STAT135: Confidence intervals and more cars

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Chapter 17 in a nutshell

- The distribution of sample means is less variable than the distribution of the underlying population
- The distribution of sample means is more normal than the distribution of the underlying population

Confidence intervals for a proportion

SE($\hat{p}$) =

Constructing a confidence interval:

Interpreting a confidence interval:

Example 1: Each of the 110 students in a statistics class selects a different random sample of 35 Quiz scores from a population of 5000 scores they are given. Using their data, each student constructs a 90% confidence interval for μ, the average Quiz score of the 5000 students. Which of the following conclusions is correct?

a) About 10% of the sample means will not be included in the confidence intervals.
b) About 90% of the confidence intervals will contain μ.
c) It is probable that 90% of the confidence intervals will be identical.
d) About 10% of the raw scores in the samples will not be found in these confidence intervals.

Example 2: Suppose two researchers want to estimate the proportion of American college students who favor abolishing the penny. They both want to have about the same margin of error to estimate this proportion. However, Researcher 1 wants to estimate with 99% confidence and Researcher 2 wants to estimate with 95% confidence. Which researcher would need more students for her study in order to obtain the desired margin of error?

a) Researcher 1.
b) Researcher 2.
c) Both researchers would need the same number of subjects.
d) It is impossible to obtain the same margin of error with the two different confidence levels.

More cars

```
ds <- read_csv("http://nhorton.people.amherst.edu/workshop/carscollated2017.csv")
ds <- mutate(ds, yearchar = as.character(year))
```

```
tally(~ year, data=ds)
```

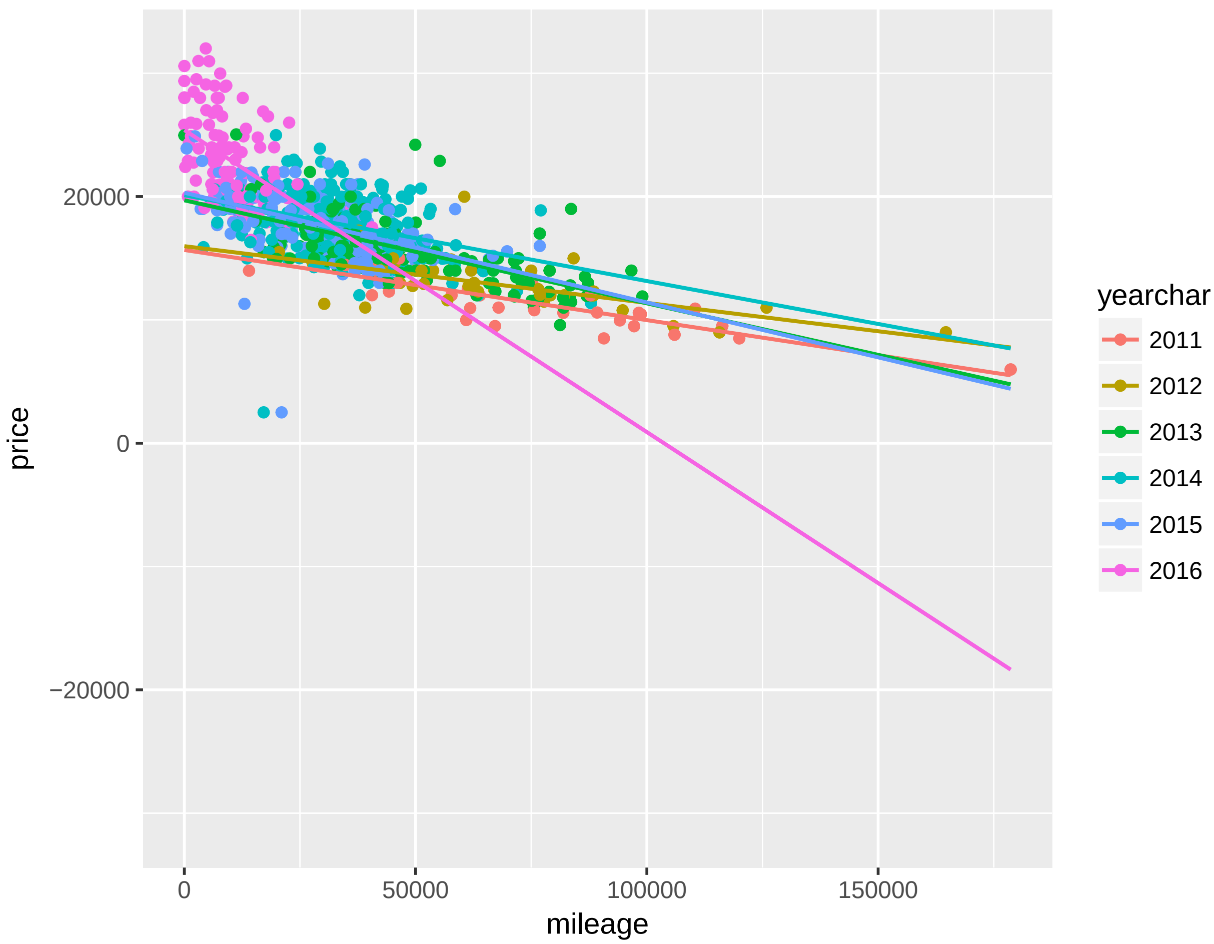
```
## year
## 2007 2010 2011 2012 2013 2014 2015 2016 2017
##    2    5   37   45  176  237  201  126    2
```

```
tally(~ location, data=ds)
```

```
## location
##           40202         Atlanta      Bangor, ME    Baton Rouge          Boston
##              40              40              40             40              40
##         Buffalo         Chicago       Cleveland         Dallas     Los Angeles
##              40              41              26             41              40
##     Minneapolis     New Orleans             NYC        Phoenix        Portland
##              59              33              40             40              40
##        Richmond Salt Lake City       San Diego  San Francisco         Seattle
##              40              33              40             39              39
##           Tampa
##              40
```

```
ds <- filter(ds, year > 2010, year < 2017)  # drop new cars and really old cars
```

```
gf_point(price ~ mileage, color = ~ yearchar, data = ds) %>%
  gf_lm()
```



