Group 03

STAT 31631 – Statistical Modelling

Group project

Activity 03 - Results and discussion

Group 03

Activity_03

```
###This is our cleaned dataset

cleaned_data<-Data_cleaned_6
head(cleaned_data)

##    Cement Blast_Furnace_Slag Fly_Ash Water Superplasticizer Coarse_Aggrega
te
## 2   540.0                0.0       0   162              2.5           1055
.0
## 6   266.0              114.0       0   228              0.0            932
.0
## 9   266.0              114.0       0   228              0.0            932
.0
## 11  198.6              132.4       0   192              0.0            978
.4
## 12  198.6              132.4       0   192              0.0            978
.4
## 14  190.0              190.0       0   228              0.0            932
.0
##    Fine_Aggregate Age_day Concrete_compressive_strength
## 2           676.0      28                         61.89
## 6           670.0      90                         47.03
## 9           670.0      28                         45.85
## 11          825.5      90                         38.07
## 12          825.5      28                         28.02
## 14          670.0      90                         42.33

nrow(cleaned_data)

## [1] 926
```

```r
#####Install packages#######

library(dplyr)

## Warning: package 'dplyr' was built under R version 4.3.3

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union

library(tidyr)

## Warning: package 'tidyr' was built under R version 4.3.3

library(MASS)

##
## Attaching package: 'MASS'

## The following object is masked from 'package:dplyr':
##
##     select

library(Metrics)

## Warning: package 'Metrics' was built under R version 4.3.3

library(ISLR)

## Warning: package 'ISLR' was built under R version 4.3.3

library(leaps)

## Warning: package 'leaps' was built under R version 4.3.3

library(ggplot2)

## Warning: package 'ggplot2' was built under R version 4.3.3

library(quantmod)

## Warning: package 'quantmod' was built under R version 4.3.3

## Loading required package: xts

## Warning: package 'xts' was built under R version 4.3.3

## Loading required package: zoo
```

```
## Warning: package 'zoo' was built under R version 4.3.3

##
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric

##
## ######################### Warning from 'xts' package ####################
#####
## #
#
## # The dplyr lag() function breaks how base R's lag() function is supposed
to  #
## # work, which breaks lag(my_xts). Calls to lag(my_xts) that you type or
#
## # source() into this session won't work correctly.
#
## #
#
## # Use stats::lag() to make sure you're not using dplyr::lag(), or you can
add #
## # conflictRules('dplyr', exclude = 'lag') to your .Rprofile to stop
#
## # dplyr from breaking base R's lag() function.
#
## #
#
## # Code in packages is not affected. It's protected by R's namespace mechan
ism #
## # Set `options(xts.warn_dplyr_breaks_lag = FALSE)` to suppress this warnin
g.  #
## #
#
## ##############################################################################
#####

##
## Attaching package: 'xts'

## The following objects are masked from 'package:dplyr':
##
##     first, last

## Loading required package: TTR

## Warning: package 'TTR' was built under R version 4.3.3
```

```
## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo
```

```r
library(corrplot)
```

```
## Warning: package 'corrplot' was built under R version 4.3.3
```

```
## corrplot 0.92 loaded
```

```r
library(caTools)
```

```
## Warning: package 'caTools' was built under R version 4.3.3
```

```r
library(car)
```

```
## Warning: package 'car' was built under R version 4.3.3
```

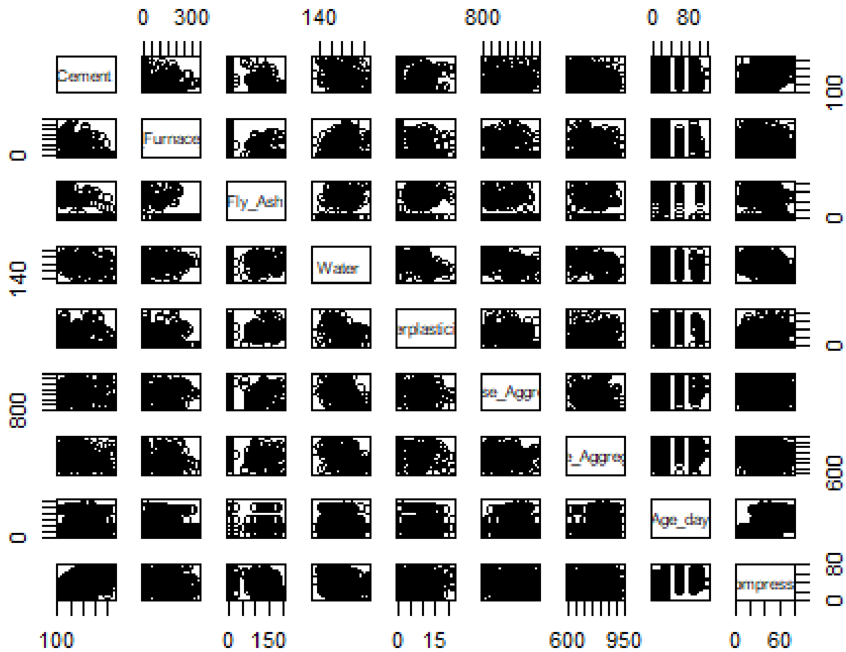
```
## Loading required package: carData
```

```
## Warning: package 'carData' was built under R version 4.3.3
```

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

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

```r
###Scatter plots
pairs(cleaned_data)
```




```r
###Correlations
cor(cleaned_data)
```

```
##                                 Cement Blast_Furnace_Slag     Fly_Ash
## Cement                      1.00000000        -0.26149938 -0.36726110
## Blast_Furnace_Slag         -0.26149938         1.00000000 -0.35142143
## Fly_Ash                    -0.36726110        -0.35142143  1.00000000
## Water                      -0.13551917         0.10569333 -0.22696940
## Superplasticizer            0.05081810         0.05161892  0.44474205
## Coarse_Aggregate           -0.09251497        -0.28998911 -0.04694758
## Fine_Aggregate             -0.21606995        -0.29829372  0.03028820
## Age_day                    -0.04225654        -0.03948894  0.06075860
## Concrete_compressive_strength  0.47948503     0.14567612 -0.05453121
##                                  Water Superplasticizer Coarse_Aggregat
e
## Cement                     -0.13551917       0.05081810      -0.0925149
7
## Blast_Furnace_Slag          0.10569333       0.05161892      -0.2899891
1
## Fly_Ash                    -0.22696940       0.44474205      -0.0469475
8
## Water                       1.00000000      -0.63365330      -0.1967245
5
## Superplasticizer           -0.63365330       1.00000000      -0.2383133
```

```
5
## Coarse_Aggregate             -0.19672455      -0.23831335       1.0000000
0
## Fine_Aggregate               -0.29379741       0.07247323      -0.2124899
5
## Age_day                      -0.03803409       0.05297613       0.0251162
0
## Concrete_compressive_strength -0.39214102       0.40835045      -0.1683218
1
##                               Fine_Aggregate     Age_day
## Cement                           -0.21606995 -0.04225654
## Blast_Furnace_Slag               -0.29829372 -0.03948894
## Fly_Ash                           0.03028820  0.06075860
## Water                            -0.29379741 -0.03803409
## Superplasticizer                  0.07247323  0.05297613
## Coarse_Aggregate                 -0.21248995  0.02511620
## Fine_Aggregate                    1.00000000  0.06241512
## Age_day                           0.06241512  1.00000000
## Concrete_compressive_strength    -0.16321125  0.52132097
##                               Concrete_compressive_strength
## Cement                                           0.47948503
## Blast_Furnace_Slag                               0.14567612
## Fly_Ash                                         -0.05453121
## Water                                           -0.39214102
## Superplasticizer                                 0.40835045
## Coarse_Aggregate                                -0.16832181
## Fine_Aggregate                                  -0.16321125
## Age_day                                          0.52132097
## Concrete_compressive_strength                    1.00000000
```

```r
###All predictors

lm_0<-lm(Concrete_compressive_strength~.,data = cleaned_data)
summary(lm_0)

##
## Call:
## lm(formula = Concrete_compressive_strength ~ ., data = cleaned_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -24.2771  -4.8401  -0.3423   5.3339  31.0682
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)        50.667660  22.544478   2.247   0.0248 *
## Cement              0.101772   0.006980  14.580  < 2e-16 ***
## Blast_Furnace_Slag  0.075480   0.008508   8.872  < 2e-16 ***
## Fly_Ash             0.047830   0.010420   4.590 5.04e-06 ***
## Water              -0.249718   0.034826  -7.170 1.54e-12 ***
## Superplasticizer    0.214624   0.085112   2.522   0.0118 *
## Coarse_Aggregate   -0.010561   0.007881  -1.340   0.1805
## Fine_Aggregate     -0.010882   0.009129  -1.192   0.2336
## Age_day             0.318878   0.009303  34.275  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7.979 on 917 degrees of freedom
## Multiple R-squared:  0.7741, Adjusted R-squared:  0.7722
## F-statistic: 392.9 on 8 and 917 DF,  p-value: < 2.2e-16
```

Interpretation

The model was fitted using the formula:
Concrete_compressive_strength~Cement+Blast_Furnace_Slag+Fly_Ash+Water+Superplasticizer+Coarse_Aggregate+Fine_Aggregate+Age_day

Residuals

The residuals summary indicates the distribution of the differences between the observed and predicted values:

- Minimum Residual: -24.2771
- 1st Quartile: -4.8401
- Median: -0.3423
- 3rd Quartile: 5.3339
- Maximum Residual: 31.0682

Coefficients

The coefficients table provides estimates for each predictor along with their standard errors, t-values, and p-values:

1. **Intercept**: 50.667660
   - Interpretation: When all predictors are at zero, the estimated concrete compressive strength is 50.67 MPa.
   - Significance: p-value = 0.0248, indicating significance at the 5% level.
2. **Cement**: 0.101772
   - Interpretation: For each unit increase in cement, the concrete compressive strength increases by approximately 0.1018 MPa.
   - Significance: Highly significant (p-value < 2e-16).
3. **Blast_Furnace_Slag**: 0.075480
   - Interpretation: For each unit increase in blast furnace slag, the concrete compressive strength increases by approximately 0.0755 MPa.
   - Significance: Highly significant (p-value < 2e-16).
4. **Fly_Ash**: 0.047830
   - Interpretation: For each unit increase in fly ash, the concrete compressive strength increases by approximately 0.0478 MPa.
   - Significance: Highly significant (p-value < 5.04e-06).
5. **Water**: -0.249718
   - Interpretation: For each unit increase in water, the concrete compressive strength decreases by approximately 0.2497 MPa.
   - Significance: Highly significant (p-value < 1.54e-12).
6. **Superplasticizer**: 0.214624
   - Interpretation: For each unit increase in superplasticizer, the concrete compressive strength increases by approximately 0.2146 MPa.
   - Significance: Significant (p-value = 0.0118).
7. **Coarse_Aggregate**: -0.010561
   - Interpretation: For each unit increase in coarse aggregate, the concrete compressive strength decreases by approximately 0.0106 MPa.
   - Significance: Not significant (p-value = 0.1805).

8. **Fine_Aggregate**: -0.010882
    - Interpretation: For each unit increase in fine aggregate, the concrete compressive strength decreases by approximately 0.0109 MPa.
    - Significance: Not significant (p-value = 0.2336).
9. **Age_day**: 0.318878
    - Interpretation: For each day increase in the age of the concrete, the compressive strength increases by approximately 0.3189 MPa.
    - Significance: Highly significant (p-value < 2e-16).

Significance Codes

- *** denotes highly significant (p < 0.001)
- ** denotes significant (0.001 <= p < 0.01)
- * denotes moderately significant (0.01 <= p < 0.05)
- . denotes marginally significant (0.05 <= p < 0.1)
- No symbol indicates not significant (p >= 0.1)

Model Fit

- **Residual Standard Error**: 7.979 on 917 degrees of freedom
- **Multiple R-squared**: 0.7741
- **Adjusted R-squared**: 0.7722
- **F-statistic**: 392.9 on 8 and 917 degrees of freedom
- **Overall Model Significance**: The model is highly significant with a p-value < 2.2e-16, indicating that the predictors jointly have a significant effect on the concrete compressive strength.

The model explains about 77.41% of the variability in concrete compressive strength (R-squared = 0.7741). The significant predictors include cement, blast furnace slag, fly ash, water, superplasticizer, and age of the concrete. Coarse and fine aggregates were not significant predictors in this model. The model's overall F-test indicates it is a good fit for the data.

```r
###Anova test

anova(lm_0)

## Analysis of Variance Table
##
## Response: Concrete_compressive_strength
##                     Df Sum Sq Mean Sq   F value    Pr(>F)
## Cement               1  59427   59427  933.4365 < 2.2e-16 ***
## Blast_Furnace_Slag   1  20386   20386  320.2074 < 2.2e-16 ***
## Fly_Ash              1  25197   25197  395.7750 < 2.2e-16 ***
## Water                1  18760   18760  294.6748 < 2.2e-16 ***
## Superplasticizer     1   1378    1378   21.6523 3.749e-06 ***
## Coarse_Aggregate     1      0       0    0.0019    0.9652
## Fine_Aggregate       1    162     162    2.5388    0.1114
## Age_day              1  74793   74793 1174.7940 < 2.2e-16 ***
## Residuals          917  58380      64
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Interpretation

- **Cement**:
  - Degrees of Freedom (Df): 1
  - Sum of Squares (Sum Sq): 59427
  - Mean Squares (Mean Sq): 59427
  - F value: 933.4365
  - p-value: < 2.2e-16
  - Interpretation: The effect of cement on concrete compressive strength is highly significant, contributing significantly to the model.
- **Blast_Furnace_Slag**:
  - Df: 1
  - Sum Sq: 20386
  - Mean Sq: 20386
  - F value: 320.2074
  - p-value: < 2.2e-16
  - Interpretation: The effect of blast furnace slag on concrete compressive strength is highly significant.
- **Fly_Ash**:

  - Df: 1
  - Sum Sq: 25197
  - Mean Sq: 25197
  - F value: 395.7750
  - p-value: < 2.2e-16
  - Interpretation: The effect of fly ash on concrete compressive strength is highly significant.
- **Water**:
  - Df: 1
  - Sum Sq: 18760
  - Mean Sq: 18760
  - F value: 294.6748
  - p-value: < 2.2e-16
  - Interpretation: The effect of water on concrete compressive strength is highly significant.
- **Superplasticizer**:
  - Df: 1
  - Sum Sq: 1378
  - Mean Sq: 1378
  - F value: 21.6523
  - p-value: 3.749e-06
  - Interpretation: The effect of superplasticizer on concrete compressive strength is significant.
- **Coarse_Aggregate**:
  - Df: 1
  - Sum Sq: 0
  - Mean Sq: 0
  - F value: 0.0019
  - p-value: 0.9652

- Interpretation: The effect of coarse aggregate on concrete compressive strength is not significant.

- **Fine_Aggregate**:
  - Df: 1
  - Sum Sq: 162
  - Mean Sq: 162
  - F value: 2.5388
  - p-value: 0.1114
  - Interpretation: The effect of fine aggregate on concrete compressive strength is not significant.
- **Age_day**:
  - Df: 1
  - Sum Sq: 74793
  - Mean Sq: 74793
  - F value: 1174.7940
  - p-value: < 2.2e-16
  - Interpretation: The effect of age on concrete compressive strength is highly significant.

Residuals

- Degrees of Freedom: 917
- Sum of Squares: 58380
- Mean Squares: 64

The ANOVA table confirms that the predictors Cement, Blast Furnace Slag, Fly Ash, Water, Superplasticizer, and Age_day significantly affect concrete compressive strength, as indicated by their low p-values (< 0.05). The predictors Coarse Aggregate and Fine Aggregate do not have significant effects on the response variable in this model. The high F-values for significant predictors suggest a strong relationship between these predictors and the concrete compressive strength.

```r
#######Model Selection##########

######Forward stepwise Selection#########
fit_frwd<-regsubsets(Concrete_compressive_strength~ .,data = cleaned_data,nvm
ax = 8,method = "forward")
frwd_summary<-summary(fit_frwd)
frwd_summary
```

```
## Subset selection object
## Call: regsubsets.formula(Concrete_compressive_strength ~ ., data = cleaned
_data,
##     nvmax = 8, method = "forward")
## 8 Variables  (and intercept)
##                     Forced in Forced out
## Cement                  FALSE      FALSE
## Blast_Furnace_Slag      FALSE      FALSE
## Fly_Ash                 FALSE      FALSE
## Water                   FALSE      FALSE
## Superplasticizer        FALSE      FALSE
## Coarse_Aggregate        FALSE      FALSE
## Fine_Aggregate          FALSE      FALSE
## Age_day                 FALSE      FALSE
## 1 subsets of each size up to 8
## Selection Algorithm: forward
##          Cement Blast_Furnace_Slag Fly_Ash Water Superplasticizer
## 1  ( 1 ) " "    " "                " "     " "   " "
## 2  ( 1 ) "*"    " "                " "     " "   " "
## 3  ( 1 ) "*"    " "                " "     " "   "*"
## 4  ( 1 ) "*"    "*"                " "     " "   "*"
## 5  ( 1 ) "*"    "*"                " "     "*"   "*"
## 6  ( 1 ) "*"    "*"                "*"     "*"   "*"
## 7  ( 1 ) "*"    "*"                "*"     "*"   "*"
## 8  ( 1 ) "*"    "*"                "*"     "*"   "*"
##          Coarse_Aggregate Fine_Aggregate Age_day
## 1  ( 1 ) " "              " "            "*"
## 2  ( 1 ) " "              " "            "*"
## 3  ( 1 ) " "              " "            "*"
## 4  ( 1 ) " "              " "            "*"
## 5  ( 1 ) " "              " "            "*"
## 6  ( 1 ) " "              " "            "*"
## 7  ( 1 ) "*"              " "            "*"
## 8  ( 1 ) "*"              "*"            "*"
```

```r
##########Find Adj R^2,Cp,BIC,RSS values
criterion<-data.frame(model=1:8,
                      Adj.R2=(frwd_summary$adjr2),
                      Cp=(frwd_summary$cp),
                      BIC=(frwd_summary$bic),
                      RSS=(frwd_summary$rss))
##Add MS_Res
n<-nrow(cleaned_data)
criterion$MS_Res<-criterion$RSS/(n-criterion$model-1)


##Standardize
criterion_std<-cbind(model=criterion$model,scale(criterion[,-1]))
criterion_std<-as.data.frame(criterion_std)

###Values
criterion_std

##   model      Adj.R2          Cp        BIC         RSS      MS_Res
## 1     1 -2.16063154  2.16269269  1.9713194  2.16000747  2.16063154
## 2     2 -0.74498413  0.74272430  0.9651614  0.74539192  0.74498413
## 3     3 -0.03653678  0.03358656  0.2414418  0.03754295  0.03653678
## 4     4  0.42127842 -0.42345558 -0.3789904 -0.41965173 -0.42127842
## 5     5  0.54734332 -0.54821230 -0.5728855 -0.54646078 -0.54734332
## 6     6  0.65821831 -0.65754292 -0.7578819 -0.65793194 -0.65821831
## 7     7  0.65736245 -0.65529905 -0.7411093 -0.65846651 -0.65736245
## 8     8  0.65794994 -0.65449370 -0.7270554 -0.66043137 -0.65794994
```

##Interpretation

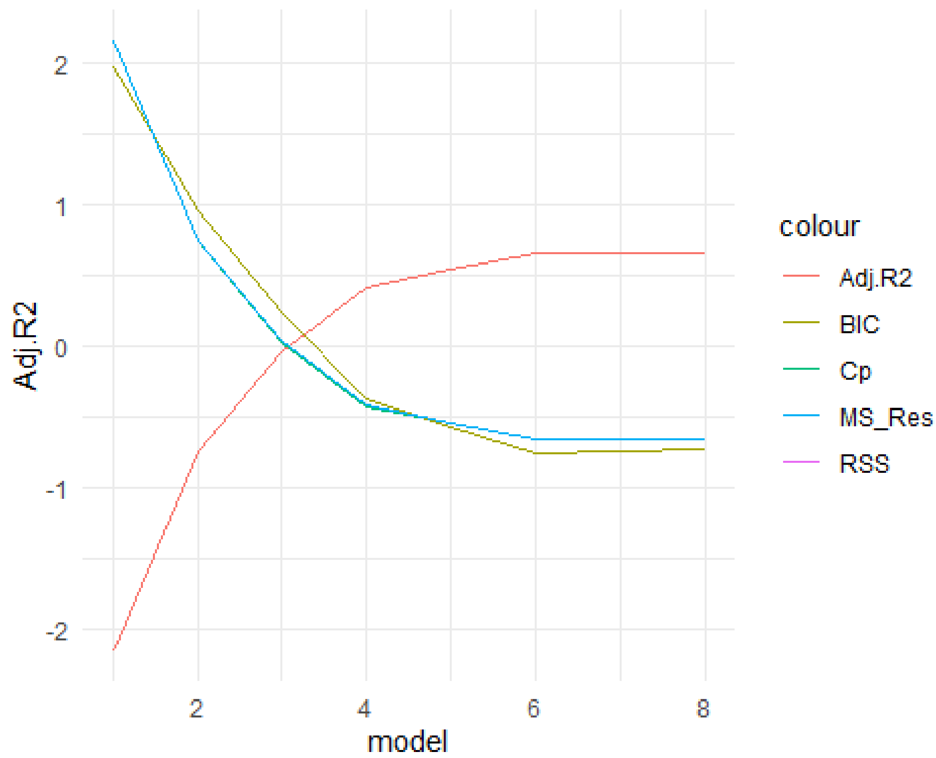
- The procedure starts with no predictor variable in the model.
- At each step, the algorithm evaluates the impact of adding each predictor variable to the current model. It selects the variable that improves the model the most based on a chosen criterion, typically the adjusted R^2, BIC, Cp, and RSS.
- Each predictor is listed, and the “Force in” and “Force out” columns show whether the variables are included or excluded at each step.
- This process repeated, with one variable being added at each step until all variables are considered or no additional variables improve the model sufficiently.
- The first model includes only “Age_day” because its adjusted R^2 has the highest value and BIC, Cp, and RSS have the lowest values.
- The second model includes “`Age_day`” and “`Cement`” variables.
- The third model includes “`Age_day`”, “`Cement`” and “`Superplasticizer`” variables.

- The fourth model includes “Age_day”, “Cement”, “Superplasticizer”, and “Blast_Furnace_Slag” variables.
- The fifth model includes “Age_day”, “Cement”, “Superplasticizer”, “Blast_Furnace_Slag” and “Water” variables.
- The sixth model includes “Age_day”, “Cement”, “Superplasticizer”, “Blast_Furnace_Slag”, “Water” and “Fly_Ash” variables.
- The seventh model includes “Age_day”, “Cement”, “Superplasticizer”, “Blast_Furnace_Slag”, “Water”, “Fly_Ash” and “Coarse_Aggregate” variables.
- The eighth model includes “Age_day”, “Cement”, “Superplasticizer”, “Blast_Furnace_Slag”, “Water”, “Fly_Ash”, “Coarse_Aggregate” and “Fine_Aggregate” variables.
- There are two methods to find the better model

  1) Formal model : Using the values of above criteria, the better model should have maximum value for adjusted R^2 and minimum values for Cp, BIC, RSS and MS_Res. Therefore according to the above values 6th model is the better model.

  2) Graphical method

```
###Graphically
ggplot(criterion_std,aes(model))+
  geom_line(aes(y=Adj.R2,colour="Adj.R2"))+
  geom_line(aes(y=Cp,colour="Cp"))+
  geom_line(aes(y=BIC,colour="BIC"))+
  geom_line(aes(y=RSS,colour="RSS"))+
  geom_line(aes(y=MS_Res,colour="MS_Res"))+
  theme_minimal()
```



- According to the plot, 6th model has maximum value for adjusted R^2 and minimum values for `Cp, BIC, RSS and MS_Res. Therefore 6th model` seems a better model.

```
##coefficients

coef(fit_frwd,6)

##       (Intercept)            Cement Blast_Furnace_Slag            Fly_As
h
##       21.33255752          0.10954513    0.08508131            0.05815821


##              Water    Superplasticizer          Age_day

##       -0.21134494         0.25171136         0.31887795
```

Coefficients

The coefficients table provides estimates for each predictor along with their standard errors, t-values, and p-values:

1. **Intercept**: 21.3326
    - Interpretation: When all predictors are at zero, the estimated concrete compressive strength is 21.3326 MPa.
2. **Cement**: 0.1095
    - Interpretation: For each unit increase in cement, the concrete compressive strength increases by approximately 0.1095 MPa.
3. **Blast_Furnace_Slag**: 0.0851
    - Interpretation: For each unit increase in blast furnace slag, the concrete compressive strength increases by approximately 0.0851 MPa.
4. **Fly_Ash**: 0.05816
    - Interpretation: For each unit increase in fly ash, the concrete compressive strength increases by approximately 0.05816 MPa.
5. **Water**: - 0.2113
    - Interpretation: For each unit increase in water, the concrete compressive strength decreases by approximately 0.2113 MPa.
6. **Superplasticizer**: 0.2517
    - Interpretation: For each unit increase in superplasticizer, the concrete compressive strength increases by approximately 0.2517 MPa.

7. **Age_day**: 0.31788

   - Interpretation: For each day increase in the age of the concrete, the compressive strength increases by approximately 0.31788 MPa.

Final Better Model

```
better_model_final<-lm(Concrete_compressive_strength~Cement+Blast_Furnace_Sla
g+Fly_Ash+Water+Superplasticizer+Age_day,data = cleaned_data)

summary(better_model_final)
```


```
better_model_final<-lm(Concrete_compressive_strength~Cement+Blast_Furnace_Sla
g+Fly_Ash+Water+Superplasticizer+Age_day,data = cleaned_data)
summary(better_model_final)
```


```
##
## Call:
## lm(formula = Concrete_compressive_strength ~ Cement + Blast_Furnace_Slag +
##     Fly_Ash + Water + Superplasticizer + Age_day, data = cleaned_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -24.5282  -4.9021  -0.2091   5.1402  31.1895
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)        21.332558   3.910394   5.455 6.29e-08 ***
## Cement              0.109545   0.003442  31.823  < 2e-16 ***
## Blast_Furnace_Slag  0.085081   0.004098  20.763  < 2e-16 ***
## Fly_Ash             0.058158   0.006477   8.979  < 2e-16 ***
## Water              -0.211345   0.019558 -10.806  < 2e-16 ***
## Superplasticizer    0.251711   0.078845   3.192  0.00146 **
## Age_day             0.317881   0.009270  34.290  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7.978 on 919 degrees of freedom
## Multiple R-squared:  0.7737, Adjusted R-squared:  0.7722
## F-statistic: 523.7 on 6 and 919 DF,  p-value: < 2.2e-16
```

###Interpretation Now all are the significant.

*Residual Standard Error (RSE)

This indicates that the average distance of the observed values from the predicted values is about 7.978 units of Concrete Compressive Strength. A lower RSE suggests a better fit of the model to the data.

*R-Squared

Approximately 77.37% of the variability in Concrete Compressive Strength can be explained by the model that includes cement, Blast furnace slag, fly ash, water, superplasticizer, age day.

*Adjusted R-Squared

An adjusted R-Squared of 77.22% indicates that the model still explains a substantial amount of variance in Concrete Compressive Strength consider the number of predictors.

H0: The regression model is not significant.

H1: The regression model is significant.

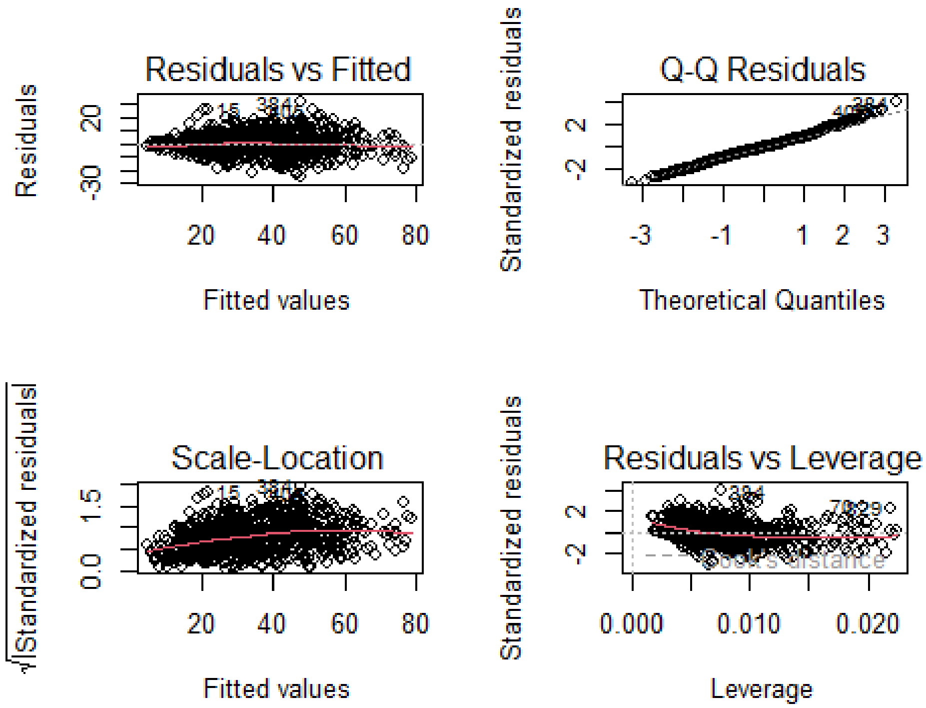
$F_{0.05, 6, 919} = 2.108$

F-Statistic = 523.7 > 2.108

We have sufficient evidence to reject the null hypothesis. Concluding that at least one of the predictors in the model significantly contributes to explaining the variability the variability in Concrete Compressive Strength.

```r
#######Residual plots for better model######

par(mfrow=c(2,2))
plot(better_model_final)
```



Interpretation

Residuals vs. Fitted Values (Top Left)

- Purpose: To check for non-linearity, unequal error variances (heteroscedasticity), and outliers.
- Interpretation: The residuals appear to be randomly scattered around the horizontal axis (y=0), suggesting that the linearity assumption is reasonable. However, the spread of residuals increases slightly as the fitted values increase, indicating some heteroscedasticity. This means that the variance of the residuals may not be constant across all levels of the fitted values.

Normal Q-Q Plot (Top Right)

- Purpose: To check if the residuals are normally distributed.

- Interpretation: The points on the Q-Q plot fall approximately along the reference line, suggesting that the residuals are roughly normally distributed. Some deviations at the tails might be observed, but they do not appear to be severe.

 Scale-Location Plot (Bottom Left)

- Purpose: To check for homoscedasticity (constant variance of residuals).
- Interpretation: The plot shows the square root of the standardized residuals against the fitted values. The residuals should be spread equally along the range of predictors for homoscedasticity. The slightly increasing trend suggests some degree of heteroscedasticity, meaning that the variance of the residuals might be increasing with the fitted values.

 Residuals vs. Leverage Plot (Bottom Right)

- Purpose: To identify influential data points that might unduly influence the model.
- Interpretation: This plot helps to find points with high leverage (influential points). The presence of points outside the red dashed lines (Cook's distance) indicates influential observations. In this plot, there do not appear to be any points that are significantly outside these lines, suggesting no highly influential data points.

```
##########Multicollinearity############

vif_values<-vif(better_frwd)
vif_values
```

```
     Cement Blast_Furnace_Slag          Fly_Ash
   1.772522           1.819121         2.532652
      Water   Superplasticizer          Age_day
   1.780078           2.560688         1.008229
```

Interpretation

All vif values are lower than 5. Therefore $VIF < 5$,then there is no problem with multicollinearity.