```
data=read.csv(file.choose(), header = T)
 head(data)
               X1 X2
                              X3 X4
 ## 1 1 2012.917 32.0 84.87882 10 24.98298 121.5402 37.9
 ## 2 2 2012.917 19.5 306.59470 9 24.98034 121.5395 42.2
 ## 3 3 2013.583 13.3 561.98450 5 24.98746 121.5439 47.3
 ## 4 4 2013.500 13.3 561.98450 5 24.98746 121.5439 54.8
 ## 5 5 2012.833 5.0 390.56840 5 24.97937 121.5425 43.1
 ## 6 6 2012.667 7.1 2175.03000 3 24.96305 121.5125 32.1
 str(data)
 ## 'data.frame': 414 obs. of 8 variables:
 ## $ No: int 1 2 3 4 5 6 7 8 9 10 ...
 ## $ X1: num 2013 2013 2014 2014 2013 ...
 ## $ X2: num 32 19.5 13.3 13.3 5 7.1 34.5 20.3 31.7 17.9 ...
 ## $ X3: num 84.9 306.6 562 562 390.6 ...
 ## $ X4: int 10 9 5 5 5 3 7 6 1 3 ...
 ## $ X5: num 25 25 25 25 ...
 ## $ X6: num 122 122 122 122 ...
 ## $ Y : num 37.9 42.2 47.3 54.8 43.1 32.1 40.3 46.7 18.8 22.1 ...
 names(data)
 ## [1] "No" "X1" "X2" "X3" "X4" "X5" "X6" "Y"
 dim(data)
 ## [1] 414 8
To check if NA values is present or not in the dataset
 sum(is.na(data))
 ## [1] 0
Correlation Matrix
 cor(data)
                                        X2
 ## No 1.000000000 -0.048657949 -0.03280811 -0.01357349 -0.012698946 -0.01010966
 ## X1 -0.04865795 1.000000000 0.01754877 0.06087995 0.009635445 0.03505776
 ## X2 -0.03280811 0.017548767 1.000000000 0.02562205 0.049592513 0.05441990
 ## X3 -0.01357349 0.060879953 0.02562205 1.000000000 -0.602519145 -0.59106657
 ## X4 -0.01269895 0.009635445 0.04959251 -0.60251914 1.000000000 0.44414331
 ## X5 -0.01010966 0.035057756 0.05441990 -0.59106657 0.444143306 1.00000000
 ## X6 -0.01105928 -0.041081778 -0.04852005 -0.80631677 0.449099007 0.41292394
 ## Y -0.02858717 0.087490606 -0.21056705 -0.67361286 0.571004911 0.54630665
               Х6
 ## No -0.01105928 -0.02858717
 ## X1 -0.04108178 0.08749061
 ## X2 -0.04852005 -0.21056705
 ## X3 -0.80631677 -0.67361286
 ## X4 0.44909901 0.57100491
 ## X5 0.41292394 0.54630665
 ## X6 1.00000000 0.52328651
 ## Y 0.52328651 1.00000000
Correlation Plot
 library(corrplot)
 ## Warning: package 'corrplot' was built under R version 4.1.2
 ## corrplot 0.92 loaded
 library(ggplot2)
 ## Warning: package 'ggplot2' was built under R version 4.1.2
 library(ggfortify)
 ## Warning: package 'ggfortify' was built under R version 4.1.2
 corrplot(cor(data), type = "upper", method="circle",
          mar=c(0.7, 0.7, 0.7, 0.7), tl.cex = 0.6)
                                                                     0.6
                                                                     0.4
                                                                     0.2
                                                                    -0.4
Regression Model
 model1=lm(Y~.~,~data=data)
 summary(model1)
 ##
 ## Call:
 ## lm(formula = Y \sim ., data = data)
 ##
 ## Residuals:
                1Q Median 3Q
       Min
 ## -36.003 -5.196 -0.990 4.181 75.384
 ## Coefficients:
 ##
                 Estimate Std. Error t value Pr(>|t|)
 ## (Intercept) -1.404e+04 6.788e+03 -2.068 0.03927 *
               -3.593e-03 3.653e-03 -0.984 0.32590
 ## No
                5.079e+00 1.559e+00 3.259 0.00121 **
 ## X1
               -2.708e-01 3.855e-02 -7.026 9.04e-12 ***
 ## X2
               -4.521e-03 7.189e-04 -6.289 8.28e-10 ***
 ## X3
            1.129e+00 1.882e-01 6.000 4.37e-09 ***
 ## X4
             2.247e+02 4.458e+01 5.040 7.02e-07 ***
 ## X5
               -1.442e+01 4.863e+01 -0.297 0.76691
 ## X6
 ## ---
 ## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
 ## Residual standard error: 8.858 on 406 degrees of freedom
 ## Multiple R-squared: 0.5834, Adjusted R-squared: 0.5762
 ## F-statistic: 81.21 on 7 and 406 DF, p-value: < 2.2e-16
 From the above model we can see that variable No and X6 are insignificant, as there P Value is not less than 0.0
 5. So we remove those variables and run the model again
 model2=lm(Y \sim .-No -X6 , data = data)
 summary(model2)
 ##
 ## Call:
 ## lm(formula = Y \sim . - No - X6, data = data)
 ##
 ## Residuals:
 ## Min 1Q Median 3Q
                                       Max
 ## -35.623 -5.371 -1.020 4.244 75.346
 ##
 ## Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
 ## (Intercept) -1.596e+04 3.233e+03 -4.936 1.17e-06 ***
 ## X1
               5.135e+00 1.555e+00 3.303 0.00104 **
 ## X2
               -2.694e-01 3.847e-02 -7.003 1.04e-11 ***
 ## X3
               -4.353e-03 4.899e-04 -8.887 < 2e-16 ***
            1.136e+00 1.876e-01 6.056 3.17e-09 ***
 ## X4
 ## X5
              2.269e+02 4.417e+01 5.136 4.36e-07 ***
 ## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
 ## Residual standard error: 8.848 on 408 degrees of freedom
 ## Multiple R-squared: 0.5823, Adjusted R-squared: 0.5772
 ## F-statistic: 113.8 on 5 and 408 DF, p-value: < 2.2e-16
Checking The Assumption Of MLR Model
 library(tidyverse)
 ## Warning: package 'tidyverse' was built under R version 4.1.2
 ## -- Attaching packages -----
                                       ----- tidyverse 1.3.1 --
 ## v tibble 3.1.5
                       v dplyr 1.0.7
 ## v tidyr 1.1.4
                       v stringr 1.4.0
 ## v readr 2.0.2
                       v forcats 0.5.1
 ## v purrr 0.3.4
 ## -- Conflicts ----- tidyverse_conflicts() --
 ## x dplyr::filter() masks stats::filter()
 ## x dplyr::lag() masks stats::lag()
 library(ggplot2)
 library(ggfortify)
 autoplot(model2)
                                               Normal Q-Q
      Residuals vs Fitted
   80 -
                              271
                                                                                271
                                           Standardized residuals
                                              144
   -40 -
                  20
                              40
                  Fitted values
                                                        Theoretical Quantiles
     Scale-Location
                                               Residuals vs Leverage
ViStandardized residuals
                                                  271
                                          Standardized Residuals
                                                                        0.09
                 20
                             40
                                               0.00
                                                       0.03
                                                                0.06
                                                                                 0.12
                  Fitted values
                                                             Leverage
Multicollinearity
To Check Multicollinearity using VIF function
 library(car)
 ## Loading required package: carData
 ## Attaching package: 'car'
 ## The following object is masked from 'package:dplyr':
 ##
        recode
 ## The following object is masked from 'package:purrr':
 ##
 ##
        some
 vif(model2)
                           Х3
          X1
                  X2
                                    X4
                                             X5
 ## 1.013834 1.013243 2.016855 1.611299 1.585635
Autocorrelation
To check autocorrelation we use Durbin Watson Test
 durbinWatsonTest(model2)
 ## lag Autocorrelation D-W Statistic p-value
 ## 1 -0.07998669 2.154158 0.128
 ## Alternative hypothesis: rho != 0
Heteroscedasticity
To check heteroscedasticity we use breusch pagan godfrey test
 library(lmtest)
 ## Warning: package 'lmtest' was built under R version 4.1.2
 ## Loading required package: zoo
 ## Warning: package 'zoo' was built under R version 4.1.2
 ## Attaching package: 'zoo'
 ## The following objects are masked from 'package:base':
 ##
       as.Date, as.Date.numeric
 bptest(model2)
 ## studentized Breusch-Pagan test
 ## data: model2
 ## BP = 5.7624, df = 5, p-value = 0.33
Multivariate Normality
To check normality we use kolmogorov smirnov normality test
 library(nortest)
 lillie.test(residuals(model2))
 ##
     Lilliefors (Kolmogorov-Smirnov) normality test
 ##
 ## data: residuals(model2)
 ## D = 0.078433, p-value = 2.105e-06
 From the above analysis we can see that the assumption of linearity and normality is violated. So we can fix this
 error by removing outliers and adding those variables in the model whose having high correlation among them
Remove outliers
 data=data[-c(345,313,271,229),]
Final Model
 model3=lm(Y \sim .-No-X6+X4:X3+X5:X3 , data = data )
 summary(model3)
 ##
 ## Call:
 ## lm(formula = Y \sim . - No - X6 + X4:X3 + X5:X3, data = data)
 ## Residuals:
 ##
        Min
                1Q Median
                                3Q
 ## -33.496 -4.411 -0.537 3.674 31.438
 ## Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
 ## (Intercept) -2.010e+04 2.837e+03 -7.086 6.24e-12 ***
 ## X1
                4.587e+00 1.257e+00 3.648 0.000299 ***
 ## X2
               -2.888e-01 3.117e-02 -9.266 < 2e-16 ***
               2.920e+00 6.623e-01 4.408 1.34e-05 ***
 ## X3
 ## X4
              1.430e+00 1.789e-01 7.995 1.39e-14 ***
               4.368e+02 5.236e+01 8.342 1.18e-15 ***
 ## X5
 ## X3:X4
               -1.200e-03 2.287e-04 -5.246 2.52e-07 ***
               -1.171e-01 2.654e-02 -4.412 1.32e-05 ***
 ## X3:X5
 ## ---
 ## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
 ## Residual standard error: 7.11 on 402 degrees of freedom
 ## Multiple R-squared: 0.7029, Adjusted R-squared: 0.6978
```

Residuals

Regression Modeling of Real Estate Data

Name of Dataset :- Real Estate data

4) X4 number of convenience stores

7) Y house price of unit area

3) X3 distance to the nearest MRT station

1) X1 transaction date (Date at which home is bought) 2) X2 house age (age of house from when it was built)

Source :- https://www.kaggle.com/dcw8161/real-estate-priceprediction/data

5) X5 latitude (represents the geographical position of property) 6) X6 longitude (represents geographical position of property)

Mayur Nagare

All About Dataset

Variables :-

Import Dataset

MSc Part II

Standardized residuals -5.0 **-144** 60 Theoretical Quantiles Fitted values Residuals vs Leverage Scale-Location 221 √|Standardized residuals| - 0.0 - 0 Standardized Residuals -5.0 60 0.2 0.6 0.0 0.4 Fitted values Leverage Conclusion Of The Final Model 1. R-squared Value Of Our Final Model Is 70.29%. 2. From The Residual Vs Fitted Graph We Can See That The Estimated Error Curve Of Our Final Model Is Almost Converge To 3. From The QQ-plot We Can See That The Our Model Behaves Like Normal Except For The Tail Parts. 4. Data Is Homoscedastic.

F-statistic: 135.9 on 7 and 402 DF, p-value: < 2.2e-16

Normal Q-Q

autoplot(model3)

Residuals

-20 -

Residuals vs Fitted