STAT 300: Used car data project

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Introduction and directions

The purpose of this project is to give you experience sourcing, reading, and using real data to answer research questions using simple linear regression. You should refer back to your previous homework assignments and R notebooks used in lecture for the relevant R codes. You are also encouraged to get help from your instructor and TA during office hours.

Collaboration rules:

You may consult with up to two classmates for help with this project, but *use your own data*. If you collaborate with someone and use the same make/model/zip code, you will both receive 50% of earned points if there are two of you and 33% if there are three of you. Please identify who you collaborate with here.

List collaborators

Project premise

Let's assume you are interested in purchasing a used car and you want to use data to help you research what you could consider a 'fair price'. Obviously, the price of a car depends on many things, including the car's age, mileage, condition, make, and model. At this time, we only have the tools to consider one predictor variable at a time so you will be using the variable 'age' to predict the price of used cars.

For this project you will source a new, never seen before dataset by scraping observations from autotrader.com for a make and model of your choosing. You'll want to ultimately have a clean dataset of at least 50 cars. Because you will likely need to eliminate some observations that are clearly errors, make sure the zip code you choose has at least 60 cars downloaded to the dataset.

To get your data, go to http://myslu.stlawu.edu/~clee/dataset/autotrader/, choose the make and model, then input a zip code. If you are choosing a more rare type of car it might be difficult to get at least 60 observations for certain zip codes. Try a zip code close to a big city like Boston (02124), Los Angeles (90010), or Chicago (60176). Save the data and choose a name for the dataset with a .csv extension. After you save the data, you should check the spreadsheet for any cases that should be deleted. For example, sometimes new cars will be included (mileage of 0), or odd entries with a price of 0 will appear. Make sure that after cleaning the data you have at least 50 observations. Note that if you are more comfortable cleaning the data in R, you are welcome to filter your dataset as part of your code.