a) interpret what insights you can make from the scatterplot

SOLUTION:

```r
options(scipen=5, show.signif.stars=FALSE, digits=4)
mod <- lm(price ~ location + mileage + yearchar + mileage*yearchar, data=ds)
msummary(mod)
```

```
##                          Estimate  Std. Error t value Pr(>|t|)
## (Intercept)            17061.06938   868.85620   19.64  < 2e-16
## locationAtlanta        -1638.41488   462.55755   -3.54  0.00042
## locationBangor, ME     -1689.69743   463.90469   -3.64  0.00029
## locationBaton Rouge     -745.21252   474.32078   -1.57  0.11656
## locationBoston          -563.64808   460.06933   -1.23  0.22089
## locationBuffalo         -581.60744   484.23517   -1.20  0.23008
## locationChicago        -2237.49897   456.49750   -4.90  1.2e-06
## locationCleveland      -1491.58656   520.87678   -2.86  0.00430
## locationDallas         -1078.11128   462.04754   -2.33  0.01988
## locationLos Angeles     2319.67933   460.04752    5.04  5.7e-07
## locationMinneapolis     -622.89582   423.72233   -1.47  0.14194
## locationNew Orleans     -573.29737   498.84387   -1.15  0.25080
## locationNYC             -594.56186   458.89342   -1.30  0.19548
## locationPhoenix         -325.96320   463.81240   -0.70  0.48239
## locationPortland          65.24543   461.66827    0.14  0.88765
## locationRichmond        -744.32172   461.18604   -1.61  0.10694
## locationSalt Lake City -1954.04693   494.67997   -3.95  8.5e-05
## locationSan Diego        257.69790   461.97731    0.56  0.57713
## locationSan Francisco   1578.28190   461.39289    3.42  0.00066
## locationSeattle         2136.54194   463.06079    4.61  4.6e-06
## locationTampa          -2152.29736   462.16712   -4.66  3.8e-06
## mileage                   -0.06065     0.00950   -6.38  3.0e-10
## yearchar2012            -251.31079  1135.10846   -0.22  0.82484
## yearchar2013            3237.23166   894.68539    3.62  0.00032
## yearchar2014            3140.19070   888.34344    3.53  0.00043
## yearchar2015            3252.51391   885.30630    3.67  0.00026
## yearchar2016            8208.61054   874.47684    9.39  < 2e-16
## mileage:yearchar2012       0.01709     0.01436    1.19  0.23445
## mileage:yearchar2013      -0.01797     0.01215   -1.48  0.13939
## mileage:yearchar2014      -0.00343     0.01396   -0.25  0.80603
## mileage:yearchar2015      -0.00989     0.01393   -0.71  0.47777
## mileage:yearchar2016      -0.18186     0.02754   -6.60  7.3e-11
##
## Residual standard error: 2040 on 790 degrees of freedom
## Multiple R-squared:  0.736,  Adjusted R-squared:  0.726
## F-statistic: 71.2 on 31 and 790 DF,  p-value: <2e-16
```

