# Practical - 1

Aim:- Write examples based on probability.

Description :-

1) Probability Definition :-
If the sample space S of an experiment is such that each elementary event is the equally likely then to each other elementary event we can assign the probability as $\frac{1}{n}$ where n is the sample size.

2) Sample Space definition :-
A sample space of an experiment is the set of all possible outcomes of the experiment.

3) Event Definition :-
An Event is a set of outcomes i.e. zero subset of the sample space to which a probability is assign.

- Types of Events :-

1) Elementary Events :-
If an Event $E_1$ only one sample points such an event E is called an elementary event.

ii) Complementary Events :-
A complement of an Event E denoted by E'
is the set of all basic outcomes in the
sample space that do not belong to E.

iii) Compound Events :-
A compound event is any subset of the
sample space.

iv) Independent Events :-
Two events A and B are independent if the
probability of the succeeding events is not
affected by the outcome of the proceeding
event.

4) Union Definition :-
$A \cup B$ is the event that consists of all sample
points that are either in A or in B or in
both A and B. The event $A \cup B$ is called the
union of events. A and B.

• Formula of Union :-
$n(A \cup B) = n(A) + n(B) - n(A \cap B)$
Simply, the number of elements in the union
of set A and B is equal to the sum of
cardinal numbers of the sets A and B, minus
that of their intersection.

5) Addition and Multiplication Formula with description:-

i) Addition theorem on probability: If A and B are any two events then the probability of happening of at least one of the events is defined as $P(A \cup B) = P(A) + P(B) - P(A \cap B)$.

ii) According to the multiplication rule of probability, the probability of occurrence of both the events A and B is equal to the product of the probability of B occurring and the conditional probability that event A occurring given that event B occurs.

$P(A \cap B) = P(A) \cdot P(B/A)$

If A and B are independent

$P(A \cap B) = P(A) \cdot P(B)$

```
> library(prob)

> tosscoin(1)

> tosscoin(3)

> rolldie(1)

> rolldie(3)

> head(cards())

> urnsamples(1:3, size = 2, replace = TRUE,
ordered = TRUE)
```

Ordered without replacement

```
> urnsamples(1:3, size=2, replace = FALSE,
ordered = TRUE)
```

Unordered Without Replacement

```
> urnsamples(1:3, size = 2, replace = FALSE,
ordered = FALSE)
```

Events

```
> s<-tosscoin(2, makespace = TRUE)
> s[1:3]
> s<- cards()
> subset(s, rank%in% 7:9)
```

Union

```
> s = cards()
> A = subset(s, suit = "Heart")
> B = subset(s, rank %in% 7:9)
> union(A, B)
> intersect(A, B)
> setdiff(A, B)
```

ecdf(x)

