Exploratory variables are geometry coefficients and the Froude number:

- 1. Longitudinal position of the center of buoyancy, adimensional.
- 2. Prismatic coefficient, adimensional.
- 3. Length-displacement ratio, adimensional.
- 4. Beam-draught ratio, adimensional.
- 5. Length-beam ratio, adimensional.
- 6. Froude number, adimensional.

The target histogram negative variable is the residuary resistance per unit weight of displacement:

7. Resistance: Residuary resistance per unit weight of displacement, adimensional.

Take the log of the target?

Yes, if we plot *Resistance* we see a significant right skew. However if we plot the histogram of the logarithm of *Resistance*, we see a distribution that looks much more like a normal distribution:

Histogram of yatch[, "Resistance"Histogram of log10(yatch[, "Resistance"Histogram of log10(yatch

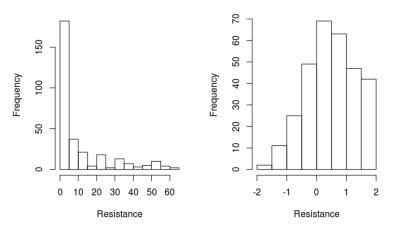


Figure 1 - log of the target

LINEAR REGRESSION

Only correlation *Froude.No – Resistance* seems significant, other columns are omited.

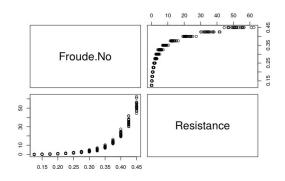


Figure 2 - correlations

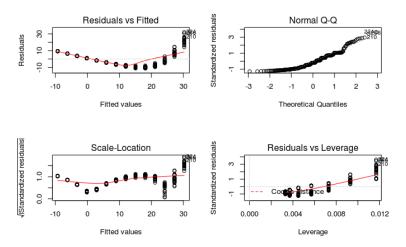


Figure 3 - model main plots

Independent variables, as well as dependent, are transformed:

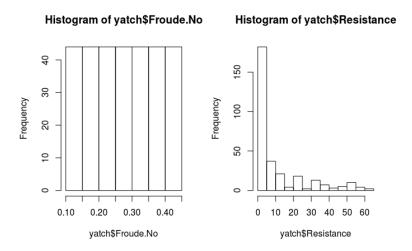


Figure 4 - original histogram independent/dependant var

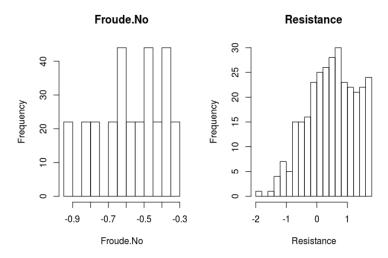


Figure 5 - histogram transformed variables - log10(x)

```
Call:
lm(formula = yacht$Resistance ~ ., data = yacht)
Residuals:
   Min
            1Q Median
                             3Q
                                   Max
-11.240
        -7.669
                -1.726
                          6.404
                                32.154
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
            -24.484
                         1.534 -15.96
                                          <2e-16 ***
(Intercept)
Froude.No
             121.668
                          5.034
                                 24.17
                                          <2e-16 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 8.903 on 306 degrees of freedom
Multiple R-squared: 0.6562, Adjusted R-squared: 0.6551
F-statistic: 584.2 on 1 and 306 DF, p-value: < 2.2e-16
```

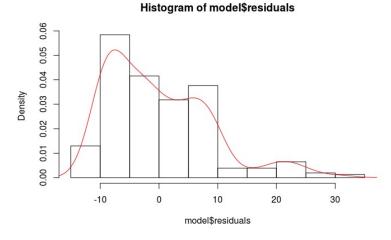


Figure 6 - Histogram of model residuals

Taking the whole variables does not provide any special benefit:

```
lm(formula = yacht$Resistance ~ ., data = yacht)
Residuals:
            1Q Median 3Q Max
   Min
-11.770 -7.565 -1.881 6.112 31.572
Coefficients:
                                                  Estimate Std. Error t value Pr(>|t|)
(Intercept)
                                                  -19.2367 27.1133 -0.709

    0.1938
    0.3381
    0.573
    0.567

    -6.4194
    44.1590
    -0.145
    0.885

    4.2330
    14.1651
    0.299
    0.765

Longitudinal.pos
Prismatic.coeff
Length.displ
                                                              5.5212 -0.320 0.749
Beam.draught.....-1.7657
                                                   -4.5164 14.2000 -0.318 0.751
Length.beam
                                                  121.6676 5.0658 24.018 <2e-16 ***
Froude.No
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 8.96 on 301 degrees of freedom
Multiple R-squared: 0.6576, Adjusted R-squared: 0.6507
F-statistic: 96.33 on 6 and 301 DF, p-value: < 2.2e-16
```

Our model does not look fine, even with centering, scaling, or with the already applied *log* transform, results do not improve much.

RIDGE REGRESSION

Find lambdas:

```
> lambdes <- seq(0.001,0.5,0.001)
> select(lm.ridge(model, lambda = lambdes))

Get model:
> lambdes[which.min(model.ridge$GCV)]
0.001
> model.ridge<-lm.ridge(model, lambda = 0.001)</pre>
```

Prediction error:

```
> norm.root.mse.LOOCV
> sqrt(model.ridge$GCV)
0.5147124
```

. . .