1 Some Important Continuous Distributions

1.1 Uniform $\mathcal{U}(a, b)$ Distribution

Random variable X has uniform $\mathcal{U}(a, b)$ distribution if its density is given by

$$f(x|a, b) = \begin{cases} \frac{1}{b-a}, & a \le x \le b \\ 0, & \text{else} \end{cases} \qquad F(x|a, b) = \begin{cases} 0, & x < a \\ \frac{x-a}{b-a}, & a \le x \le b \\ 1, & x > b \end{cases}$$

- Moments: $EX^k = \frac{1}{b-a}\frac{b^{k+1}-a^{k+1}}{k+1}, \ k = 1, 2, \dots$
- Variance $VarX = \frac{(b-a)^2}{12}$.
- Characteristic Function $\varphi(t) = \frac{1}{b-a}\frac{e^{itb}-e^{ita}}{it}$.
- If $X \sim \mathcal{U}(a, b)$ then $Y = \frac{X-a}{b-a} \sim \mathcal{U}(0, 1)$.
- Typical model: Rounding (to the nearest integer) Error is often modeled as $\mathcal{U}(-1/2, 1/2)$
- If $X \sim F$, where F is a continuous cdf, then $Y = F(X) \sim \mathcal{U}(0, 1)$.

1.2 Exponential $\mathcal{E}(\lambda)$ Distribution

Random variable X has exponential $\mathcal{E}(\lambda)$ distribution if its density and cdf are given by

$$f(x|\lambda) = \begin{cases} \lambda e^{-\lambda x}, & x \ge 0 \\ 0, & \text{else} \end{cases}, \qquad F(x|\lambda) = \begin{cases} 1 - e^{-\lambda x}, & x \ge 0 \\ 0, & \text{else} \end{cases}$$

- Moments: $EX^k = \frac{k!}{\lambda^k}, \ k = 1, 2, \dots$
- Variance $VarX = \frac{1}{\lambda^2}$.
- Characteristic Function $\varphi(t) = \frac{\lambda}{\lambda - it}$.
- Exponential random variable X possesses memoryless property $P(X > t + s|X > s) = P(X > t)$.
- Typical model: Lifetime in reliability.
- Alternative parametrization, λ' as scale. $f(x|\lambda') = \frac{1}{\lambda'}e^{-\frac{x}{\lambda'}}$, $EX^k = k!(\lambda')^k, \ k = 1, 2, \dots, VarX = (\lambda')^2$.

1.3 Double Exponential $\mathcal{DE}(\mu, \sigma)$ Distribution

Random variable X has double exponential $\mathcal{DE}(\mu, \sigma)$ distribution if its density and cdf are given by

$$f(x|\mu, \sigma) = \frac{1}{2\sigma}e^{-|x-\mu|/\sigma}, \qquad F(x|\mu, \sigma) = \frac{1}{2}\left(1 + \text{sgn}(x - \mu)(1 - e^{-|x-\mu|/\sigma}\right), \qquad x, \mu \in R; \sigma > 0.$$

- Moments: $EX = \mu, \ EX^{2k} = [\frac{\mu^{2k}}{(2k)!} + \frac{\mu^{2(k-1)}\sigma^2}{(2(k-1))!} + \dots \frac{\sigma^{2k}}{1}](2k)! \quad EX^{2k+1} = \mu^{2k+1}(2k + 1)!$
- Variance $VarX = 2\sigma^2$.
- Characteristic Function $\varphi(t) = \frac{e^{i\mu t}}{1+(\sigma t)^2}$.

1.4 Normal (Gaussian) $\mathcal{N}(\mu, \sigma^2)$ Distribution

Random variable X has normal $\mathcal{N}(\mu, \sigma^2)$ distribution with parameters $\mu \in R$ (mean, center) and $\sigma^2 > 0$ (variance) if its density is given by

$$f(x|\alpha, \beta) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}, \quad -\infty < x < \infty$$

• Moments: $EX = \mu, E(X-\mu)^{2k-1} = 0; E(X-\mu)^{2k} = (2k-1)(2k-3)\dots 5 \cdot 3 \cdot 1 \cdot \sigma^{2k} = (2k-1)!!\sigma^{2k},\ k = 1, 2, \dots$

• Characteristic function $\varphi(t) = e^{i\mu t - t^2\sigma^2/2}$.

• $Z = \frac{X-\mu}{\sigma}$ has *standard* normal distribution $\phi(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$. The cdf of standard normal distribution is a special function $\Phi(x) = \int_{-\infty}^{x} \phi(t)dt$ and its values are tabulated in many introductory statistical texts.

• Standard half-Normal distribution is given by $f(x) = 2\phi(x)\mathbf{1}(x \geq 0)$.

1.5 Chi-Square χ^2_n Distribution

Random variable X has chi-square χ^2_n distribution distribution with n degrees of freedom if its density is given by

$$f(x) = \begin{cases} \frac{1}{2^{n/2}\Gamma(n/2)} x^{n/2-1} e^{-x/2}, & x > 0 \\ 0, & \text{else} \end{cases}$$

• Moments: $EX^k = n(n+2)\dots(n+2(k-1)), k = 1, 2, \dots.$

• Expectation $EX = n$, Variance $VarX = 2n$, and Mode $m = n-2,\ n > 2$.

• Characteristic function $\varphi(t) = (1-2it)^{-n/2}$.

• Noncentral chi-square $nc\chi^2_n$ distribution is the distribution of sum of squares of n normals: $\mathcal{N}(\mu_i, 1)$. The non-centrality parameter is $\delta = \sum_i \mu_i^2$. Density of $nc\chi^2_n$ distribution involves Bessel function of the first kind. The simplest representation for the cdf of $nc\chi^2_n$ is an infinite Poisson mixture of central χ^2's where degrees of freedom are mixed:

$$F(x|n, \delta) = \sum_{i=0}^{\infty} \frac{(\delta/2)^i}{i!} e^{-\delta/2} P(\chi^2_{n+2i} \leq x).$$

• χ^2_n is $\mathcal{G}(n/2, 2)$ or in alternative parametrization $\mathcal{G}amma(n/2, 1/2)$.

• Inverse χ^2_n, $inv - \chi^2_n$ is defined as $\mathcal{IG}(n/2, 2)$ or $\mathcal{IG}amma(n/2, 1/2)$. Scaled inverse χ^2_n, $inv - \chi^2(n, s^2)$ is $\mathcal{IG}(n/2, 2/(ns^2))$ or $\mathcal{IG}amma(n/2, ns^2/2)$.

1.6 Chi χ_n Distribution

Random variable X has chi-square χ_n distribution distribution with n degrees of freedom if its density is given by

$$f(x) = \begin{cases} \frac{1}{2^{n/2-1}\Gamma(n/2)} x^{n-1} e^{-x^2/2}, & x > 0 \\ 0, & \text{else} \end{cases}$$

- Moments: $EX^k = \frac{2^{k/2}\Gamma(\frac{n+k}{2})}{\Gamma(n/2)}, k = 1, 2, \ldots$.
- Variance $VarX = n - 2\left[\frac{\Gamma((n+1)/2)}{\Gamma(n/2)}\right]^2$.
- Characteristic function $\varphi(t) = \frac{1}{\Gamma(n/2)}\sum_{k=0}^{\infty}\frac{(i\sqrt{2}t)^k}{k!}\Gamma((n+k)/2)$.
- χ_n for $n = 2$ is Raleigh Distribution, for $n = 3$ Maxwell distribution.

1.7 Gamma $\mathcal{G}(\alpha, \beta)$ Distribution

Random variable X has gamma $\mathcal{G}(\alpha, \beta)$ distribution with parameters $\alpha > 0$ (shape) and $\beta > 0$ (scale) if its density is given by

$$f(x|\alpha,\beta) = \begin{cases} \frac{1}{\Gamma(\alpha)\beta^\alpha}x^{\alpha-1}e^{-x/\beta}, & x \geq 0 \\ 0, & \text{else} \end{cases} \qquad F(x|\alpha,\beta) = \begin{cases} 0, & x \leq 0 \\ inc\Gamma(x|\alpha,\beta), & x \geq 0 \end{cases}$$

