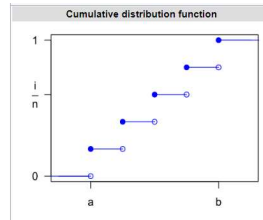
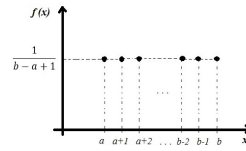


<div>DISCRETE UNIFORM DISTRIBUTION: U(a,b) and U(a,b)</div> <div>Domain/Sample space: $x \in \{a, a + 1, \dots, b\}$</div> <div>Parameters: $a,b \in \mathbb{Z}$ with $b \geq a$ or $n = b - a + 1$</div> <div>Graph: </div> <div>PMF: $P[X = x] = \frac{1}{b-a+1}$ or $\frac{1}{n}$ where $n = b - a + 1$</div> <div>CDF: $F[X] = \begin{cases} 0 & \text{for } x < a \\ \frac{x-a+1}{b-a+1} \text{ or } \frac{x-a+1}{n} & \text{for } a \leq x < b \\ 1 & \text{for } x \geq b \end{cases}$</div> <div>Mean E[X]: $E[X] = \frac{a+b}{2}$</div> <div>Variance V[X]: $V[X] = \frac{(b-a+1)^2 - 1}{12}$ or $\frac{(n^2 - 1)}{12}$ where $n = b - a + 1$</div> <div>MGF(Moment Generating Function): $M_X(t) = \frac{e^{bt} - e^{at}}{n(t - a)}$</div> <div>Higher Moments and Cumulants: $E[X^k] = \frac{1}{n} \sum_{i=1}^n i^k$ $E[(X - E(X))^k] = \mu_k = (1-p)(-p)^k + p(1-p)^k$ where $k \in \mathbb{N}$</div> <div>Relation with other distributions: If $X_1, X_2, \dots, X_n \sim \text{Bernoulli}(p)$ then, $\sum_{i=1}^n X_i \sim B(n, p)$</div>	<div>BERNOULLI DISTRIBUTION: Ber(p)</div> <div>e.g: Tossing a coin once</div> <div>Domain/Sample space: X: Occurrence of success $x \in \{0, 1\}$</div> <div>Parameters: $0 \leq p \leq 1$</div> <div>Graph: </div> <div>PMF: $P[X = x] = \begin{cases} q = 1-p & \text{if } x = 0 \\ p & \text{if } x = 1 \end{cases}$ DIFFERENT FORMS: $f(x, p) = p^x \cdot (1-p)^{1-x}$ $f(x, p) = px + (1-p)(1-x)$</div> <div>CDF: $F[X] = \begin{cases} 0 & \text{if } x < 0 \\ q = 1-p & \text{if } 0 \leq x < 1 \\ 1 & \text{if } x = 1 \end{cases}$</div> <div>Mean E[X]: $E[X] = p$</div> <div>Variance V[X]: $V[X] = p(1-p)$</div> <div>MGF(Moment Generating Function): $M_X(t) = q + pe^t$</div> <div>Higher Moments and Cumulants: $E[X^k] = p$ $E[(X - E(X))^k] = \mu_k = (1-p)(-p)^k + p(1-p)^k$ where $k \in \mathbb{N}$</div> <div>Relation with other distributions: • When n=1 the binomial distribution is Bernoulli distribution with parameter p i.e: X~B(1,p) is just X~Bernoulli(p) • As n approaches to ∞ and p remains fixed the distribution of X~B(n,p) turns to normal distribution i.e. $\frac{X-np}{\sqrt{np(1-p)}} \sim N(0,1)$ • As n approaches to ∞ and p approaches to 0 with the product np held fixed the binomial distribution is Poisson distribution with parameter λ = np i.e: $\frac{X-np}{\sqrt{np(1-p)}} \xrightarrow{n \rightarrow \infty} \text{Pois}(\lambda)$ $X \sim B(n, p) \xrightarrow{n \rightarrow \infty} \text{Pois}(\lambda)$ $np = \lambda$</div>	<div>BINOMIAL DISTRIBUTION: Bin(p)</div> <div>e.g: Tossing a coin n number of times</div> <div>Domain/Sample space: X: No. of success $x \in \{0, 1, \dots, n\}$</div> <div>Parameters: $n \in \{0, 1, \dots\}, p \in [0, 1]$</div> <div>Graph: </div> <div>PMF: $P[X = x] = \binom{n}{x} p^x \cdot (1-p)^{n-x}$ or $P[X = x] = \binom{n}{x} p^x q^{n-x}$ where $q = 1 - p$</div> <div>Mean E[X]: $E[X] = np$</div> <div>Variance V[X]: $V[X] = np(1-p) = npq$</div> <div>MGF(Moment Generating Function): $M_X(t) = (q + pe^t)^n$</div> <div>Higher Moments and Cumulants: $E[X^k] = \sum_{i=0}^k \binom{n}{i} p^i (1-p)^{n-i} i^k$</div> <div>Relation with other distributions: • X~B(n,p) $\xrightarrow{n \rightarrow \infty} \text{Pois}(\lambda)$ $np = \lambda$ The Poisson distribution is limiting case to Binomial distribution as $n \rightarrow \infty, p \rightarrow 0$ and np is constant • If X_1, X_2, \dots, X_n are independent Poisson r.v., with parameters $\lambda_1, \lambda_2, \dots, \lambda_n$ then given $\sum_{i=1}^n \lambda_i = k$, it follows that $X_i \sum_{j=1}^n X_j = k \sim B(n = k, p = \frac{\lambda_i}{\sum_{j=1}^n \lambda_j})$ • For sufficiently large values of λ $X \sim \text{Pois}(\lambda) \xrightarrow{\lambda \rightarrow \infty} N(\lambda, \lambda)$</div>	<div>POISSON DISTRIBUTION: Poi(λ)</div> <div>e.g: A meteorite hitting the earth (rare events)</div> <div>Domain/Sample space: $x \in \{0, 1, \dots\}$ (natural numbers starting from zero)</div> <div>Parameters: $\lambda \in (0, \infty)$</div> <div>Graph: </div> <div>PMF: $P[X = x] = \frac{\lambda^x e^{-\lambda}}{x!}$</div> <div>Mean E[X]: $E[X] = \lambda$</div> <div>Variance V[X]: $V[X] = \lambda$</div> <div>MGF(Moment Generating Function): $M_X(t) = e^{\lambda(e^t - 1)}$</div> <div>Higher Moments and Cumulants: $E[X^k] = \sum_{i=0}^k \frac{\lambda^i}{i!} e^{-\lambda} i^k$ where $k \in \mathbb{N}$</div> <div>Relation with other distributions: • If $\lambda = \frac{1}{2}$ then $X \sim \chi^2_2$ i.e. X has chi square with 2 degrees of freedom.</div>	<div>EXPONENTIAL DISTRIBUTION: Exp(λ)</div> <div>e.g: Interarrival time between customers</div> <div>Domain/Sample space: X: Interarrival time (Most common example) $x \in [0, \infty)$</div> <div>Parameters: $\lambda > 0$</div> <div>Graph: </div> <div>PDF: $f(x) = \lambda e^{-\lambda x}$</div> <div>CDF: $F[X] = \begin{cases} 0 & \text{for } x < 0 \\ 1 - e^{-\lambda x} & \text{for } x \in [0, \infty) \end{cases}$</div> <div>Mean E[X]: $E[X] = \frac{1}{\lambda}$</div> <div>Variance V[X]: $V[X] = \frac{1}{\lambda^2}$</div> <div>MGF(Moment Generating Function): $M_X(t) = \frac{\lambda}{\lambda - t}$</div> <div>Higher Moments and Cumulants: $E[X^k] = \frac{k!