b) interpret the regression results

SOLUTION:

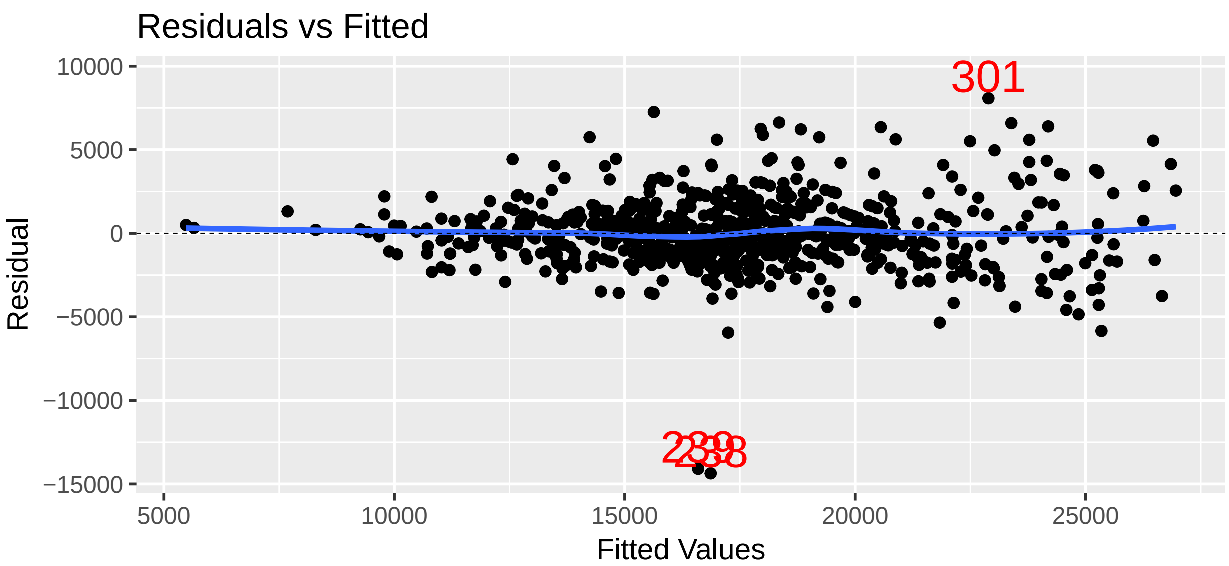
c) Predicted values

```
modfun <- makeFun(mod)
modfun(location = "Chicago", mileage = 0, yearchar = "2016")
```

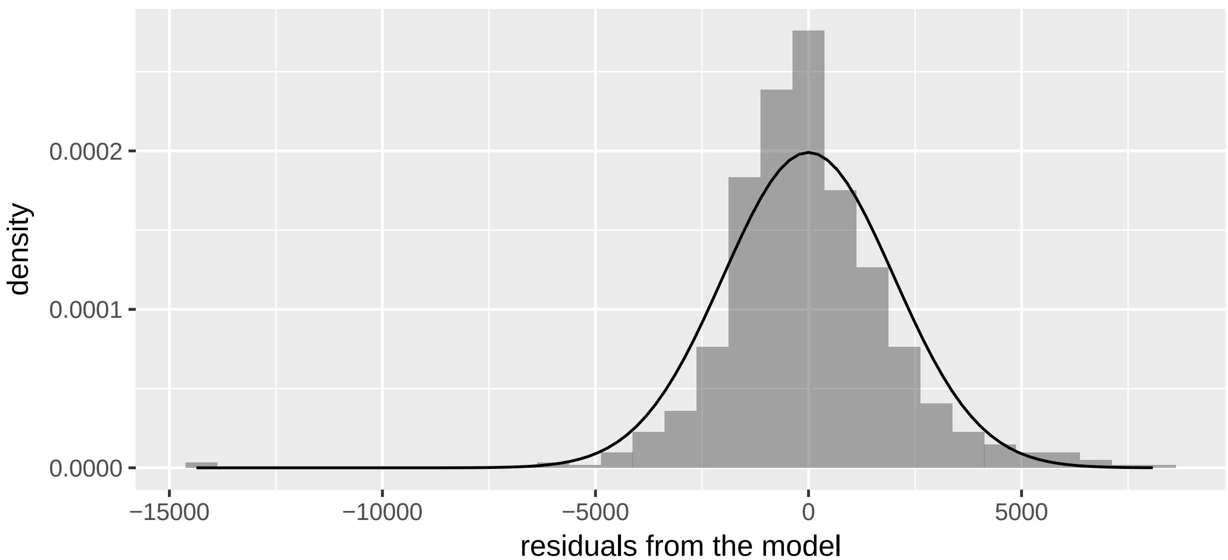
```
##     1
## 23032
```

```
mplot(mod, which=1)    # Figure 1
```

```
## `geom_smooth()` using method = 'loess'
```

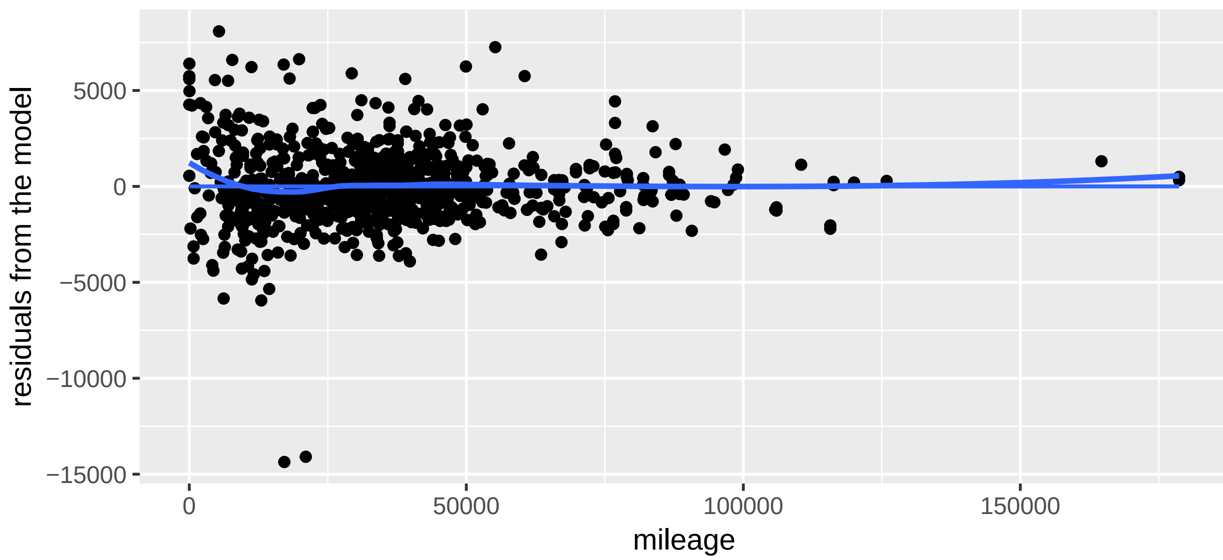



```
gf_dhistogram(~ resid(mod), fit="normal", binwidth = 750,
              main="Figure 2", xlab="residuals from the model") %>%
  gf_fitdistr()
```



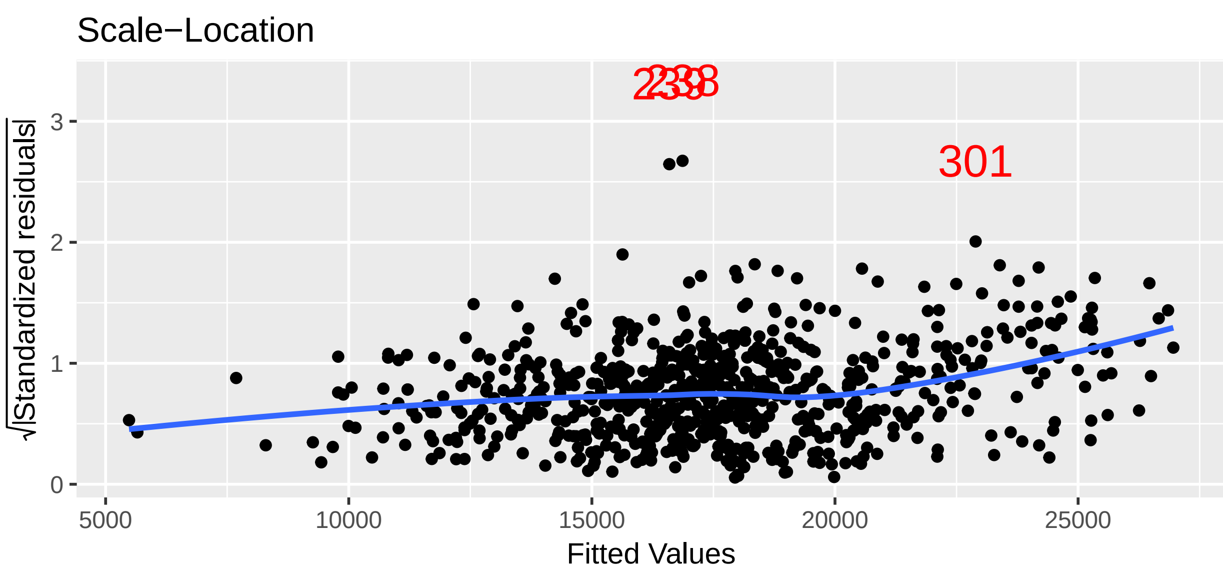

```
gf_point(resid(mod) ~ mileage, ylab="residuals from the model",
  main="Figure 3", data=ds) %>%
  gf_lm() %>%
  gf_smooth(se = FALSE)
```

```
## `geom_smooth()` using method = 'loess'
```




```r
mplot(mod, which=3)   # Figure 4
```

```
## `geom_smooth()` using method = 'loess'
```



d) interpret the regression diagnostics

(be sure to specify which assumption is being verified using which figure)

SOLUTION:

```r
ds <- mutate(ds, fitted = predict(mod), resid = resid(mod))
filter(ds, resid(mod)< -10000)
```

```
## # A tibble: 2 x 9
##   car          model price  year mileage location yearchar fitted   resid
##   <chr>        <chr> <dbl> <int>   <dbl> <chr>    <chr>     <dbl>   <dbl>
## 1 Toyota Prius four   2500  2014   17152 Chicago  2014     16865. -14365.
## 2 Toyota Prius four   2500  2015   21027 Chicago  2015     16593. -14093.
```

e) what might we conclude about the large residuals?

SOLUTION: