STATS 3001 / STATS 4104 / STATS 7054 Statistical Modelling III Practical 1 - Linear model recap Solutions

Week 1

The following exercises are intended as revision of basic regression calculation and matrix manipulation functions in R.

For the purpose of this exercise, we will use built-in data set Rubber that is provided with the MASS library. The data set comprises three variables recorded on thirty samples of tyre rubber that were being tested for durability:

- loss: The abrasion loss in grams per hour;
- hard: The hardness in Shore units; and
- tens: The tensile strength in kg per square metre.

STEPS

• Load packages using the command

```
pacman::p_load(tidyverse, gglm)
```

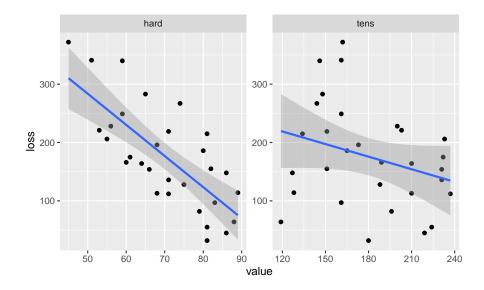
• Load the rubber dataset from the MASS package

```
data(Rubber, package = "MASS")
```

• Obtain scatter-plots of loss against each of the other predictors.

```
Rubber %>%
  pivot_longer(-loss) %>%
  ggplot(aes(value, loss)) +
  geom_point() +
  facet_wrap(~name, scales = "free") +
  geom_smooth(method = lm)
```

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



• Use the lm() function to fit the following model.

$$E(loss_i) = \beta_0 + \beta_1 \times hard_i + \beta_2 \times tens_i.$$

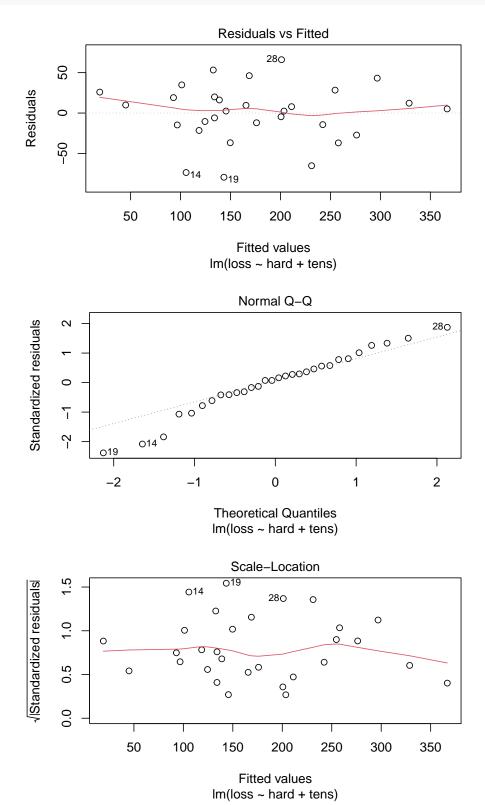
```
rubber_lm <- lm(loss ~ hard + tens, data = Rubber)
summary(rubber_lm)</pre>
```

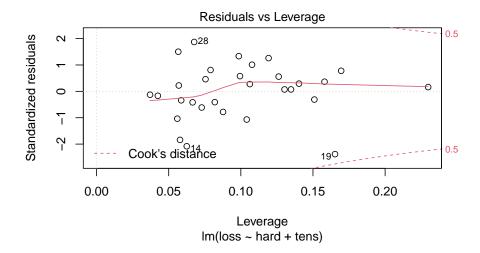
```
##
## Call:
##
  lm(formula = loss ~ hard + tens, data = Rubber)
##
##
  Residuals:
##
       Min
                1Q
                    Median
                                3Q
                                        Max
   -79.385 -14.608
                     3.816
                            19.755
##
                                    65.981
##
##
  Coefficients:
               Estimate Std. Error t value Pr(>|t|)
##
  (Intercept) 885.1611
                                   14.334 3.84e-14 ***
                           61.7516
                -6.5708
                            0.5832 -11.267 1.03e-11 ***
## hard
                -1.3743
                            0.1943 -7.073 1.32e-07 ***
## tens
                   0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
## Signif. codes:
##
## Residual standard error: 36.49 on 27 degrees of freedom
## Multiple R-squared: 0.8402, Adjusted R-squared: 0.8284
                   71 on 2 and 27 DF, p-value: 1.767e-11
## F-statistic:
```

