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STATOLOGY

MENU

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How to Create a Prediction Interval for Linear Regression in R

This tutorial explains how to create a **prediction interval** for linear regression in R.

What is a Prediction Interval?

A **linear regression model** can be useful for two things:

(1) Quantifying the relationship between one or more predictor variables and a response variable.

(2) Using the model to predict future values.

In regards to **(2)**, when we use a regression model to predict future values, we are often interested in predicting both an *exact value* as well as an *interval* that contains a range of likely values. This interval is known as a **prediction interval**.

For example, suppose we fit a simple linear regression model using *hours studied* as a predictor variable and *exam score* as the response variable. Using this model, we might predict that a student who studies for 6 hours will receive an exam score of **91**.

However, because there is uncertainty around this prediction, we might create a prediction interval that says there is a 95% chance that a student who studies for 6 hours will receive an exam score between **85** and **97**. This range of values is known as a 95% prediction interval and it's often more useful to us than just knowing the exact predicted value.

How to Create a Prediction Interval in R

To illustrate how to create a prediction interval in R, we will use the built-in *mtcars* dataset, which contains information about characteristics of several different cars:

```
#view first six rows of mtcars
head(mtcars)

#                    mpg cyl disp  hp drat    wt  qsec vs am gear carb
#Mazda RX4          21.0   6  160 110 3.90 2.620 16.46  0  1    4    4
#Mazda RX4 Wag      21.0   6  160 110 3.90 2.875 17.02  0  1    4    4
#Datsun 710         22.8   4  108  93 3.85 2.320 18.61  1  1    4    1
#Hornet 4 Drive     21.4   6  258 110 3.08 3.215 19.44  1  0    3    1
#Hornet Sportabout 18.7   8  360 175 3.15 3.440 17.02  0  0    3    2
#Valiant            18.1   6  225 105 2.76 3.460 20.22  1  0    3    1
```

First, we'll fit a simple linear regression model using *disp* as the predictor variable and *mpg* as the response variable.

```
#fit simple linear regression model
model <- lm(mpg ~ disp, data = mtcars)

#view summary of fitted model
summary(model)

#Call:
#lm(formula = mpg ~ disp, data = mtcars)
#
#Residuals:
#    Min      1Q  Median      3Q     Max
#-4.8922 -2.2022 -0.9631  1.6272  7.2305
#
#Coefficients:
#             Estimate Std. Error t value Pr(>|t|)
#(Intercept) 29.599855   1.229720  24.070  < 2e-16 ***
#disp        -0.041215   0.004712  -8.747 9.38e-10 ***
#---
#Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
#Residual standard error: 3.251 on 30 degrees of freedom
#Multiple R-squared:  0.7183,   Adjusted R-squared:  0.709
#F-statistic: 76.51 on 1 and 30 DF,  p-value: 9.38e-10
```

Then, we'll use the fitted regression model to predict the value of *mpg* based on three new values for *disp*.

```
#create data frame with three new values for disp
new_disp <- data.frame(disp= c(150, 200, 250))

#use the fitted model to predict the value for mpg based on the three new values
#for disp
predict(model, newdata = new_disp)

#       1        2        3
#23.41759 21.35683 19.29607
```

The way to interpret these values is as follows:

- For a new car with a *disp* of 150, we predict that it will have a *mpg* of **23.41759**.
- For a new car with a *disp* of 200, we predict that it will have a *mpg* of **21.35683** .
- For a new car with a *disp* of 250, we predict that it will have a *mpg* of **19.29607**.

Next, we'll use the fitted regression model to make prediction intervals around these predicted values:

```
#create prediction intervals around the predicted values
predict(model, newdata = new_disp, interval = "predict")

#       fit      lwr      upr
#1 23.41759 16.62968 30.20549
#2 21.35683 14.60704 28.10662
#3 19.29607 12.55021 26.04194
```

The way to interpret these values is as follows:

- The 95% prediction interval of the *mpg* for a car with a *disp* of 150 is between **16.62968** and **30.20549**.
- The 95% prediction interval of the *mpg* for a car with a *disp* of 200 is between **14.60704** and **28.10662**.
- The 95% prediction interval of the *mpg* for a car with a *disp* of 250 is between **12.55021** and **26.04194**.

By default, R uses a 95% prediction interval. However, we can change this to whatever we'd like using the **level** command. For example, the following code illustrates how to create 99% prediction intervals:

```
#create 99% prediction intervals around the predicted values
predict(model, newdata = new_disp, interval = "predict", level = 0.99)

#       fit      lwr      upr
#1 23.41759 14.27742 32.55775
#2 21.35683 12.26799 30.44567
#3 19.29607 10.21252 28.37963
```

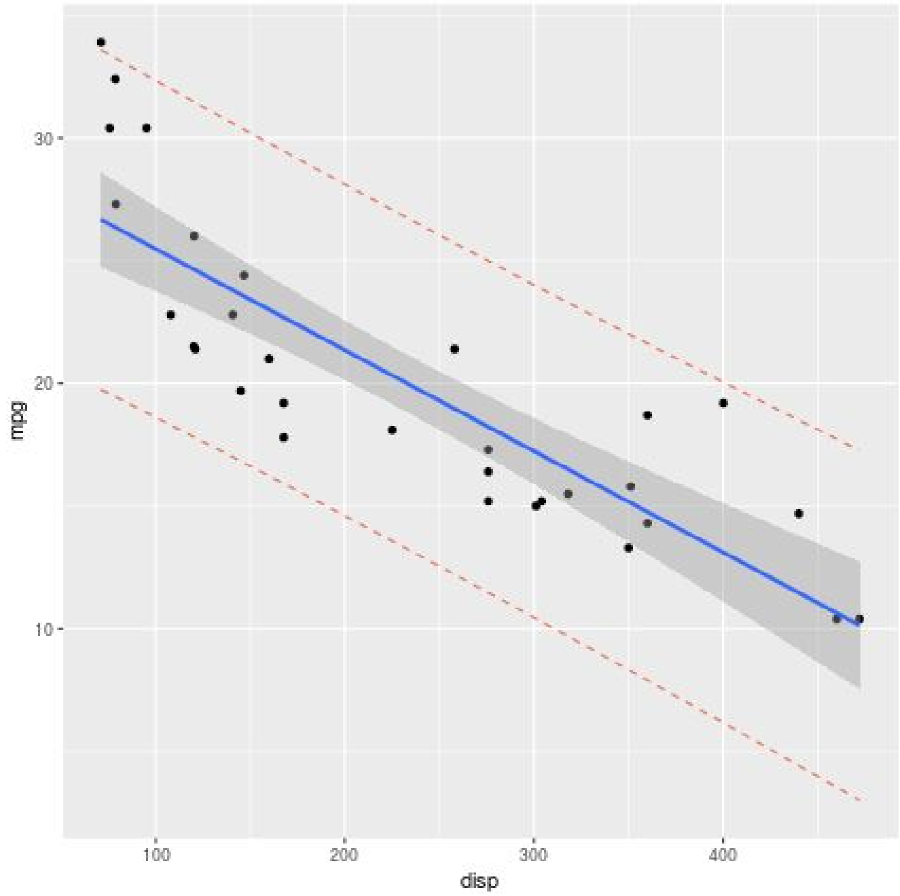
Note that the 99% prediction intervals are wider than the 95% prediction intervals. This makes sense because the wider the interval, the higher the likelihood that it will contain the predicted value.

How to Visualize a Prediction Interval in R

The following code illustrates how to create a chart with the following features:

- A scatterplot of the data points for *disp* and *mpg*
- A blue line for the fitted regression line
- Gray confidence bands
- Red prediction bands

```
#define dataset
data <- mtcars[ , c("mpg", "disp")]

#create simple linear regression model
model <- lm(mpg ~ disp, data = mtcars)

#use model to create prediction intervals
predictions <- predict(model, interval = "predict")

#create dataset that contains original data along with prediction intervals
all_data <- cbind(data, predictions)

#load ggplot2 library
library(ggplot2)

#create plot
ggplot(all_data, aes(x = disp, y = mpg)) + #define x and y axis variables
  geom_point() + #add scatterplot points
  stat_smooth(method = lm) + #confidence bands
  geom_line(aes(y = lwr), col = "coral2", linetype = "dashed") + #lwr pred interval
  geom_line(aes(y = upr), col = "coral2", linetype = "dashed") #upr pred interval
```



When to Use a Confidence Interval vs. a Prediction Interval

A **prediction interval** captures the uncertainty around a single value. A **confidence interval** captures the uncertainty around the mean predicted values. Thus, a prediction interval will always be wider than a confidence interval for the same value.

You should use a prediction intervalwhen you are interested in specific individual predictions because a confidence interval will produce too narrow of a range of values, resulting in a greater chance that the interval will not contain the true value.

For an in-depth explanation of when to use prediction intervals vs. when to use confidence intervals, I recommend reading this post from *Statistics By Jim*.

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