

1

$n = 81$, $\bar{x} = \$800000$, $\sigma = \$90000$

Checking conditions:

1. Independence: random sample and $n < 10\%$ of all houses in New York.
2. Sample size/skew: $n \geq 30$.

So, we can assume that the sampling distribution of average house price in New York from samples of size 81 will be nearly normal.

Central Limit Theorem (CLT)

$$\bar{x} \sim N\left(\text{mean} = \mu, SE = \frac{\sigma}{\sqrt{n}}\right) = N(800000, 10000)$$

General Form of Confidence Interval

$$\text{point estimate} \pm \text{margin of error} \\ \bar{x} \pm z^* SE$$

- a

$$CI = 98\% \rightarrow (1 - 0.98) / 2 = 0.01$$

$$> qnorm(0.01) = 2.32$$

approximate 98% CI for μ : $800000 \pm 2.32 SE$

$$(776800, 823200)$$

We are 98% confidence that the mean point of house price in New York is between \$776800 and \$823200.

- b

$$CI = 95\% \rightarrow (1 - 0.95) / 2 = 0.025$$

$$> qnorm(0.025) = 1.96$$

approximate 95% CI for μ : $800000 \pm 1.96 SE$

$$(780400, 819600)$$

We are 95% confidence that the mean point of house price in New York is between \$780400 and \$819600.

- c

$$CI = 90\% \rightarrow (1 - 0.9) / 2 = 0.05$$

$$> qnorm(0.05) = 1.64$$

approximate 90% CI for μ : 800000 \pm 1.64 SE

$$(783600, 816400)$$

We are 90% confidence that the mean point of house price in New York is between \$783600 and \$816400.

- d

$$CI = 50\% \rightarrow (1 - 0.5) / 2 = 0.25$$

$$> qnorm(0.25) = .67$$

approximate 50% CI for μ : 800000 \pm 0.67 SE

$$(793300, 806700)$$

We are 50% confidence that the mean point of house price in New York is between \$793300 and \$806700.

- e

A range of values so defined that there is a specified probability that the value of a parameter lies within it.

- f

Decreasing the level of confidence can narrow your confidence interval.

- g

$$\text{margin of error} = \$5000$$

$$CI = 99\% \rightarrow (1 - 0.99) / 2 = 0.005$$

$$> qnorm(0.005) = 2.57$$

$$2.57 \times \frac{5000}{\sqrt{n}} = 5000 \rightarrow n \geq \boxed{2140}$$

- h

$$\text{margin of error} = \$2500$$

The margin of error is halved. As a result, n must multiply by 4.

$$\begin{aligned} \frac{1}{2}ME &= \frac{1}{2}z^* \frac{s}{\sqrt{n}} \\ &= z^* \frac{s}{\sqrt{4n}} \\ &\rightarrow n \geq \boxed{8560} \end{aligned}$$

2

$n = 70$ high school teens, $\bar{x} = 10$ hours, $\mu = 7$ hours

$H_0 : \boxed{x < 7}$ *We never ever test a sample statistic. We KNOW everything about the sample, so we don't need to test it. Thus they should be μ , not x .
On average, high school teens spend almost seven hours each weekday—on educational activities so must use $=$ not $<$.*

$H_a : \boxed{x > 10}$ *We never ever test a sample statistic. We should use μ instead of x value.*

Let's define null hypothesis (H_0) and alternative hypothesis (H_A):

$H_0 : \mu = 7$ on average, high school teens spend seven hours each weekday.

$H_a : \mu > 7$ on average, high school teens have spent more than 7 hours each weekday.

and p-value like:

$$\begin{aligned} p\text{-value} &= P(\text{observed or more extreme outcome} \mid H_0 \text{ true}) \\ &= P(\bar{x} \geq 10 \mid H_0 : \mu = 7) \\ &= P\left(\bar{z} \geq \frac{10 - 7}{\frac{s}{\sqrt{70}}}\right) \end{aligned}$$

According to the value of the p-value, we can decide about the result of this test reject H_0 or not.

3

$n = 20$, $\bar{x} = 4.6$, $sd = 2.2$, $\alpha = 0.05$, $\mu = 5$ years

Checking conditions:

1. Independence: random sample and $n < 10\%$ of all children from the city which is renowned for its music school. it is a small city!
2. Sample size/skew: $n \geq 30$.

So, we can't assume that the sampling distribution of average year from learn music in this school from samples of size 20 will be nearly normal.

But we can use Student's t-distribution for this problem.

Estimating the Mean

point estimate \pm margin of error

$$\bar{x} \pm t_{df}^* SE$$

$$df = n - 1 = 19$$

$$SE = \frac{s}{\sqrt{n}} = \frac{2.2}{\sqrt{20}} \simeq 0.491$$

$H_0 : \mu = 5$ on average, child from this city takes at least 5 years of piano.

$H_a : \mu < 5$ on average, child from this city takes less than 5 years of piano.

$$t = \frac{\text{observation} - \text{null}}{SE}$$

and p-value like:

$$\begin{aligned} p\text{-value} &= P(\text{observed or more extreme outcome} \mid H_0 \text{ true}) \\ &= P(\bar{x} < 4.6 \mid H_0 : \mu = 5) \\ &= P\left(T < \frac{4.6 - 5}{0.491}\right) \\ &= P(T < -0.814) \end{aligned}$$

• a

$$> pt(-0.814, df = 19) = 0.21 \not< \alpha = 0.05 \rightarrow \text{Can't reject } H_0 \text{ in favor of } H_a.$$

• b

$$CI = 95\% \rightarrow (1 - 0.95) / 2 = 0.025$$

$$> qt(0.025, df = 19) = -2.093$$

approximate 95% CI for μ : $4.6 \pm 2.093 \times SE$

$(3.57, 5.62)$

- c

Yes, because μ is this range we can't reject H_0 hypothesis.

4

$n = 52, \bar{x} = 98.2846, s = 0.6824, \mu = 98.6$

- a

Checking conditions:

1. Independence: random sample and $n < 10\%$ of all healthy adults.
2. Sample size/skew: $n \geq 30$.

So, we can assume that the sampling distribution of average the body temperature from samples of size 52 healthy adults will be nearly normal.

$$SE = \frac{s}{\sqrt{n}} = \frac{0.6824}{\sqrt{52}} = 0.0946$$

Central Limit Theorem (CLT)

$$\bar{x} \sim N(\text{mean} = \mu, SE) = N(98.6, 0.0946)$$

- b

We have a random variable with a Normal Distribution. We should standardize it with Z score:

$$Z = \frac{\text{observation} - \mu}{SE} = \frac{98.2846 - 98.6}{0.0946} = -3.334$$

Setting the hypothesis:

$H_0 : \mu = 98.6$ on average, the normal body temperature in degrees Fahrenheit is 98.6.

$H_a : \mu > 98.6$ on average, the normal body temperature in degrees Fahrenheit is more than 98.6.

and p-value like:

$$\begin{aligned} p\text{-value} &= P(\text{observed or more extreme outcome} \mid H_0 \text{ true}) \\ &= P(\bar{x} \geq 98.2846 \mid H_0 : \mu = 98.6) \\ &= P(Z \geq -3.334) \\ &\simeq 0 < \alpha = 0.05 \end{aligned}$$

Null Hypothesis is rejected in favor of H_a . we can believe that this temperature is an underestimate and the normal body temperature in degrees Fahrenheit is more than 98.6.

- c

General Form of Confidence Interval

$$\begin{aligned} & \text{point estimate} \pm \text{margin of error} \\ & \bar{x} \pm z^* SE \end{aligned}$$

$$CI = 98\% \rightarrow (1 - 0.98) / 2 = 0.01$$

$$> qnorm(0.01) = 2.32$$

approximate 98% CI for μ : $98.2846 \pm 2.32SE$

$$(98.0646, 98.2846)$$

We are 98% confidence that the mean point of the normal body temperature in degrees Fahrenheit is between 98.0646 and 98.2846.

- d

Setting two-sided the hypothesis:

$H_0 : \mu = 98.6$ on average, the normal body temperature in degrees Fahrenheit is 98.6.

$H_a : \mu \neq 98.6$ on average, the normal body temperature in degrees Fahrenheit is not equal 98.6.

and p-value like:

$$\begin{aligned} p - \text{value} &= P(-98.2846 < \bar{x} < 98.2846 \mid H_0 : \mu = 98.6) \\ &= P(Z > -3.334) + P(Z < -3.334) \\ &\simeq 0 < \alpha = 0.05 \end{aligned}$$

Null Hypothesis is rejected in favor of H_a . we can believe that the normal body temperature in degrees Fahrenheit is not 98.6.

5

Suppose that $X \sim \text{Binomial}(100, p)$, so $n = 100$ and according to the hypothesis $p = 0.5$ therefore $q = 1 - p = 0.5$.

- a

Using the normal to approximate this we have that $\mu = np = 50$ and $\sigma^2 = npq = 25$ and so we have:

$$X \sim N(X|\mu, \sigma^2) = N(100, 25)$$

We know that α is the probability of rejecting the null when it is true. Since we have that H_0 is true then $X \sim \text{Binomial}(100, \hat{p} = 0.5)$, and so we can write the following:

$$\begin{aligned} \alpha &= P(|X - 50| > 10) \\ &= P\left(\frac{|X - 50|}{5} > 2\right) \\ &= P\left(\frac{|X - 50|}{\sqrt{25}} > 2\right) \\ &= P\left(\frac{|X - \mu|}{\sigma} > 2\right) \\ &= P(Z > 2 \text{ or } Z < -2) \\ &= P(Z > 2) + P(Z < -2) \\ &= 2 \times \text{pnorm}(-2) = 0.0455 \end{aligned}$$

so $\alpha \geq 0.0455$ for rejecting H_0 in this situation.

- b

The power is the probability of correctly rejecting the null given H_A is true. We write this as:

$$\beta = 1 - P(|X - 50| > 10) = 1 - P(40 < X < 60)$$

```
n = 100
x <- seq(-1, 1, by = .01)
curve(1 - ( pnorm(60, mean=n*x, sd=sqrt(n*x*(1-x))) +
           pnorm(40, mean=n*x, sd=sqrt(n*x*(1-x)), lower.tail = FALSE )))
```

Figure 1: Q5-b code

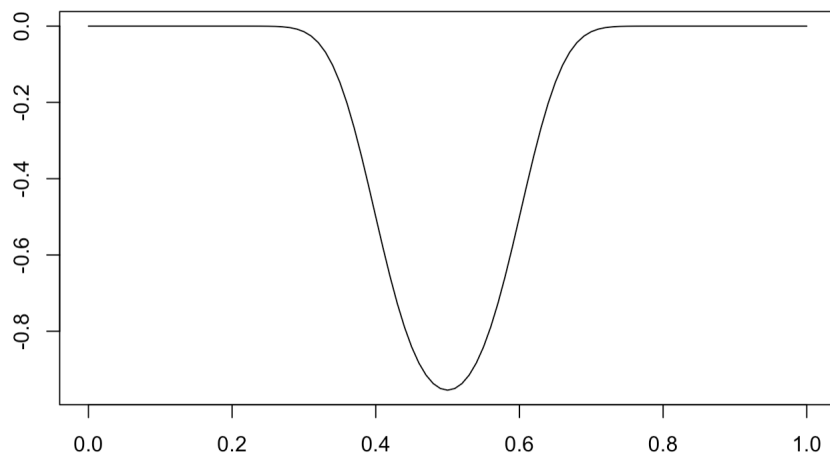


Figure 2: Q5-b curve of the power function of p

6

$n = 50, \bar{y} = 25.9, s = 5.6$

Checking conditions:

1. Independence: random sample and $n < 10\%$ of all population of interest.
2. Sample size/skew: $n \geq 30$.

So, we can assume that the sampling distribution of size 50 will be nearly normal.

Central Limit Theorem (CLT)

$$\bar{y} \sim N \left(\text{mean} = \mu, SE = \frac{\sigma}{\sqrt{n}} \right) = N(28, 0.79)$$

$$H_0 : \mu \geq 28$$

$$H_a : \mu < 28$$

• a

$$Z = \frac{\text{observation} - \mu}{SE} = \frac{25.9 - 28}{0.79} = -2.65$$

and p-value like:

$$\begin{aligned} p\text{-value} &= P(\bar{y} < 25.9 \mid H_0 : \mu = 28) \\ &= P(Z < -2.65) \\ &\simeq 0.004 < \alpha = 0.05 \end{aligned}$$

Null Hypothesis is rejected in favor of H_a .

• b

Let us suppose that the actual mean number is 27 so:

$$\mu_a = 27 \rightarrow \bar{y} \sim N \left(\mu = 27, SE = \frac{s}{\sqrt{n}} = 0.79 \right)$$

$\alpha = 0.05$, one sided test $\rightarrow z_a = ?$

$$P(Z < z_a) = 0.05 \rightarrow z_a = qnorm(0.05) = -1.644$$

$$\begin{aligned} \text{Type III Error} &= \beta = P(\text{fail to reject } H_0 \mid \mu = \mu_a) \\ &= P \left(\frac{\bar{y} - 28}{0.79} < -1.644 \mid \bar{y} \sim N(\mu = 27, SE = 0.79) \right) \\ &= P(\bar{y} < 26.70 \mid \bar{y} \sim N(\mu = 27, SE = 0.79)) \\ &= P \left(Z < \frac{26.7 - 27}{0.79} \right) \\ &= pnorm(-0.379) = 0.352 \end{aligned}$$

$Power = 1 - \beta = 0.647$

- c

No, because a type II error will be made if we fail to reject H_0 , which means that confirms an idea that should have been rejected, such as, for instance, claiming that two observances are the same, despite them being different. A type II error does not reject the null hypothesis, even though the alternative hypothesis is the true state of nature. In other words, a false finding is accepted as true. as you see in part (a), the p-value is too small and we reject H_0 .

7

- a

```
n = 50
alpha = 0.05
x <- seq(22,27,1)

mu = 28
s = 5.6

se = s/sqrt(n)
z_a = qnorm(alpha, 0, 1)

plot(x, pnorm( z_a - ((x-mu)/(se)) ), type="l", xlab = "Means", ylab = "Error")
```

Figure 3: Q7-a code

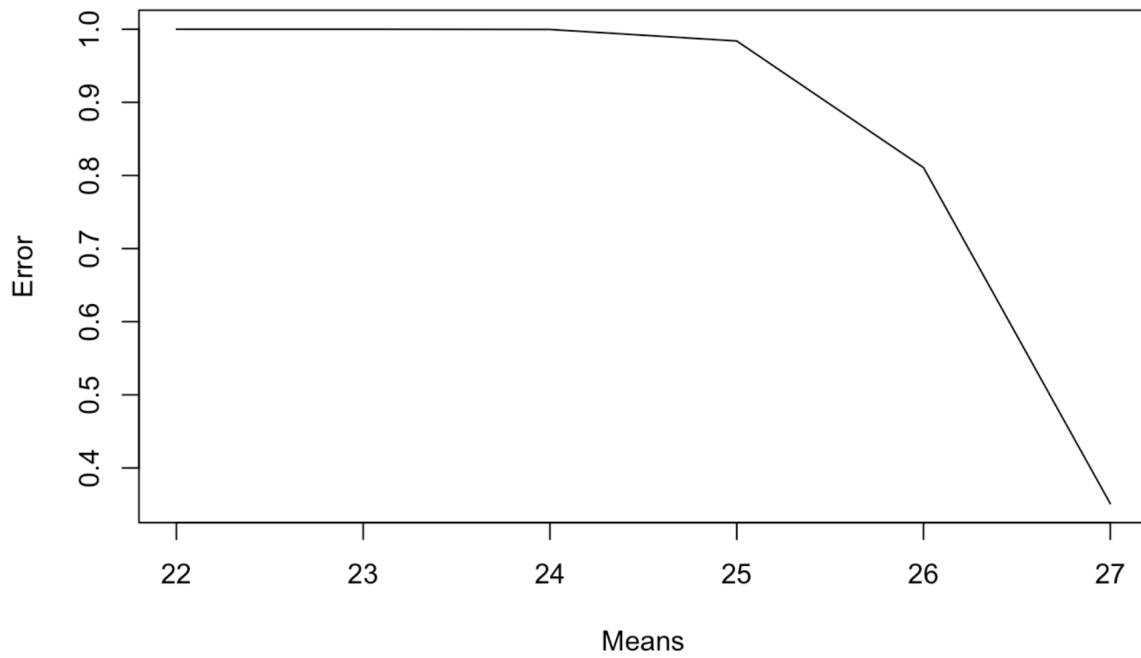


Figure 4: Q7-Error Type II curve

- b

```

n = 50
alpha = 0.05

mu = 28
s = 5.6
x <- seq(22,27,1)

se = s/sqrt(n)
z_a = qnorm(alpha, 0, 1)

plot(x, pnorm( z_a - ((x-mu)/(se)) ), type="l", xlab = "Means", ylab = "Error")

alpha<-0.01
n<-50

z_a_new = qnorm(alpha, 0, 1)
se_new = s/sqrt(n)

lines(x, pnorm( z_a_new - ((x-mu)/(se_new)) ), type="l", xlab = "Means", ylab = "Error", col='red')

```

Figure 5: Q7-b code

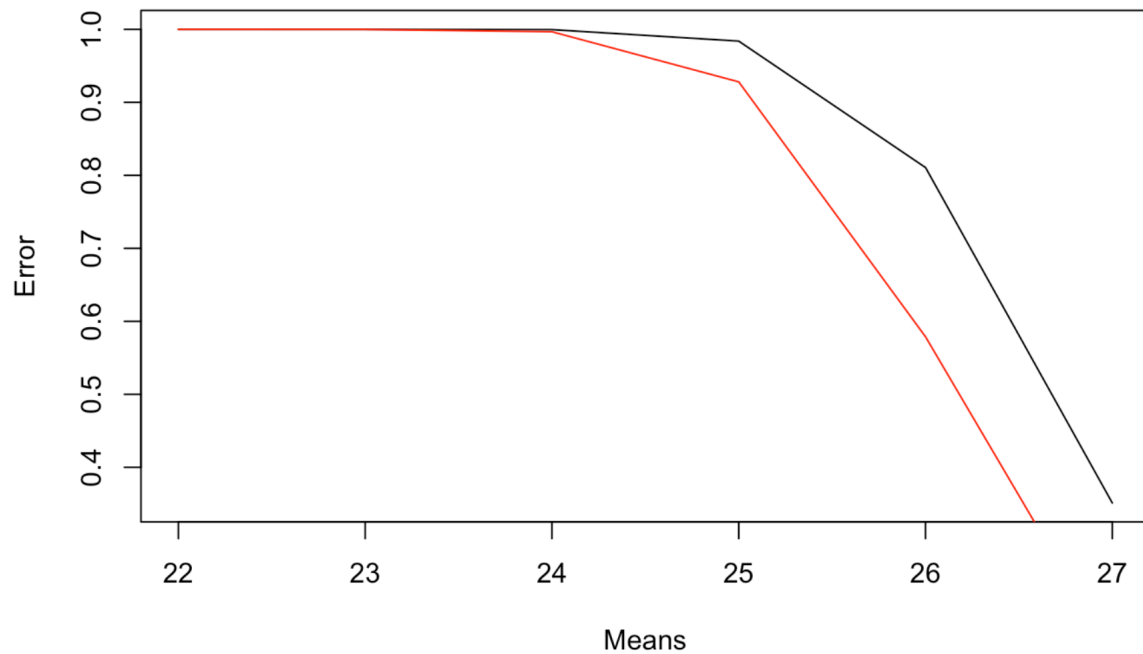


Figure 6: Q7-b Error Type II curve

• c

```

n = 50
alpha = 0.05

mu = 28
s = 5.6
x <- seq(22,27,1)

se = s/sqrt(n)
z_a = qnorm(alpha, 0, 1)

plot(x, pnorm( z_a - ((x-mu)/(se)) ), type="l", xlab = "Means", ylab = "Error")

alpha<-0.05
n<-10

z_a_new = qnorm(alpha, 0, 1)
se_new = s/sqrt(n)

lines(x, pnorm( z_a_new - ((x-mu)/(se_new)) ), type="l", xlab = "Means", ylab = "Error", col='red')

```

Figure 7: Q7-c code

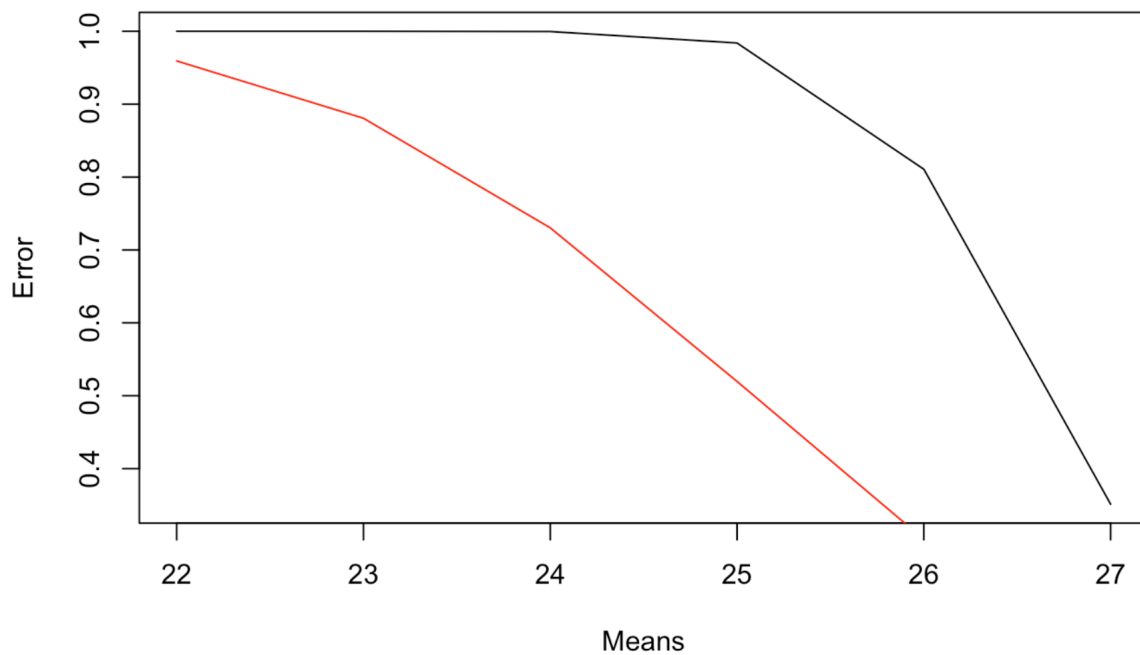


Figure 8: Q7-c Error Type II curve

8 R

Please see this file: "Q8-R.Rmd" and "Q8-R.html"
Code and explanation are provided.

- a

```
k = 0
mu = mean(galton$child)
times = 2000

# seq(1, times, by=1)
for (i in 1:times) {

  n = 60
  #reads the dataset 'galton' and take the 60 rows as sample
  sdf<- sample(1:nrow(galton), n)

  #sample 60 rows
  sub_galton <- galton[sdf,]

  sub_galton.mean = mean(sub_galton$child)

  ci = 0.97
  z = qnorm((1-ci)/2)

  se <- sd(sub_galton$child) / sqrt(n) #SE = s/sqrt(n)

  lower <- sub_galton.mean + z * se
  upper <- sub_galton.mean - z * se

  if (mu>= lower & mu<=upper){
    k = k+1
  }
}
print((k/times)*100)
```

Figure 9: Q8-a code

```
## [1] 97.25
```

Figure 10: percentage of the intervals include the real mean of the society

- b

```
k = 0
mu = mean(galton$child)
times = 1000
# seq(1, times, by=1)
for (i in 1:times) {

  n = 10
  #reads the dataset 'galton' and take the 10 rows as sample
  sdf<- sample(1:nrow(galton), n)

  #sample 10 rows
  sub_galton <- galton[sdf,]

  sub_galton.mean = mean(sub_galton$child)

  ci = 0.9
  z = qnorm((1-ci)/2)

  se <- sd(sub_galton$child) / sqrt(n) #SE = s/sqrt(n)

  lower <- sub_galton.mean + z * se
  upper <- sub_galton.mean - z * se

  if (mu>= lower & mu<=upper){
    k = k+1
  }
}
print((k/times)*100)
```

Figure 11: Q8-b code

```
## [1] 88.3
```

Figure 12: percentage of the intervals include the real mean of the society

Conclusion: the percentage of the intervals includes the actual mean of the society close to the confidence interval.

- c

Use normal distribution because it satisfies the condition of CLT.

```
n = 70
sdf<- sample(1:nrow(galton), n)
sub_galton <- galton[sdf,]

z <- (mean(sub_galton$parent)-60)/(sd(sub_galton$parent)/sqrt(length(sub_galton$parent)))
pvalue = 2*pnorm(-abs(z))

ci = 0.95
z = qnorm((1-ci)/2)

se <- sd(sub_galton$parent) / sqrt(n) #SE = s/sqrt(n)

lower <- sub_galton.mean + z * se
upper <- sub_galton.mean - z * se

muactual = mean(galton$parent)
s = sd(sub_galton$parent)

Zleft <- (lower-muactual)/(s/sqrt(n))
Zright <-(upper-muactual)/(s/sqrt(n))
b <- pnorm(Zright)-pnorm(Zleft)
power = 1-b
power
```

Figure 13: Q8-c code

```
## [1] 0.9949705
```

Figure 14: power

- d

Use t'Student distribution because it does not satisfy the condition of CLT.

```
n = 10
sdf<- sample(1:nrow(galton), n)
sub_galton <- galton[sdf,]

t <- (mean(sub_galton$parent)-60)/(sd(sub_galton$parent)/sqrt(length(sub_galton$parent)))
pvalue = 2*pt(-abs(z),df=n-1)

ci = 0.95
t = qnorm((1-ci)/2)

se <- sd(sub_galton$parent) / sqrt(n) #SE = s/sqrt(n)

lower <- sub_galton.mean + t * se
upper <- sub_galton.mean - t * se

muactual = mean(galton$parent)
s = sd(sub_galton$parent)

Zleft <- (lower-muactual)/(s/sqrt(n))
Zright <- (upper-muactual)/(s/sqrt(n))
b <- pt(Zright, df = n-1)-pt(Zleft, df = n-1)

power = 1-b
power
```

Figure 15: Q8-d code

```
## [1] 0.5041667
```

Figure 16: power

- e

It follows that the sample size decreases as the power decreases, which is a positive correlation(in this interval).

For our test, ten samples do not fit the minimum requirement because we need more than ten samples to achieve statistical power(at least 80%) and effect size for our analysis.