- Interpret the output
- The least squares estimate of β_1 is $\hat{\beta}_1 = -6.57$. The interpretation of this estimate is that and increase of 1 unit of hardness, with tensile strength kept constant, would reduce the rate of abrasion by 6.57 grams per hour.
- The least squares estimate of β_2 is $\hat{\beta}_2 = -1.37$. The interpretation of this estimate is that and increase of 1 unit of tensile strength, with hardness kept constant, would reduce the rate of abrasion by 1.37 grams per hour.

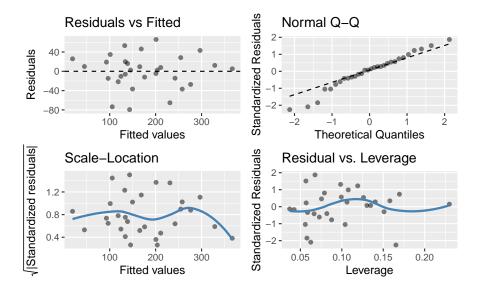
• What are the assumptions of the linear regression model. Produce appropriate plots to check them.

plot(rubber_lm)





gglm(rubber_lm)



Linearity:

The residuals are roughly randomly scattered about the zero line in the residuals versus fitted values plot, apart from slight curvature near the endpoints. The residuals versus hardness plot shows a random scatter but the slight curvature is apparent in the residuals versus tensile strength plot. On balance, the linearity assumption is close to reasonable.

Homoscedasticity

The spread about the zero line appears roughly constant in all three plots indicating that the assumption of constant variance is reasonable.

Normality

There is some departure from normality in the lower tail of the distribution of residuals, with more large negative residuals than expected for a normal distribution. The bulk of the data is close to normally distributed however.

• Predict the loss for the following points:

```
\frac{\text{hard tens}}{50}
\frac{50}{65}
\frac{200}{190}
```

 $\bullet\,$ Calculate 95% CI and PI for the above points.

```
new_pts <- tibble(</pre>
 hard = c(50, 65),
  tens = c(200, 190)
new_pts
## # A tibble: 2 x 2
      hard
           tens
##
     <dbl> <dbl>
## 1
        50
             200
## 2
        65
             190
predict(rubber_lm)
##
                      2
                                3
                                          4
                                                     5
                                                               6
                                                                          7
## 366.83526 203.55082 165.50016 134.02032 101.16617
                                                        92.92030
                                                                  45.07805
                                                                             19.09546
##
                    10
                               11
                                          12
                                                    13
                                                              14
                                                                         15
## 257.92184 231.16639 176.02253 149.73921
                                             96.70044 105.54777 242.33228 200.58874
                                         20
                                                              22
                                                                         23
## 133.97826 118.51804 143.38498 276.21795 211.11111 132.73328 138.83198 124.44535
##
          25
                               27
                                          28
## 328.78459 296.83263 254.65903 201.01880 168.76611 145.53215
predict(rubber_lm, newdata = new_pts)
##
          1
## 281.7573 196.9379
predict(rubber_lm, newdata = new_pts, interval = "confidence")
                   lwr
          fit
## 1 281.7573 254.8762 308.6383
## 2 196.9379 181.8821 211.9938
predict(rubber_lm, newdata = new_pts, interval = "prediction")
          fit
                   lwr
## 1 281.7573 202.2079 361.3066
## 2 196.9379 120.5692 273.3067
```

