

# R Intermediate Short Course

## Session 2 - Estimation and Hypothesis Testing

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**(5:00pm - 7:00pm)**  
**(online)**

# Estimation of Probability Distributions

A **probability distribution** is a function or rule that assigns probabilities to each value of a random variable.

Probability distributions may be discrete or continuous. The binomial and poisson distributions are discrete.

Six sided die example with sides numbered: 1, 2, 3, 3, 4, and 6

## Binomial distribution

A discrete random variable  $X$ , with probability mass function  $f$ , has a **Binomial** distribution with parameters  $n$  and  $p$  if:

$$f(x) = P(X = x) = \binom{n}{x} p^x (1 - p)^{n-x} \text{ for } x = 0, 1, 2, \dots, n$$

where  $n$  = number of trials,  $p$  = probability of success

and  $\binom{n}{x} = {}^n C_x = \frac{n!}{x!(n-x)!}$

For  $X \sim \text{Binomial}(n,p)$ :

population mean,  $\mu = E(X) = np$

population variance,  $\sigma^2 = \text{Var}(X) = np(1 - p)$

In R, the mean and variance of probability distributions are estimated as the sample mean,  $\bar{x}$  and the sample variance,  $s^2$ .

To generate a sample of random values which all follow a Binomial( $n,p$ ):

```
x = rbinom(sample size, n, p)
```

Each time this code is run, a different set of random values may be generated. We can guarantee the same random values are generated using the `set.seed` command eg. > `set.seed(123)`

**Example:** Let  $X$  be a discrete random variable which follows a binomial distribution with parameters  $n = 125$  and  $p = 0.04$ . Estimate the mean and variance for a sample of 10000 values of  $X$ .

```
> pop.mean = 125 * 0.04 [1] 5  
> pop.var = 125 * 0.04 * (1-0.04) [1] 4.8  
  
> set.seed(25)  
> x = rbinom(10000,125,0.04)  
> mean(x) [1] 5.0117  
> var(x) [1] 4.806244
```

Application of the probability mass function,  $f(x)$

Compute the following: a)  $P(X = 5)$  and b)  $P(X \leq 1)$ .

1. Manually:

$$a) P(X = 5) = \binom{125}{5} 0.04^5 (1 - 0.04)^{125-5} = 0.1791$$

$$\begin{aligned} b) P(X \leq 1) &= P(X = 0) + P(X = 1) \\ &= \binom{125}{0} 0.04^0 (1 - 0.04)^{125-0} + \binom{125}{1} 0.04^1 (1 - 0.04)^{125-1} \\ &= 0.0061 + 0.0317 = 0.0378 \end{aligned}$$

2. Simulated:

```
dbinom(x, n, p, log=FALSE)                      #P (X=x)
pbinom(x, n, p, lower.tail=TRUE, log.p=FALSE)    #P (X<=x)
```

a) > dbinom(5, 125, 0.04, log=F)

```
[1] 0.1790807
```

b) > pbinom(1, 125, 0.04, lower.tail=TRUE, log.p=F)

```
[1] 0.03774671
```

## Poisson distribution

A discrete random variable  $X$  is said to have a **Poisson** distribution with parameter  $\lambda$  ( $\lambda > 0$ ), if the probability mass function of  $X$  is:

$$f(x) = P(X = x) = \frac{e^{-\lambda} \lambda^x}{x!} \text{ for } x = 0, 1, 2, \dots$$

where  $\lambda$  = mean/average and  $x$  can take an infinite number of values.

For  $X \sim \text{Poisson}(\lambda)$ :

population mean,  $\mu = E(X) = \lambda$

population variance,  $\sigma^2 = \text{Var}(X) = \lambda$

To generate a sample of random values which all follow a  $\text{Poisson}(\lambda)$ :

```
x = rpois(sample size, lambda)
```

To compute probabilities associated with this distribution:

```
dpois(x, lambda, log=FALSE) #P (X=x)  
ppois(x, lambda, lower.tail=TRUE, log.p=FALSE) #P (X<=x)
```