You should have a dataset with variables 'year', 'price' (in $1,000's), and 'mileage' (in 1,000's) ready to load into R. Run the front-matter below to load your data into the workspace and load the packages you are most likely to need for this project.

```
#add a variable that is named 'age', which is 2021 - year
used_cars$age <- 2021 - used_cars$year

# filter observations
UsedCars <- used_cars %>%
  filter(mileage > 0) %>%
  filter(price >0)

glimpse(UsedCars)
```

```
## Rows: 278
## Columns: 4
## $ year    <int> 2010, 2019, 2018, 2018, 2015, 2016, 2019, 2018, 2017,
2019, 20…
## $ price   <dbl> 16.998, 58.798, 46.604, 45.850, 26.961, 26.888, 59.900,
35.980…
## $ mileage <dbl> 82.078, 33.714, 57.669, 20.807, 87.231, 96.695, 22.843,
94.844…
## $ age     <dbl> 11, 2, 3, 3, 6, 5, 2, 3, 4, 2, 2, 4, 3, 3, 3, 8, 6, 2, 4,
5, 8…
```

```
# get down to 50
set.seed(4)
UsedCars <- UsedCars[-sample(1:60,10,replace=F),]

glimpse(UsedCars)
```

```
## Rows: 268
## Columns: 4
## $ year    <int> 2010, 2019, 2018, 2015, 2016, 2018, 2017, 2019, 2017,
2018, 20…
## $ price   <dbl> 16.998, 58.798, 45.850, 26.961, 26.888, 35.980, 48.995,
57.675…
## $ mileage <dbl> 82.078, 33.714, 20.807, 87.231, 96.695, 94.844, 67.879,
42.919…
## $ age     <dbl> 11, 2, 3, 6, 5, 3, 4, 2, 4, 3, 3, 3, 8, 6, 2, 4, 5, 8, 4,
7, 7…
```

```
UsedCars
```

```
##     year  price mileage age
## 1   2010 16.998  82.078  11
## 2   2019 58.798  33.714   2
## 4   2018 45.850  20.807   3
## 5   2015 26.961  87.231   6
## 6   2016 26.888  96.695   5
## 8   2018 35.980  94.844   3
## 9   2017 48.995  67.879   4
```

```
## 10  2019 57.675  42.919   2
## 12  2017 41.990  31.649   4
## 13  2018 49.858  29.116   3
## 14  2018 46.998  35.545   3
## 15  2018 45.798  43.319   3
## 16  2013 20.990  71.715   8
## 17  2015 29.977  66.065   6
## 18  2019 57.499  31.975   2
## 19  2017 36.648  45.176   4
## 20  2016 29.495  75.869   5
## 21  2013 20.990  70.391   8
## 22  2017 36.999  52.146   4
## 23  2014 24.990  85.877   7
## 24  2014 28.900  69.714   7
## 25  2013 18.990  91.230   8
## 26  2015 25.999  91.697   6
## 27  2017 31.995  94.619   4
## 28  2018 57.400  20.331   3
## 29  2013  7.500 126.527   8
## 31  2018 45.998  40.151   3
## 32  2019 51.440  52.864   2
## 33  2018 47.277  33.455   3
## 34  2015 26.900  93.447   6
## 35  2016 30.987  56.001   5
## 36  2019 59.998  31.687   2
## 37  2018 47.419  30.881   3
## 38  2018 41.839  30.195   3
## 39  2017 33.590  63.064   4
## 40  2017 36.990  43.844   4
## 41  2017 41.990  35.514   4
## 42  2018 52.647  13.082   3
## 43  2019 72.500  35.854   2
## 45  2018 50.025  31.262   3
## 46  2018 46.998  47.475   3
## 47  2019 64.898  44.246   2
## 48  2018 41.799  57.116   3
## 49  2013  7.995 125.955   8
## 50  2019 51.390  46.621   2
## 52  2018 39.990  37.906   3
## 55  2017 32.950  76.542   4
## 57  2018 45.990  25.989   3
## 59  2014 22.744  83.997   7
## 60  2018 42.990  32.541   3
## 61  2017 32.030  59.455   4
## 62  2018 55.277  20.100   3
## 63  2018 43.990  42.290   3
## 64  2018 47.699  18.333   3
## 65  2017 41.805  51.240   4
## 66  2014 23.898  82.472   7
## 67  2018 42.995  32.525   3
```

```
## 68  2018 43.944  21.636   3
## 69  2018 48.995  31.600   3
## 70  2018 50.685  31.884   3
## 71  2017 32.295  69.891   4
## 72  2018 51.800  16.908   3
## 73  2017 35.798  57.092   4
## 74  2017 35.990  52.564   4
## 75  2016 29.995  87.302   5
## 76  2014 24.999 113.108   7
## 77  2018 45.650  34.420   3
## 78  2009 13.995  75.033  12
## 79  2018 43.990  43.903   3
## 80  2018 41.397  54.231   3
## 81  2018 50.999  17.771   3
## 82  2018 45.500  39.142   3
## 83  2018 54.488  28.201   3
## 84  2019 59.990  28.488   2
## 85  2018 50.988  19.314   3
## 86  2015 19.995 119.000   6
## 87  2018 50.998  13.608   3
## 88  2018 45.162  28.594   3
## 89  2016 33.499  84.040   5
## 90  2018 48.995  37.029   3
## 91  2013 15.995 119.138   8
## 92  2018 46.998  47.019   3
## 93  2017 36.495  51.217   4
## 94  2019 58.887  33.549   2
## 95  2018 45.675  31.609   3
## 96  2018 44.995  17.491   3
## 97  2011 12.995 117.683  10
## 98  2018 48.500  30.349   3
## 99  2018 46.850  35.671   3
## 100 2013 23.990  37.445   8
## 101 2019 58.561  32.233   2
## 102 2019 54.785  52.498   2
## 103 2012 21.995  80.219   9
## 104 2015 26.990  87.143   6
## 105 2018 41.623  54.420   3
## 106 2019 56.998  34.493   2
## 107 2018 45.975  46.834   3
## 108 2019 59.988  34.220   2
## 109 2015 27.750  71.794   6
## 110 2018 53.800  27.773   3
## 111 2018 47.000  21.829   3
## 112 2016 30.990  65.414   5
## 113 2018 42.512  49.628   3
## 114 2016 33.990  43.332   5
## 115 2019 56.994  43.053   2
## 116 2018 46.998  36.311   3
## 117 2019 66.995  40.818   2
```

```