}{\lambda^k}$ where $k \in \mathbb{N}$</div> <div>Relation with other distributions: • If $\lambda = \frac{1}{2}$ then $X \sim \chi^2_2$ i.e. X has chi square with 2 degrees of freedom.</div>	<div>NORMAL DISTRIBUTION: N(μ, σ²)</div> <div></div> <div>Domain/Sample space: $x \in \mathbb{R}$</div> <div>Parameters: $\mu \in \mathbb{R}, \sigma^2 > 0$</div> <div>Graph: </div> <div>PDF: $f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$</div> <div>CDF: $F(x) = \frac{1}{2} [1 + \text{erf}(\frac{x-\mu}{\sigma\sqrt{2}})]$ $\Phi(1.644854) = 0.95$ $\Phi(1.959964) = 0.975$ $\Phi(1.281552) = 0.90$</div> <div>Mean E[X]: $E[X] = \mu$</div> <div>Variance V[X]: $V[X] = \sigma^2$</div> <div>MGF(Moment Generating Function): $M_X(t) = e^{(\mu t + \frac{\sigma^2 t^2}{2})}$</div> <div>Higher Moments and Cumulants: $E[(X - \mu)^k] = \begin{cases} 0 & \text{if } k \text{ is odd} \\ \frac{k!}{2^{k/2}} \sigma^k & \text{if } k \text{ is even} \end{cases}$ up here the k stands for double factorial where $k \in \mathbb{N}$</div> <div>Relation with other distributions: • The binomial distribution B(n,p) is approximately normal with mean np and variance np(1-p) for large n and for p not too close to 0 or 1. • The Poisson distribution with parameter λ is approximately normal with mean λ and variance λ, for large values of λ. • The chi-squared distribution $\chi^2(k)$ is approximately normal with mean k and variance 2k, for large k. • The Student's t-distribution t(v) is approximately normal with mean 0 and variance 1 when v is large.</div>	<div>UNIFORM DISTRIBUTION: U(a,b)</div> <div></div> <div>Domain/Sample space: $x \in [a, b]$</div> <div>Parameters: $a,b \in \mathbb{R}, b > a$</div> <div>Graph: </div> <div>PDF: $f(x) = \frac{1}{b-a}$</div> <div>CDF: $F[X] = \begin{cases} 0 & \text{for } x < a \\ \frac{x-a}{b-a} & \text{for } a \leq x < b \\ 1 & \text{for } x \geq b \end{cases}$</div> <div>Mean E[X]: $E[X] = \frac{a+b}{2}$</div> <div>Variance V[X]: $V[X] = \frac{(b-a)^2}{12}$</div> <div>MGF(Moment Generating Function): $M_X(t) = \frac{e^{bt} - e^{at}}{t(b-a)}$</div> <div>Higher Moments and Cumulants: $E[X^k] = \frac{b^{k+1} - a^{k+1}}{(k+1)(b-a)}$ where $k \in \mathbb{N}$</div>			
