Linear Regression (Lab)

adapted from Trevor Hastie et al., by TLS

Lab: Linear Regression

Libraries

The `library()` function is used to load *libraries*, or groups of functions and data sets that are not included in the base `R` distribution. Basic functions that perform least squares linear regression and other simple analyses come standard with the base distribution, but more exotic functions require additional libraries. Here we load the `MASS` package, which is a very large collection of data sets and functions. We also load the `ISLR2` package, which includes the data sets associated with this book.

```
library(MASS)
library(ISLR2)
library(mosaic)
```

If you receive an error message when loading any of these libraries, it likely indicates that the corresponding library has not yet been installed on your system. Some libraries, such as `MASS`, come with `R` and do not need to be separately installed on your computer. However, other packages, such as `ISLR2`, must be downloaded the first time they are used. This can be done directly from the `Packages` tab. Alternatively, this can be done at the `R` console via `install.packages("ISLR2")`. This installation only needs to be done the first time you use a package. However, you may find you need to use the `library()` function in each `R` session.

Simple Linear Regression

The `ISLR2` library contains the `Boston` data set, which records `medv` (median house value) for 506 census tracts in Boston. We will seek to predict `medv` using 12 predictors such as `rmvar` (average number of rooms per house), `age` (average age of houses), and `lstat` (percent of households with low socioeconomic status).

```
head(Boston)
```

```
##      crim zn indus chas   nox    rm  age    dis rad tax ptratio lstat medv
## 1 0.00632 18  2.31    0 0.538 6.575 65.2 4.0900   1 296    15.3  4.98 24.0
## 2 0.02731  0  7.07    0 0.469 6.421 78.9 4.9671   2 242    17.8  9.14 21.6
## 3 0.02729  0  7.07    0 0.469 7.185 61.1 4.9671   2 242    17.8  4.03 34.7
## 4 0.03237  0  2.18    0 0.458 6.998 45.8 6.0622   3 222    18.7  2.94 33.4
## 5 0.06905  0  2.18    0 0.458 7.147 54.2 6.0622   3 222    18.7  5.33 36.2
## 6 0.02985  0  2.18    0 0.458 6.430 58.7 6.0622   3 222    18.7  5.21 28.7
```

To find out more about the data set, we can type `?Boston`.

We will start by using the `lm()` function to fit a simple linear regression model, with `medv` as the response and `lstat` as the predictor.

```
lm.fit <- lm(medv ~ lstat)
```

```
## Error in eval(predvars, data, env): object 'medv' not found
```

The command causes an error because `R` does not know where to find the variables `medv` and `lstat`. The next line tells `R` that the variables are in `Boston`. If we attach `Boston`, the first line works fine because `R` now recognizes the variables.

```
lm.fit <- lm(medv ~ lstat, data = Boston)
attach(Boston)
lm.fit <- lm(medv ~ lstat)
```

If we type `lm.fit`, some basic information about the model is output. For more detailed information, we use `summary(lm.fit)`. This gives us p-values and standard errors for the coefficients, as well as the R^2 statistic and F-statistic for the model.

```
lm.fit
```

```
##
## Call:
## lm(formula = medv ~ lstat)
##
## Coefficients:
## (Intercept)        lstat
##       34.55        -0.95
```

```
summary(lm.fit)
```

```
##
## Call:
## lm(formula = medv ~ lstat)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -15.168  -3.990  -1.318   2.034  24.500
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 34.55384    0.56263   61.41   <2e-16 ***
## lstat       -0.95005    0.03873  -24.53   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.216 on 504 degrees of freedom
## Multiple R-squared:  0.5441, Adjusted R-squared:  0.5432
## F-statistic: 601.6 on 1 and 504 DF,  p-value: < 2.2e-16
```

We can use the `names()` function in order to find out what other pieces of information are stored in `lm.fit`. Although we can extract these quantities by name—e.g. `lm.fit$coefficients`—it is safer to use the extractor functions like `coef()` to access them.

```
names(lm.fit)
```

```
##  [1] "coefficients"  "residuals"     "effects"       "rank"
##  [5] "fitted.values" "assign"        "qr"            "df.residual"
##  [9] "xlevels"       "call"          "terms"         "model"
```

```
coef(lm.fit)
```

```
## (Intercept)       lstat
##  34.5538409  -0.9500494
```

In order to obtain a confidence interval for the coefficient estimates, we can use the `confint()` command.

Type `confint(lm.fit)` at the command line to obtain the confidence intervals.

```
confint(lm.fit)
```

```
##                 2.5 %     97.5 %
## (Intercept) 33.448457 35.6592247
## lstat       -1.026148 -0.8739505
```

To produce confidence intervals and prediction intervals for the prediction of `medv` for a given value of `lstat`, we can use `makeFun()` from the `mosaic` package, and specify levels of `lstat` as a list.

```
medvPredictor <- makeFun(lm.fit)
medvPredictor(lstat=c(5,10,15), interval="confidence")
```

```
##        fit      lwr      upr
## 1 29.80359 29.00741 30.59978
## 2 25.05335 24.47413 25.63256
## 3 20.30310 19.73159 20.87461
```

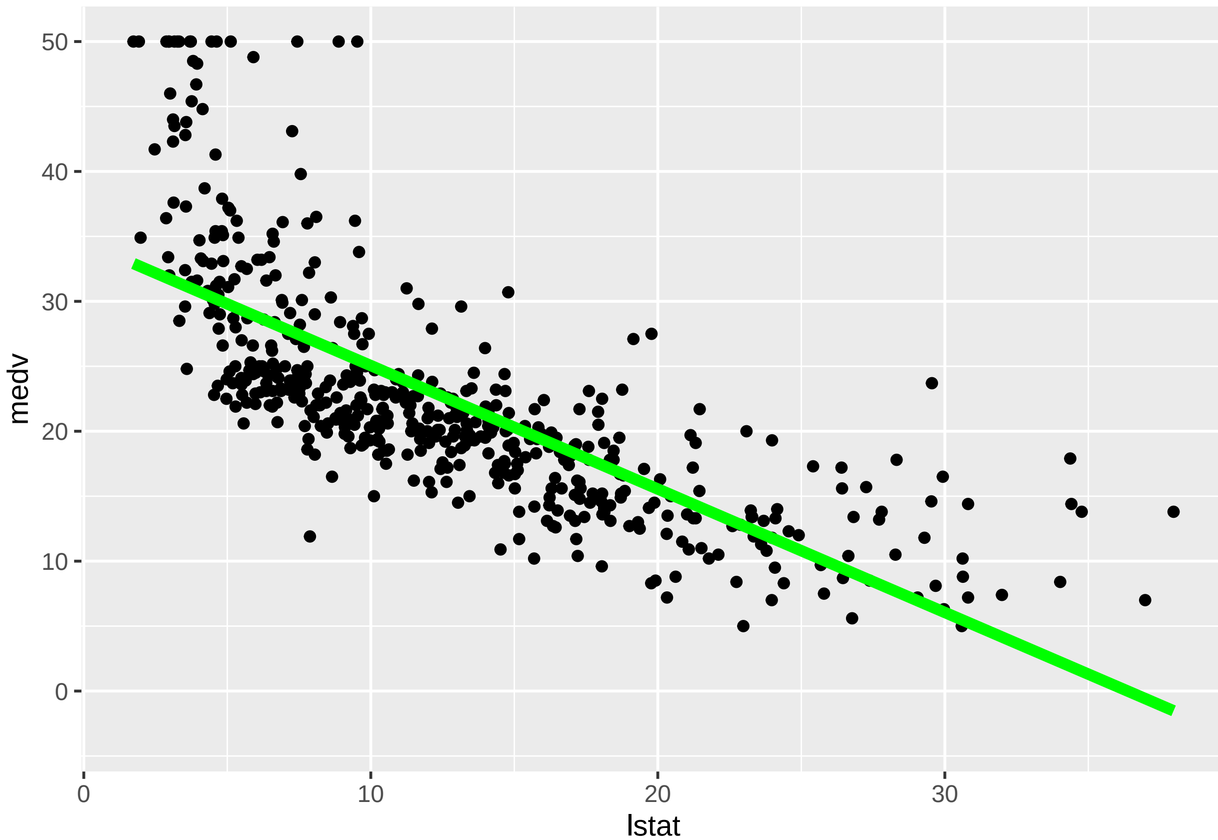
```
medvPredictor(lstat=c(5,10,15), interval="prediction")
```

```
##        fit       lwr      upr
## 1 29.80359 17.565675 42.04151
## 2 25.05335 12.827626 37.27907
## 3 20.30310  8.077742 32.52846
```

For instance, the 95,% confidence interval associated with a `lstat` value of 10 is $(24.47, 25.63)$, and the 95,% prediction interval is $(12.828, 37.28)$. As expected, the confidence and prediction intervals are centered around the same point (a predicted value of 25.05 for `medv` when `lstat` equals 10), but the latter are substantially wider.

We will now plot `medv` and `lstat` along with the least squares regression line using the `gf_point()` and `gf_lm()` functions.

```
gf_point(medv ~ lstat) %>% gf_lm(lwd=2, color="green")
```

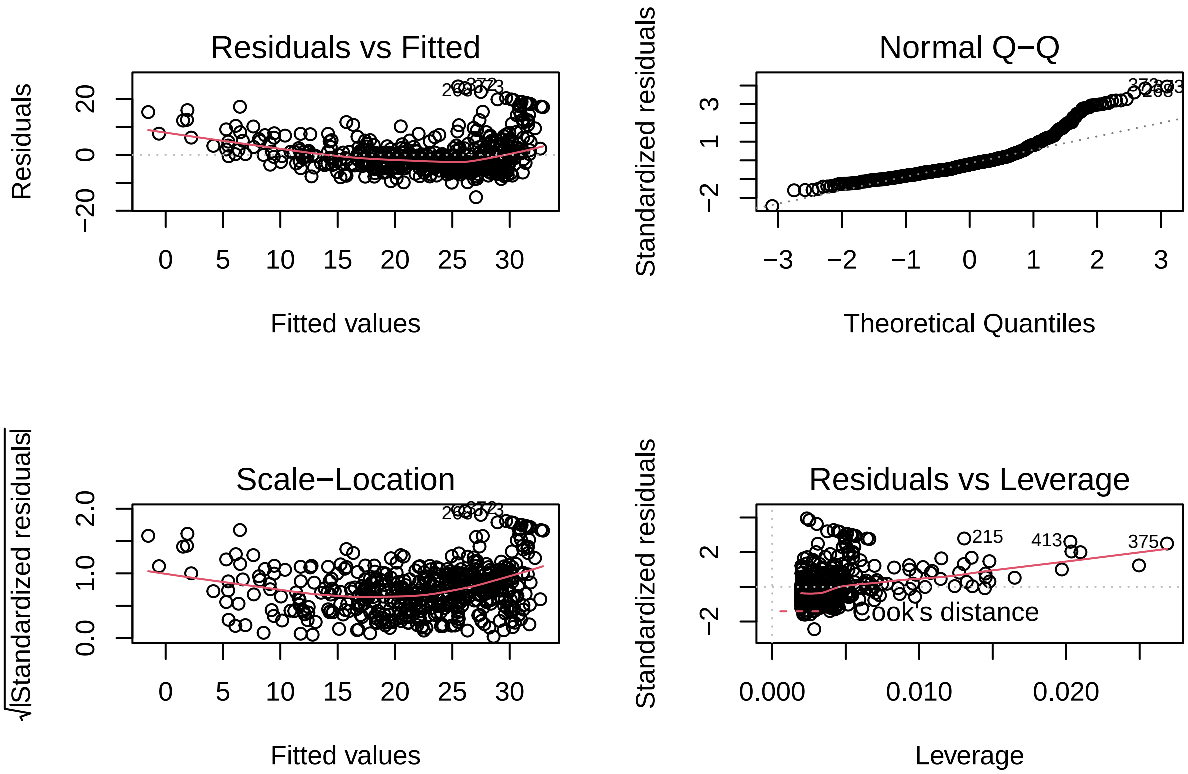


There is some evidence for non-linearity in the relationship between `lstat` and `medv`. We will explore this issue later in this lab.

In the `gf_lm()` command above we used some additional settings for plotting. The `lwd = 2` command causes the width of the regression line to be increased by a factor of 2.

Next let's examine the diagnostic plots obtained automatically by applying the `plot()` function directly to the output from `lm()`. In general, this command will produce one plot at a time, and hitting *Enter* will generate the next plot. However, it is often convenient to view all four plots together. We can achieve this by using the `par()` and `mfrow()` functions, which tell `R` to split the display screen into separate panels so that multiple plots can be viewed simultaneously. For example, `par(mfrow = c(2, 2))` divides the plotting region into a 2×2 grid of panels.

```
par(mfrow = c(2, 2))
plot(lm.fit)
```

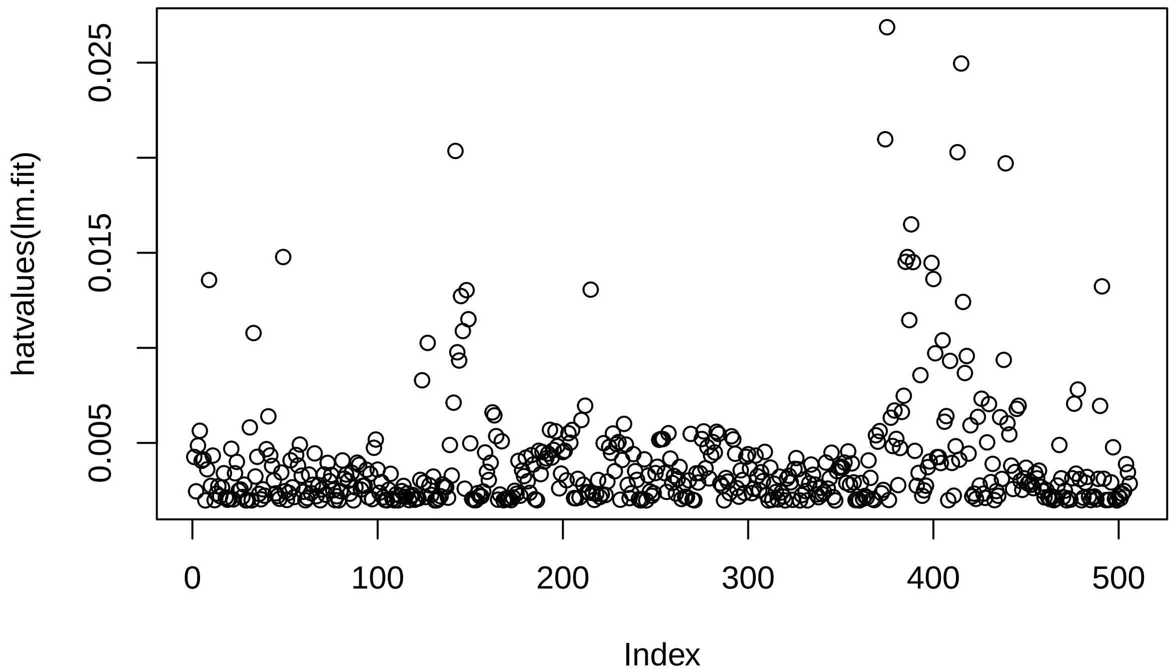


We have seen ways to produce two of these plots. Here are commands (not executed) for all four (though the vertical scale is different using `gf_qq()`).

```
gf_point(residuals(lm.fit) ~ predict(lm.fit)) %>% gf_labs(x="fitted values", y="residuals")  # NW plot
gf_point(sqrt(abs(rstudent(lm.fit))) ~ predict(lm.fit))  # SW plot
gf_point(rstudent(lm.fit) ~ hatvalues(lm.fit))  # SE plot ```

On the basis of the residual plots, there is some evidence of non-linearity.
Leverage statistics can be computed for any number of predictors using the `hatvalues()` function.
```

```
plot(hatvalues(lm.fit))
```




```
which.max(hatvalues(lm.fit))
```

```
## 375
## 375
```

The `which.max()` function identifies the index of the largest element of a vector. In this case, it tells us which observation holds the most leverage to influence the best-fit line.

Non-linear Transformations of the Predictors

The `lm()` function can also accommodate non-linear transformations of the predictors. For instance, given a predictor X, we can create a predictor X^2 using `I(X^2)`. The function `I()` is needed since the `^` has a special meaning in a formula object; wrapping as we do allows the standard usage in `R`, which is to raise `X` to the power `2`. We now perform a regression of `medv` onto `lstat` and `lstat^2`.

```
lm.fit2 <- lm(medv ~ lstat + I(lstat^2))
summary(lm.fit2)
```

```
##
## Call:
## lm(formula = medv ~ lstat + I(lstat^2))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -15.2834  -3.8313  -0.5295   2.3095  25.4148
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 42.862007   0.872084   49.15   <2e-16 ***
## lstat       -2.332821   0.123803  -18.84   <2e-16 ***
## I(lstat^2)   0.043547   0.003745   11.63   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 5.524 on 503 degrees of freedom
## Multiple R-squared:  0.6407, Adjusted R-squared:  0.6393
## F-statistic: 448.5 on 2 and 503 DF,  p-value: < 2.2e-16
```

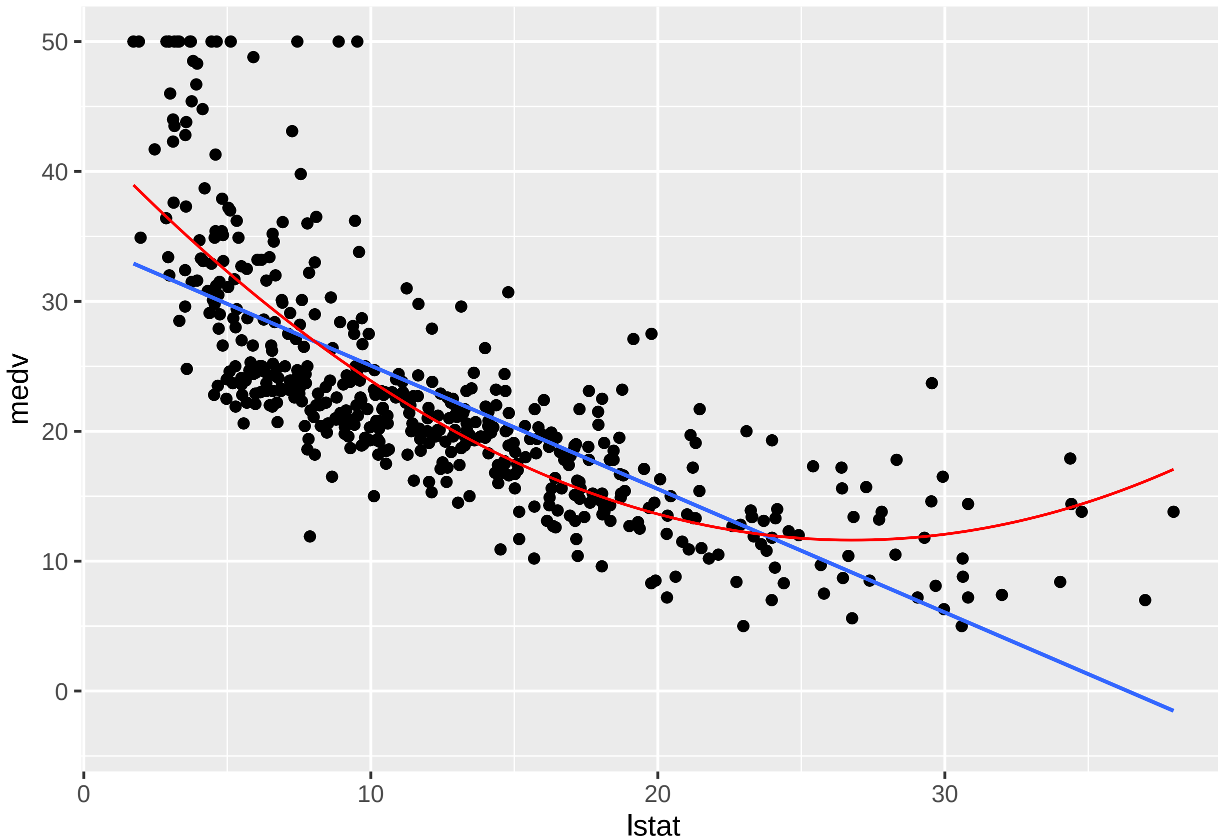
The near-zero p-value associated with the quadratic term suggests that it leads to an improved model. We use the `anova()` function to further quantify the extent to which the quadratic fit is superior to the linear fit.

```
lm.fit <- lm(medv ~ lstat)
anova(lm.fit, lm.fit2)
```

```
## Analysis of Variance Table
##
## Model 1: medv ~ lstat
## Model 2: medv ~ lstat + I(lstat^2)
##   Res.Df   RSS Df Sum of Sq     F    Pr(>F)
## 1    504 19472
## 2    503 15347  1    4125.1 135.2 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Here Model 1 represents the linear submodel containing only one predictor, `lstat`, while Model 2 corresponds to the larger quadratic model that has two predictors, `lstat` and `lstat^2`. The `anova()` function performs a hypothesis test comparing the two models. The null hypothesis is that the two models fit the data equally well, and the alternative hypothesis is that the full model is superior. Here the F-statistic is 135 and the associated p-value is virtually zero. This provides very clear evidence that the model containing the predictors `lstat` and `lstat^2` is far superior to the model that only contains the predictor `lstat`. This is not surprising, since earlier we saw evidence for non-linearity in the relationship between `medv` and `lstat`. A scatterplot with the fitted curves might be similarly convincing.

```
gf_point(medv ~ lstat) %>%
  gf_lm() %>%
  gf_fun(42.862 - 2.33282*x + .043547*x^2 ~ x, xlim=c(0,40), color="red")
```



Look at a plot of residuals vs. fitted values and confirm for yourself that there is little discernible pattern in the residuals.

In order to create a cubic fit, we can include a predictor of the form `I(X^3)`. However, this approach can start to get cumbersome for higher-order polynomials. A better approach involves using the `poly()` function to create the polynomial within `lm()`. For example, the following produces a 3rd-order polynomial fit:

```
lm.fit3 <- lm(medv ~ poly(lstat, 3, raw=TRUE))
summary(lm.fit3)
gf_point(medv ~ lstat, data=Boston) %>%
  gf_fun(48.6496 - 3.86559*x + .148786*x^2 - .002004*x^3 ~ x, xlim=c(0,10),
   color="red")
```

The 4th-order polynomial fit:

```
lm.fit4 <- lm(medv ~ poly(lstat, 4, raw=TRUE))
summary(lm.fit4)
gf_point(medv ~ lstat, data=Boston) %>%
  gf_fun(57.31 - 7.028*x + .4955*x^2 - .01631*x^3 + .0001949*x^4 ~ x,
         xlim=c(0,40), color="red")
```

The 5th-order polynomial fit:

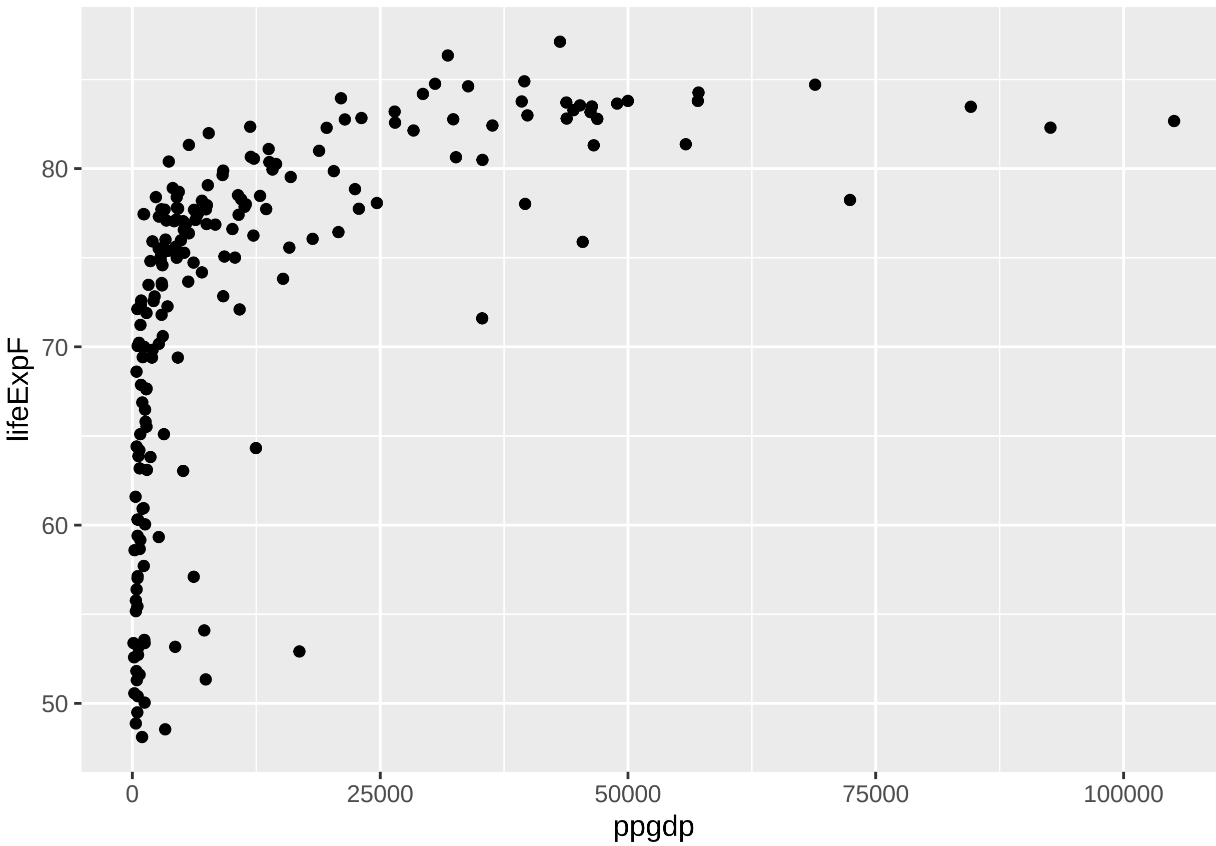
```
lm.fit5 <- lm(medv ~ poly(lstat, 5, raw=TRUE))
summary(lm.fit5)
gf_point(medv ~ lstat, data=Boston) %>%
gf_point(medv ~ lstat, data=Boston) %>%
  gf_fun(67.6997 - 11.99112*x + 1.2728*x^2 - .068274*x^3 + .001726*x^4 - .00001632*x^5 ~ x, xlim=c(0,40
```

This suggests that including additional polynomial terms, up to fifth order, leads to an improvement in the model fit! However, further investigation of the data reveals that no polynomial terms beyond fifth order have significant p-values in a regression fit.

By default, the `poly()` function orthogonalizes the predictors: this means that the features output by this function are not simply a sequence of powers of the argument. However, a linear model applied to the output of the `poly()` function will have the same fitted values as a linear model applied to the raw polynomials (although the coefficient estimates, standard errors, and p-values will differ). In order to obtain the raw polynomials from the `poly()` function, the argument `raw = TRUE` must be used.

We are in no way restricted to using polynomial transformations of the predictors. Here we load a United Nations dataset and produce a scatterplot of `lifeExpF` vs. `ppgdp`.

```
un <- read.csv("https://urldefense.proofpoint.com/v2/url?u=http-3A__users.stat.umn.edu_-7Esandy_alr4ed_d
gf_point(lifeExpF ~ ppgdp, data = un)
```



The shape suggests we might do better taking the natural logarithm of the predictor:

```
gf_point(lifeExpF ~ log(ppgdp), data = un)
```

Multiple Linear Regression

In order to fit a multiple linear regression model using least squares, we again use the `lm()` function. The syntax is like we have seen before, but with a plus sign between predictors, `x1`, `x2`, and `x3`. The `summary()` function now outputs the regression coefficients for all the predictors.

```
lm.fit <- lm(medv ~ lstat + age, data = Boston)
summary(lm.fit)
```

```
##
```

```
## Call:
## lm(formula = medv ~ lstat + age, data = Boston)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -15.981  -3.978  -1.283   1.968  23.158
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 33.22276    0.73085  45.458  < 2e-16 ***
## lstat       -1.03207    0.04819 -21.416  < 2e-16 ***
## age          0.03454    0.01223   2.826  0.00491 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.173 on 503 degrees of freedom
## Multiple R-squared:  0.5513, Adjusted R-squared:  0.5495
## F-statistic:   309 on 2 and 503 DF,  p-value: < 2.2e-16
```

The `Boston` data set contains 12 variables, and so it would be cumbersome to have to type all of these in order to perform a regression using all of the predictors. Instead, we can use the following short-hand:

```r
lm.fit <- lm(medv ~ ., data = Boston)
summary(lm.fit)
```

```
##
## Call:
## lm(formula = medv ~ ., data = Boston)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -15.1304  -2.7673  -0.5814   1.9414  26.2526
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  41.617270   4.936039   8.431 3.79e-16 ***
## crim         -0.121389   0.033000  -3.678 0.000261 ***
## zn            0.046963   0.013879   3.384 0.000772 ***
## indus         0.013468   0.062145   0.217 0.828520
## chas          2.839993   0.870007   3.264 0.001173 **
## nox         -18.758022   3.851355  -4.870 1.50e-06 ***
## rm            3.658119   0.420246   8.705  < 2e-16 ***
## age           0.003611   0.013329   0.271 0.786595
## dis          -1.490754   0.201623  -7.394 6.17e-13 ***
## rad           0.289405   0.066908   4.325 1.84e-05 ***
## tax          -0.012682   0.003801  -3.337 0.000912 ***
## ptratio      -0.937533   0.132206  -7.091 4.63e-12 ***
## lstat        -0.552019   0.050659 -10.897  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.798 on 493 degrees of freedom
## Multiple R-squared:  0.7343, Adjusted R-squared:  0.7278
## F-statistic: 113.5 on 12 and 493 DF,  p-value: < 2.2e-16
```

We can access the individual components of a summary object by name (type `?summary.lm` to see what is available). Hence `summary(lm.fit)$r.sq` gives us the R^2, and `summary(lm.fit)$sigma` gives us the RSE. The `vif()` function, part of the `car` package, can be used to compute variance inflation factors. Most VIF's are low to moderate for this data. The `car` package is not part of the base `R` installation so it must be downloaded the first time you use it via the `install.packages()` function in `R`.

```
library(car)
```

```
## Loading required package: carData
```

```
##
## Attaching package: 'car'
```

```
## The following objects are masked from 'package:mosaic':
##
##     deltaMethod, logit
```

```
## The following object is masked from 'package:dplyr':
##
##     recode
```

```
vif(lm.fit)
```

```
##     crim       zn    indus     chas      nox       rm      age      dis
## 1.767486 2.298459 3.987181 1.071168 4.369093 1.912532 3.088232 3.954037
##      rad      tax  ptratio    lstat
## 7.445301 9.002158 1.797060 2.870777
```

What if we would like to perform a regression using all of the variables but one? For example, in the above regression output, `age` has a high p-value. So we may wish to run a regression excluding this predictor. The following syntax results in a regression using all predictors except `age`.

```
lm.fit1 <- lm(medv ~ . - age, data = Boston)
summary(lm.fit1)
```

```
##
## Call:
## lm(formula = medv ~ . - age, data = Boston)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -15.1851  -2.7330  -0.6116   1.8555  26.3838
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  41.525128   4.919684   8.441 3.52e-16 ***
## crim         -0.121426   0.032969  -3.683 0.000256 ***
## zn            0.046512   0.013766   3.379 0.000785 ***
## indus         0.013451   0.062086   0.217 0.828577
## chas          2.852773   0.867912   3.287 0.001085 **
## nox         -18.485070   3.713714  -4.978 8.91e-07 ***
## rm            3.681070   0.411230   8.951  < 2e-16 ***
## dis          -1.506777   0.192570  -7.825 3.12e-14 ***
## rad           0.287940   0.066627   4.322 1.87e-05 ***
## tax          -0.012653   0.003796  -3.333 0.000923 ***
## ptratio      -0.934649   0.131653  -7.099 4.39e-12 ***
## lstat        -0.547409   0.047669 -11.483  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 4.794 on 494 degrees of freedom
## Multiple R-squared:  0.7343, Adjusted R-squared:  0.7284
## F-statistic: 124.1 on 11 and 494 DF,  p-value: < 2.2e-16
```

Alternatively, the `update()` function can be used.

```
lm.fit1 <- update(lm.fit, ~ . - age)
```

Interaction Terms

It is easy to include interaction terms in a linear model using the `lm()` function. The syntax `lstat:black` tells `R` to include an interaction term between `lstat` and `black`. The syntax `lstat * age` simultaneously includes `lstat`, `age`, and the interaction term `lstat`×`age` as predictors; it is a shorthand for `lstat + age + lstat:age`. %We can also pass in transformed versions of the predictors.

```
summary(lm(medv ~ lstat * age, data = Boston))
```

```
##
## Call:
## lm(formula = medv ~ lstat * age, data = Boston)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -15.806  -4.045  -1.333   2.085  27.552
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) 36.0885359  1.4698355  24.553  < 2e-16 ***
## lstat       -1.3921168  0.1674555  -8.313 8.78e-16 ***
## age         -0.0007209  0.0198792  -0.036   0.9711
## lstat:age    0.0041560  0.0018518   2.244   0.0252 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.149 on 502 degrees of freedom
## Multiple R-squared:  0.5557, Adjusted R-squared:  0.5531
## F-statistic: 209.3 on 3 and 502 DF,  p-value: < 2.2e-16
```

Qualitative Predictors

We will now examine the `Carseats` data, which is part of the `ISLR2` library. We will attempt to predict `Sales` (child car seat sales) in 400 locations based on a number of predictors.

```
head(Carseats)
```

```
##   Sales CompPrice Income Advertising Population Price ShelveLoc Age Education
## 1  9.50       138     73          11        276   120       Bad  42        17
## 2 11.22       111     48          16        260    83      Good  65        10
## 3 10.06       113     35          10        269    80    Medium  59        12
## 4  7.40       117    100           4        466    97    Medium  55        14
## 5  4.15       141     64           3        340   128       Bad  38        13
## 6 10.81       124    113          13        501    72       Bad  78        16
##   Urban  US
## 1   Yes Yes
```

```
## 2   Yes Yes
## 3   Yes Yes
## 4   Yes Yes
## 5   Yes  No
## 6    No Yes
```

The `Carseats` data includes qualitative predictors such as `shelveloc`, an indicator of the quality of the shelving location—that is, the space within a store in which the car seat is displayed—at each location. The predictor `shelveloc` takes on three possible values: *Bad*, *Medium*, and *Good*. Given a qualitative variable such as `shelveloc`, `R` generates dummy variables automatically. Below we fit a multiple regression model that includes some interaction terms.

```r
lm.fit <- lm(Sales ~ . + Income:Advertising + Price:Age,
    data = Carseats)
summary(lm.fit)
```

```
##
## Call:
## lm(formula = Sales ~ . + Income:Advertising + Price:Age, data = Carseats)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.9208 -0.7503  0.0177  0.6754  3.3413
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)         6.5755654  1.0087470   6.519 2.22e-10 ***
## CompPrice           0.0929371  0.0041183  22.567  < 2e-16 ***
## Income              0.0108940  0.0026044   4.183 3.57e-05 ***
## Advertising         0.0702462  0.0226091   3.107 0.002030 **
## Population          0.0001592  0.0003679   0.433 0.665330
## Price              -0.1008064  0.0074399 -13.549  < 2e-16 ***
## ShelveLocGood       4.8486762  0.1528378  31.724  < 2e-16 ***
## ShelveLocMedium     1.9532620  0.1257682  15.531  < 2e-16 ***
## Age                -0.0579466  0.0159506  -3.633 0.000318 ***
## Education          -0.0208525  0.0196131  -1.063 0.288361
## UrbanYes            0.1401597  0.1124019   1.247 0.213171
## USYes              -0.1575571  0.1489234  -1.058 0.290729
## Income:Advertising  0.0007510  0.0002784   2.698 0.007290 **
## Price:Age           0.0001068  0.0001333   0.801 0.423812
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.011 on 386 degrees of freedom
## Multiple R-squared:  0.8761, Adjusted R-squared:  0.8719
## F-statistic:   210 on 13 and 386 DF,  p-value: < 2.2e-16
```

The `contrasts()` function returns the coding that `R` uses for the dummy variables.

```r
attach(Carseats)
contrasts(ShelveLoc)
```

```
##        Good Medium
## Bad       0      0
## Good      1      0
## Medium    0      1
```

Use `?contrasts` to learn about other contrasts, and how to set them.

`R` has created a `ShelveLocGood` dummy variable that takes on a value of 1 if the shelving location is good, and 0 otherwise. It has also created a `ShelveLocMedium` dummy variable that equals 1 if the shelving location is medium, and 0 otherwise. A bad shelving location corresponds to a zero for each of the two dummy variables. The fact that the coefficient for `ShelveLocGood` in the regression output is positive indicates that a good shelving location is associated with high sales (relative to a bad location). And `ShelveLocMedium` has a smaller positive coefficient, indicating that a medium shelving location is associated with higher sales than a bad shelving location but lower sales than a good shelving location.

Writing Functions

As we have seen, `R` comes with many useful functions, and still more functions are available by way of `R` libraries. However, we will often be interested in performing an operation for which no function is available. In this setting, we may want to write our own function. For instance, below we provide a simple function that reads in the `ISLR2` and `MASS` libraries, called `LoadLibraries()`. Before we have created the function, `R` returns an error if we try to call it.

```
LoadLibraries
```

```
## Error in eval(expr, envir, enclos): object 'LoadLibraries' not found
```

```
LoadLibraries()
```

```
## Error in LoadLibraries(): could not find function "LoadLibraries"
```

We now create the function. Note that the `+` symbols are printed by `R` and should not be typed in. The `{` symbol informs `R` that multiple commands are about to be input. Hitting *Enter* after typing `{` will cause `R` to print the `+` symbol. We can then input as many commands as we wish, hitting {*Enter*} after each one. Finally the `}` symbol informs `R` that no further commands will be entered.

```
LoadLibraries <- function() {
 library(ISLR2)
 library(MASS)
 print("The libraries have been loaded.") }
```

Now if we type in `LoadLibraries`, `R` will tell us what is in the function.

```
LoadLibraries
```

```
## function() {
##  library(ISLR2)
##  library(MASS)
##  print("The libraries have been loaded.") }
```

If we call the function, the libraries are loaded in and the print statement is output.

```
LoadLibraries()
```

```
## [1] "The libraries have been loaded."
```