## 118 2014 26.998  62.570   7
## 119 2017 36.500  47.520   4
## 120 2019 57.966  28.904   2
## 121 2018 46.998  34.625   3
## 122 2018 42.999  44.714   3
## 123 2019 57.991  42.111   2
## 124 2018 46.064  31.454   3
## 125 2018 45.500  36.935   3
## 126 2013 19.995  93.078   8
## 127 2015 23.999  99.650   6
## 128 2018 39.344  55.236   3
## 129 2019 55.400  36.513   2
## 130 2018 45.400  36.387   3
## 131 2018 48.400  32.114   3
## 132 2019 58.491  38.214   2
## 133 2019 59.998  27.539   2
## 134 2017 38.495  56.252   4
## 135 2018 47.900  28.966   3
## 136 2011 18.590  20.490  10
## 137 2018 59.550  26.187   3
## 138 2018 45.900  39.169   3
## 139 2018 39.900  58.195   3
## 140 2013 17.500  93.612   8
## 141 2018 44.800  32.121   3
## 142 2018 44.991  48.964   3
## 143 2013 16.849  87.350   8
## 144 2016 32.444  69.158   5
## 145 2018 48.995  30.998   3
## 146 2018 46.456  32.953   3
## 147 2018 46.277  27.897   3
## 148 2009  5.995 197.487  12
## 149 2016 33.371  64.222   5
## 150 2019 59.950  11.669   2
## 151 2017 38.499  53.498   4
## 152 2018 56.798  38.901   3
## 153 2018 49.025  46.656   3
## 154 2018 52.646  11.641   3
## 155 2015 26.590  74.543   6
## 156 2018 46.900  35.772   3
## 157 2017 25.988 139.553   4
## 158 2018 49.800  24.407   3
## 159 2018 46.975  30.840   3
## 160 2018 35.990  82.382   3
## 161 2019 56.524  35.690   2
## 162 2018 45.998  41.879   3
## 163 2019 63.698  31.803   2
## 164 2019 60.800  38.057   2
## 165 2015 26.590  81.230   6
## 166 2018 41.590  49.478   3
## 167 2017 36.447  29.560   4
```

```
## 168 2018 53.800  39.274   3
## 169 2019 54.900  31.921   2
## 170 2018 41.800  39.124   3
## 171 2018 45.975  47.629   3
## 172 2017 35.800  49.630   4
## 173 2018 40.999  61.830   3
## 174 2018 46.500  45.000   3
## 175 2013 16.299  86.754   8
## 176 2017 35.569  55.003   4
## 177 2016 32.995  32.398   5
## 178 2019 58.986  30.689   2
## 179 2015 34.989  51.049   6
## 180 2018 38.698  56.223   3
## 181 2015 25.900  82.241   6
## 182 2013 20.990  68.494   8
## 183 2018 46.988  64.807   3
## 184 2015 32.888  57.456   6
## 185 2017 33.990  61.850   4
## 186 2013 17.995  95.179   8
## 187 2018 45.988  31.622   3
## 188 2019 57.894  33.417   2
## 189 2019 58.968  23.495   2
## 190 2014 25.295  79.319   7
## 191 2019 58.598  32.948   2
## 192 2018 45.590  30.035   3
## 193 2019 53.995  45.066   2
## 194 2019 56.800  19.764   2
## 195 2018 44.999  35.650   3
## 196 2006  8.989  97.305  15
## 197 2019 59.995  41.607   2
## 198 2019 74.900  17.598   2
## 199 2017 38.310  36.906   4
## 200 2019 69.995   1.000   2
## 201 2018 51.100  20.961   3
## 202 2011 14.995 139.469  10
## 203 2018 46.750  21.694   3
## 204 2016 35.968  63.615   5
## 205 2014 23.199  97.856   7
## 206 2018 53.950  26.144   3
## 207 2014 27.900  78.281   7
## 208 2018 42.998  32.764   3
## 209 2019 57.499  32.950   2
## 210 2018 47.500  25.565   3
## 211 2017 38.984  29.838   4
## 212 2014 35.995  78.533   7
## 213 2019 59.949  25.205   2
## 214 2019 56.454   1.000   2
## 215 2018 46.850  29.982   3
## 216 2015 26.276  84.665   6
## 217 2015 32.990  67.526   6
```

```
## 218 2018 44.999  44.165   3
## 219 2018 46.975  48.761   3
## 220 2015 28.990  65.581   6
## 221 2018 52.634  30.727   3
## 222 2017 32.337  93.022   4
## 223 2019 59.277  24.115   2
## 224 2019 58.033  35.686   2
## 225 2019 57.488  24.019   2
## 226 2018 40.590  56.260   3
## 227 2019 55.995  55.174   2
## 228 2019 59.698  24.952   2
## 229 2018 43.590  33.390   3
## 230 2019 57.700  15.529   2
## 231 2019 59.488  21.149   2
## 232 2018 46.994  27.684   3
## 233 2018 45.900  27.593   3
## 234 2018 48.500  14.804   3
## 235 2011 12.995 120.089  10
## 236 2016 36.700  42.959   5
## 237 2014 18.725 154.550   7
## 238 2018 42.598  45.265   3
## 239 2017 34.646  65.804   4
## 240 2018 45.965  36.174   3
## 241 2018 40.988  54.629   3
## 242 2005  7.599 108.519  16
## 243 2018 44.898  40.080   3
## 244 2014 23.495 102.459   7
## 245 2016 26.500 107.259   5
## 246 2018 48.995  25.421   3
## 247 2018 46.998  24.102   3
## 248 2019 57.900  33.430   2
## 249 2018 48.900  25.334   3
## 250 2017 40.977  46.369   4
## 251 2018 44.990  31.920   3
## 252 2018 48.800  35.472   3
## 253 2018 47.745   8.673   3
## 254 2019 65.800  25.574   2
## 255 2018 45.590  28.047   3
## 256 2012 18.590  91.249   9
## 257 2018 52.888  13.187   3
## 258 2018 43.500  45.188   3
## 259 2018 44.590  26.906   3
## 260 2016 32.027  62.543   5
## 261 2018 42.995  88.488   3
## 262 2018 58.900  31.854   3
## 263 2011 13.995 115.981  10
## 264 2018 54.896  32.370   3
## 265 2018 46.790  32.113   3
## 266 2013 19.486 105.359   8
## 267 2009  9.990 116.000  12
```

```
## 268 2018 47.500  34.261   3
## 269 2018 47.850  46.196   3
## 270 2018 44.718  41.302   3
## 271 2018 52.995  34.353   3
## 272 2016 39.995  78.285   5
## 273 2015 24.999  87.613   6
## 274 2016 29.900  91.204   5
## 275 2019 74.888  14.364   2
## 276 2011 17.990  69.860  10
## 277 2018 46.998  27.111   3
## 278 2018 49.995  35.801   3
```

