$, ∞ otherwise
$\text{Var}(X)$	$\frac{\sigma^2\alpha}{(\alpha-1)^2(\alpha-2)}$ for $\alpha > 2$, ∞ otherwise
Median	$\sigma 2^{1/\alpha}$
Mode	σ
$\phi(t)$	Calculated numerically

Estimation of parameters.

Frequentist inference. Log-likelihood function is

$$\ln \mathcal{L}(\alpha, \sigma | X) = n \ln \alpha + n\alpha \ln \sigma - (\alpha + 1) \sum_{i=1}^{n} \ln X_i.$$

We assume that $\sigma \leq X_{(1)}$, otherwise sample X couldn't have been generated from such distribution. It is obvious, that $\ln \mathcal{L}(\alpha, \sigma|X)$ is an increasing function in terms of σ, therefore $\hat{\sigma} = X_{(1)}$ is an optimal estimator. Let's take derivative with respect to α:

$$\frac{\partial \ln \mathcal{L}(\alpha, \sigma|X)}{\partial \alpha} = \frac{n}{\alpha} + n \ln \sigma - \sum_{i=1}^{n} \ln X_i.$$

From this we conclude that the maximum-likelihood estimator of shape is

$$\hat{\alpha} = \frac{1}{\frac{1}{n}(\sum_{i=1}^{n} \ln X_i) - \ln \hat{\sigma}}.$$

It is known that $\hat{\sigma} \sim \text{Pareto}(n\alpha, \sigma)$ and $\hat{\alpha} \sim \text{Inv-}\Gamma(n-1, n\alpha)$ and they are independent. Then

$$\mathbb{E}[\hat{\sigma}] = \frac{\sigma}{1 - \frac{1}{n\alpha}}$$

and

$$\mathbb{E}[\hat{\alpha}] = \frac{n\alpha}{n-2}.$$

Therefore, in order to get unbiased estimators we need to make the following transformations:

$$\tilde{\alpha} = \frac{n-2}{n}\hat{\alpha} \quad \text{and} \quad \tilde{\sigma} = \hat{\sigma}\left(1 - \frac{1}{(n-1)\hat{\alpha}}\right).$$

Note that if we estimate parameters separately, then $\hat{\alpha} \sim \text{Inv-}\Gamma(n, n\alpha)$ and transformations are different.

Bayesian inference. We now assume that σ is known and prior distribution of α is $\Gamma(\kappa, \beta)$:

$$h(\alpha) = \frac{\beta^\kappa}{\Gamma(\kappa)}\alpha^{\kappa-1}e^{-\beta\alpha}.$$

The density of posterior distribution is

$$f(\alpha|X) \propto \prod_{i=1}^{n} \frac{\sigma^\alpha}{X_i^{\alpha-1}} \cdot \alpha^{\kappa+n-1}e^{-\beta\alpha} \propto \alpha^{\kappa+n-1}e^{-(\beta+\sum_{i=1}^n \ln(X_i/\sigma))\alpha}.$$

Therefore, $\alpha|X \sim \Gamma(\kappa+n, \beta+\sum_{i=1}^n \ln(X_i/\sigma))$ and Bayesian estimator is

$$\mathbb{E}[\alpha|X] = \frac{\kappa+n}{\beta+\sum_{i=1}^n \ln(X_i/\sigma)}.$$

MAP estimator is

$$\alpha_{MAP} = \frac{\kappa+n-1}{\beta+\sum_{i=1}^n \ln(X_i/\sigma)}.$$

Note on fitting scale with Bayes: let it be vice versa, α is known while σ is not. Then we say that a priori $\sigma \sim \text{Pareto}(\kappa, \theta)$:

$$h(\sigma) = \frac{\kappa\theta^\kappa}{\sigma^{\kappa+1}}.$$

Then posterior distribution is:

$$f(\sigma|X) \propto \prod_{i=1}^{n} \frac{1}{X_i^{\alpha-1}} \cdot \sigma^{\alpha n-\kappa-1}\mathbf{1}_{\{\theta<\sigma<X_{(1)}\}} \sim \text{Bounded-Pareto}(\kappa-\alpha n, \theta, X_{(1)}).$$

This imposes the following additional constraints on the prior hyperparameters: $\kappa > \alpha n$ and $\theta < X_{(1)}$. Bayesian estimator:

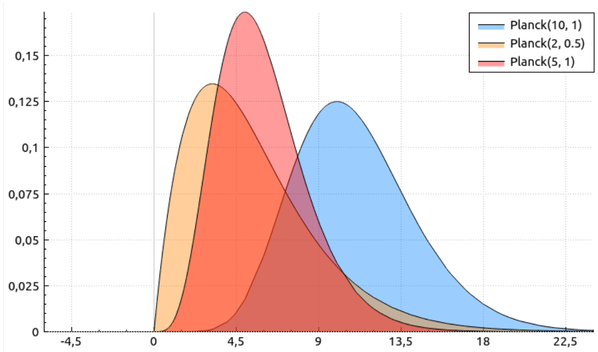
$$\mathbb{E}[\sigma|X] = \frac{\theta^{\alpha'}}{1-\left(\frac{\theta}{X_{(1)}}\right)^{\alpha'}} \cdot \left(\frac{\alpha'}{\alpha'-1}\right) \cdot \left(\frac{1}{\theta^{\alpha'}} - \frac{1}{X_{(1)}^{\alpha'}}\right)$$

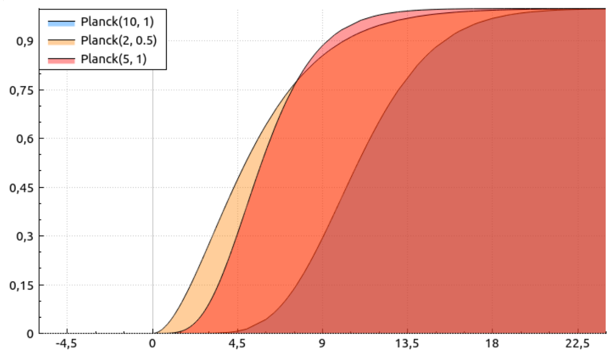
with $\alpha' = \kappa - \alpha n$. MAP estimator is just

$$\sigma_{MAP} = \theta.$$

However, Bounded-Pareto distribution is not yet supported in RandLib.

15 Planck distribution





Notation	$X \sim \text{Planck}(a, b)$
Parameters	$a, b > 0$
Domain	$x \in \mathbb{R}^+$
$f(x)$	$\frac{b^{a+1}}{\Gamma(a+1)\zeta(a+1)} \cdot \frac{x^a}{e^{bx}-1}$
$F(x)$	Calculated numerically
$\mathbb{E}[X]$	$\frac{(a+1)\zeta(a+2)}{b\zeta(a+1)}$
$\text{Var}(X)$	$\frac{(a+1)(a+2)\zeta(a+3)}{b^2\zeta(a+1)} - (\mathbb{E}[X])^2$
Median	Searched numerically
Mode	$\frac{W_0(-ae^{-a})+a}{b}$, if $a > 1$, otherwise 0
$\phi(t)$	Calculated numerically

Calculation of cumulative distribution function. For $a \geq 1$ $F(x)$ can be calculated by straightforward numerical integration:

$$F(x) = \frac{b^{a+1}}{\Gamma(a+1)\zeta(a+1)} \int_0^x \frac{t^a}{e^{bt}-1} dt.$$

Note that for $\alpha < 1$ integrand has a singularity point at $t = 0$. In such case we define

$$h(t) = \frac{b^{a+2}t^{a+1}}{\Gamma(a+1)\zeta(a+1)} \cdot \left(\frac{1}{e^{bt}-1} - \frac{1}{bt} \right)$$

and then

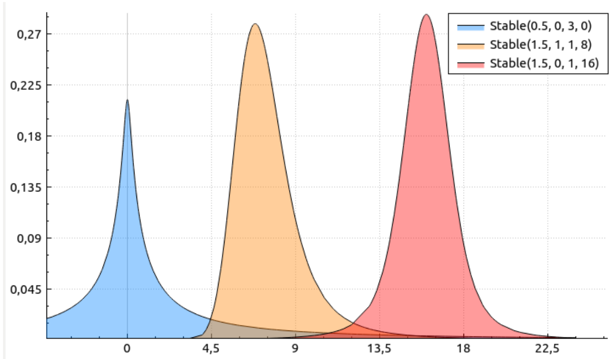
$$F(x) = \int_0^x h(t)dt + \frac{(bx)^a}{a\Gamma(a+1)\zeta(a+1)}.$$

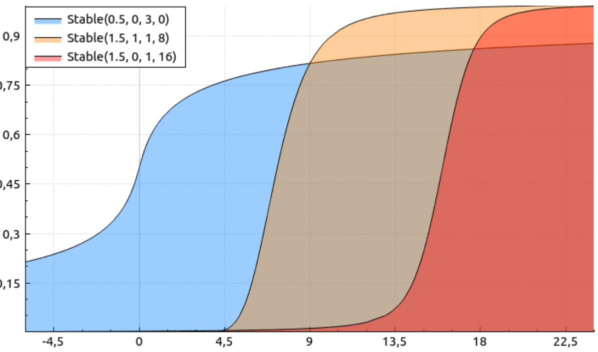
Calculation of characteristic function. The idea of calculations for $a < 1$ is near the same. We split the real part of $\phi(t)$ into 3 different integrals:

$$\Re(\phi(t)) = \int_0^1 \cos(tx)h(x)dx + \int_1^\infty \cos(tx)f(x)dx + \frac{b^a}{a\Gamma(a+1)\zeta(a+1)} \left(\cos(t) + t\int_0^1 \sin(tx)x^a dx \right).$$

All the indegrands now have no singularity points.

16 Stable distribution





Notation	$X \sim S_\alpha(\beta, \gamma, \mu)$
Parameters	$\alpha \in (0, 2], \beta \in [-1, 1],$ $\gamma > 0, \mu \in \mathbb{R}$
Domain	$x \in \mathbb{R}$, if $\beta \neq 1$, $x \in [\mu, \infty)$, if $\beta = 1$, $\alpha < 2$, $x \in (-\infty, \mu]$, if $\beta = -1$, $\alpha < 2$
$f(x)$	Calculated numerically
$F(x)$	Calculated numerically
$\mathbb{E}[X]$	μ for $\alpha > 1$, otherwise undefined
$\mathrm{Var}(X)$	$2\gamma^2 1_{\{\alpha=2\}} + \infty 1_{\{\alpha<2\}}$
Median	μ for $\beta = 0$, otherwise searched numerically
Mode	μ, if $\beta = 0$ or $\alpha = 2$, $\mu + \frac{\beta\gamma}{3}$, if $\lvert\beta\rvert = 1$ and $\alpha = \frac{1}{2}$, otherwise searched numerically
$\phi(t)$	...

Calculation of p.d.f.

Calculation of c.d.f.

16.1 Cauchy distribution

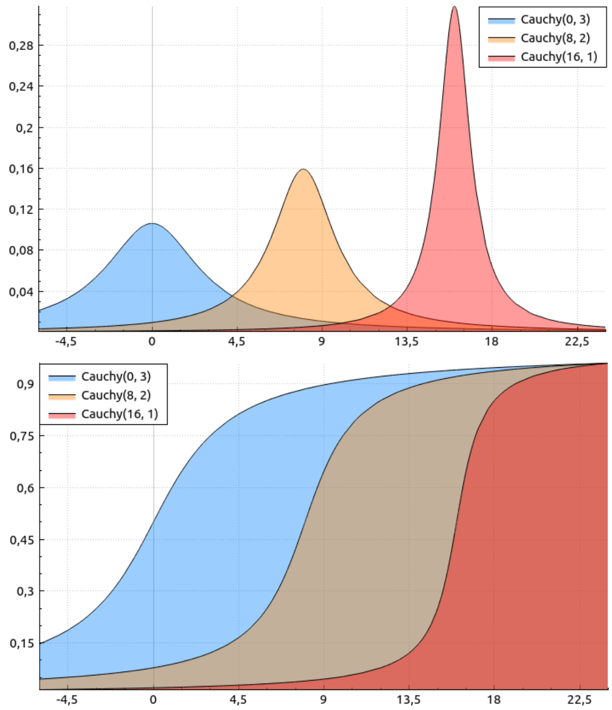
Relation to Stable distribution:

$$X \sim S_1(0, \gamma, \mu)$$

16.2 Levy distribution

Relation to Stable distribution:

$$X \sim S_{\frac{1}{2}}(1, \gamma, \mu)$$



Notation	$X \sim \text{Cauchy}(\mu, \gamma)$
Parameters	$\mu \in \mathbb{R}, \gamma^2 > 0$
Domain	$x \in \mathbb{R}$
$f(x)$	$\frac{1}{\pi\gamma\left[1+\left(\frac{x-\mu}{\gamma}\right)^2\right]}$
$F(x)$	$\frac{1}{\pi}\,\text{atan}\left(\frac{x-\mu}{\gamma}\right)+\frac{1}{2}$
$\mathbb{E}[X]$	Undefined
$\text{Var}(X)$	∞
Median	μ
Mode	μ
$\phi(t)$	$e^{i\mu t-\gamma\|t\|}$

16.3 Normal distribution

Relation to Stable distribution:

$$X \sim S_2(\cdot, \sigma^2/2, \mu)$$

Estimation of parameters

Frequentist inference. Maximum-likelihood estimators for Normal distribution are very well-known:

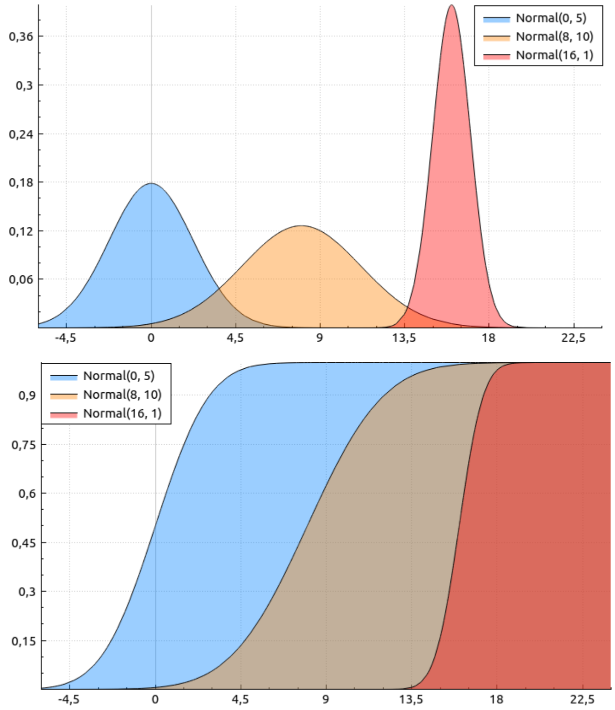
$$\hat{\mu} = \overline{X}_n \quad \text{and} \quad \hat{\sigma^2} = \frac{1}{n}\sum_{i=1}^{n}(X_i - \mu)^2.$$

However, for unknown μ the value of $\hat{\sigma^2} \sim \frac{\sigma^2}{n}\chi^2_{n-1}$. Therefore, unbiased estimator in this case would be

$$\widetilde{\sigma^2} = \frac{1}{n-1}\sum_{i=1}^{n}(X_i - \overline{X}_n)^2.$$

Moreover, if one is interested in estimating scale σ with known μ, then maximum likelihood estimator is

$$\hat{\sigma} = \sqrt{\hat{\sigma^2}} \sim \frac{\sigma}{\sqrt{n}}\chi_n$$



Notation	$X \sim \mathcal{N}(\mu, \sigma^2)$
Parameters	$\mu \in \mathbb{R}, \sigma^2 > 0$
Domain	$x \in \mathbb{R}$
$f(x)$	$\frac{1}{\sqrt{2\sigma^2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$
$F(x)$	$\frac{1}{2}\,\mathrm{erfc}\left(\frac{\mu - x}{\sqrt{2\sigma^2}}\right)$
$\mathbb{E}[X]$	μ
$\mathrm{Var}(X)$	σ^2
Median	μ
Mode	μ
$\phi(t)$	$e^{i\mu t - \frac{1}{2}\sigma^2 t^2}$

and

$$\mathbb{E}[\hat{\sigma}] = \frac{\sigma}{\sqrt{n}} \sqrt{2} \frac{\Gamma((n+1)/2)}{\Gamma(n/2)}.$$

Then unbiased estimator is

$$\widetilde{\sigma} = \hat{\sigma} \sqrt{\frac{n}{2}} \frac{\Gamma(n/2)}{\Gamma((n+1)/2)}$$

Bayesian inference. ...

16.4 Holtsmark distribution

Relation to Stable distribution:

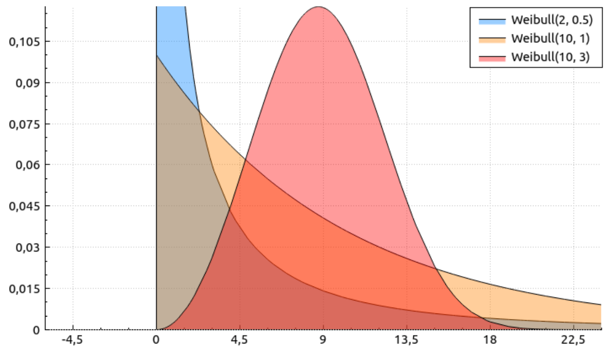
$$X \sim S_{\frac{3}{2}}(0, \gamma, \mu)$$

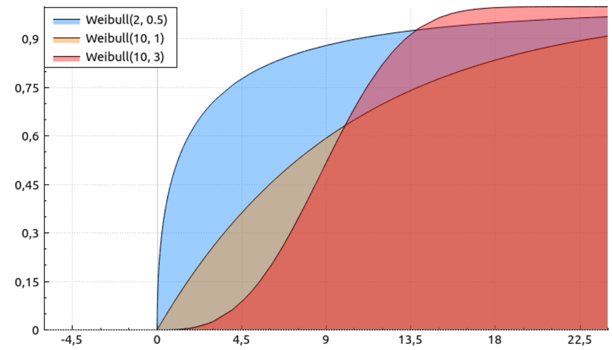
16.5 Landau distribution

Relation to Stable distribution:

$$X \sim S_1(1, \gamma, \mu)$$

17 Weibull





Notation	$X \sim \text{Weibull}(\lambda, k)$
Parameters	$\lambda, k > 0$
Domain	$x \in \mathbb{R}^+$
$f(x)$	$\frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1}\exp(-(x/\lambda)^k)$
$F(x)$	$1 - \exp(-(x/\lambda)^k)$
$\mathbb{E}[X]$	$\lambda\Gamma(1 + 1/k)$
$\text{Var}(X)$	$\lambda^2\Gamma(1 + 2/k) - (\mathbb{E}[X])^2$
Median	$\lambda(\ln 2)^{\frac{1}{k}}$
Mode	$\lambda\big(1 - \frac{1}{k}\big)^{\frac{1}{k}}$
$\phi(t)$	Calculated numerically

Estimation of scale .

Frequentist inference. Log-likelihood function:

$$\ln \mathcal{L}(\lambda, k|X) = n(\ln k - \ln \lambda) + (k-1)\sum_{i=1}^{n}(\ln X_i - \ln \lambda) - \frac{1}{\lambda^k}\sum_{i=1}^{n} X_i^k.$$

The derivative with respect to scale:

$$\frac{\partial \ln \mathcal{L}(\lambda, k|X)}{\partial \lambda} = -\frac{nk}{\lambda} + \frac{k}{\lambda^{k+1}}\sum_{i=1}^{n} X_i^k = 0.$$

Therefore, maximum-likelihood estimation for λ is

$$\hat{\lambda} = \left(\frac{1}{n}\sum_{i=1}^{n} X_i^k\right)^{\frac{1}{k}}.$$

Bayesian inference. Assume k is known. Instead of estimating λ we give an estimation for λ^k. Let's say that prior distribution of λ^k is Inv-$\Gamma(\alpha, \beta)$:

$$h(\lambda^k) = \frac{\beta^\alpha}{\Gamma(\alpha)} \lambda^{-k(\alpha+1)} e^{-\beta/\lambda^k}.$$

Posterior distribution then:

$$f(\lambda^k|X) \propto \lambda^{-k(\alpha+1+n)} e^{-\frac{1}{\lambda^k}(\beta+\sum_{i=1}^n X_i^k)} \sim \text{Inv-}\Gamma\left(\alpha+n, \beta+\sum_{i=1}^n X_i^k\right).$$

Bayesian estimator:

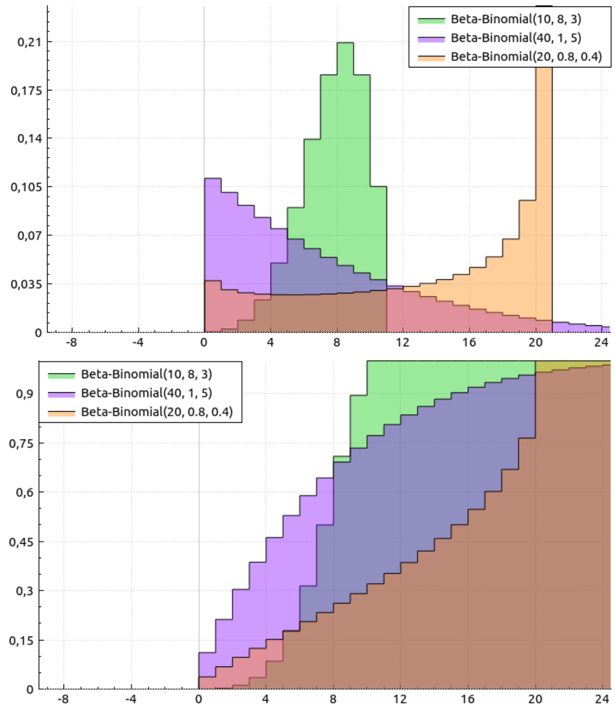
$$\mathbb{E}[\lambda^k|X] = \frac{\beta+\sum_{i=1}^n X_i^k}{\alpha+n-1},$$

MAP estimator:

$$\lambda^k_{MAP} = \frac{\beta+\sum_{i=1}^n X_i^k}{\alpha+n+1}.$$

Part III
Discrete univariate distributions

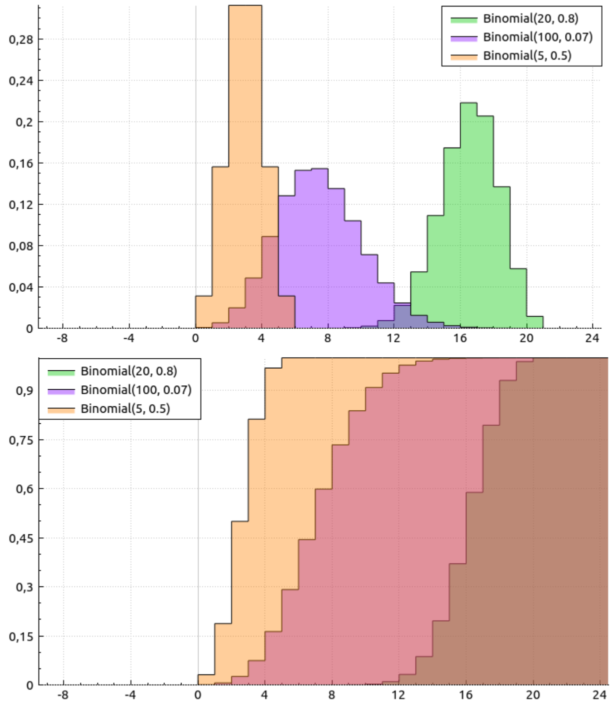
18 Beta-binomial distribution



Notation	$X \sim \mathrm{BB}(n, \alpha, \beta)$
Parameters	$n \in \mathbb{N}, \alpha, \beta > 0$
Domain	$k \in \{0, \dots, n\}$
$\mathbb{P}(X = k)$	$\binom{n}{k} \frac{B(k+\alpha, n-k+\beta)}{B(\alpha,\beta)}$
$\mathbb{P}(X \leq k)$	Calculated numerically
$\mathbb{E}[X]$	$n \frac{\alpha}{\alpha+\beta}$
$\mathrm{Var}(X)$	$\frac{n\alpha\beta(\alpha+\beta+n)}{(\alpha+\beta)^2(\alpha+\beta+1)}$
Median	Searched numerically
Mode	Searched numerically
$\phi(t)$	Calculated numerically

Relation to other distributions: if $p \sim \mathcal{B}(\alpha, \beta)$, then $\mathrm{Bin}(n, p) \sim \mathrm{BB}(n, \alpha, \beta)$.

19 Binomial distribution



Notation	$X \sim \mathrm{Bin}(n, p)$
Parameters	$n \in \mathbb{N}, p \in [0, 1]$
Domain	$k \in \{0, \dots, n\}$
$\mathbb{P}(X = k)$	$\binom{n}{k} p^k (1-p)^{n-k}$
$\mathbb{P}(X \leq k)$	$I_{1-p}(n-k, 1+k)$
$\mathbb{E}[X]$	np
$\mathrm{Var}(X)$	$np(1-p)$
Median	$[np]$
Mode	$[(n+1)p]$
$\phi(t)$	$(1 - p + pe^{it})^n$

Estimation of probability p with known number n.

Frequentist inference. Log-likelihood function:

$$\ln \mathcal{L}(p|X) \propto \sum_{i=1}^{k} \big(X_i \log p + (n - X_i) \log(1-p)\big)$$

The derivative with respect to p is:

$$\frac{\partial \ln \mathcal{L}(p|X)}{\partial p} = \frac{\sum_{i=1}^{k} X_i}{p} - \frac{nk - \sum_{i=1}^{k} X_i}{1-p}.$$

Therefore we reach the maximum value of log-likelihood if

$$p = \frac{\overline{X}_k}{n}.$$

Bayesian inference. We set prior Beta distribution $\mathcal{B}(\alpha, \beta)$:

$$h(p) = \frac{p^{\alpha-1}(1-p)^{\beta-1}}{B(\alpha, \beta)}.$$

Then posterior is

$$f(p|X) \propto p^{\alpha-1+\sum_{i=1}^{k} X_i}(1-p)^{\beta-1+\sum_{i=1}^{k}(n-X_i)} \sim \mathcal{B}\left(\alpha + \sum_{i=1}^{k} X_i, \beta + nk - \sum_{i=1}^{k} X_i\right).$$

Thus Bayesian estimator is

$$\mathbb{E}[p|X] = \frac{\alpha + \sum_{i=1}^{k} X_i}{\alpha + \beta + nk}$$

and MAP estimator is

$$p_{MAP} = \frac{\alpha + \sum_{i=1}^{k} X_i - 1}{\alpha + \beta + nk - 2}.$$

Also, Minimax estimator is equal to Bayes estimator if $\alpha = \beta = \frac{1}{2}\sqrt{n}$.

19.1 Bernoulli

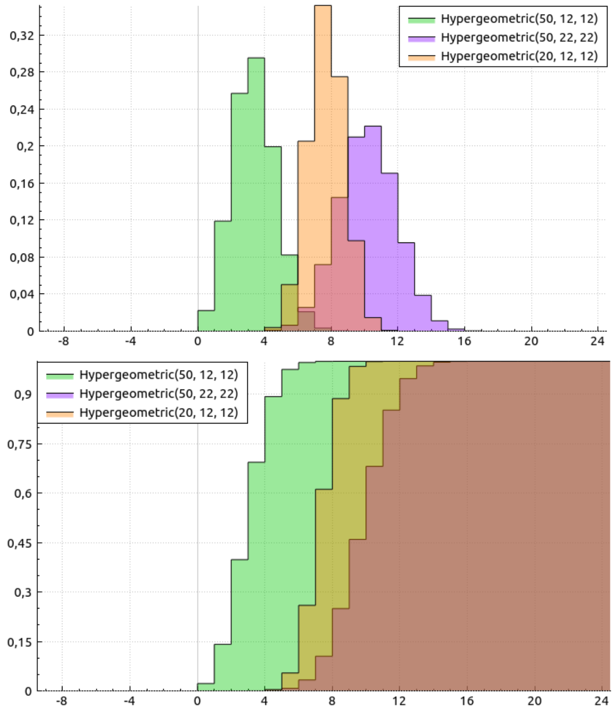
Notation:

$$X \sim \text{Bernoulli}(p).$$

Relation to Binomial distribution:

$$X \sim \text{Bin}(1, p).$$

20 Hypergeometric distribution



Notation	$X \sim \mathrm{HG}(N, K, n)$
Parameters	$N \in \mathbb{N}, K \in \{1, 2, \cdots, N\}$, $n \in \{1, 2, \cdots, N\}$
Domain	$\max(0, n + K - N) \leq k \leq \min(n, K)$
$\mathbb{P}(X = k)$	$\frac{\binom{K}{k}\binom{N-K}{n-k}}{\binom{N}{n}}$
$\mathbb{P}(X \leq k)$	Calculated numerically
$\mathbb{E}[X]$	$\frac{nK}{N}$
$\mathrm{Var}(X)$	$\frac{nK(N-K)(N-n)}{N^2(N-1)}$
Median	Searched numerically
Mode	$\left\lfloor \frac{(n+1)(K+1)}{N+2} \right\rfloor$
$\phi(t)$	Calculated numerically

Estimation of number of target members of population K.

Bayesian inference. Let prior distribution of K be Beta-Binomial distribution $BB(N, \alpha, \beta)$:

$$h(K) = \binom{N}{K} \frac{B(K + \alpha, N - K + \beta)}{B(\alpha, \beta)}.$$

Then for one sample X:

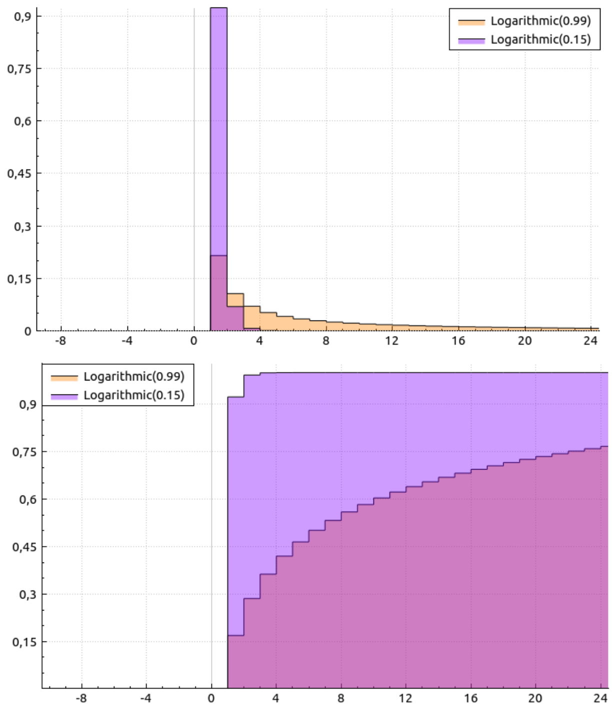
$$K - X \sim BB\big(N - n, \alpha + X, \beta + nk - X\big)$$

and therefore

$$\mathbb{E}[K|X] = X + (N - n)\frac{\alpha}{\alpha + \beta}.$$

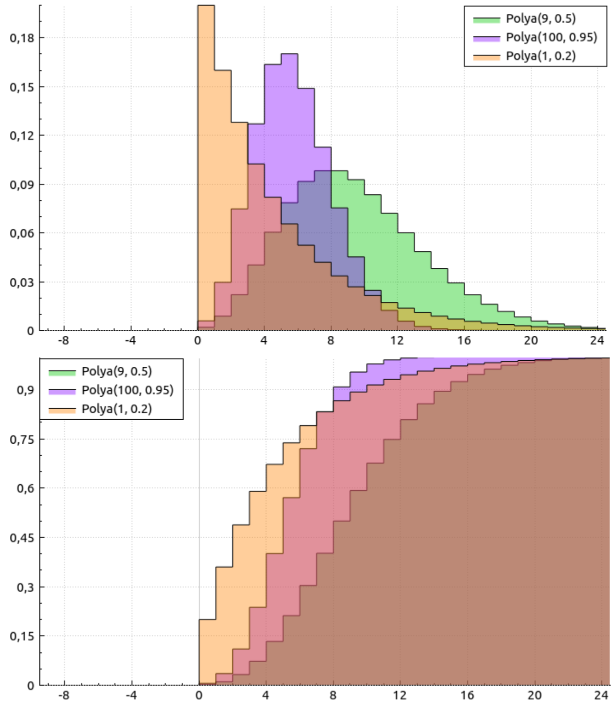
However, RandLib doesn't support Bayesian fitting for Hypergeometric distribution yet.

21 Logarithmic distribution



Notation	$X \sim \text{Log}(p)$
Parameters	$p \in (0, 1)$
Domain	$k \in \mathbb{N}$
$\mathbb{P}(X = k)$	$-\frac{p^k}{k \log(1-p)}$
$\mathbb{P}(X \leq k)$	$1 + \frac{B(p,k+1,0)}{\log(1-p)}$
$\mathbb{E}[X]$	$-\frac{p}{(1-p)\log(1-p)} r$
$\text{Var}(X)$	$-\frac{p(p+\log(1-p))}{(\log(1-p)(1-p))^2}$
Median	Searched numerically
Mode	1
$\phi(t)$	$\frac{\log(1-pe^{it})}{\log(1-p)}$

22 Negative-Binomial (Polya) distribution



Notation	$X \sim \mathrm{NB}(r, p)$
Parameters	$r > 0,\ p \in (0, 1)$
Domain	$k \in \mathbb{N}_0$
$\mathbb{P}(X = k)$	$\binom{k+r-1}{k} p^r (1-p)^k$
$\mathbb{P}(X \leq k)$	$I_p(r, k+1)$
$\mathbb{E}[X]$	$\frac{1-p}{p} r$
$\mathrm{Var}(X)$	$\frac{1-p}{p^2} r$
Median	Searched numerically
Mode	$\max\left(\left\lfloor \frac{(r-1)(1-p)}{p} \right\rfloor, 0\right)$
$\phi(t)$	$\left(\frac{p}{1-(1-p)e^{it}}\right)^r$

Relation to other distributions: if $\lambda \sim \mathrm{Gamma}\left(r, \frac{p}{1-p}\right)$, then $\mathrm{Po}(\lambda) \sim \mathrm{NB}(r, p)$.

22.1 Geometric distribution

Notation:

$$X \sim \mathrm{Geometric}(p).$$

Relation to Negative-Binomial distribution:

$$X \sim \mathrm{NB}(1, p).$$

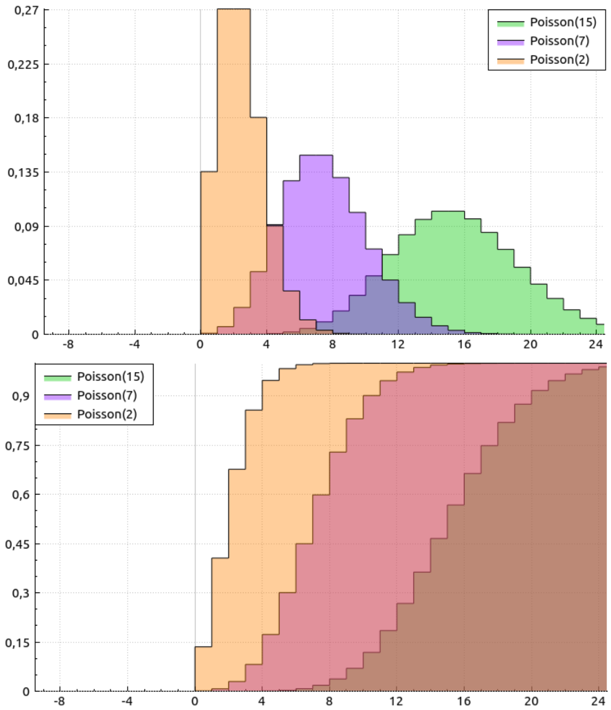
22.2 Pascal distribution

Notation:

$$X \sim \mathrm{Pascal}(r, p).$$

The only difference with Negative-Binomial distribution is that for Pascal distribution shape r is an integer.

23 Poisson distribution



Notation	$X \sim \mathrm{Po}(\lambda)$
Parameters	$\lambda > 0$
Domain	$k \in \mathbb{N}_0$
$\mathbb{P}(X = k)$	$\frac{\lambda^k e^{-\lambda}}{k!}$
$\mathbb{P}(X \leq k)$	$Q(k+1, \lambda)$
$\mathbb{E}[X]$	λ
$\mathrm{Var}(X)$	λ
Median	$\sim \max\left([\lambda + \frac{1}{3} - \frac{0.02}{\lambda}], 0\right)$
Mode	$[\lambda]$
$\phi(t)$	$\exp\{\lambda(e^{it} - 1)\}$

Estimation of rate.

Frequentist inference. Log-likelihood function:

$$\ln \mathcal{L}(\lambda|X) \propto -\lambda n + \sum_{i=1}^{n} X_i \log \lambda.$$

Setting the derivative w.r.t. rate to 0 we get the optimal value:

$$\lambda = \overline{X}_n.$$

Bayesian inference. Let set prior distribution of $\lambda \sim \Gamma(\alpha, \beta)$:

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

Posterior distribution:

$$f(\lambda|X) \propto e^{-\lambda(\beta+n)} \lambda^{\alpha - 1 + \sum_{i=1}^{n} X_i} \sim \Gamma(\alpha + \sum_{i=1}^{n} X_i, \beta + n).$$

Therefore, Bayesian estimator:

$$\mathbb{E}[\lambda|X] = \frac{\alpha + \sum_{i=1}^{n} X_i}{\beta + n}.$$

And MAP estimator:

$$\lambda_{MAP} = \max\left(\frac{\alpha + \sum_{i=1}^{n} X_i - 1}{\beta + n}, 0\right).$$

Exponential family parameterization Logarithm of probability mass function:

$$\log \mathbb{P}(X = x) = x \log \lambda - \lambda - \log(x!).$$

Therefore, sufficient statistics $T(x) = x$, natural parameter $\theta = \log \lambda$, log-normalizer $F(\theta) = \exp(\theta)$, carrier measure $k(x) = \log(x!)$. We conclude that adjusted cross-entropy is

$$\begin{aligned} H_F(\theta_q \| \theta_p) &= F(\theta_q) - \langle \theta_q, \nabla F(\theta_p) \rangle \\ &= \exp(\theta_q) - \theta_q \exp(\theta_p). \end{aligned}$$

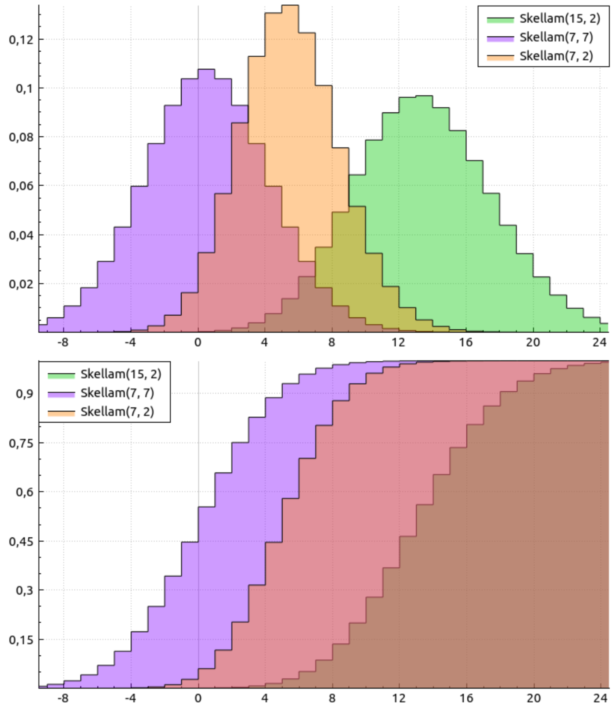
Adjusted entropy is

$$H_F(\theta) = \exp(\theta)(1 - \theta) = \lambda(1 - \log \lambda).$$

And Kullback-Leibler divergence:

$$\begin{aligned} \mathrm{KL}(p \| q) &= H_F(\theta_q \| \theta_p) - H_F(\theta_p) \\ &= \lambda_q - \lambda_p \left(1 + \log\left(\frac{\lambda_p}{\lambda_q}\right)\right). \end{aligned}$$

24 Skellam distribution

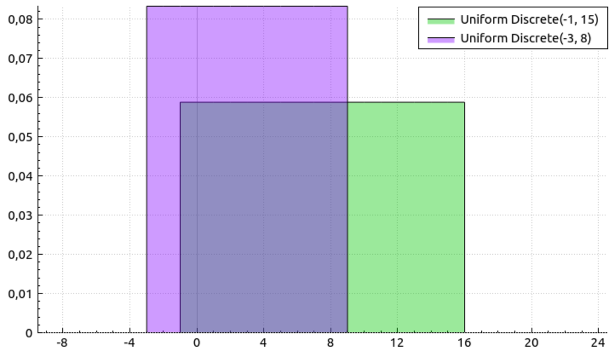


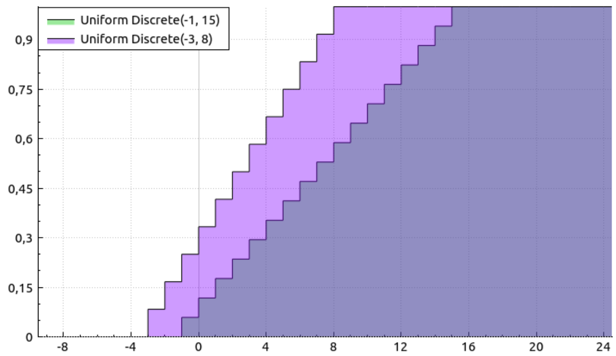
Notation	$X \sim \text{Skellam}(\mu_1, \mu_2)$
Parameters	$\mu_1, \mu_2 > 0$
Domain	$k \in \mathbb{Z}$
$\mathbb{P}(X = k)$.	$e^{-(\mu_1+\mu_2)}\left(\frac{\mu_1}{\mu_2}\right)^{\frac{k}{2}} I_k(2\sqrt{\mu_1\mu_2})$
$\mathbb{P}(X \leq k)$	$\text{MarcumP}_{k+1}(\mu_2, \mu_1),\ k \geq 0$ $\text{MarcumQ}_{-k}(\mu_1, \mu_2),\ k < 0$
$\mathbb{E}[X]$	$\mu_1 - \mu_2$
$\text{Var}(X)$	$\mu_1 + \mu_2$
Median	Searched numerically
Mode	$[\mu_1 - \mu_2]$
$\phi(t)$	$\exp\{\mu_1(e^{it} - 1) - \mu_2(e^{it} - 1)\}$