	<div>Transformations: • If $X_1, X_2, \dots, X_n \sim \text{Bernoulli}(p)$ then, $\sum_{i=1}^n X_i \sim B(n, p)$ • If $X_1 \sim \text{Bernoulli}(p)$ then, $X_1 + a \sim \text{Bernoulli}(p)$ here the values of X_i changes from 0,1 to a,a+1 where $P[X_1 = a] = 1-p$ and $P[X_1 = a+1] = p$</div>	<div>Transformations: If $X \sim B(n, p)$ and $Y \sim B(m, p)$ are independent binomial variables with same probability p then $X+Y \sim B(n+m, p)$</div>	<div>Transformations: If $\{X_i \sim \text{Poi}(\lambda_i) \mid i=1, 2, \dots, n\}$ are independent then $\sum_{i=1}^n X_i \sim \text{Poi}(\sum_{i=1}^n \lambda_i)$</div>	<div>Transformations: Sum of independent exponential r.v. is not exponential r.v.</div>	<div>Transformations: If $\{X_i \sim N(\mu_i, \sigma_i^2) \mid i=1, 2, \dots, n\}$ are independent then $\sum_{i=1}^n X_i \sim N(\sum_{i=1}^n \mu_i, \sum_{i=1}^n \sigma_i^2)$ If $\{X_i \sim N(\mu, \sigma^2) \mid i=1, 2, \dots, n\}$ are independent then $\sum_{i=1}^n X_i \sim N(n\mu, n\sigma^2)$ If $\{X_i \sim N(\mu, \sigma^2) \mid i=1, 2, \dots, n\}$ are independent then $\sum_{i=1}^n \frac{X_i - \mu}{\sigma} \sim N(0, n)$</div>	<div>MLE: $L_n(x_1, x_2, \dots, x_n; p) = p^{\sum_{i=1}^n x_i} (1-p)^{n-\sum_{i=1}^n x_i}$ $\hat{p}_{MLE} = \frac{\sum_{i=1}^n x_i}{n}$</div>	<div>MLE: $L_n(x_1, x_2, \dots, x_n; \lambda) = \lambda^n e^{-\lambda \sum_{i=1}^n x_i}$ $\hat{\lambda}_{MLE} = \frac{n}{\sum_{i=1}^n x_i}$ $\hat{\lambda}_{MLE} = \sum_{i=1}^n \frac{1}{x_i}$</div>	<div>MLE: $L_n(x_1, x_2, \dots, x_n; \mu, \sigma^2) = \frac{1}{(\sigma\sqrt{2\pi})^n} e^{-\frac{\sum_{i=1}^n (x_i - \mu)^2}{2\sigma^2}}$ $\hat{\mu}_{MLE} = \frac{\sum_{i=1}^n x_i}{n}$ $\hat{\sigma}_{MLE}^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \hat{\mu})^2$</div>	<div>MLE: $X_i \sim U(0, b)$ then : $L_n(x_1, x_2, \dots, x_n, b) = \frac{1}{b^n} \prod_{i=1}^n I(\max(x_i \leq b))$ $\hat{b}_{MLE} = X_{(n)}$ where $X_{(n)}$ is the nth order statistic</div>
	<div>Confidence Interval: $\hat{p} = \bar{X}_n$ • Conservative bound $\left[\hat{p} - \frac{q_0}{\sqrt{n}}, \hat{p} + \frac{q_0}{\sqrt{n}} \right]$ • Plug in $\left[\hat{p} - \frac{q_0 \sqrt{\hat{p}(1-\hat{p})}}{\sqrt{n}}, \hat{p} + \frac{q_0 \sqrt{\hat{p}(1-\hat{p})}}{\sqrt{n}} \right]$</div>				<div>Confidence Interval for mean μ: $\hat{\mu} = \bar{X}_n$ • Plug in asymptotically: $\left[\hat{\mu} - \frac{q_0 \cdot \sigma}{\sqrt{n}}, \hat{\mu} + \frac{q_0 \cdot \sigma}{\sqrt{n}} \right]$</div>				