Project

Introduce your data using complete sentences. What kind of car are you looking at? Where did these car listings come from (zip code and town)? Example:

I chose to study BMW X5s from the downtown Boston area and the zip code is 02101.

Model: Choose

Use R to compute each of the summary statistics below, writing them in the text next to their names.

- average age: 4.1007463 4.101 years
- standard deviation of age: 2.3672863 2.367 years.
- average price: 41.7751306 41.775 thousands of dollars
- standard deviation of price: 13.8578111 13.858 thousands of dollars

Average age

```
mean(UsedCars$age)

## [1] 4.100746
```

Standard deviation of age

```
sd(UsedCars$age)

## [1] 2.367286
```

Average price

```
mean(UsedCars$price)

## [1] 41.77513
```

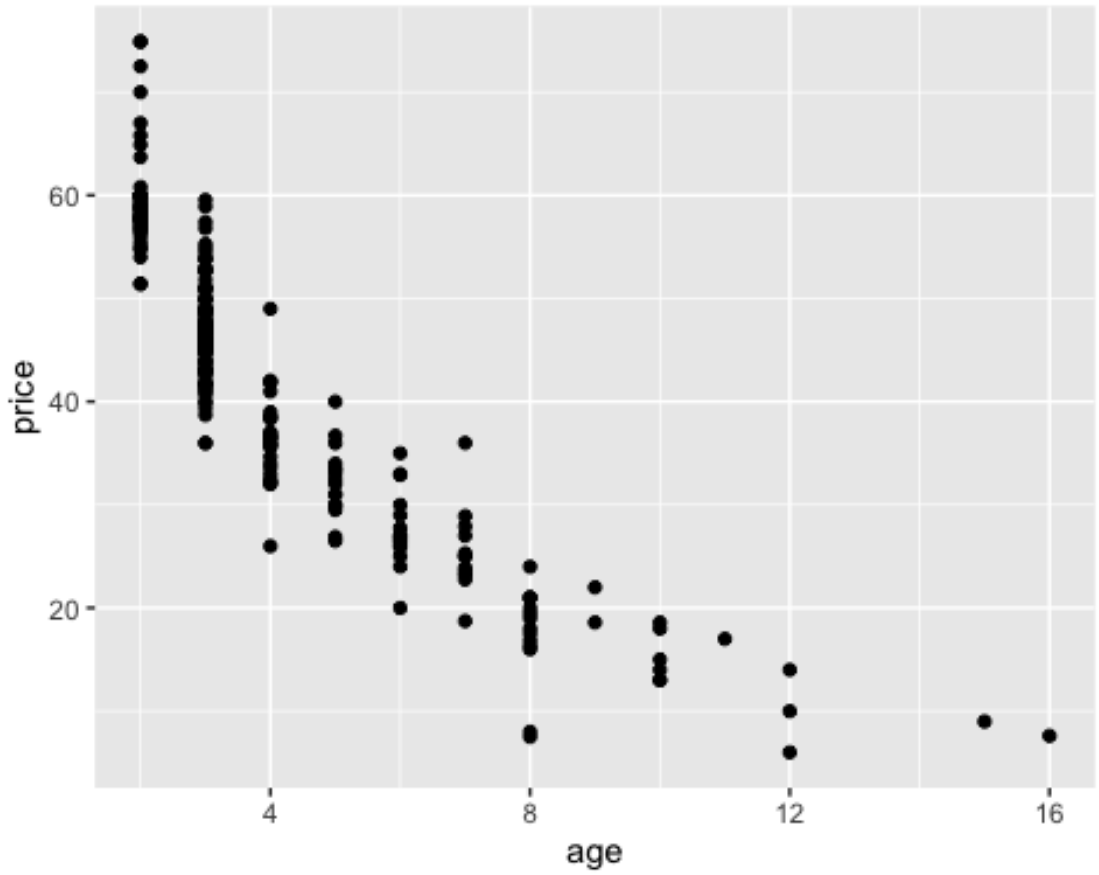
Standard deviation of price

```
sd(UsedCars$price)

## [1] 13.85781
```

Produce a scatterplot of the relationship between age and price.

```
gf_point(price ~ age, data = UsedCars)
```



Using complete sentences, describe what you've learned from your exploratory data analysis. Make sure you are thorough, and include information about what you learned from the scatterplot.

Most cars in the dataset are under 5 years old and the range goes from 0 to 16 years. The average age of the cars is 4.101 years and the standard deviation is 2.367 years. The majority of the cars are around 2 to 6 years old.. The average price of the cars is 41,775 dollars and the standard deviation of price is 13,858 dollars. It seems like the younger the car, the more expensive the car will be which means there a negative relationship between age and price of the car. It lools like a negative expoential relationship.

Model: Fit

Fit a simple linear model to your data. Use R to compute each of the summary statistics below, writing them in the text next to their names.

```
MyCarModel <- lm(price ~ age, data = UsedCars)
summary(MyCarModel)
```

```
##
## Call:
## lm(formula = price ~ age, data = UsedCars)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -16.3105  -4.2427  -0.6433   3.8433  27.6381
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  63.0777     0.7831   80.55   <2e-16 ***
## age          -5.1948     0.1655  -31.40   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.4 on 266 degrees of freedom
## Multiple R-squared:  0.7875, Adjusted R-squared:  0.7867
## F-statistic: 985.8 on 1 and 266 DF,  p-value: < 2.2e-16
```

```
summary(MyCarModel)$coeff[1,1] ## estimated intercept
```

```
## [1] 63.0777
```

```
summary(MyCarModel)$coeff[2,1] ## estimated slope
```

```
## [1] -5.194802
```

```
summary(MyCarModel)$r.squared ## standard error of regression
```

```
## [1] 0.7874995
```

```
anova(MyCarModel)$Sum[1] ## SSModel
```

```
## [1] 40378.56
```

```
anova(MyCarModel)$Sum[2] ## SSError
```

```
## [1] 10895.83
```

```
anova(MyCarModel)$Sum[1]+anova(MyCarModel)$Sum[2] ## SSTotal
```

```
## [1] 51274.39
```

- degrees of freedom: 1 and 48

Interpret, in context, what the slope estimate tells you about age and price in your used car model. Make sure you add a sentence about why the sign (positive or negative) makes sense.

The slope is -5.195 In context, this tells me that as age increases by 1 year, the price of the car will decrease by 5.195 thousand dollar. The negative sign makes sense because as cars get older their value decreases so therefore the price will decrease over time.

