Linear_model

2024-05-27

Using diamonds as example

```
head(diamonds)
```

```
## # A tibble: 6 x 10
##   carat cut       color clarity depth table price     x     y     z
##   <dbl> <ord>     <ord> <ord>   <dbl> <dbl> <int> <dbl> <dbl> <dbl>
## 1  0.23 Ideal     E     SI2      61.5    55   326  3.95  3.98  2.43
## 2  0.21 Premium   E     SI1      59.8    61   326  3.89  3.84  2.31
## 3  0.23 Good      E     VS1      56.9    65   327  4.05  4.07  2.31
## 4  0.29 Premium   I     VS2      62.4    58   334  4.2   4.23  2.63
## 5  0.31 Good      J     SI2      63.3    58   335  4.34  4.35  2.75
## 6  0.24 Very Good J     VVS2     62.8    57   336  3.94  3.96  2.48
```

```
str(diamonds)
```

```
## tibble [53,940 x 10] (S3: tbl_df/tbl/data.frame)
##  $ carat  : num [1:53940] 0.23 0.21 0.23 0.29 0.31 0.24 0.24 0.26 0.22 0.23 ...
##  $ cut    : Ord.factor w/ 5 levels "Fair"<"Good"<..: 5 4 2 4 2 3 3 3 1 3 ...
##  $ color  : Ord.factor w/ 7 levels "D"<"E"<"F"<"G"<..: 2 2 2 6 7 7 6 5 2 5 ...
##  $ clarity: Ord.factor w/ 8 levels "I1"<"SI2"<"SI1"<..: 2 3 5 4 2 6 7 3 4 5 ...
##  $ depth  : num [1:53940] 61.5 59.8 56.9 62.4 63.3 62.8 62.3 61.9 65.1 59.4 ...
##  $ table  : num [1:53940] 55 61 65 58 58 57 57 55 61 61 ...
##  $ price  : int [1:53940] 326 326 327 334 335 336 336 337 337 338 ...
##  $ x      : num [1:53940] 3.95 3.89 4.05 4.2 4.34 3.94 3.95 4.07 3.87 4 ...
##  $ y      : num [1:53940] 3.98 3.84 4.07 4.23 4.35 3.96 3.98 4.11 3.78 4.05 ...
##  $ z      : num [1:53940] 2.43 2.31 2.31 2.63 2.75 2.48 2.47 2.53 2.49 2.39 ...
```

```
anyNA(diamonds)
```

```
## [1] FALSE
```

```
diamonds_no_na <- na.omit(diamonds)
anyDuplicated(diamonds)
```

```
## [1] 1006
```

```
diamonds_unique <- diamonds[!duplicated(diamonds), ]
```

Select data for lm

We want know the linear relationship in carat and price and is it influenced by cut.
So cut = ideal and fair selected

```
data_ideal <- subset(diamonds, cut == "Ideal")[ , c("carat", "price")]
data_fair <- subset(diamonds, cut == "Fair")[ , c("carat", "price")]
head(data_fair)
```

```
## # A tibble: 6 x 2
##   carat price
##   <dbl> <int>
## 1  0.22   337
## 2  0.86  2757
## 3  0.96  2759
## 4  0.7   2762
## 5  0.7   2762
## 6  0.91  2763
```

Firstly caculating the correlation of carat and price in both cut quality

```
correlation_ideal <- cor.test(data_ideal$carat,data_ideal$price, use = "complete.obs")
correlation_fair <- cor.test(data_fair$carat,data_fair$price, use = "complete.obs")
print(correlation_ideal)
```

```
##
##  Pearson's product-moment correlation
##
## data:  data_ideal$carat and data_ideal$price
## t = 374.94, df = 21549, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.9293791 0.9329287
## sample estimates:
##      cor
## 0.931176
```

```
print(correlation_fair)
```

```
##
##  Pearson's product-moment correlation
##
## data:  data_fair$carat and data_fair$price
## t = 67.369, df = 1608, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.8459582 0.8715640
## sample estimates:
##       cor
## 0.8592985
```

