## **STATS 330**

# Handout 11 A closer look at confidence intervals and prediction intervals

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Suppose we get the 95% confidence interval (5.18, 46.74) for our intercept parameter  $\beta_0$ . What does this mean?

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  - ► NO!

The "confidence" we have in a confidence interval is from the way confidence intervals perform under repetition of the experiment.

If the experiment is repeated a large number of times, and a 95% confidence interval for  $\beta_0$  is calculated each time, then about 95% of those intervals will contain  $\beta_0$ . That is, we expect the coverage of those intervals to be about 95%.

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  - ► Does this sound familiar?
  - ► It's precisely what we were doing in the previous handout!

So, we are "confident" in the confidence interval (5.18, 46.74) in the sense that this type of interval contains  $\beta_0$  19 times out of 20 under repetition of the experiment, on average.

That is, the confidence we have in a confidence interval is due to the properties of the method that was used to produce the interval.

The interval (5.18, 46.74) may be a "good" interval (i.e., contain  $\beta_0$ ), or it could be a "bad" interval (i.e., not contain  $\beta_0$ ). We might never know which.

# Intervals for $\mu$ and new values of Y

In the remainder of this handout we will look at confidence intervals for  $\mu_i$  and prediction intervals for  $Y_i$ . We will continue working with the simple linear model from the previous handout:

$$\mu_i = \beta_0 + \beta_1 x_i,$$
  
 $Y_i \sim \text{Normal}(\mu_i, \sigma^2),$ 

where we have ten observations for which

- $x_1 = 2, x_2 = 4, \dots, x_{10} = 20,$
- ▶  $\beta_0 = 20$ ,
- $\triangleright$   $\beta_1 = 3$ , and
- $\sigma = 10.$

# Intervals for $\mu$ and new values of Y

This means the expected value for each observation is

$$\mu_1 = 20 + 3 \times 2 = 26,$$
  
 $\mu_2 = 20 + 3 \times 4 = 32,$   
 $\vdots$   
 $\mu_{10} = 20 + 3 \times 20 = 80.$ 

So the first observation comes from a normal distribution with a mean of 26 and a standard deviation of 10, the second observation comes from a normal distribution with a mean of 32 and a standard deviation of 10, and so on.

We'll further our simulation study to investigate the performance of confidence intervals for  $\mu$  and prediction intervals for new values of Y when x=7. For x=7,  $\mu=41$ .

#### Confidence intervals for $\mu$

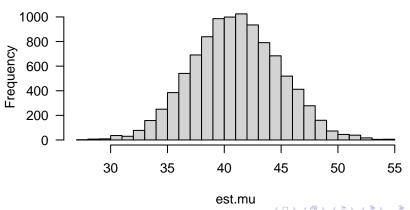
The simulation code requires only minor modification from the previous handout. We now need to use predict(...,interval="conf") to get the confidence intervals.

```
mu = b0 + b1 * 7
## Creating vector in which to store estimates.
est.mu <- numeric(n.sims)
## Creating matrix in which to store CIs.
ci.mu <- matrix(0, nrow = n.sims, ncol = 2)</pre>
## The for loop.
for (i in 1:n.sims) {
  ## Simulating the responses.
  y <- rnorm(10, means, sigma)
  ## Fitting the model.
  fit <-lm(y ~x)
  ## Extracting muhat and CI.
  pred <- predict(fit, newdata=data.frame(x=7), interval="conf")</pre>
  est.mu[i] <- pred[1]</pre>
  ci.mu[i, ] <- pred[2:3]</pre>
```

#### Estimator performance: Unbiasedness

Here is a histogram of the estimates of  $\mu=41$ . Does our estimator appear to be more or less unbiased?

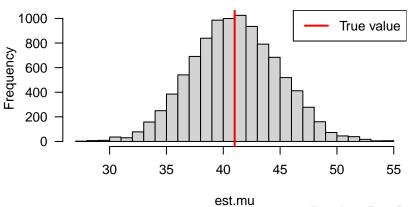
hist(est.mu)



#### Estimator performance: Unbiasedness

Here is a histogram of the estimates of  $\mu=41$ . Does our estimator appear to be more or less unbiased? Yes!

```
hist(est.mu); abline(v = mu, col = "blue")
```



#### Confidence interval coverage

We can compute if we captured the true value:

```
mu.ci.captured <- (mu >= ci.mu[, 1]) & (mu <= ci.mu[, 2])
table(mu.ci.captured)

## mu.ci.captured
## FALSE TRUE
## 491 9509

mean(mu.ci.captured)

## [1] 0.9509</pre>
```

Out of the 10 000 confidence intervals computed for  $\mu$ , 9509 of them contained the true value  $\mu=41$ .

So our method for calculating 95% confidence intervals works for  $\mu$ , because approximately 95% of intervals calculated using this method contain the true value.

## Prediction intervals for new values of Y

Now, let's examine the performance of prediction intervals.

For 95% prediction intervals, we need the intervals to contain the new value of Y 95% of the time (on average) when both the experiment and the new value of Y are replicated a large number of times.

Prediction intervals for new values of Y

Our simulation code now needs to be modified to use predict(...,interval="pred"), and to generate a new value of Y each iteration.

```
mu = b0 + b1 * 7
## Creating vector in which to store new Y.
new.v <- numeric(n.sims)</pre>
## Creating matrix in which to store PIs.
pi.y <- matrix(0, nrow = n.sims, ncol = 2)</pre>
## The for loop.
for (i in 1:n.sims) {
  ## Simulating the responses.
  y <- rnorm(10, means, sigma)
  new.y[i] <- rnorm(1, mu, sigma)</pre>
  ## Fitting the model.
  fit \leftarrow lm(v \sim x)
  ## Extracting muhat and CI.
  pred <- predict(fit, newdata=data.frame(x=7), interval="pred")</pre>
  pi.y[i,] <- pred[2:3]
```

#### Prediction interval coverage

We can compute if we captured the value of Y:

```
y.pi.captured <- (new.y >= pi.y[, 1]) & (new.y <= pi.y[, 2])
table(y.pi.captured)

## y.pi.captured
## FALSE TRUE
## 495 9505

mean(y.pi.captured)

## [1] 0.9505</pre>
```

Out of the  $10\,000$  prediction intervals, 9505 of them contained the new value of Y.

So our method for calculating 95% prediction intervals works because approximately 95% of the intervals calculated using this method contain the new value.