Model: Assess

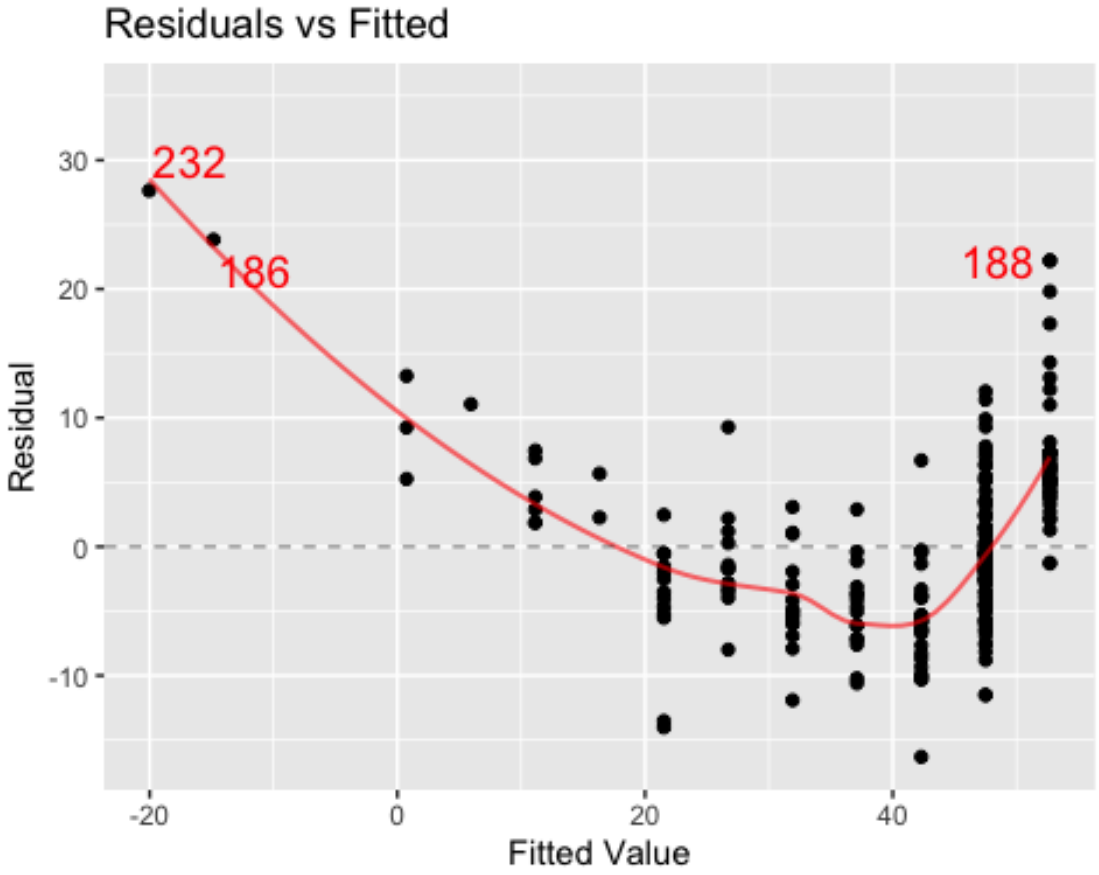
Residual plots

Produce the appropriate residual plots

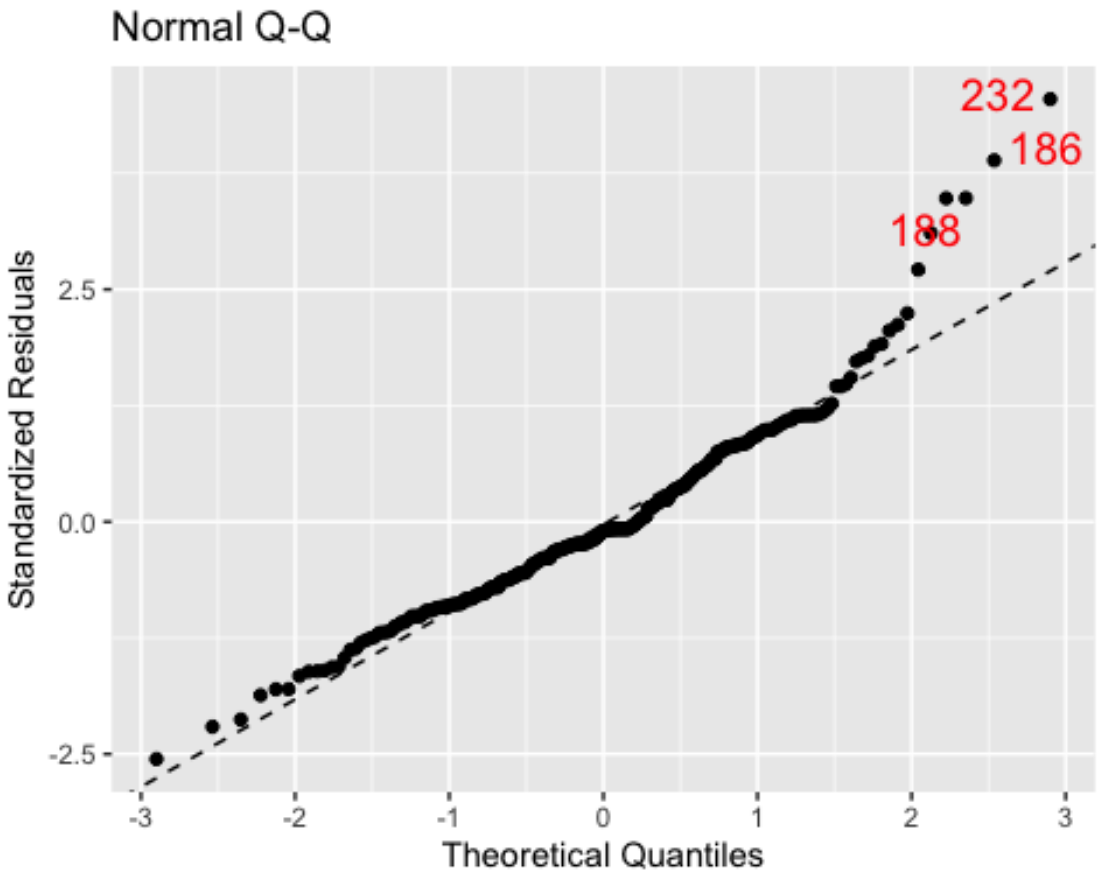
```
mplot(MyCarModel, which = c(1,2))
```

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

```
## `geom_smooth()` using formula 'y ~ x'
```




```
##
## [[2]]
```



Comment on how well your data appear to fit the conditions for a simple linear model. At this point, don't worry about doing any transformations if there are problems with the conditions, just mention them.

The residual vs fitted plot shows us that the data does not fit the conditions for a simple linear model. The data is not shapeless because there is clearly a curved pattern in the data. The data is clustered on the right side together instead of distributed symmetrically. The model also doesn't meet the condition of zero mean. there are outliers that are skewing the data and it doesn't meet the condition of normality. The normal q-q plot shows that the line fits well but there on both sides there are outliers that don't fit the line so it is not noramlly distributed.

