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Exercises ISLR – Ch.5

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Ex.2) Bootstrap Probability (a)

(a) What is the probability that the first bootstrap observation is not the jth observation from the original sample? Justify your answer.

$$P(1^{st} \text{ not } j) = (n-1)/n = (1-1/n)$$

Ex.2) Bootstrap Probability (b-c)

(b) What is the probability that the second bootstrap observation is not the jth observation from the original sample?

Since the bootstrap is run with replacement, the probability is the same as in (a)

$$P(2^{nd} \text{ not } j) = (n-1)/n = (1-1/n)$$

(c) Argue that the probability that the jth observation is not in the bootstrap sample is (1 − 1/n)ⁿ.

P(j not in sample) = P(1st not j) * P(2nd not j) * ... * P(nth not j) =
$$(1-1/n)^n$$

Ex.2) Bootstrap Probability (d-f)

(d) When n = 5, what is the probability that the jth observation is in the bootstrap sample?

P (j in sample) = 1 - P(j not in sample) = 1 -
$$(1-1/5)^5 \sim 0.67232$$

(e) When n = 100, what is the probability that the jth observation is in the bootstrap sample?

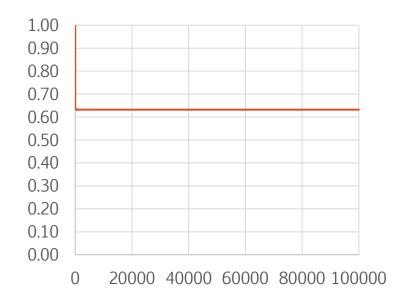
P (j in sample) =
$$1 - (1-1/100)^100 \sim 0.63397$$

(f) When n = 10,000, what is the probability that the jth observation is in the bootstrap sample?

P (j in sample) =
$$1 - (1-1/10000)^10000 \sim 0.63214$$

Ex.2) Bootstrap Probability (g)

(g) Create a plot that displays, for each integer value of n from 1 to 100,000, the probability that the jth observation is in the bootstrap sample. Comment on what you observe.



P (j in sample) =
$$\lim 1 - (1-1/n)^n$$

= $1 - \lim (1 + (-1)/n)^n$
= $1 - e^{-1} = 1 - 1/e = 0.632121$

The probability of being part of the bootstrap sample rapidly converge to 1-1/e (63.21%), which does not converge to 1.

Ex.2) Bootstrap Probability (h)

(h) We will now investigate numerically the probability that a bootstrap sample of size n = 100 contains the jth observation. Here j = 4. We first create an array store with values that will subsequently be overwritten using the function np.empty(). We then repeatedly create bootstrap samples, and each time we record whether or not the fifth observation is contained in the bootstrap sample.

```
rng = np.random.default_rng(10)
store = np.empty(10000)
for 1 in range(10000):
    store[1] = np.sum(rng.choice(100, replace=True) == 4)
    > 0
np.mean(store)
```

Comment on the results obtained.

```
N = 10.000 samples

N (j in sample) = 6357

→P (j in sample) = 0.6357
```

This value is very close to the expected value of large samples 0.6321 (0.5% relative difference).



Applied

Exercise 9 – Boston dataset

Ex.9) Mean of Residence Value (a-b)



(a) Based on this data set, provide an estimate for the population mean of medv. Call this estimate μ̂.

medv

Min. : 5.00 1st Qu.:17.02

Median :21.20 > print(mu)

Mean :22.53

[1] 22.53281

3rd Qu.:25.00 Max. :50.00

(b) Provide an estimate of the standard error of μ̂. Interpret this result.

Hint: We can compute the standard error of the sample mean by dividing the sample standard deviation by the square root of the number of observations. mean(mu) ~ N(mu, sigma2/n) CLT

 $SE = mu_hat/sqrt (s2/n)$ approx.

> print(se_mu) [1] 0.4088611

Ex.9) Mean of Residence Value (c)

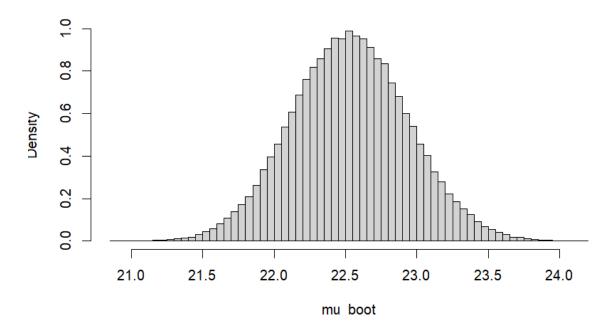


(c) Now estimate the standard error of μ̂ using the bootstrap. How does this compare to your answer from (b)?

B = 100.000 bootstrap samples

n = 506 datapoints

Histogram of mu_boot



Mean

> print(mu_hat_boot)
[1] 22.53182

> print(mu) [1] 22.53281

Standard Error

> print(se_mu_boot)
[1] 0.4070665

> print(se_mu)
[1] 0.4088611

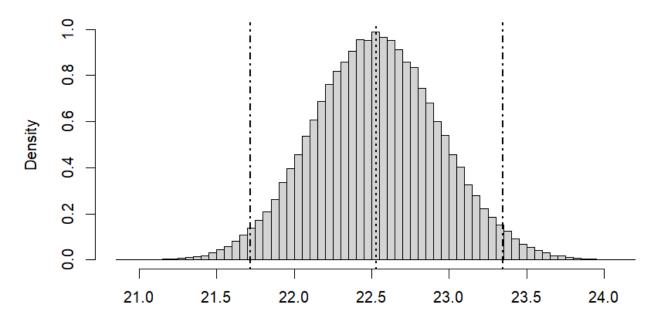
Ex.9) Mean of Residence Value (d)



(d) Based on your bootstrap estimate from (c), provide a 95 % confidence interval for the mean of medv. Compare it to the results obtained by using Boston['medv'].std() and the two standard error rule (3.9).

Hint: You can approximate a 95 % confidence interval using the formula $[\hat{\mu} - 2SE(\hat{\mu}), \hat{\mu} + 2SE(\hat{\mu})]$.

Histogram of mu_boot



Confidence Interval

> print(ci_mu_hat)
[1] 21.71508 23.35053

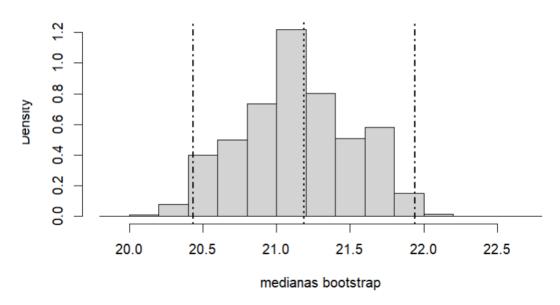
> print(ci_mu_hat_boot) [1] 21.71769 23.34596

Ex.9) Median of Residence Value (e-f)



- (e) Based on this data set, provide an estimate, μ̂_{med}, for the median value of medv in the population.
- (f) We now would like to estimate the standard error of μ̂_{med}. Unfortunately, there is no simple formula for computing the standard error of the median. Instead, estimate the standard error of the median using the bootstrap. Comment on your findings.

Bootstrap da mediana de medv



Median

> print(mu med_hat)
[1] 21.2

> print(mu_med_hat_boot)
[1] 21.18717

Standard Error

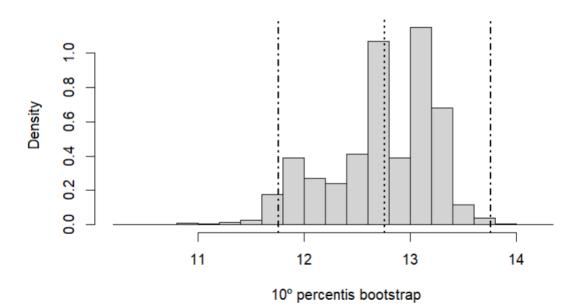
> print(se mu_med_boot)
[1] 0.3774551

Ex.9) Percentile 10% of Value (g-h)



- (g) Based on this data set, provide an estimate for the tenth percentile of medv in Boston census tracts. Call this quantity μ̂_{0.1}. (You can use the np.percentile() function.)
- (h) Use the bootstrap to estimate the standard error of μ̂_{0.1}. Comment on your findings.

Bootstrap do 10º percentil de medv



Percentile 10%

> print(mu_p10_hat)

> print(mu_p10_hat_boot)
[1] 12.7537

Standard Error

> print(se_mu_p10_boot)
[1] 0.5009613

Ex.9) Bootstrap Takeaways - Applied



 Estimated values through bootstrap are very to those obtained using sample statistics and their distribution (ex. sample mean follows asymptotically a normal distribution)

› Bootstrap allows to estimate parameters, which do not have a well-know formula or a known distribution (ex. median and percentile 10% do not seem to follow a normal distribution)