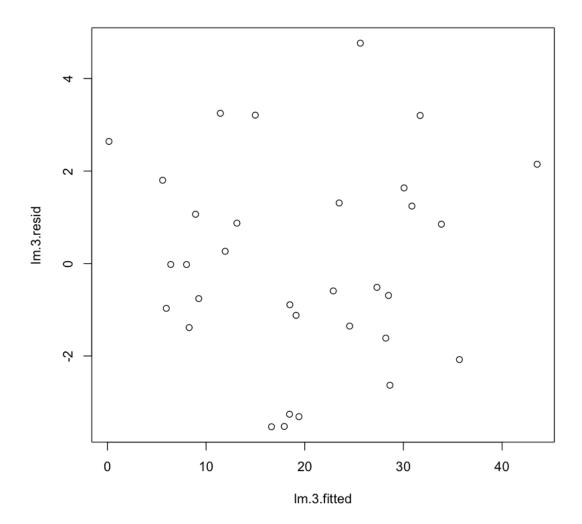
Diagnostics

May 8, 2020

```
In [9]: library(MASS)
In [1]: df <- read.table('oil.txt', col.names = c('spirit', 'gravity', 'pressure', 'distil', 'endpended of the color 
0.1 Fit a model with the three best explanatory variables
In [2]: lm.3 <- lm(spirit ~ gravity + distil + endpoint, data=df)</pre>
                          summary(lm.3)
Call:
lm(formula = spirit ~ gravity + distil + endpoint, data = df)
Residuals:
             Min
                                           1Q Median
                                                                                                3Q
                                                                                                                       Max
-3.5303 -1.3606 -0.2681 1.3911 4.7658
Coefficients:
                                          Estimate Std. Error t value Pr(>|t|)
(Intercept) 4.032034 7.223341
                                                                                                                   0.558
                                                                                                                                             0.5811
                                          0.221727
                                                                               0.102061
                                                                                                                   2.173
                                                                                                                                              0.0384 *
gravity
                                                                               0.015922 -11.718 2.61e-12 ***
distil
                                       -0.186571
                                          0.156527
                                                                               0.006462 24.224 < 2e-16 ***
endpoint
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1
Residual standard error: 2.283 on 28 degrees of freedom
Multiple R-squared: 0.959, Adjusted R-squared: 0.9546
F-statistic: 218.5 on 3 and 28 DF, p-value: < 2.2e-16
```

0.2 Manually extracting the fitted and residual values, and then plotting them

```
In [3]: lm.3.fitted <- fitted(lm.3)
    lm.3.resid <- residuals(lm.3)</pre>
```

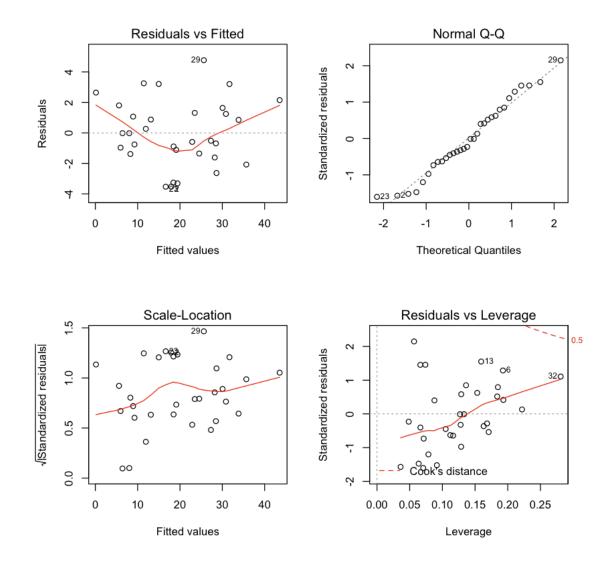


0.3 Or using R's built in plot function with the model as the argument

0.4 Residual plots

- 1) Plot of standardised residuals Vs fitted values tests the assumption that the random error terms are mean zero and of constant variance
- e'_i against \hat{y}
- If there is a trend to the data, rather than being randomly dispersed around mean zero, then this indicates that the constant variance assumption does not hold in the model

- 2) Plot the standardised residuals (which, as the name suggests, is approximately a standard normal distribution) Vs the theoretical quantiles of a standard normal
- This tests the assumption of normality of the random error term in the model (which also applies to the assumption of normality in the dependant variable, *y*.
- 3) Plot the root of the standardised residuals against the fitted values
- Line is a running average curve
- Shouldn't be a trend with the average line, otherwise this is problematic for our constant variance assumption



0.5 Model adequecy

Plot the standardised residuals against EACH EXPLANATORY VARIABLE

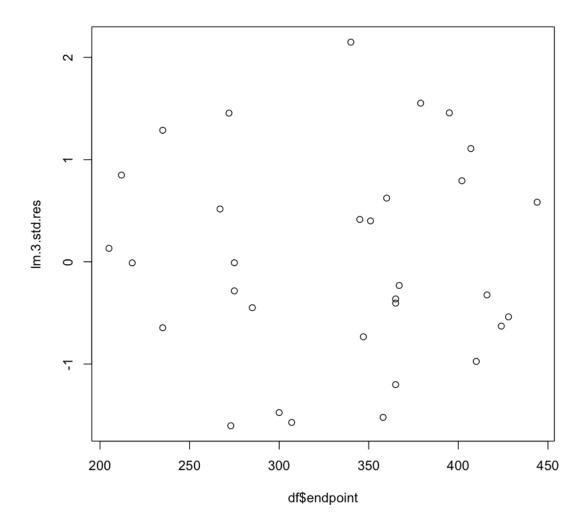
Expect mean zero, random dispersion

If there's trend:

- And the variable is already in the model, indicates a higher order variable term is needed (i.e. x^2)
- If the variable is **NOT** already in the model, then it indicates it should be.

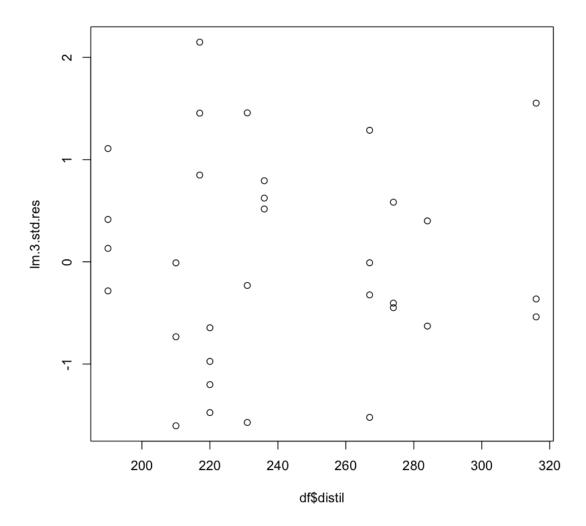
0.6 Plotting standardised residuals from the MASS library against endpoint

In [13]: plot(df\$endpoint, lm.3.std.res)



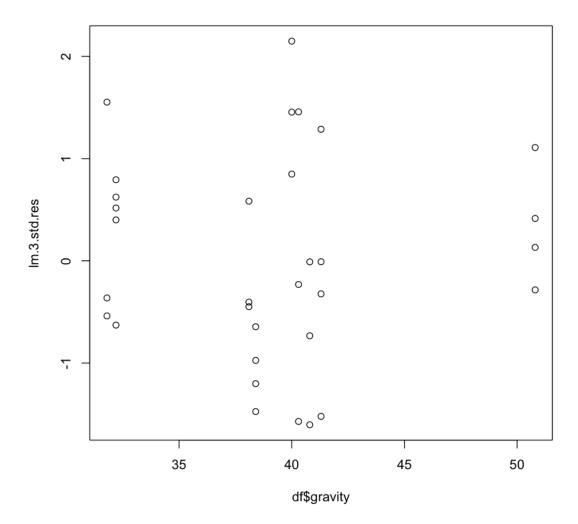
0.7 Plotting standardised residuals from the MASS library against distil