Unusual points

Find the car in your sample with the largest (in magnitude) residual. **What is the age and price of this car?** The car with the largest residual of 22.19 is 275 and the age of this car is 2 so it is from 2019. The price of this car is 74.888 thousand dollars.

```
mod1 = lm(price ~ age, data = UsedCars)
mod1$residuals
```

```
##             1             2             4             5             6
##  11.063126323   6.109908534  -1.643289489  -4.947883559 -10.215685536
```

```
##             8             9            10            12            13
## -11.513289489   6.696512487   4.986908534  -0.308487513   2.364710511
##            14            15            16            17            18
##  -0.495289489  -1.695289489  -0.529279606  -1.931883559   4.810908534
##            19            20            21            22            23
##  -5.650487513  -7.608685536  -0.529279606  -5.299487513  -1.724081583
##            24            25            26            27            28
##   2.185918417  -2.529279606  -5.909883559 -10.303487513   9.906710511
##            29            31            32            33            34
## -14.019279606  -1.495289489  -1.248091466  -0.216289489  -5.008883559
##            35            36            37            38            39
##  -6.116685536   7.309908534  -0.074289489  -5.654289489  -8.708487513
##            40            41            42            43            45
##  -5.308487513  -0.308487513   5.153710511  19.811908534   2.531710511
##            46            47            48            49            50
##  -0.495289489  12.209908534  -5.694289489 -13.524279606  -1.298091466
##            52            55            57            59            60
##  -7.503289489  -9.348487513  -1.503289489  -3.970081583  -4.503289489
##            61            62            63            64            65
## -10.268487513   7.783710511  -3.503289489   0.205710511  -0.493487513
##            66            67            68            69            70
##  -2.816081583  -4.498289489  -3.549289489   1.501710511   3.191710511
##            71            72            73            74            75
## -10.003487513   4.306710511  -6.500487513  -6.308487513  -7.108685536
##            76            77            78            79            80
##  -1.715081583  -1.843289489  13.254928300  -3.503289489  -6.096289489
##            81            82            83            84            85
##   3.505710511  -1.993289489   6.994710511   7.301908534   3.494710511
##            86            87            88            89            90
## -11.913883559   3.504710511  -2.331289489  -3.604685536   1.501710511
##            91            92            93            94            95
##  -5.524279606  -0.495289489  -5.803487513   6.198908534  -1.818289489
##            96            97            98            99           100
##  -2.498289489   1.865324347   1.006710511  -0.643289489   2.470720394
##           101           102           103           104           105
##   5.872908534   2.096908534   5.670522370  -4.918883559  -5.870289489
##           106           107           108           109           110
##   4.309908534  -1.518289489   7.299908534  -4.158883559   6.306710511
##           111           112           113           114           115
##  -0.493289489  -6.113685536  -4.981289489  -3.113685536   4.305908534
##           116           117           118           119           120
##  -0.495289489  14.306908534   0.283918417  -5.798487513   5.277908534
##           121           122           123           124           125
##  -0.495289489  -4.494289489   5.302908534  -1.429289489  -1.993289489
##           126           127           128           129           130
##  -1.524279606  -7.909883559  -8.149289489   2.711908534  -2.093289489
##           131           132           133           134           135
##   0.906710511   5.802908534   7.309908534  -3.803487513   0.406710511
##           136           137           138           139           140
##   7.460324347  12.056710511  -1.593289489  -7.593289489  -4.019279606
```

```
##          141          142          143          144          145
##  -2.693289489  -2.502289489  -4.670279606  -4.659685536   1.501710511
##          146          147          148          149          150
##  -1.037289489  -1.216289489   5.254928300  -3.732685536   7.261908534
##          151          152          153          154          155
##  -3.799487513   9.304710511   1.531710511   5.152710511  -5.318883559
##          156          157          158          159          160
##  -0.593289489 -16.310487513   2.306710511  -0.518289489 -11.503289489
##          161          162          163          164          165
##   3.835908534  -1.495289489  11.009908534   8.111908534  -5.318883559
##          166          167          168          169          170
##  -5.903289489  -5.851487513   6.306710511   2.211908534  -5.693289489
##          171          172          173          174          175
##  -1.518289489  -6.498487513  -6.494289489  -0.993289489  -5.220279606
##          176          177          178          179          180
##  -6.729487513  -4.108685536   6.297908534   3.080116441  -8.795289489
##          181          182          183          184          185
##  -6.008883559  -0.529279606  -0.505289489   0.979116441  -8.308487513
##          186          187          188          189          190
##  -3.524279606  -1.505289489   5.205908534   6.279908534  -1.419081583
##          191          192          193          194          195
##   5.909908534  -1.903289489   1.306908534   4.111908534  -2.494289489
##          196          197          198          199          200
##  23.833334229   7.306908534  22.211908534  -3.988487513  17.306908534
##          201          202          203          204          205
##   3.606710511   3.865324347  -0.743289489  -1.135685536  -3.515081583
##          206          207          208          209          210
##   6.456710511   1.185918417  -4.495289489   4.810908534   0.006710511
##          211          212          213          214          215
##  -3.314487513   9.280918417   7.260908534   3.765908534  -0.643289489
##          216          217          218          219          220
##  -5.632883559   1.081116441  -2.494289489  -0.518289489  -2.918883559
##          221          222          223          224          225
##   5.140710511  -9.961487513   6.588908534   5.344908534   4.799908534
##          226          227          228          229          230
##  -6.903289489   3.306908534   7.009908534  -3.903289489   5.011908534
##          231          232          233          234          235
##   6.799908534  -0.499289489  -1.593289489   1.006710511   1.865324347
##          236          237          238          239          240
##  -0.403685536  -7.989081583  -4.895289489  -7.652487513  -1.528289489
##          241          242          243          244          245
##  -6.505289489  27.638136206  -2.595289489  -3.219081583 -10.603685536
##          246          247          248          249          250
##   1.501710511  -0.495289489   5.211908534   1.406710511  -1.321487513
##          251          252          253          254          255
##  -2.503289489   1.306710511   0.251710511  13.111908534  -1.903289489
##          256          257          258          259          260
##   2.265522370   5.394710511  -3.993289489  -2.903289489  -5.076685536
##          261          262          263          264          265
##  -4.498289489  11.406710511   2.865324347   7.402710511  -0.703289489
```

```
##           266           267           268           269           270
##  -2.033279606   9.249928300   0.006710511   0.356710511  -2.775289489
##           271           272           273           274           275
##   5.501710511   2.891314464  -6.909883559  -7.203685536  22.199908534
##           276           277           278
##   6.860324347  -0.495289489   2.501710511
```

Use R to find this car's studentized residual, leverage, and Cook's distance. Would any of these values be considered unusual? Why or why not? Again, use complete sentences.

The standardized residual, for this car(275) is 3.480305250. This value is definitely considered influential because the standardized residual value is much higher than all the other standardized residuals values.

```
rstandard(MyCarModel)

##            1            2            4            5            6
8
##  1.760139539  0.957857404 -0.257343374 -0.775475178 -1.599586344 -
1.803010843
##            9           10           12           13           14
15
##  1.048268428  0.781803399 -0.048290468  0.370319768 -0.077563612 -
0.265486709
##           16           17           18           19           20
21
## -0.083278644 -0.302781529  0.754211676 -0.884524246 -1.191378634 -
0.083278644
##           22           23           24           25           26
27
## -0.829578897 -0.270650019  0.343150154 -0.397965409 -0.926248152 -
1.612902339
##           28           29           31           32           33
34
##  1.551416430 -2.205840878 -0.234166192 -0.195664738 -0.033871492 -
0.785035627
##           35           36           37           38           39
40
## -0.957759185  1.145982787 -0.011633926 -0.885476324 -1.363221906 -
0.830987752
##           41           42           43           45           46
47
## -0.048290468  0.807084365  3.105935737  0.396472399 -0.077563612
1.914161435
##           48           49           50           52           55
57
## -0.891740428 -2.127955904 -0.203503295 -1.175034496 -1.463407158 -
0.235419013
##           59           60           61           62           63
64
```

```
## -0.623231909 -0.705226754 -1.607423458  1.218949151 -0.548624174
0.032214797
##           65           66           67           68           69
70
## -0.077250267 -0.442074518 -0.704443742 -0.555827893  0.235171741
0.499830102
##           71           72           73           74           75
76
## -1.565940502  0.674441979 -1.017582785 -0.987527209 -1.113087934 -
0.269237180
##           77           78           79           80           81
82
## -0.288663890  2.119751169 -0.548624174 -0.954694665  0.549003312 -
0.312154278
##           83           84           85           86           87
88
##  1.095389715  1.144728618  0.547280684 -1.867247049  0.548846710 -
0.365085950
##           89           90           91           92           93
94
## -0.564426708  0.235171741 -0.869208841 -0.077563612 -0.908474783
0.971810036
##           95           96           97           98           99
100
## -0.284748826 -0.391238581  0.295465138  0.157653464 -0.100740794
0.388751505
##          101          102          103          104          105
106
##  0.920702640  0.328734768  0.894891324 -0.770930047 -0.919302482
0.675669329
##          107          108          109          110          111
112
## -0.237768052  1.144415075 -0.651816262  0.987647140 -0.077250407 -
0.957289441
##          113          114          115          116          117
118
## -0.780082788 -0.487545241  0.675042244 -0.077563612  2.242910542
0.044570121
##          119          120          121          122          123
124
## -0.907692086  0.827423805 -0.077563612 -0.703817331  0.831343083 -
0.223830422
##          125          126          127          128          129
130
## -0.312154278 -0.239835310 -1.239705480 -1.276199763  0.425149027 -
0.327814536
##          131          132          133          134          135
136
##  0.141993206  0.909728660  1.145982787 -0.595395870  0.063691915
1.181706423
```

```
##          137          138          139          140          141
142
##  1.888111977 -0.249513245 -1.189128728 -0.632407050 -0.421776084 -
0.391864991
##          143          144          145          146          147
148
## -0.734837592 -0.729620085  0.235171741 -0.162442211 -0.190474073
0.840377266
##          149          150          151          152          153
154
## -0.584469127  1.138457771 -0.594769712  1.457141676  0.239869818
0.806927762
##          155          156          157          158          159
160
## -0.833621512 -0.092910665 -2.553234857  0.361236818 -0.081165471 -
1.801444817
##          161          162          163          164          165
166
##  0.601359802 -0.234166192  1.726036052  1.271713251 -0.833621512 -
0.924470367
##          167          168          169          170          171
172
## -0.915988677  0.987647140  0.346763451 -0.891583825 -0.237768052 -
1.017269706
##          173          174          175          176          177
178
## -1.017022492 -0.155551697 -0.821376453 -1.053430320 -0.643343734
0.987330380
##          179          180          181          182          183
184
##  0.482742534 -1.377365030 -0.941764290 -0.083278644 -0.079129638
0.153455611
##          185          186          187          188          189
190
## -1.300606123 -0.554522075 -0.235732218  0.816136282  0.984508500 -
0.222770466
##          191          192          193          194          195
196
##  0.926503173 -0.298060045  0.204885557  0.644628641 -0.390612170
3.889019266
##          197          198          199          200          201
202
##  1.145512473  3.482186504 -0.624355669  2.713224000  0.564820173
0.612262737
##          203          204          205          206          207
208
## -0.116401052 -0.177827231 -0.551805034  1.011137527  0.186168013 -
0.703973934
##          209          210          211          212          213
214
```

```
##  0.754211676  0.001050883 -0.518848075  1.456938448  1.138301000
0.590385822
##          215          216          217          218          219
220
## -0.100740794 -0.882834313  0.169441935 -0.390612170 -0.081165471 -
0.457472720
##          221          222          223          224          225
226
##  0.805048531 -1.559365845  1.032950786  0.837927472  0.752487194 -
1.081072947
##          227          228          229          230          231
232
##  0.518427863  1.098951441 -0.611265206  0.785722678  1.066029499 -
0.078190022
##          233          234          235          236          237
238
## -0.249513245  0.157653464  0.295465138 -0.063209646 -1.254143136 -
0.766614966
##          239          240          241          242          243
244
## -1.197916239 -0.239334078 -1.018745120  4.547816706 -0.406429031 -
0.505338321
##          245          246          247          248          249
250
## -1.660339927  0.235171741 -0.077563612  0.817076909  0.220294496 -
0.206864938
##          251          252          253          254          255
256
## -0.392021594  0.204634238  0.039418516  2.055569015 -0.298060045
0.357532548
##          257          258          259          260          261
262
##  0.844825587 -0.625359438 -0.454662626 -0.794914529 -0.704443742
1.786320300
##          263          264          265          266          267
268
##  0.453863938  1.159283568 -0.110136949 -0.319923092  1.479264609
0.001050883
##          269          270          271          272          273
274
##  0.055861786 -0.434617495  0.861582063  0.452726067 -1.082976816 -
1.127963167
##          275          276          277          278
##  3.480305250  1.086667143 -0.077563612  0.391774321

hatvalues(MyCarModel)[265]

##         275
## 0.006680748
```

```
2*(2/275)
```

```
## [1] 0.01454545
```

```
3*(2/275)
```

```
## [1] 0.02181818
```