• Get the design matrix of the model using the command model.matrix().

```
X <- model.matrix(rubber_lm)
X</pre>
```

```
##
      (Intercept) hard tens
## 1
                     45
                         162
                1
## 2
                1
                     55
                         233
## 3
                         232
                     61
                1
                         231
## 4
                1
                     66
## 5
                1
                     71
                         231
## 6
                         237
                     71
## 7
                1
                     81
                         224
## 8
                         219
                1
                     86
## 9
                1
                     53
                         203
## 10
                     60
                         189
## 11
                1
                     64
                         210
## 12
                1
                     68
                         210
## 13
                     79
                        196
                1
## 14
                1
                     81
                        180
                         200
## 15
                1
                     56
## 16
                1
                     68
                         173
## 17
                     75
                        188
                1
## 18
                1
                     83
                        161
## 19
                1
                     88
                        119
## 20
                     59
                        161
                1
## 21
                1
                     71
                         151
## 22
                1
                     80
                        165
## 23
                1
                     82
                         151
## 24
                1
                     89
                         128
## 25
                        161
                1
                     51
## 26
                     59
                         146
                1
## 27
                1
                     65
                         148
## 28
                1
                     74
                         144
## 29
                     81
                         134
## 30
                         127
                1
                     86
## attr(,"assign")
## [1] 0 1 2
```

• Assign the response variable loss to a variable Y.

```
Y <- Rubber$loss
Y
```

```
## [1] 372 206 175 154 136 112 55 45 221 166 164 113 82 32 228 196 128 97 64 ## [20] 249 219 186 155 114 341 340 283 267 215 148
```

• Using the R commands %*%, solve(), and t(), calculate

$$\hat{\boldsymbol{\beta}} = (X^T X)^{-1} X^T Y$$

```
beta_hat <- solve(t(X) %*% X) %*% t(X) %*% Y beta_hat
```

```
[,1]
## (Intercept) 885.161109
## hard
               -6.570830
                -1.374312
## tens
summary(rubber_lm)
##
## Call:
## lm(formula = loss ~ hard + tens, data = Rubber)
## Residuals:
##
                1Q Median
       Min
                                3Q
                                       Max
## -79.385 -14.608
                   3.816 19.755 65.981
##
## Coefficients:
##
               Estimate Std. Error t value Pr(>|t|)
## (Intercept) 885.1611
                           61.7516 14.334 3.84e-14 ***
                            0.5832 -11.267 1.03e-11 ***
               -6.5708
## hard
                -1.3743
                            0.1943 -7.073 1.32e-07 ***
## tens
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
## Residual standard error: 36.49 on 27 degrees of freedom
## Multiple R-squared: 0.8402, Adjusted R-squared: 0.8284
                  71 on 2 and 27 DF, p-value: 1.767e-11
## F-statistic:
Is it the same as the answer from lm()?
  • Calculate the fitted values
```

$$\hat{\boldsymbol{\eta}} = X\hat{\boldsymbol{\beta}}$$

```
eta <- X %*% beta_hat
head(eta)
```

```
[,1]
## 1 366.8353
## 2 203.5508
## 3 165.5002
## 4 134.0203
## 5 101.1662
## 6 92.9203
```

• Calculate the residual variance, s_e^2 directly from the observed and fitted values. Compare the result to the residual standard error produced by lm()

```
n <- nrow(Rubber)</pre>
se \leftarrow sqrt(sum((Y - eta)^2) / (n - 3))
```

[1] 36.48934

- Calculate the estimated variance matrix for $\hat{\pmb{\beta}}$ using

$$(X^T X)^{-1} \times s_e^2$$

Compare this to the result of the built-in calculation vcov().

vcov(rubber_lm)

```
## (Intercept) hard tens

## (Intercept) 3813.25821 -30.01766345 -9.19635018

## hard -30.01766 0.34010794 0.03390882

## tens -9.19635 0.03390882 0.03775595
```

solve(t(X) %*% X) * se^2

##		(Intercept)	hard	tens
##	(Intercept)	3813.25821	-30.01766345	-9.19635018
##	hard	-30.01766	0.34010794	0.03390882
##	tens	-9.19635	0.03390882	0.03775595