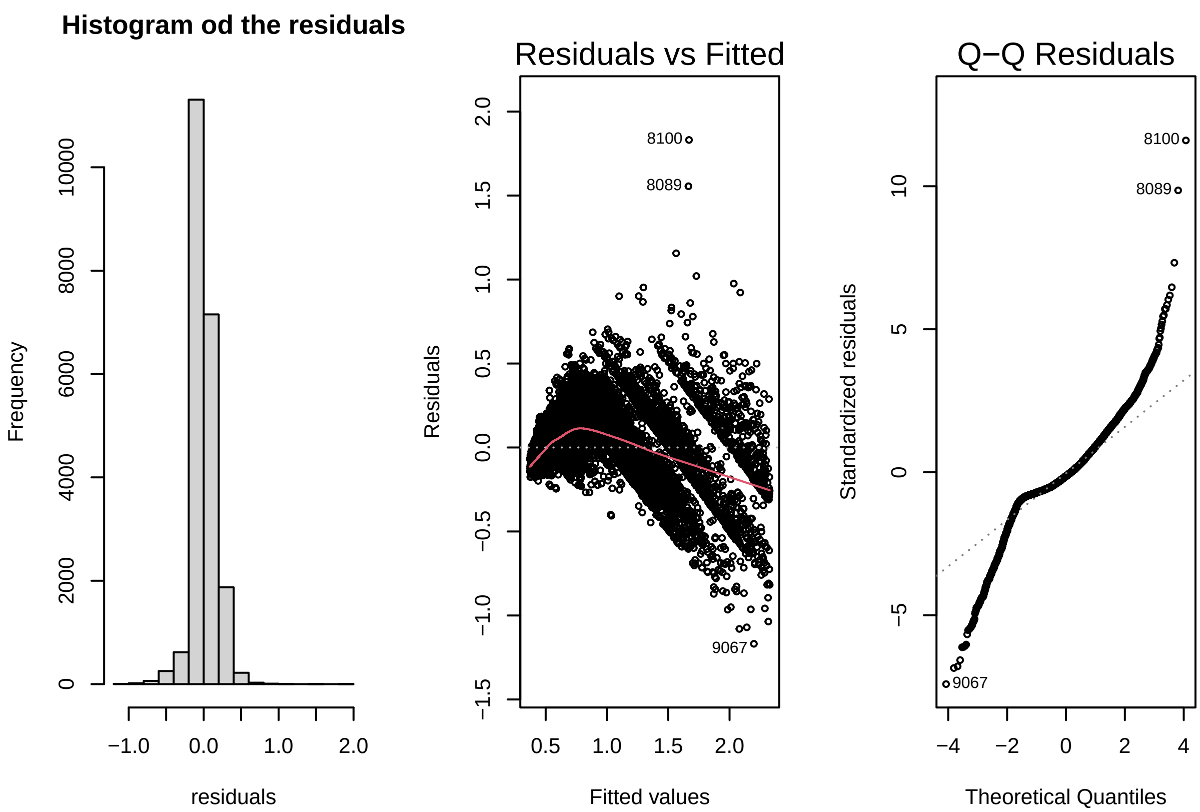
Both value greater than 0.85 and it can said that in two different cuts, there is an linear relationship exists.

Model building and Evaluation

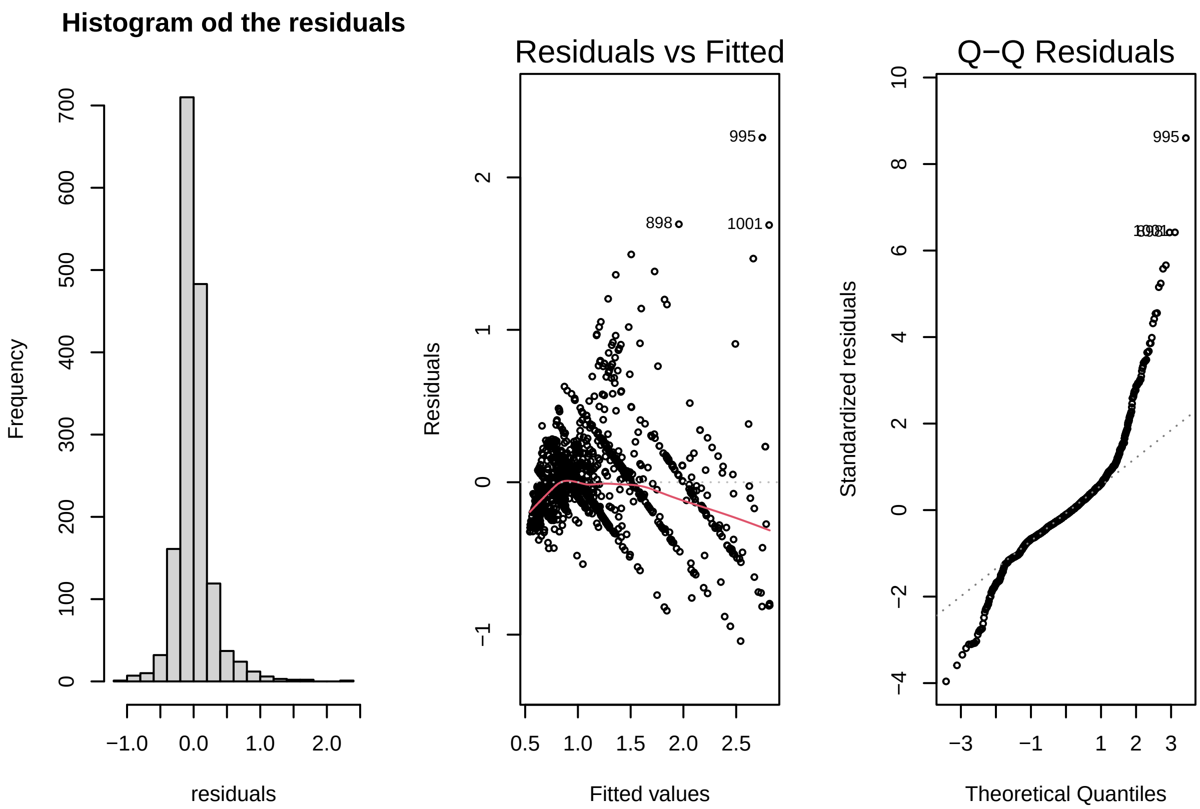
```
model_ideal <- lm(data_ideal$carat ~ data_ideal$price)
model_fair <- lm(data_fair$carat ~ data_fair$price)
```

Evaluate

```
#For ideal
par(mfrow = c(1,3))
hist(residuals((model_ideal),breaks = 5, col = "grey"),
     main = "Histogram od the residuals", xlab = "residuals", cex = 0.6)
plot(model_ideal, which= c(1,2), cex = 0.6)
```




```
#For fair
par(mfrow = c(1,3))
hist(residuals((model_fair),breaks = 5, col = "grey"),
     main = "Histogram od the residuals", xlab = "residuals", cex = 0.6)
plot(model_fair, which= c(1,2), cex = 0.6)
```



Normality: The histogram of the residuals is bell-shaped and the points on the Q-Q plot are distributed roughly along the 45-degree diagonal, indicating that the residuals are approximately normally distributed.

Independence and homoscedasticity: The plots of fitted values and residuals show that there is no clear pattern or correlation between the residuals, and that the residuals are uniformly distributed above and below the zero line.

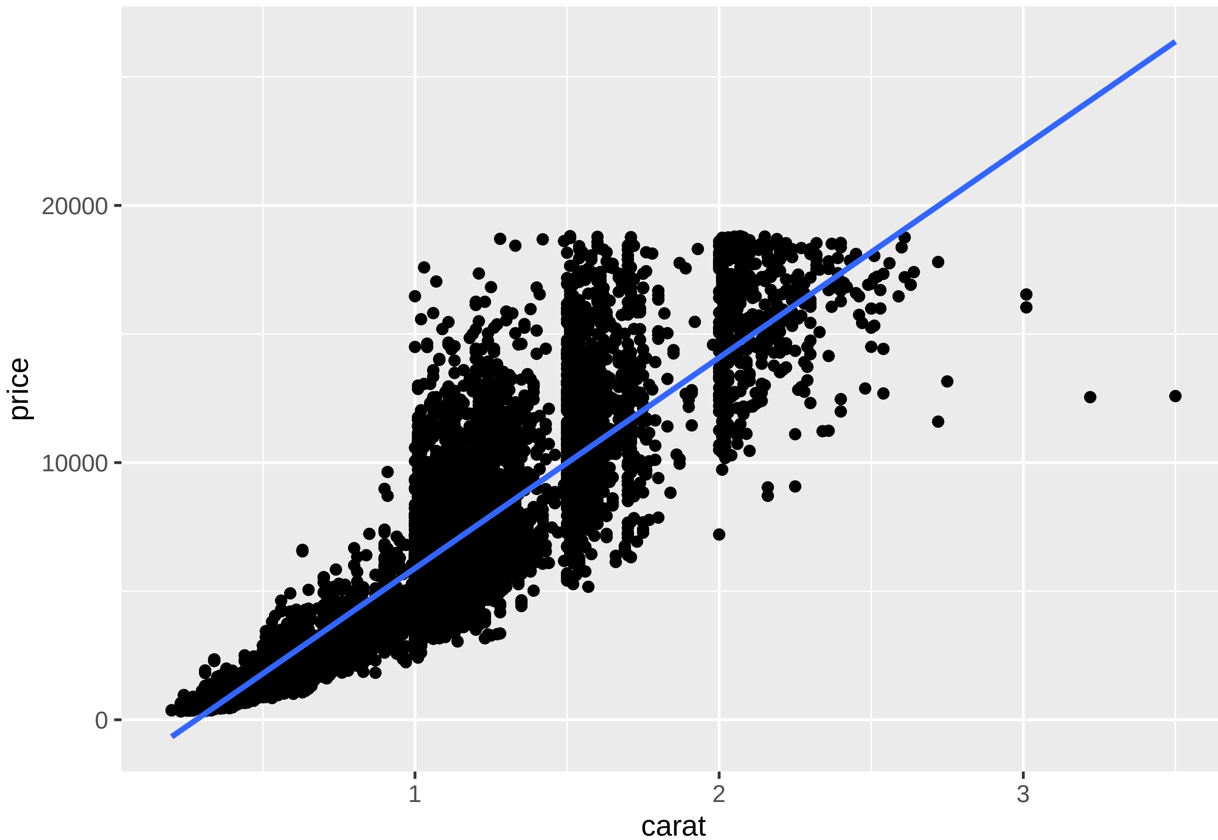
Linearity: The absence of curvilinear trends in the plots of fitted values versus residuals indicates that the model captures a linear relationship in the data.

Visulizaton

```
library(ggplot2)
p <- ggplot(data_ideal, aes(x = carat, y = price))
p <- p + geom_point()
p <- p + geom_smooth(method = "lm", se = FALSE)
print(p)
```

Only one group

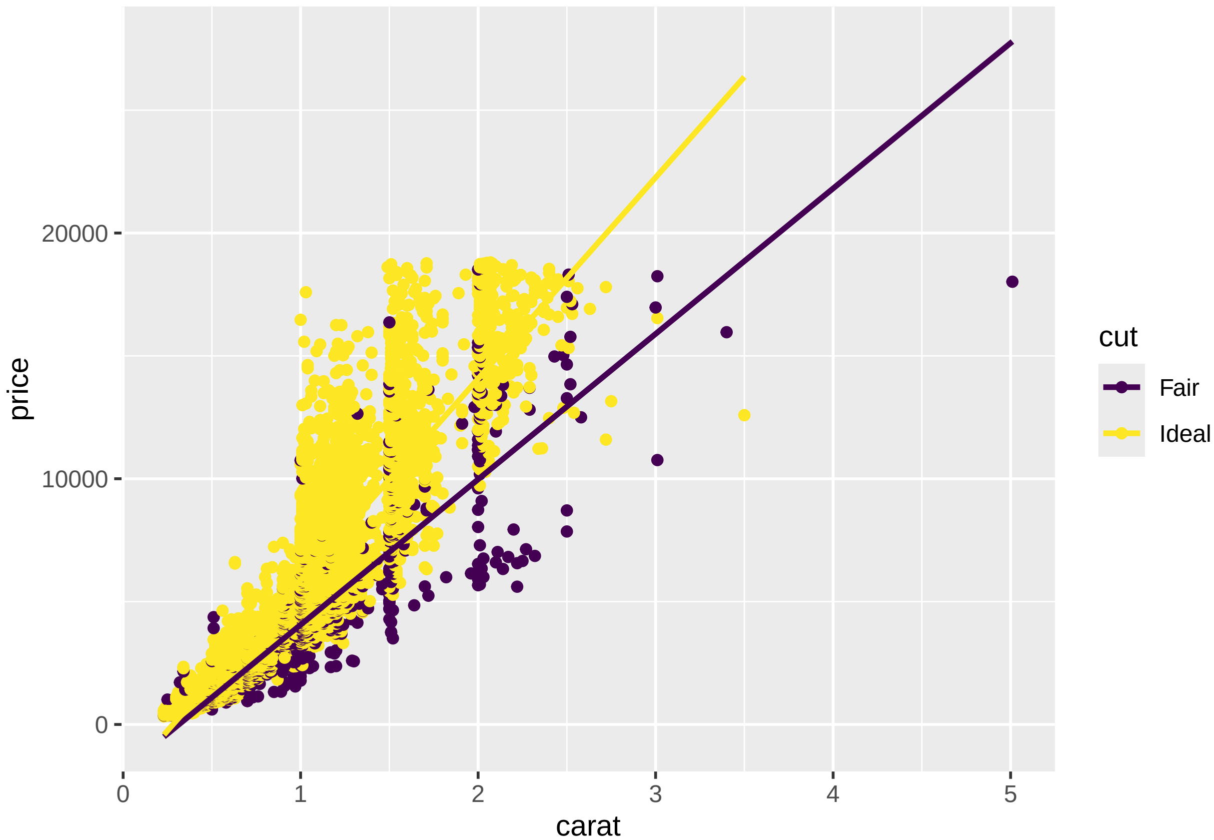
```
## `geom_smooth()` using formula = 'y ~ x'
```




```r
data_selected <- subset(diamonds, cut == c("Ideal","Fair"))[ , c("carat", "price","cut")]
p <- ggplot(data_selected, aes(x = carat, y = price, color = cut))
p <- p + geom_point()
p <- p + geom_smooth(method = "lm", se = FALSE)
print(p)
```

Two group need in one data frame

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



Calculate Z score

Next, z score is calculated to determine whether the slop of two fitted lines are significantly differently.
H0: There is no difference between the two correlation coefficients.
H1: There is significant difference between the two correlation coefficients.

```r
# Extract regression coefficients and standard errors
beta1 <- summary(model_ideal)$coefficients["data_ideal$price", "Estimate"]

## price is x intercept is 0.33

se_beta1 <- summary(model_ideal)$coefficients["data_ideal$price", "Std. Error"]
beta2 <- summary(model_fair)$coefficients["data_fair$price", "Estimate"]
se_beta2 <- summary(model_fair)$coefficients["data_fair$price", "Std. Error"]
# Calculate z-score
z <- (beta1 - beta2) / sqrt(se_beta1^2 + se_beta2^2)
print(z) # badly
```

```
## [1] -10.04229
```

Here, **z is greater than 1.96 (significance level 0.05), indicating a significant difference between the two correlation coefficients, so we reject H0.** This suggests that there is a gender difference in the impact of drug addiction, with males being more affected and having a higher growth rate.