**Example:** Let  $Y$  be discrete random variable which follows a poisson distribution with parameter  $\lambda = 5$ .

- a) Estimate the mean for a sample of 10000 values of  $Y$ .
- b) Calculate  $P(Y = 2)$  and  $P(Y \leq 2)$

a) > `set.seed(12)`  
> `y = rpois(10000, 5)`  
> `mean(y)`  
[1] 5.0316

b) Manually:

$$P(X = 2) = \frac{e^{-5} 5^2}{2!} = 0.0842$$

$$\begin{aligned} P(X \leq 2) &= P(X = 0) + P(X = 1) + P(X = 2) \\ &= \frac{e^{-5} 5^0}{0!} + \frac{e^{-5} 5^1}{1!} + \frac{e^{-5} 5^2}{2!} = e^{-5} \left[ \frac{5^0}{0!} + \frac{5^1}{1!} + \frac{5^2}{2!} \right] \\ &= 18.5e^{-5} = 0.1246 \end{aligned}$$

Simulated:

```
> dpois(2, 5, log=F)
[1] 0.08422434
> ppois(2, 5, lower.tail=T, log.p=F)
[1] 0.124652
```

The binomial distribution  $X \sim Binomial(n, p)$  can be approximated to a poisson distribution  $X \sim Poisson(\lambda = np)$  if n is large ( $n \rightarrow \infty$ ) and p is small ( $p \rightarrow 0$ ).

(See R script)

# Covariance and Correlation

**Covariance** is a measure used to determine how the change in one variable affects the other.

$$\text{Cov}(X, Y) = E(XY) - E(X)E(Y)$$

If  $\text{Cov}(X, Y) = 0$  then X and Y are independent.

$$[P(A \cap B) = P(A)*P(B)]$$

If  $\text{Cov}(X, Y) < 0$  there is a negative or inverse relationship between X and Y (as X increases Y decreases and vice versa).

If  $\text{Cov}(X, Y) > 0$  there is a positive or direct relationship between X and Y (as X increase Y increases and vice versa).

**Correlation** is a standardised measure of covariance and is used to determine the strength of the relationship between two variables.

$$\text{Cor}(X, Y) = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X) \times \text{Var}(Y)}}$$

Correlation values r, lie between -1 and 1:  $-1 \leq r \leq 1$

A negative correlation value close to 0 indicates a weak and inverse relationship between X and Y while a correlation value close to -1 indicates a strong and inverse relationship.

A positive correlation value close to 0 indicates a weak and direct relationship between X and Y while a correlation value close to 1 indicates a strong and direct relationship.

In addition to the correlation value, a scatter plot can be used to deduce the strength of the relationship between two variables.

Plots in R:

```
plot(x, y, type="p/l/o")
```

type="p" gives a scatter plot (points)

type="l" gives a line plot (line)

type="o" gives both points and line (over-fitted)

If a linear pattern can be seen in a scatter plot of variables X and Y, then this indicates there is a strong correlation.

The direction of this pattern specifies positive or negative correlation.

No apparent pattern indicates a weak and insignificant correlation.

**Example 1:** Simulate the covariance and correlation of the samples previously generated for variables X and Y. Also comment on the relationship between X and Y.

```
> cov(x,y)  
[1] -0.01347107  
  
> cor(x,y)  
[1] -0.002709111
```

The covariance and correlation values indicate a weak and negative relationship between X and Y.

**Example 2:** Simulate the correlation between vectors x and y defined below. What does this tell you about the relationship between x and y? Construct a scatter plot to support your interpretation.

```
> x = c(106,125,42,51,64,76,72,84,40,171,180,210,  
101,41,70)  
> y = c(10,44,0,2,8,14,21,18,24,17,26,52,16,11,37)  
> cor(x,y)  
[1] 0.6041182
```

There is a fairly strong and positive relationship between x and y.

```
> plot(x, y, type="p", main = "Scatterplot")
```

(See R script for output)

The scatter plot showed a linear relationship in an upward or positive direction. This gives the same interpretation as before.

## Hypothesis Testing (one sample T tests)

The **T distribution** commonly referred to as student's t-distribution, can be represented by a symmetric or bell-shaped curve. It is a continuous probability distribution and as such, the area under the curve = 1.

It utilizes degrees of freedom (df) which is the number of values that have the freedom to vary.

The T distribution is used when the sample size  $n \leq 30$ .

A **hypothesis test** is a statistical test used to determine whether the hypotheses formulated hold true for the entire population.

The hypotheses involved in a hypothesis test are:

1. Null hypothesis,  $H_0$  - a statement regarding the parameter of interest which always contains equality.
2. Alternate hypothesis,  $H_1$  - a statement contradicting the null hypothesis which always contains inequality.

There are three main types of hypothesis test:

1. **Two tailed test**       $H_0 : \mu = \mu_0$  vs  $H_1 : \mu \neq \mu_0$
2. **Upper tailed test** (one tail)       $H_0 : \mu \leq \mu_0$  vs  $H_1 : \mu > \mu_0$
3. **Lower tailed test** (one tail)       $H_0 : \mu \geq \mu_0$  vs  $H_1 : \mu < \mu_0$

The type of test is determined by the sign of the alternate hypothesis,  $H_1$ .

Note that the null hypothesis may be written as  $H_0 : \mu = \mu_0$  regardless of the type of test.

## Formulating hypotheses

First identify the null or alternate hypothesis given in the question. Then state along with the opposing hypothesis. Examples:

1. Test the hypothesis that the mean is significantly different from 1.  
i.e Test  $H_0 : \mu = 1$  versus  $H_1 : \mu \neq 1$
2. Does the average blood pressure exceed 100 mmHg?  
i.e. Required to test  $H_0 : \mu \leq 100$  versus  $H_1 : \mu > 100$

## Testing hypotheses

The decision of a hypothesis test revolves around the null hypothesis; either  $H_0$  is rejected or failed to be rejected. If rejected then  $H_1$  holds true and if failed to be rejected then  $H_0$  is true.

We reject the null hypothesis  $H_0$ , if the 3 following conditions hold:

1. The confidence interval does not contain the value at  $H_0$
2. The  $|$ test statistic $| \geq$  critical value  
i.e.  $+|$ test statistic $\geq$  critical value or  $-|$ test statistic $\leq -$ critical value
3. P-value  $<$  level of significance,  $\alpha$

1. A confidence interval (CI) is a range of values which contains the population value with a given degree of confidence or certainty.

On the other hand, the level of significance  $\alpha$ , gives an estimate of the percentage of uncertainty.

It is computed by,  $\alpha = 1 - \text{confidence level} = 1 - CL$

2. The test statistic derived from the data given is denoted by t.

The critical value for a two-tailed test is  $t_{\alpha/2, df}$  and for a one-tailed test is  $t_{\alpha, df}$  where  $df = n - 1$ .

3. A p-value is a probability calculated on the assumption that  $H_0$  is true.

### Performing One sample T tests in R:

```
t.test(data, mu=mu0)                      #two tailed  
t.test(data, mu=mu0, alternative="greater") #upper  
t.test(data, mu=mu0, alternative="less")    #lower
```

The default confidence level is 95%. This can be changed by specifying.

```
t.test(data, mu=mu0, alternative=" ", conf.level=0.99)  
                                #for 99% confidence
```

### Critical values:

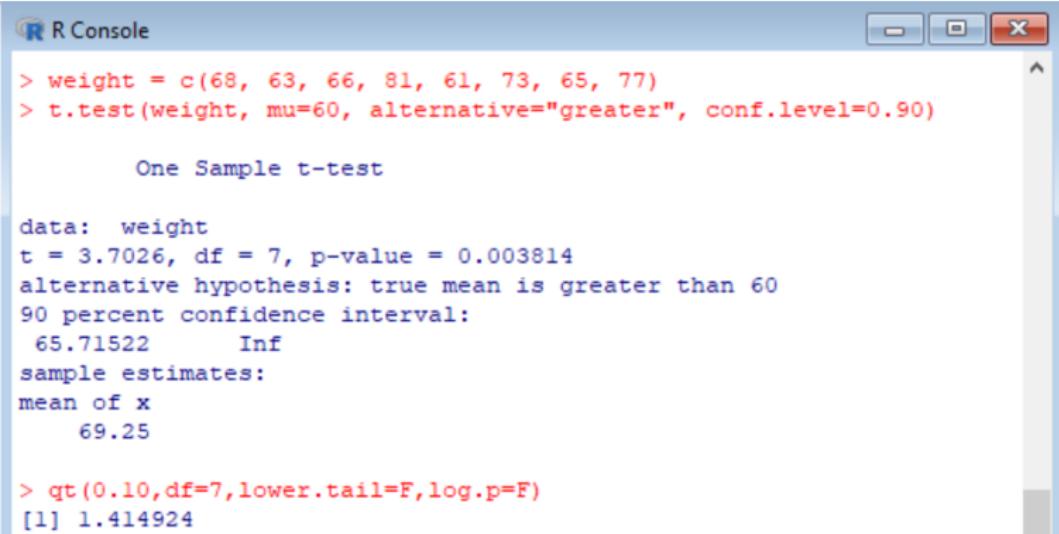
```
qt(alpha/2, df, lower.tail=F, log.p=F)      # $t_{\alpha/2, df}$   
qt(alpha, df, lower.tail=F, log.p=F)         # $t_{\alpha, df}$ 
```

**Example 1:** The weight in kilograms of 8 25-year old men are as follows:

68    63    66    81    61    73    65    77

Test the hypothesis that the average weight of 25-year old men is significantly greater than 60 kg. Use  $\alpha = 0.10$ .

Required to test  $H_0: \mu \leq 60$  vs  $H_1: \mu > 60$  at CL = 1 - 0.10 = 0.90



R Console window showing R code and output for a one-sample t-test.

```
> weight = c(68, 63, 66, 81, 61, 73, 65, 77)
> t.test(weight, mu=60, alternative="greater", conf.level=0.90)

One Sample t-test

data: weight
t = 3.7026, df = 7, p-value = 0.003814
alternative hypothesis: true mean is greater than 60
90 percent confidence interval:
65.71522      Inf
sample estimates:
mean of x
69.25

> qt(0.10,df=7,lower.tail=F,log.p=F)
[1] 1.414924
```

Method 1: The 90% confidence interval is  $(65.715, \infty)$ . Since this interval does not contain 60 we can reject  $H_0$ .

Method 2: The test statistic,  $t = 3.703$  is greater than the critical value,  $t_{0.10,7} = 1.415$  so we can reject  $H_0$ .

Method 3: The p-value =  $0.004 < 0.10$  so we can reject  $H_0$ .

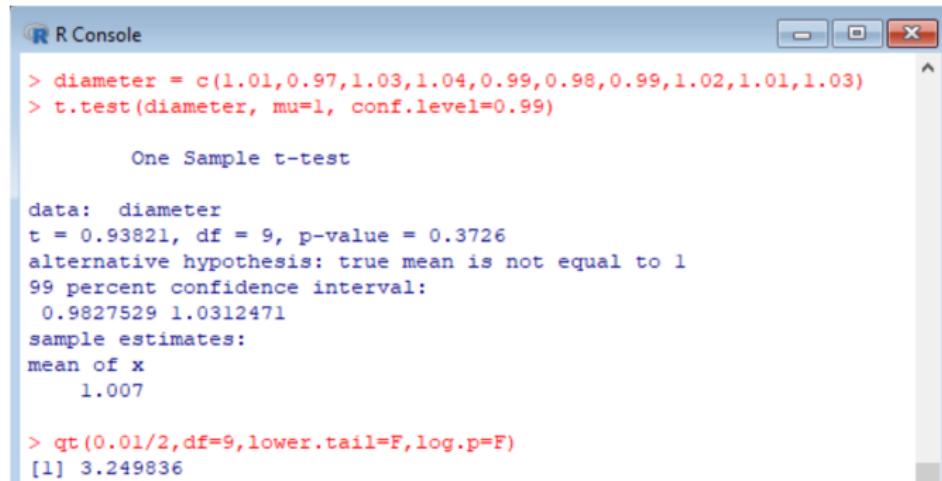
Conclusion: At  $\alpha = 0.10$ , the average weight of 25-year old men is significantly greater than 60 kg.

**Example 2:** A machine produces metal pieces that are cylindrical in shape. A sample of the pieces were taken and their diameters in cm are found to be:

1.01 0.97 1.03 1.04 0.99 0.98 0.99 1.02 1.01 1.03

By conducting a hypothesis test at  $\alpha = 0.01$ , determine whether the mean diameter is equal to 1.00 cm.

Required to test  $H_0 : \mu = 1.00$  vs  $H_1 : \mu \neq 1.00$  at CL = 1 - 0.01 = 0.99



```
R Console

> diameter = c(1.01,0.97,1.03,1.04,0.99,0.98,0.99,1.02,1.01,1.03)
> t.test(diameter, mu=1, conf.level=0.99)

One Sample t-test

data: diameter
t = 0.93821, df = 9, p-value = 0.3726
alternative hypothesis: true mean is not equal to 1
99 percent confidence interval:
0.9827529 1.0312471
sample estimates:
mean of x
1.007

> qt(0.01/2,df=9,lower.tail=F,log.p=F)
[1] 3.249836
```

Method 1: The confidence interval (0.983, 1.031) contains 1

Method 2: The test statistic, t (= 0.938) <  $t_{0.01/2,9}$  (= 3.250)

Method 3: The p-value (= 0.373) > 0.01

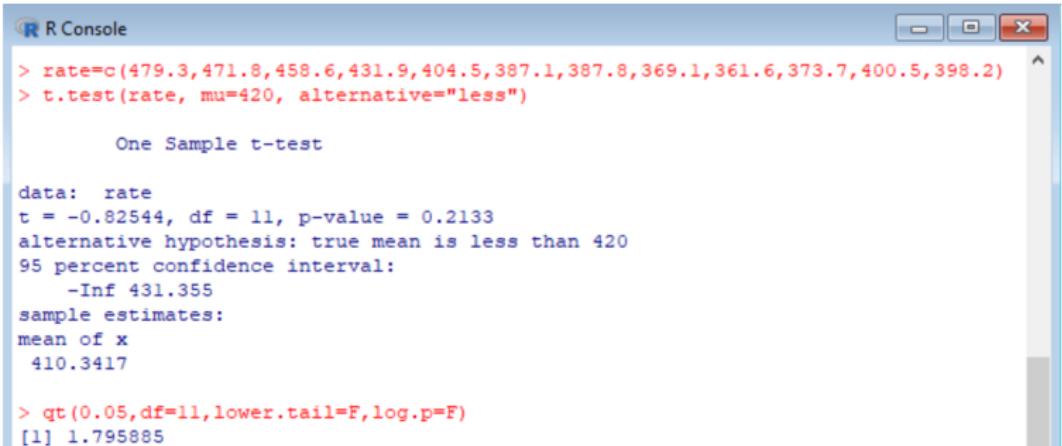
Conclusion: We fail to reject  $H_0$  at  $\alpha = 0.01$ , therefore the mean diameter is significantly equal to 1.00 cm.

**Example 3:** The rate of violent crimes committed in the United States over 12 years are as follows:

479.3	471.8	458.6	431.9	404.5	387.1
387.8	369.1	361.6	373.7	400.5	398.2

Test at  $\alpha = 0.05$  whether the mean rate of violent crimes is less than 420.

Required to test  $H_0: \mu \geq 420$  vs  $H_1: \mu < 420$



```
R Console
> rate=c(479.3,471.8,458.6,431.9,404.5,387.1,387.8,369.1,361.6,373.7,400.5,398.2)
> t.test(rate, mu=420, alternative="less")

One Sample t-test

data: rate
t = -0.82544, df = 11, p-value = 0.2133
alternative hypothesis: true mean is less than 420
95 percent confidence interval:
-Inf 431.355
sample estimates:
mean of x
410.3417

> qt(0.05,df=11,lower.tail=F,log.p=F)
[1] 1.795885
```

Method 1: The confidence interval  $(-\infty, 431.355)$  contains 420

Method 2: The test statistic,  $|t| (= 0.825) < t_{0.05,11} (= 1.796)$

Method 3: The p-value ( $= 0.213$ )  $> 0.05$

Conclusion: We do not reject  $H_0$  at  $\alpha = 0.05$ . There is insufficient evidence to conclude that the rate of violent crimes is less than 420.