# Practical - 2

Aim :- Condition Probability and Independence

```
> outcomes <- rolldie(1)
> rolldie(1)
> p <- rep(1/6, times = 6)
> probspace
> probspace(outcomes, probs = p)
> probspace(1:6, probs = p)
> probspace (1:6)
> rolldie(1, makespace = TRUE)
> probspace(tosscoin(1), probs = c(0.7, 0.3))
> S <- cards(makespace = TRUE)
> A <- subset(S, suit == "Heart")
> A
> B <- subset(S, rank %in% 7:9)
> B
> prob(A)
> prob(S, suit == "Heart")
> nsamp(n = 3, k=2, replace = TRUE, ordered = TRUE)
> nsamp(n=3, k=2, replace = FALSE, ordered = TRUE)
> nsamp(n=3, k=2, replace = FALSE, ordered = FALSE)
> nsamp(n=3, k=2, replace = TRUE, ordered = FALSE)
> n <- c(11, 7, 31)
> n
> k <- c(3, 4, 3)
> k
> r <- c(FALSE, FALSE, TRUE)
> r
```

```
> x<-nsamp(n, k, rep=r, ord=TRUE)
> x
> prod(x)
> (11 * 10 * 9) * (7 * 6 * 5 * 4) * 313
> prod(9:11) * prod(4:7) * 313
> prod(factorial(c(11,7))/ factorial(c(8,3))) * 313
> library(Rcmdr)
> library(RcmdrPlugin.IPSUR)
> g<-Vectorize(pbirthday.ipsur)
> plot(1:50, g(1:50),
+ xlab="Number of people in room",
+ ylab="Prob(at least one match)",
+ main=" The Birthday Problem")
> abline(h= 0.5)
> abline(v=23, lty=2)
> library(prob)
> S<-rolldie(2, makespace=TRUE)
> head(S)
> A<- subset(S, x1 == x2)
> ~~B~~ A ~~subset~~
> B<- subset(S, x1 + x2 >= 8)
> B
> prob(A, given = B)
> prob(B, given = A)
> prob(S, x1 ==x2, given = (x1+ x2 >= 8))
> prob(S, x1+x2 >=8, given =(x1 == x2))
> library(prob)
> L<- cards()
```

```
> M <- urnsamples (L, size = 2)
> N <- probspace (M)
> prob(N, all (rank == "A"))
> library(prob)
> L<- rep (c ("red", "green"), times = c(7, 3))
> M<- urnsamples(L, size = 3, replace = FALSE,
  ordered = TRUE)
> N <- probspace (M)
> prob (N, isrep(N, "red", 3))
> prob (N, isrep (N, "red", 2))
> prob (N, isin (N, c("red", "green", "red"),
  ordered = TRUE))
> prob(N, isin (N, c("red", "green", "red")))
> S <- tosscoin (10, makespace = TRUE)
> A <- subset (S, isrep (S, vals = "T", nrep = 10))
> 1 - prob (A)
> iidspace(c("H", "T"), ntrials = 3, probs = c (0.7, 0.3))
> prior <- c(0.6, 0.3, 0.1)
> like <- c( 0.003, 0.007, 0.01)
> post <- prior * like
> post /sum (post)
> newprior <- post
> post <- newprior * like^7
> post / sum(post)
> fastpost <- prior * like^8
> fastpost /sum (fastpost)
```

ecdf(x)

# Practical - 3

Aim :- Discrete Random Variable

Description :-

a) Probability distribution of discrete random variable.

→ The probability of a discrete random variable X is a list of each possible value of X together with the probability that X takes that value in one trial of the experiment.

b) Probability mass function.

→ A probability mass function (pmf) is a function over the sample space of a discrete random variable X which gives the probability that X is equal to a certain value.

Creating discrete random variables

```
> ~~(X <- RV(outcomes = 1:6, probs = 1/6))~~
> library ~~(rv)~~ (discreteRV)
> (X <- RV(outcomes = 1:6, probs = 1/6))
> (X <- RV(1:6))
> pois.func <- function(y, lambda) { return (lambda^y *
  exp(-lambda) / factorial (y)) }
> (Y <- RV(outcomes = c(0, Inf), probs = pois.func,
  lambda = 2))
> (Y <- RV("poison", lambda = 2))
> (X.loaded <- RV(outcomes = 1:6, odds = c(4,1,1,1,1,1)))
```

Probability Calculations

```
> P(X == 2)
```

```
> P(X < 3)
> P(X < 3 | X < 4)
> delta <- 3
> lambda <- 2
> P((Y >= lambda - delta) %AND% (Y <= lambda +
delta))
> P((Y - lambda)^2 <= delta^2)
> E(X)
> V(X)
> E((X - E(X))^2)
```

Joint Distributions

```
> (AandB <- jointRV(outcomes = list(1:3, 0:2), probs =
1:9 / sum(1:9)))
> A <- marginal(AandB, 1)
> B <- marginal(AandB, 2)
> P(A < B)
> P(A == 2 | B < 0)
> P(A == 2 | B > 0)
> P(A == 2 | (B == 1) %OR% (B == 2))
> independent(A, B)
> A | (A > 1)
> A | (B == 2)
> E(A | (B == 2))
> (X2 <- iid(X, n = 2))
> (X3 <- iid(X, n = 3))
> (X2 <- SofIID(X, n = 2)
> (X20 <- SofIID(X, n = 20, progress = FALSE))
> RV(1:6) + RV(1:6)
```

ecdf(x)

# Practical - 4

Aim :- Discrete Distributions

Description :-

1) Discrete random variables -

i) Probability mass functions :- A probability mass function (pmf) is a function over the sample space of a discrete random variable X which gives the probability that X is equal to a certain value. $f(x) = P[X = x]$.

ii) Mean, Varience and Standard Deviation :- Varience is a measure of how data points vary from the mean, whereas standard deviation is the measure of the distribution of statistical data.

2) The Binomial Distribution :- The binomial distribution is based on a Bernoulli trial, which is a random experiment in which there are only two possible outcomes: success (S) and failure (F).

3) An empirical distribution :- It is one for which each possible event is assigned a probability derived from experimental observation.

```
> x <- c(0, 1, 2, 3)
> f <- c(1/8, 3/8, 3/8, 1/8)
> mu <- sum (x * f)
> mu
> sigma2 <- sum((x - mu)^2 * f)
> sigma2
> sigma <- sqrt(sigma2)
> sigma
> F = cumsum(f)
> F
> library (distrEx)
> X <- DiscreteDistribution (supp = 0:3, prob = c(1,3,3,1)/8)
> E(X); var(X); sd (X)
> Pr
> pbinom (9, size = 12, prob = 1/6) - pbinom (6, size =
12, prob = 1/6)
> diff(pbinom (c (6, 9), size = 12, prob = 1/6))
> library (distr)
> X <- Binom (size = 3, prob = 1/2)
> X
> d (X) (1)
> p(X) (2)
> X <- Binom( size = 3, prob = 0.45)
> library (distr Ex)
> E(X)
> E(3 * X + 4)
> var (X)
> sd (X)
```

```
> x <- c(4, 7, 9, 11, 12)
ecdf (x)
> plot (ecdf (x))
> epdf <- function(x) function (t){sum (x %in% t)/
length (x)}
> x <- c (0, 0, 1)
> epdf (x) (0)
> x <- c (0, 0, 1)
> sample (x, size = 7, replace = TRUE)
```

# Practical - 5

Aim :- Continuous Distributions

Description :-

1) Continuous Random Variables :-
A random variable is called continuous if its range is uncountably infinite.

2) The Continuous Uniform Distribution :-
This is one of the simplest probability distributions in statistics. It is a continuous distribution, this means that it takes values within a specified range, eg. between 0 and 1.

3) The Normal Distribution :-
A normal distribution is a type of continuous probability distribution in which most data points cluster toward the middle of the range, while the rest taper off symmetrically toward either extreme.

4) The Chi-Square Distribution :-
A chi-square ($\chi^2$) distribution is a continuous probability distribution that is used in many hypothesis tests. This distribution has a single parameter called the degrees of freedom.

```
> f <- function(x) 3*x^2
> integrate(f, lower = 0.14, upper = 0.71)
> g <- function(x) 3/x^3
> integrate(g, lower = 1, upper = Inf)
> library(distr)
> f{ <- function(x) 3*x^2
> X <- AbscountDistribution(d = f, low1 = 0, up1 = 1)
> p(X)(0.71) - p(X)(0.14)
> library(distrEx)
> E(X)
> var(X)
> 3/80
> pnorm(1:3) - pnorm(-(1:3))
> g <- function(x) pnorm(x, mean = 100, sd = 15) - 0.99
```

```
> uniroot(g, interval = c(130, 145))

> qnorm(0.99, mean = 100, sd = 15)

> qnorm(c(0.025, 0.01, 0.005), lower.tail = FALSE)

> library(distr)

> X <- Norm(mean = 0, sd = 1)

> Y <- 4 - 3 * X
> Y

> Y <- exp(X)
> Y

> W <- sin(exp(X) + 27)
> W

> p(W)(0.5)

> W <- sin(exp(X) + 27)

> p(W)(0.5)

> curve(dchisq(x, df = 3), from = 0, to = 20, ylab = "y")

> ind <- c(4, 5, 10, 15)
```

```
> for(i in ind) curve(dchisq(x, df = i), 0, 20, add = TRUE)

> library(actuar)

> mgamma(1:4, shape = 13, rate = 1)

> plot(function(x) {
+ mgfgamma(x, shape = 13, rate = 1)
+ }, from = -0.1, to = 0.1, ylab = "gamma mgf")

> pnorm(2.64, lower.tail = FALSE)

> pnorm(0.87) - 1/2

> 2 * pnorm(-1.39)
```