The leverage is less than two or three times the average leverage that is according to the linear model.

Model: Use

Confidence interval

Compute and interpret a 95% confidence interval for the slope of your model.

```
confint(MyCarModel, level = 0.95)
```

```
##                 2.5 %    97.5 %
## (Intercept) 61.535894 64.619497
## age         -5.520572 -4.869032
```

There is a 95% chance that the true slope of the data falls between -5.521 and -4.869.

Coefficient of determination

Report the coefficient of determination (r-squared) and show how it can be computed using values from the ANOVA table.

R^2 = 1 - SSE / SST 1- (10896/(40379+10896)) = 0.787

```
anova(MyCarModel)
```

```
## Analysis of Variance Table
##
## Response: price
##            Df Sum Sq Mean Sq F value    Pr(>F)
## age         1  40379   40379  985.76 < 2.2e-16 ***
## Residuals 266  10896      41
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Interpret the value in context using a complete sentence.

The value of R^2 shows how well the regression line fits with the data. The closer it is to 1 the better of a fit it is. The value is 0.787 so the fit is fairly good.

```
summary(MyCarModel)
```

```
##
## Call:
## lm(formula = price ~ age, data = UsedCars)
```

```
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -16.3105  -4.2427  -0.6433   3.8433  27.6381
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  63.0777     0.7831   80.55   <2e-16 ***
## age          -5.1948     0.1655  -31.40   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.4 on 266 degrees of freedom
## Multiple R-squared:  0.7875, Adjusted R-squared:  0.7867
## F-statistic: 985.8 on 1 and 266 DF,  p-value: < 2.2e-16
```

Hypothesis tests

Test the strength of the linear relationship between age and price using all three methods discussed in class. For each of them, write the hypotheses (it's fine to type them out without using special symbols), discuss how to calculate test statistic and show its value, indicate the reference distribution (t or F including degrees of freedom), and report the p-values. At the end, you can write one conclusion in context that reflects the conclusion based on all three p-values.

```
cor(UsedCars$price, UsedCars$age)
```

```
## [1] -0.8874117
```

1. Test for correlation H0: r; age = 0 HA: r; age =/ 0 The r value is -0.887 which means there is a strong negative relationship between age and price. As the age of the car goes up the price of the car does down.

2. Test for slope H0:βAge=0.0 HA:βAge>0.0 The p-value is really really low so it is approximately 0. This tells us that there is strong evidence to reject the null hypothesis. There is enough evidence to reject the null and conclude that there is a relationship between variables age and price.

3. ANOVA for regression H0: βAge=0 HA: βAge=/0 The test shows that the f value is 985.76 and the p-value is 2.2e-16 which is approximately 0. We can rehect the null and say that there is a relationship between varibles age and price.

```
anova(MyCarModel)
```

```
## Analysis of Variance Table
##
## Response: price
##            Df Sum Sq Mean Sq F value    Pr(>F)
## age         1  40379   40379  985.76 < 2.2e-16 ***
## Residuals 266  10896      41
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Conclusion in context:

Predictions

Suppose you are interested in purchasing a car of this make and model that is five years old. For each of quantities below, show how to complete the calculations using formulas (with the correct numbers in the correct places). For the intervals, write a sentence that carefully interprets each in terms of car prices.

```
newdata=data.frame(age = 5)
predict.lm(MyCarModel, newdata, interval = "confidence", level = 0.9)

##        fit      lwr      upr
## 1 37.10369 36.41323 37.79414

predict.lm(MyCarModel, newdata, interval = "prediction", level = 0.9)

##        fit      lwr      upr
## 1 37.10369 26.51706 47.69031
```

1. Predicted value for price of a car that is five years old
2. 90% confidence interval for the *mean price* of a car at this age is 37.104 thousand dollars and we are 90% confident that the mean price of a car of this model that is 5 years old falls between 36.413 and 37.794 thousand dollars.
3. 90% prediction interval for the price of an *individual* car of this age falls between 26.517 and 47.690 thousand dollars. This means we are 90% confident that the price of an individual car falls between 26.517 and 47.690 thousand dollars.

Discussion

According to your model, is there an age at which the car should be free? If so, find out what this age is and comment on what the 'free car phenomenon' says about the appropriateness of your model.

```
63.0777/5.1948

## [1] 12.14247
```

0 = -5.1948(age) + 63.0777 age = 12.142

At approximately at 12.142 years the car should be free according to my model. This shows that my model is only useful for certain ages and after a certain age the model will start making no sense. Cars do not accurately follow the rate of depreciation in this model.