Relation to other distributions: if $Y \sim \text{Po}(\mu_1)$ and $Z \sim \text{Po}(\mu_2)$, then

$$Y - Z \sim \text{Skellam}(\mu_1, \mu_2).$$

25 Uniform discrete distribution

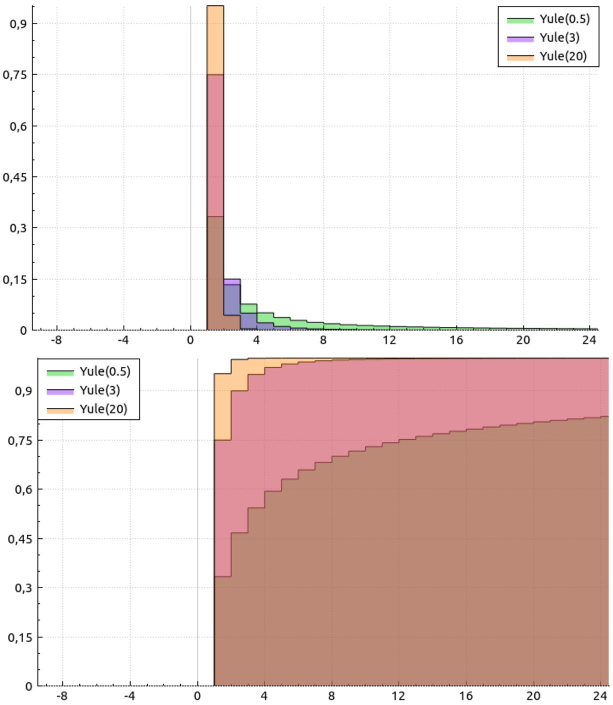




Notation	$X \sim \mathcal{U}\{a, \ldots, b\}$
Parameters	$a, b \in \mathbb{R}, a \leq b$
Domain	$k \in \{a, \ldots, b\}$
$\mathbb{P}(X = k)$	$\frac{1}{n}$, where $n = b - a + 1$.
$\mathbb{P}(X \leq k)$	$\frac{k-a+1}{n}$
$\mathbb{E}[X]$	$\frac{a+b}{2}$
$\mathrm{Var}(X)$	$\frac{(n-1)(n+1)}{12}$
Median	$\frac{a+b}{2}$
Mode	Any value between a and b
$\phi(t)$	$\frac{e^{iat}-e^{i(b+1)t}}{n(1-e^{it})}$

Relation to other distributions: if $X \sim BB(n, 1, 1)$, then $X \sim \mathcal{U}\{0, \ldots, n\}$.

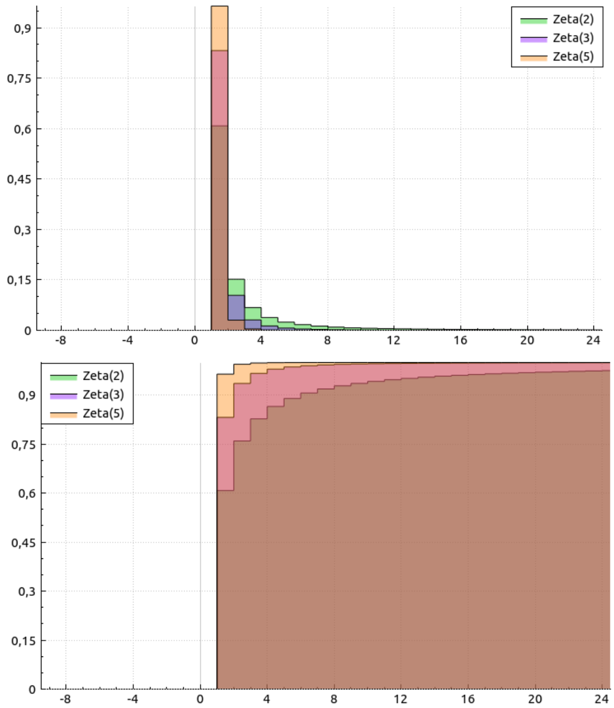
26 Yule distribution



Notation	$X \sim \text{Yule}(\rho)$
Parameters	$\rho \in \mathbb{R}^+$
Domain	$k \in \mathbb{N}$
$\mathbb{P}(X = k)$	$\rho \frac{\Gamma(1+\rho)(k-1)!}{\Gamma(k+\rho+1)}$
$\mathbb{P}(X \leq k)$	$1 - k\frac{\Gamma(1+\rho)(k-1)!}{\Gamma(k+\rho+1)}$
$\mathbb{E}[X]$	$\frac{\rho}{\rho-1}$, $\rho > 1$ ∞, otherwise
$\text{Var}(X)$	$\frac{\rho^2}{(\rho-1)^2(\rho-2)}$, $\rho > 2$ ∞, otherwise
Median	Searched numerically
Mode	1
$\phi(t)$	Calculated numerically

Relation to other distributions: if $X \sim \text{Pareto}(\alpha, 1)$, then $\text{Geometric}(1/X) \sim \text{Yule}(\alpha)$.

27 Zeta distribution



Notation	$X \sim \text{Zeta}(s)$
Parameters	$s > 1$
Domain	$k \in \mathbb{N}$
$\mathbb{P}(X = k)$	$\frac{1}{\zeta(s)k^s}$
$\mathbb{P}(X \leq k)$	$\frac{H(s,k)}{\zeta(s)}$
$\mathbb{E}[X]$	$\frac{\zeta(s-1)}{\zeta(s)}$, $s > 2$ ∞, otherwise
$\text{Var}(X)$	$\frac{\zeta(s-2)}{\zeta(s)} - (\mathbb{E}[X])^2$, $\rho > 3$ ∞, otherwise
Median	Searched numerically
Mode	1
$\phi(t)$	Calculated numerically

28 Zipf distribution

Part IV

Bivariate distributions

29 Bivariate Normal distribution

30 Normal-Inverse-Gamma distribution

31 Trinomial distribution

Part V

Circular distributions

32 von Mises distribution

33 Wrapped Exponential distribution

Part VI

Singular distributions

34 Cantor distribution