- Moments: $EX^k = \alpha(\alpha+1)\ldots(\alpha+k-1)\beta^k,\ k = 1, 2, \ldots$
- Mean $EX = \alpha\beta$, Variance $VarX = \alpha\beta^2$.
- Mode $m = (\alpha - 1)\beta$.
- Characteristic function $\varphi(t) = \frac{1}{(1-it\beta)^\alpha}$.
- Alternative parametrization, $\mathcal{G}amma(a, b)$: $f(x|a,b) = \frac{b^a}{\Gamma(a)}x^{a-1}e^{-bx},\ x \geq 0,\ EX^k = \frac{a(a+1)\ldots(a+k-1)}{b^k},\ k = 1, 2, \ldots\ \ VarX = a/b^2$.
- Special cases $\mathcal{E}(\lambda) \equiv \mathcal{G}(1, 1/\lambda) \equiv \mathcal{G}amma(1, \lambda)$ and $\chi^2_n \equiv \mathcal{G}(n/2, 2) \equiv \mathcal{G}amma(n/2, 1/2)$.
- If α is an integer, $\mathcal{G}a(\alpha,\beta) \stackrel{d}{=} -\frac{1}{\beta}\sum_{i=1}^{\alpha}\log(U)$. If $\alpha < 1$, then if $Y \sim \mathcal{B}e(\alpha, 1-\alpha)$ and $Z \sim \mathcal{E}(\infty)$, $X = YZ \sim \mathcal{G}a(\alpha, 1)$.

1.8 Inverse Gamma $\mathcal{IG}(\alpha, \beta)$ Distribution

Random variable X has gamma $\mathcal{IG}(\alpha, \beta)$ distribution with parameters $\alpha > 0$ and $\beta > 0$ if its density is given by

$$f(x|\alpha,\beta) = \begin{cases} \frac{1}{\Gamma(\alpha)\beta^\alpha x^{\alpha+1}}e^{-1/(\beta x)}, & x \geq 0 \\ 0, & \text{else} \end{cases}$$

- Moments: $EX^k = \{(\alpha-1)(\alpha-2)\ldots(\alpha-k)\beta^k\}^{-1},\ k = 1, 2, \ldots\ \ (\alpha > k)$.
- Mean $EX = \frac{1}{\beta(\alpha-1)},\ \alpha > 1$, Variance $VarX = \frac{1}{(\alpha-1)^2(\alpha-2)\beta^2},\ \alpha > 2$
- Mode $m = \frac{1}{(\alpha+1)\beta}$.
- Characteristic function $\varphi(t) =$.
- If $X \sim \mathcal{G}(\alpha,\beta)$ then $X^{-1} \sim \mathcal{IG}(\alpha,\beta)$.
- Alternative parametrization, $\mathcal{IG}amma(a, b)$. $f(x|a,b) = \frac{b^a}{\Gamma(a)x^{a+1}}e^{-b/x},\ x \geq 0,\ EX^k = \frac{b^k}{(a-1)\ldots(a-k)},\ k = 1, 2, \ldots\ \ VarX = b^2/((a-1)^2(a-2))$.

1.9 Beta $\mathcal{B}e(\alpha, \beta)$ Distribution

Random variable X has beta $\mathcal{B}e(\alpha, \beta)$ distribution with parameters $\alpha > 0$ and $\beta > 0$ if its density is given by

$$f(x|\alpha,\beta) = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1}(1-x)^{\beta-1}, & 0 \le x \le 1 \\ 0, & \text{else} \end{cases} \qquad F(x|\alpha,\beta) = \begin{cases} 0, & x \le 0 \\ \textit{incBeta}(x|\alpha,\beta), & 0 \le x \le 1 \\ 1, & x \ge 1 \end{cases}$$

• Moments: $EX^k = \frac{\Gamma(\alpha+k)\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\alpha+\beta+k)} = \frac{\alpha(\alpha+1)\dots(\alpha+k-1)}{(\alpha+\beta)(\alpha+\beta+1)\dots(\alpha+\beta+k-1)}$.
• Mean $EX = \frac{\alpha}{\alpha+\beta}$; Variance $VarX = \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$.
• Mode $m = \frac{\alpha-1}{\alpha+\beta-2}$, if $\alpha > 1, \beta > 1$
• Characteristic function $\varphi(t) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)} \sum_{k=0}^{\infty} \frac{(it)^k}{k!} \frac{\Gamma(\alpha+k)}{\Gamma(\alpha+\beta+k)}$
• If $X_1, X_2, \dots, X_n$ is a sample from the uniform $\mathcal{U}(0,1)$ distribution, and $X_{(1)}, X_{(2)}, \dots, X_{(n)}$ its order statistics. Then $X_{(k)} \sim \mathcal{B}e(k, n-k+1)$.
• $\mathcal{B}e(1,1) \equiv \mathcal{U}(0,1)$; $\mathcal{B}e(1/2,1/2) \equiv$ Arcsine Law

1.10 Student t_n Distribution

Random variable X has Student t_n distribution with n degrees of freedom if its density is given by

$$f_n(x) = \frac{\Gamma(\frac{n+1}{2})}{\sqrt{n\pi}\,\Gamma(\frac{n}{2})} \left(1 + \frac{x^2}{n}\right)^{-\frac{n+1}{2}}, \quad -\infty < x < \infty.$$

• Moments: $EX^{2k} = \frac{n^k}{\sqrt{\pi}} \frac{\Gamma(n/2-k)\Gamma(k+1/2)}{\Gamma(n/2)}$, $2k < n$. $EX^{2k-1} = 0$, $k = 1, 2, \dots$.
• $VarX = \frac{n}{n-2}$, $n > 2$
• Characteristic function $\varphi(t) = \frac{\sqrt{\pi}\,\Gamma(m)}{\Gamma(n/2)} \frac{e^{-\sqrt{n}|t|}}{2^{2(m-1)}(m-1)!} \sum_{k=0}^{m-1} (2k)! \binom{m-1+k}{2k} (2\sqrt{n}|t|)^{m-1-k}$,
for $m = \frac{n+1}{2}$ integer.
• t_{2k-1}, $k = 1, 2, \dots$ is infinitely divisible.
• If $Z \sim \mathcal{N}(0,1)$ and $Y \sim \chi^2_n$, then $X = Z/\sqrt{Y/n}$ has t_n distribution.
• $t_1 \equiv \mathcal{C}a(0,1)$.

1.11 Cauchy $\mathcal{C}a(a,b)$ Distribution

Random variable X has Cauchy $\mathcal{C}a(a,b)$ distribution with center $a \in \mathbb{R}$ and scale $b \in \mathbb{R}^+$ if its density is given by

$$f(x) = \frac{1}{b\pi} \frac{1}{1 + (\frac{x-a}{b})^2} = \frac{b}{\pi(b^2 + (x-a)^2)}, \quad -\infty < x < \infty.$$

If $a = 0$ and $b = 1$, the distribution is called standard Cauchy. The cdf is

$$F(x) = 1/2 + \frac{1}{\pi} \arctan \frac{x-a}{b}, \quad -\infty < x < \infty.$$

• Moments: No finite moments. Value $x = a$ is the mode and median of the distribution.
• Characteristic function. $\varphi(t) = e^{iat-b|t|}$. Cauchy distribution is infinitely divisible. Since $\varphi(t) = (\varphi(t/n))^n$, if $X_1, \dots, X_n$ are iid Cauchy, $\bar{X}$ is also a Cauchy.
• If Y, Z are independent standard normal $\mathcal{N}(0,1)$ then $X = Y/Z$ has Cauchy $\mathcal{C}a(0,1)$ distribution. If a variable U is uniformly distributed between $-\pi/2$ and $\pi/2$, then $X = \tan U$ will follow standard Cauchy distribution.
• The Cauchy distribution is sometimes called the Lorentz distribution (especially in engineering community).

1.12 Fisher $F_{m,n}$ Distribution

Random variable X has Fisher $F_{m,n}$ distribution with m and n degrees of freedom if its density is given by

$f(x|m,n) = \frac{m^{m/2} n^{n/2} x^{m/2-1}}{B(m/2,n/2)} \, (n+mx)^{-(m+n)/2}, \; x > 0.$

The cdf $F(x)$ is of no closed form.

- Moments $E(X^k) = \left(\frac{n}{m}\right)^k \frac{\Gamma(m/2+k)\Gamma(n/2-k)}{\Gamma(m/2)\Gamma(n/2)}, 2k < n.$
- Mean $EX = \frac{n}{n-2}, n > 2,$ Variance $VarX = \frac{2n^2(m+n-2)}{m(n-2)^2(n-4)}, n > 4.$
- Mode $n/m \cdot (m-2)/(n+2)$

1.13 Logistic $\mathcal{L}o(\mu, \sigma^2)$ Distribution

Random variable X has logistic $\mathcal{L}o(\mu, \sigma^2)$ distribution with parameters $\mu \in R$ and $\sigma^2 > 0$ if its density is given by

$$f(x|\mu, \sigma^2) = \frac{\pi \exp\left[-\frac{\pi}{\sqrt{3}}\left(\frac{x-\mu}{\sigma}\right)\right]}{\sigma\sqrt{3}\left\{1 + \exp\left[-\frac{\pi}{\sqrt{3}}\left(\frac{x-\mu}{\sigma}\right)\right]\right\}^2}$$

- Expectation: $EX = \mu$ Variance: $VarX = \sigma^2$.
- Characteristic function $\varphi(t) = e^{it\mu}\Gamma(1 - i\frac{\sigma\sqrt{3}}{\pi}t)\Gamma(1 + i\frac{\sigma\sqrt{3}}{\pi}t).$
- Used in modeling in biometry (drug response, toxicology, etc.)
- Alternative parametrization

1.14 Lognormal $\mathcal{LN}(\mu, \sigma^2)$ Distribution

Random variable X has lognormal $\mathcal{LN}(\mu, \sigma^2)$ distribution with parameters $\mu \in \mathbb{R}$ and $\sigma^2 > 0$ if its density is given by

$$f(x|\alpha, \beta) = \begin{cases} \frac{1}{x\sigma\sqrt{2\pi}} e^{-\frac{(\ln(x)-\mu)^2}{2\sigma^2}}, & x > 0 \\ 0, & \text{else} \end{cases}$$

- Moments: $EX^k = \exp\{\frac{1}{2}k^2\sigma^4 + k\mu\}.$
- Variance $VarX = e^{\sigma^4+\mu}[e^{\sigma^4} - 1].$
- Mode $e^{\mu-\sigma^2}$
- If $Z \sim \mathcal{N}(0,1)$ then $X = \exp\{\sigma^2 Z + \mu\} \sim \mathcal{LN}(\mu, \sigma^2).$

1.15 Pareto $\mathcal{P}a(x_0, \alpha)$ Distribution.

Random variable X has Pareto $\mathcal{P}a(x_0, \alpha)$ distribution with parameters $0 < x_0 < \infty$ and $\alpha > 0$ if its density and cdf are given by

$f(x|x_0, \alpha) = \frac{\alpha}{x_0} \left(\frac{x_0}{x}\right)^{\alpha+1} \mathbf{1}(x \geq x_0), \; \alpha > 0, \qquad F(x) = (1 - \left(\frac{x_0}{x}\right)^{\alpha}) \, \mathbf{1}(x \geq x_0)$

$EX^n = \frac{\alpha x_0^n}{\alpha - n}, \; \alpha > n$

Random Pareto observations can be obtained as $x_0[1/(1-U)]^{1/\alpha}$, where $U \sim \mathcal{U}(0,1)$.

2 Some Important Discrete Distributions

2.1 Point Mass δ_a Distribution

Random variable X has point mass δ_a distribution concentrated at $a \in \mathbb{R}$ if its probability mass function is given by

$$f(x|a) = \delta_a = \begin{cases} 1, & x = a \\ 0, & x \neq a \end{cases}$$

• Moments: $EX^k = a^k$ Variance: $VarX = 0$.
• Characteristic function $\varphi(t) = e^{ita}$.

2.2 Bernoulli $\mathcal{B}er(p)$ Distribution

Random variable X has Bernoulli $\mathcal{B}er(p)$ distribution with parameter $0 \leq p \leq 1$ if its probability mass function is given by

$$f(x|p) = p^x(1-p)^{1-x},\ x \in \{0, 1\}.$$

• Moments: $EX^k = p$ Variance: $VarX = p(1-p)$.
• Characteristic function $\varphi(t) = 1 + p(e^{it} - 1)$.

2.3 Binomial $\mathcal{B}in(n, p)$ Distribution

Random variable X has Binomial $\mathcal{B}in(n, p)$ distribution with parameters $n \in \mathbb{N}$, and $0 \leq p \leq 1$ if its probability mass function is given by

$$f(x|p) = \binom{n}{x} p^x(1-p)^{n-x},\ x \in \{0, 1, \ldots, n\}.$$

• Moments: $EX = np,\ EX^2 = np + n(n-1)p^2,\ EX^3 = np(1-p)(1-2p),\ EX^4 = 3n^2p^2(1-p^2) + np(1-p)(1-6p(1-p))$ Variance: $VarX = np(1-p)$.
• Skewness: $\gamma = \frac{p}{\sqrt{np(1-p)}}$.
• Characteristic function $\varphi(t) = \left[1 + p(e^{it} - 1)\right]^n$.

2.4 Geometric $\mathcal{G}eom(p)$ Distribution

Random variable X has geometric $\mathcal{G}eom(p)$ distribution with parameter $0 \leq p \leq 1$ if its probability mass function is given by

$$f(x|p) = p(1-p)^x,\ x = 0, 1, 2, \ldots$$

• Expectation: $EX = \frac{1-p}{p}$ Variance: $VarX = \frac{1-p}{p^2}$.
• Characteristic function $\varphi(t) = \frac{p}{1-(1-p)e^{it}}$.

• Geometric distribution is the only discrete distribution with *memoryless property*,

$$P(X \geq m+n|X \geq m) = P(X \geq n).$$

• $X \sim \mathcal{G}eom(p)$ models the number of failures until first success in the Binomial setup.
• Alternative definition of Geometric distribution is $Y \sim \mathcal{G}e(p)$,

$$f(y|p) = p(1-p)^{y-1},\ y = 1, 2, \ldots$$

representing total number of experiments until the first success. Of course, $Y = X + 1$, $EY = \frac{1-p}{p} - 1 = \frac{1}{p},\ \ varY = VarX.$

2.5 Negative Binomial $\mathcal{NB}(r, p)$ Distribution

Random variable X has negative binomial $\mathcal{NB}(r, p)$ distribution with parameters $r \in \mathbb{N}$ and $0 \leq p \leq 1$ if its probability mass function is given by

$$f(x|r,p) = \binom{x+r-1}{r-1} p^r (1-p)^x,\ x = 0, 1, 2, \ldots$$

• Expectation: $EX = \frac{r(1-p)}{p}$ Variance: $VarX = \frac{r(1-p)}{p^2}$.
• Characteristic function $\varphi(t) = \left[\frac{p}{1-(1-p)e^{it}}\right]^r$.
• If r is integer, random variable X having negative binomial $\mathcal{NB}(r, p)$ distribution represents the number of failures in the binomial setup until r successes are obtained. If $r = 1, \mathcal{NB}(r, p) \equiv \mathcal{G}eom(p)$.
• Negative binomial is a marginal distribution for Poisson likelihood and Gamma prior, i.e., if $X|\theta \sim \mathcal{P}oi(\theta)$ and $\theta \sim \mathcal{G}(r, \frac{1-p}{p})$, then the marginal for X is $\mathcal{NB}(r, p)$.

2.6 Poisson $\mathcal{P}oi(\lambda)$ Distribution

Random variable X has Poisson $\mathcal{P}oi(\lambda)$ distribution with parameter$\lambda > 0$ if its probability mass function is given by

$$f(x|\lambda) = \frac{\lambda^x}{x!} e^{-\lambda},\ x = 0, 1, 2, \ldots$$

• Expectation: $EX = \lambda$, $EX^2 = \lambda^2 + \lambda$ Variance: $VarX = \lambda$.
• Characteristic function $\varphi(t) = e^{\lambda(e^{it-1})}$.
• If $np \to \lambda,\ n \to \infty$, then $\binom{n}{x} p^x (1-p)^{n-x} \to \frac{\lambda^x}{x!} e^{-\lambda}$.
• A random variable X having Poisson $\mathcal{P}oi(\lambda)$ distribution models the number of rare events (in a time interval or in a part of space).
• If λ is large, $\sqrt{X} \overset{\text{approx}}{\sim} \mathcal{N}(\sqrt{\lambda}, \frac{1}{4})$.