Uniform Distribution(Discrete and Continous):

Discrete Uniform Distribution:

Notation	$U\{a,b\}$ or $\text{unif}\{a,b\}$
Sample space/Domain	$x \in \{a, a+1, \dots, b\}$
Paramters	$a, b \in \mathbb{Z}$ with $b \geq a$
PDF	$P[X = x] = \frac{1}{b-a+1}$ or $\frac{1}{n}$ where $n = b - a + 1$
CDF	$F[X] = \begin{cases} 0 & \text{for } x < a \\ \frac{x-a+1}{b-a+1} \text{ or } \frac{x-a+1}{n} & \text{for } a \leq x < b \\ 1 & \text{for } x \geq b \end{cases}$
Mean $E[X]$	$E[X] = \frac{a+b}{2}$
Variance $V[X]$	$V[X] = \frac{(b-a+1)^2 - 1}{12}$ or $\frac{(n^2 - 1)}{12}$ where $n = b - a + 1$
MGF $M_X(t)$	$M_X(t) = \frac{e^{at} - e^{(b+1)t}}{n(1 - e^t)}$



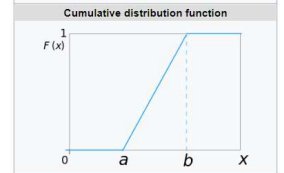
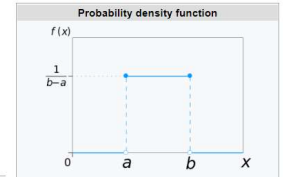
Using R to generate Discrete Uniform Distribution:(Rpackages needed:purrr,extraDistr)

To generate a r.v. following Discrete Uniform Distribution use:	rdunif (n=no. of data points you wanna generate, min=a,max=b) Eg:Generate 1000 data points from unif{1,12} Code: rdunif (n=1000,min=1,max=12)
Finding Probability at certain point:	ddunif (x=point for which you want to calculate the probability, min=a,max=b) Eg:Calculate probability of x=2 when x follows unif{1,12}i.e. $P[X = 2]$ Code: ddunif (x=2,min=1,max=12)
Finding CDF at certain point:	pdunif (q=point for which you want to calculate the cumulative probability, min=a,max=b) Eg:Calculate CDF at x=2 when x follows unif{1,12}i.e. $P[X \leq 2]$ Code: pdunif (q=2,min=1,max=12)
Finding Quantiles for specific probabilities:	qdnif (p=probability, min=a,max=b) Eg:Calculate the point at which p=0.1667 when x follows unif{1,12} Rember the qdnif will return the value of small x for which $P[X < x] = 0.1667$. Code: qdnif (p=0.1666667,min=1,max=12)

Uniform Distribution:

Notation	$U[a,b]$
Sample space/Domain	$x \in [a, b]$
PDF	$f(x) = \frac{1}{b-a}$
CDF	$F[X] = \begin{cases} 0 & \text{for } x < a \\ \frac{x-a}{b-a} & \text{for } a \leq x < b \\ 1 & \text{for } x \geq b \end{cases}$
Mean $E[X]$	$E[X] = \frac{a+b}{2}$
Variance $V[X]$	$V[X] = \frac{(b-a)^2}{12}$
MGF $M_X(t)$	$M_X(t) = \frac{e^{bt} - e^{at}}{t(b-a)}$
MLE	$X_i \sim U(0, b)$ then : $L_n(x_1, x_2, \dots, x_n, b) = \frac{1}{b^n} \prod_{i=1}^n (\max(x_i \leq b))$ $\widehat{b_{MLE}} = X_{(n)} \text{ where } X_{(n)} \text{ is the } n\text{th order statistic}$

Continuous uniform distribution with parameters a and b



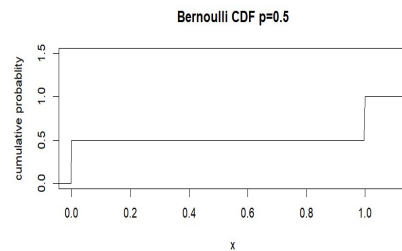
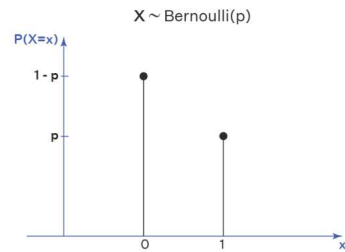
Using R to generate Discrete Uniform Distribution:

To generate a r.v. following Discrete Uniform Distribution use:	runif (n=no. of data points you wanna generate, min=a,max=b) Eg:Generate 1000 data points from unif[1,12] Code: runif (n=1000,min=1,max=12)
Finding Probability at certain point:	dunif (x=point for which you want to calculate the probability, min=a,max=b) Eg:Calculate probability of x=1 when x follows unif[1,12]i.e. $f(x = 1)$ Code: dunif (x=1,min=1,max=12)
Finding CDF at certain point:	pnunif (q=point for which you want to calculate the cumulative probability, min=a,max=b) Eg:Calculate CDF at x=2 when x follows unif{1,12}i.e. $f[X \leq 2]$ Code: pnunif (x=2,min=1,max=12)
Finding Quantiles for specific probabilities:	qunif (p=probability, min=a,max=b) Eg:Calculate the point at which p=0.09090909 when x follows unif[1,12] Code: qdnif (p=0.09090909,min=1,max=12)

Bernolli & Binomial Distribution:

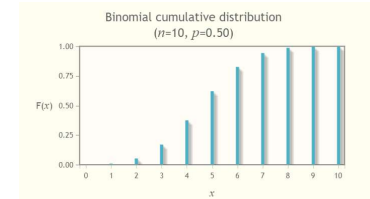
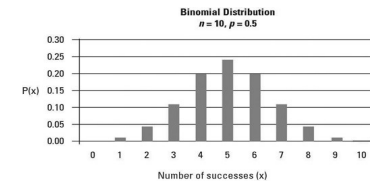
• **Bernolli Distribution:**

Notation	Ber{p}
Sample space/Domain	$x \in \{0,1\}$
Parameter	$0 \leq p \leq 1$
PDF	$P[X = x]$ $= \begin{cases} q = 1 - p & \text{if } x = 0 \\ p & \text{if } x = 1 \end{cases}$ DIFFERENT FORMS: $f(x, p) = p^x * (1 - p)^{1-x}$ $f(x, p) = px + (1 - p)(1 - x)$
CDF	$F[X] = \begin{cases} 0 & \text{if } x < 0 \\ q = 1 - p & \text{if } 0 \leq x < 1 \\ 1 & \text{if } x = 1 \end{cases}$
Mean E[X]	$E[X] = p$
Variance V[X]	$V[X] = p(1 - p)$
MGF	$M_X(t) = q + pe^t$
MLE	$L_n(x_1, x_2, \dots, x_n, p) = p^{\sum_{i=1}^n x_i} (1 - p)^{n - \sum_{i=1}^n x_i}$ $\widehat{p}_{MLE} = \sum_{i=1}^n X_i / n$
Confidence Interval	$\hat{p} = \overline{X}_n$ • Conservative bound $\left[\hat{p} - \frac{q_{\alpha/2}}{2\sqrt{n}}, \hat{p} + \frac{q_{\alpha/2}}{2\sqrt{n}} \right]$ • Plug in $\left[\hat{p} - \frac{q_{\alpha/2} \sqrt{\hat{p}(1 - \hat{p})}}{\sqrt{n}}, \hat{p} + \frac{q_{\alpha/2} \sqrt{\hat{p}(1 - \hat{p})}}{\sqrt{n}} \right]$



• **Binomial Distribution:**

Notation	B(n,p)
Sample space/Domain	$x \in \{0, 1, \dots, n\}$
Parameter	$n \in \{0, 1, \dots\}, p \in [0, 1]$
PDF	$P[X = x] = \binom{n}{x} p^x (1 - p)^{n-x}$ or $P[X = x] = \binom{n}{x} p^x q^{n-x}$ where $q = 1 - p$
Mean E[X]	$E[X] = np$
Variance V[X]	$V[X] = np(1 - p) = npq$
MGF	$M_X(t) = (q + pe^t)^n$



Using R to generate r.v. following bernolli Distribution:

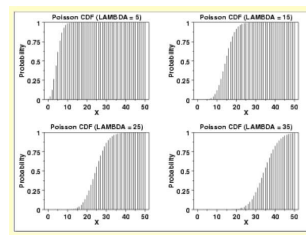
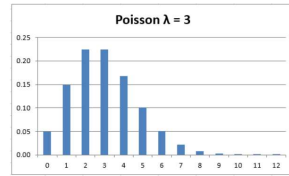
To generate a r.v. following Discrete Uniform Distribution use:	rbinom (n=no. of data points you wanna generate, size=no. of trails(n), prob=p) Eg: Generate 1000 data points from B(2,0.6) Code: <code>rbinom(n=1000, size=2, prob=0.6)</code>
Finding Probability at certain point:	dbinom (x=point for which you want to calculate the probability, size=no. of trails(n), prob=p) Eg: Calculate probability of x=2 when x follows B(2,0.6) i.e. $P[X = 2]$ Code: <code>dbinom(x=1, size=2, prob=0.6)</code>
Finding CDF at certain point:	pbinom (q=point for which you want to calculate the cumulative probability, size=no. of trails(n), prob=p) Eg: Calculate CDF at x=2 when x follows B(2,0.6) i.e. $P[X \leq 1]$ Code: <code>pbinom(q=2, size=2, prob=0.6)</code>
Finding Quantiles for specific probabilities:	qbinom (p=probability, size=no. of trails(n), prob=p) Eg: Calculate the point at which cumulative probability=1 when x follows Bern(2,0.6). Code: <code>qbinom(p=1, size=2, prob=0.6)</code>

Using R to generate r.v. following bernolli Distribution:
Use the same codes as Binomial just put size=1

Poisson and Exponential Distribution

Poisson distribution Distribution:

Notation	$\text{Pois}(\lambda)$
Sample space/Domain	$x \in \{0, 1, \dots\}$
Parameter	$\lambda \in (0, \infty)$
PDF	$P[X = x] = \frac{\lambda^x e^{-\lambda}}{x!}$
Mean E[X]	$E[X] = \lambda$
Variance V[X]	$V[X] = \lambda$
MGF	$M_X(t) = e^{\lambda(e^t - 1)}$

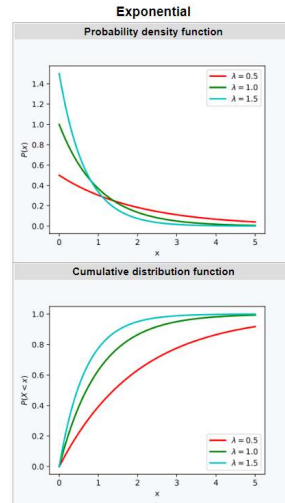


Using R to generate r.v. following bernolli Distribution:

To generate a r.v. following Discrete Uniform Distribution use:	rpois (n=no. of data points you wanna generate, lambda = λ) Eg:Generate 1000 data points from $\text{Pois}(\lambda = 1)$ Code: rpois (n=1000,lambda=1)
Finding Probability at certain point:	dpois (x=point for which you want to calculate the probability, lambda = λ) Eg:Calculate probability of x=2 when x follows $\text{Pois}(\lambda = 1)$ i.e. $P[X = 2]$ Code: dpois (x=2,lambda=1)
Finding CDF at certain point:	ppois (q=point for which you want to calculate the cumulative probability, lambda = λ) Eg:Calculate CDF at x=1 when x follows $\text{Pois}(\lambda = 1)$ i.e. $P[X \leq 1]$ Code: ppois (q=1,lambda=1)
Finding Quantiles for specific probabilities:	qpois (p=probability, lambda = λ) Eg:Calculate the point at which cumulative probability=1 when x follows $\text{Pois}(\lambda = 1)$ Code: qpois (p=0.9196986,lambda=1)

Exponential Distribution:

Notation	$\text{Exp}(\lambda)$
Sample space/Domain	$x \in [0, \infty)$
Parameter	$\lambda > 0$
PDF	$f(x) = \lambda e^{-\lambda x}$
CDF	$F[X] = \begin{cases} 1 - e^{-\lambda x} & \text{for } x > 0 \\ 0 & \text{for } x \leq 0 \end{cases}$
Mean E[X]	$E[X] = \frac{1}{\lambda}$
Variance V[X]	$V[X] = \frac{1}{\lambda^2}$
MGF	$M_X(t) = \frac{\lambda}{\lambda - t}$



Using R to generate r.v. following bernolli Distribution:

Remember rate here is lambda(e.g:rate= customers per minutes)

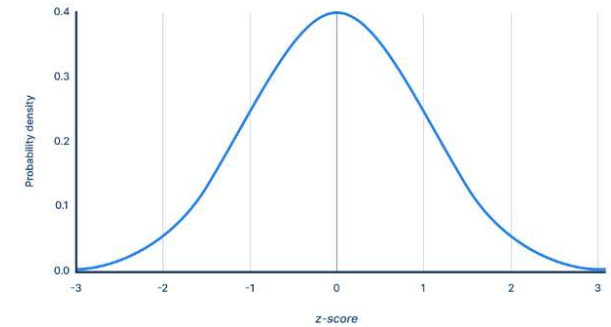
To generate a r.v. following Discrete Uniform Distribution use:	rexp (n=no. of data points you wanna generate, rate = λ) Eg:Generate 1000 data points from $\text{Pois}(\lambda = 1)$ Code: rexp (n=1000,rate=1)
Finding Probability at certain point:	dexp (x=point for which you want to calculate the probability, rate = λ) Eg:Calculate probability of x=2 when x follows $\text{Pois}(\lambda = 1)$ i.e. $P[X = 2]$ Code: dexp (x=2,rate=1)
Finding CDF at certain point:	pexp (q=point for which you want to calculate the cumulative probability, rate = λ) Eg:Calculate CDF at x=1 when x follows $\text{Pois}(\lambda = 1)$ i.e. $P[X \leq 1]$ Code: pexp (q=1,rate=1)
Finding Quantiles for specific probabilities:	qexp (p=probability, rate = λ) Eg:Calculate the point at which cumulative probability=1 when x follows $\text{Pois}(\lambda = 1)$ Code: qexp (p=0.9196986,rate=1)

Normal Distribution

- Binomial Distribution:**

Notation	$N(\mu, \sigma^2)$
Sample space/Domain	$x \in \mathbb{R}$
Parameter	$\mu \in \mathbb{R}, \sigma^2 > 0$
PDF	$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$
Mean $E[X]$	$E[X] = \mu$
Variance $V[X]$	$V[X] = \sigma^2$
MGF	$M_X(t) = e^{\left(\mu t + \frac{\sigma^2 t^2}{2}\right)}$
MLE:	$L_n(x_1, x_2, \dots, x_n, \mu, \sigma^2) = \frac{1}{(\sigma\sqrt{2\pi})^n} e^{-\frac{\sum_{i=1}^n (x_i - \mu)^2}{2\sigma^2}}$

Standard normal distribution



Using R to generate r.v. following bernolli Distribution:

To generate a r.v. following Discrete Uniform Distribution use:	rnorm (n=no. of data points you wanna generate, mean = μ , sd = σ) Eg:Generate 1000 data points from $N(0,1)$ Code: rnorm (n=1000,mean=0,sd=1)
Finding Probability at certain point:	dnorm (x=point for which you want to calculate the probability, mean = μ , sd = σ) Eg:Calculate probability of $x=0$ when x follows $N(0,1)$ i.e. $f(x=0)$ Code: dnorm (x=0,mean=0,sd=1)
Finding CDF at certain point:	pnorm (q=point for which you want to calculate the probability, mean = μ , sd = σ) Eg:Calculate CDF at $x=0$ when x follows $N(0,1)$ i.e. $P[X \leq 0]$ Code: pnorm (q=0,mean=0,sd=1)
Finding Quantiles for specific probabilities:	qnorm (p=probability, mean = μ , sd = σ) Eg:Calculate the point at which cumulative probability=0.5 when x follows $N(0,1)$ Code: qnorm (p=0.5,mean=0,sd=1)