In [14]: plot(df\$distil, lm.3.std.res)



0.8 Plotting standardised residuals from the MASS library against gravity

In [15]: plot(df\$gravity, lm.3.std.res)

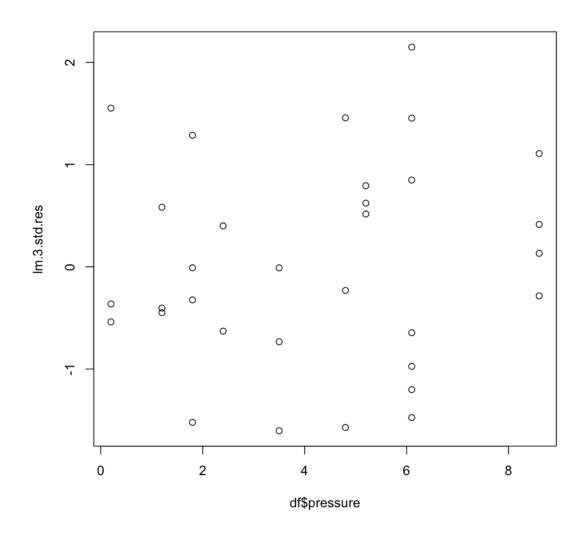


0.9 Plotting standardised residuals from the MASS library against pressure, which is NOT in the model.

If there was a significant trend here, we'd be tempted to add **pressure** back into the model, despite it not appearing as significant in our goodness-of-fit tests

Looks random, so we can be happy leaving it out.

In [16]: plot(df\$pressure, lm.3.std.res)



1 Let's fit a model without the main predictor variable, endpoint, then plot the residuals of that model against endpoint to see if we see a trend.

Note it doesn't pass the null hypothesis test so we wouldn't normally take this any further...

Call:

lm(formula = spirit ~ gravity + pressure + distil, data = df)

Residuals:

Min 1Q Median 3Q Max -15.5787 -7.5048 -0.0363 7.2252 17.9925

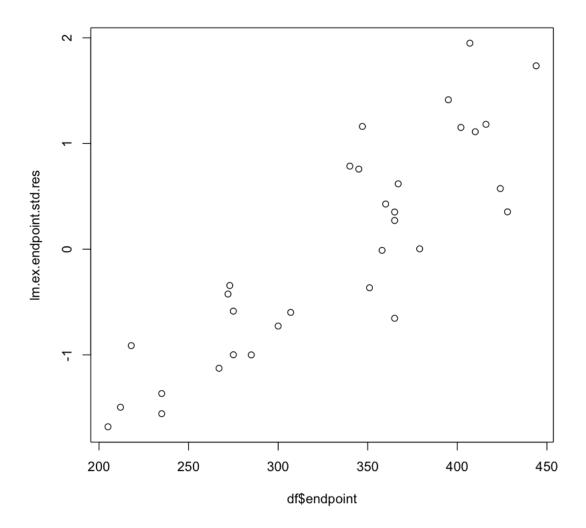
Coefficients:

Estimate Std. Error t value Pr(>|t|) 46.95654 -0.235 (Intercept) -11.01312 0.816 gravity 0.12505 0.46321 0.270 0.789 2.27819 pressure 1.68264 1.354 0.187 distil 0.06724 0.12896 0.521 0.606

Residual standard error: 10.37 on 28 degrees of freedom Multiple R-squared: 0.1558, Adjusted R-squared: 0.06536 F-statistic: 1.723 on 3 and 28 DF, p-value: 0.1851

In [18]: lm.ex.endpoint.std.res <- stdres(lm.ex.endpoint)</pre>

In [19]: plot(df\$endpoint, lm.ex.endpoint.std.res)



1.1 We see clear, clear trend that endpoint should be added to the model!

In []: