

Actividad Integradora 2

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```
# Carga de datos
data = read.csv("C:\\Users\\jcsg6\\Downloads\\precios_autos.csv")
group_data = subset(data, select = c("symboling", "CarName", "fueltype",
"wheelbase", "horsepower", "price"))
group_data = data.frame(group_data)
```

```
# Gas = 1, Diesel = 0
group_data$fueltype = ifelse(group_data$fueltype == "gas", 1, 0)
group_data
```

```
##      symboling      CarName fueltype wheelbase
horsepower
## 1           3      alfa-romero giulia         1      88.6
111
## 2           3      alfa-romero stelvio         1      88.6
111
## 3           1      alfa-romero Quadrifoglio         1      94.5
154
## 4           2          audi 100 ls         1      99.8
102
## 5           2          audi 100ls         1      99.4
115
## 6           2          audi fox         1      99.8
110
## 7           1          audi 100ls         1     105.8
110
## 8           1          audi 5000         1     105.8
110
## 9           1          audi 4000         1     105.8
140
## 10          0      audi 5000s (diesel)         1      99.5
160
## 11          2          bmw 320i         1     101.2
101
## 12          0          bmw 320i         1     101.2
101
## 13          0          bmw x1         1     101.2
121
## 14          0          bmw x3         1     101.2
121
## 15          1          bmw z4         1     103.5
121
```

## 16	0	bmw x4	1	103.5
182				
## 17	0	bmw x5	1	103.5
182				
## 18	0	bmw x3	1	110.0
182				
## 19	2	chevrolet impala	1	88.4
48				
## 20	1	chevrolet monte carlo	1	94.5
70				
## 21	0	chevrolet vega 2300	1	94.5
70				
## 22	1	dodge rampage	1	93.7
68				
## 23	1	dodge challenger se	1	93.7
68				
## 24	1	dodge d200	1	93.7
102				
## 25	1	dodge monaco (sw)	1	93.7
68				
## 26	1	dodge colt hardtop	1	93.7
68				
## 27	1	dodge colt (sw)	1	93.7
68				
## 28	1	dodge coronet custom	1	93.7
102				
## 29	-1	dodge dart custom	1	103.3
88				
## 30	3	dodge coronet custom (sw)	1	95.9
145				
## 31	2	honda civic	1	86.6
58				
## 32	2	honda civic cvcc	1	86.6
76				
## 33	1	honda civic	1	93.7
60				
## 34	1	honda accord cvcc	1	93.7
76				
## 35	1	honda civic cvcc	1	93.7
76				
## 36	0	honda accord lx	1	96.5
76				
## 37	0	honda civic 1500 gl	1	96.5
76				
## 38	0	honda accord	1	96.5
86				
## 39	0	honda civic 1300	1	96.5
86				
## 40	0	honda prelude	1	96.5
86				

## 41 86	0	honda accord	1	96.5
## 42 101	0	honda civic	1	96.5
## 43 100	1	honda civic (auto)	1	96.5
## 44 78	0	isuzu MU-X	1	94.3
## 45 70	1	isuzu D-Max	1	94.5
## 46 70	0	isuzu D-Max V-Cross	1	94.5
## 47 90	2	isuzu D-Max	1	96.0
## 48 176	0	jaguar xj	1	113.0
## 49 176	0	jaguar xf	1	113.0
## 50 262	0	jaguar xk	1	102.0
## 51 68	1	maxda rx3	1	93.1
## 52 68	1	maxda glc deluxe	1	93.1
## 53 68	1	mazda rx2 coupe	1	93.1
## 54 68	1	mazda rx-4	1	93.1
## 55 68	1	mazda glc deluxe	1	93.1
## 56 101	3	mazda 626	1	95.3
## 57 101	3	mazda glc	1	95.3
## 58 101	3	mazda rx-7 gs	1	95.3
## 59 135	3	mazda glc 4	1	95.3
## 60 84	1	mazda 626	1	98.8
## 61 84	0	mazda glc custom l	1	98.8
## 62 84	1	mazda glc custom	1	98.8
## 63 84	0	mazda rx-4	1	98.8
## 64 64	0	mazda glc deluxe	0	98.8
## 65 84	0	mazda 626	1	98.8

## 66 120	0	mazda glc	1	104.9
## 67 72	0	mazda rx-7 gs	0	104.9
## 68 123	-1	buick electra 225 custom	0	110.0
## 69 123	-1	buick century luxus (sw)	0	110.0
## 70 123	0	buick century	0	106.7
## 71 123	-1	buick skyhawk	0	115.6
## 72 155	-1	buick opel isuzu deluxe	1	115.6
## 73 155	3	buick skylark	1	96.6
## 74 184	0	buick century special	1	120.9
## 75 184	1	buick regal sport coupe (turbo)	1	112.0
## 76 175	1	mercury cougar	1	102.7
## 77 68	2	mitsubishi mirage	1	93.7
## 78 68	2	mitsubishi lancer	1	93.7
## 79 68	2	mitsubishi outlander	1	93.7
## 80 102	1	mitsubishi g4	1	93.0
## 81 116	3	mitsubishi mirage g4	1	96.3
## 82 88	3	mitsubishi g4	1	96.3
## 83 145	3	mitsubishi outlander	1	95.9
## 84 145	3	mitsubishi g4	1	95.9
## 85 145	3	mitsubishi mirage g4	1	95.9
## 86 88	1	mitsubishi montero	1	96.3
## 87 88	1	mitsubishi pajero	1	96.3
## 88 116	1	mitsubishi outlander	1	96.3
## 89 116	-1	mitsubishi mirage g4	1	96.3
## 90 69	1	Nissan versa	1	94.5

## 91	1	nissan gt-r	0	94.5
55				
## 92	1	nissan rogue	1	94.5
69				
## 93	1	nissan latio	1	94.5
69				
## 94	1	nissan titan	1	94.5
69				
## 95	1	nissan leaf	1	94.5
69				
## 96	1	nissan juke	1	94.5
69				
## 97	1	nissan latio	1	94.5
69				
## 98	1	nissan note	1	94.5
69				
## 99	2	nissan clipper	1	95.1
69				
## 100	0	nissan rogue	1	97.2
97				
## 101	0	nissan nv200	1	97.2
97				
## 102	0	nissan dayz	1	100.4
152				
## 103	0	nissan fuga	1	100.4
152				
## 104	0	nissan otti	1	100.4
152				
## 105	3	nissan teana	1	91.3
160				
## 106	3	nissan kicks	1	91.3
200				
## 107	1	nissan clipper	1	99.2
160				
## 108	0	peugeot 504	1	107.9
97				
## 109	0	peugeot 304	0	107.9
95				
## 110	0	peugeot 504 (sw)	1	114.2
97				
## 111	0	peugeot 504	0	114.2
95				
## 112	0	peugeot 504	1	107.9
95				
## 113	0	peugeot 604sl	0	107.9
95				
## 114	0	peugeot 504	1	114.2
95				
## 115	0	peugeot 505s turbo diesel	0	114.2
95				

## 116 97	0	peugeot 504	1	107.9
## 117 95	0	peugeot 504	0	107.9
## 118 142	0	peugeot 604sl	1	108.0
## 119 68	1	plymouth fury iii	1	93.7
## 120 102	1	plymouth cricket	1	93.7
## 121 68	1	plymouth fury iii	1	93.7
## 122 68	1	plymouth satelllite custom (sw)	1	93.7
## 123 68	1	plymouth fury gran sedan	1	93.7
## 124 88	-1	plymouth valiant	1	103.3
## 125 145	3	plymouth duster	1	95.9
## 126 143	3	porsche macan	1	94.5
## 127 207	3	porcshce panamera	1	89.5
## 128 207	3	porsche cayenne	1	89.5
## 129 207	3	porsche boxter	1	89.5
## 130 288	1	porsche cayenne	1	98.4
## 131 90	0	renault 12tl	1	96.1
## 132 90	2	renault 5 gtl	1	96.1
## 133 110	3	saab 99e	1	99.1
## 134 110	2	saab 99le	1	99.1
## 135 110	3	saab 99le	1	99.1
## 136 110	2	saab 99gle	1	99.1
## 137 160	3	saab 99gle	1	99.1
## 138 160	2	saab 99e	1	99.1
## 139 69	2	subaru	1	93.7
## 140 73	2	subaru dl	1	93.7

## 141 73	2	subaru dl	1	93.3
## 142 82	0	subaru	1	97.2
## 143 82	0	subaru brz	1	97.2
## 144 94	0	subaru baja	1	97.2
## 145 82	0	subaru r1	1	97.0
## 146 111	0	subaru r2	1	97.0
## 147 82	0	subaru trezia	1	97.0
## 148 94	0	subaru tribeca	1	97.0
## 149 82	0	subaru dl	1	96.9
## 150 111	0	subaru dl	1	96.9
## 151 62	1	toyota corona mark ii	1	95.7
## 152 62	1	toyota corona	1	95.7
## 153 62	1	toyota corolla 1200	1	95.7
## 154 62	0	toyota corona hardtop	1	95.7
## 155 62	0	toyota corolla 1600 (sw)	1	95.7
## 156 62	0	toyota carina	1	95.7
## 157 70	0	toyota mark ii	1	95.7
## 158 70	0	toyota corolla 1200	1	95.7
## 159 56	0	toyota corona	0	95.7
## 160 56	0	toyota corolla	0	95.7
## 161 70	0	toyota corona	1	95.7
## 162 70	0	toyota corolla	1	95.7
## 163 70	0	toyota mark ii	1	95.7
## 164 70	1	toyota corolla liftback	1	94.5
## 165 70	1	toyota corona	1	94.5

## 166 112	1	toyota celica gt liftback	1	94.5
## 167 112	1	toyota corolla tercel	1	94.5
## 168 116	2	toyota corona liftback	1	98.4
## 169 116	2	toyota corolla	1	98.4
## 170 116	2	toyota starlet	1	98.4
## 171 116	2	toyota tercel	1	98.4
## 172 116	2	toyota corolla	1	98.4
## 173 116	2	toyota cressida	1	98.4
## 174 92	-1	toyota corolla	1	102.4
## 175 73	-1	toyota celica gt	0	102.4
## 176 92	-1	toyota corona	1	102.4
## 177 92	-1	toyota corolla	1	102.4
## 178 92	-1	toyota mark ii	1	102.4
## 179 161	3	toyota corolla liftback	1	102.9
## 180 161	3	toyota corona	1	102.9
## 181 156	-1	toyota starlet	1	104.5
## 182 156	-1	toyouta tercel	1	104.5
## 183 52	2	vokswagen rabbit	0	97.3
## 184 85	2	volkswagen 1131 deluxe sedan	1	97.3
## 185 52	2	volkswagen model 111	0	97.3
## 186 85	2	volkswagen type 3	1	97.3
## 187 85	2	volkswagen 411 (sw)	1	97.3
## 188 68	2	volkswagen super beetle	0	97.3
## 189 100	2	volkswagen dasher	1	97.3
## 190 90	3	vw dasher	1	94.5

## 191	3	vw rabbit	1	94.5
90				
## 192	0	volkswagen rabbit	1	100.4
110				
## 193	0	volkswagen rabbit custom	0	100.4
68				
## 194	0	volkswagen dasher	1	100.4
88				
## 195	-2	volvo 145e (sw)	1	104.3
114				
## 196	-1	volvo 144ea	1	104.3
114				
## 197	-2	volvo 244dl	1	104.3
114				
## 198	-1	volvo 245	1	104.3
114				
## 199	-2	volvo 264gl	1	104.3
162				
## 200	-1	volvo diesel	1	104.3
162				
## 201	-1	volvo 145e (sw)	1	109.1
114				
## 202	-1	volvo 144ea	1	109.1
160				
## 203	-1	volvo 244dl	1	109.1
134				
## 204	-1	volvo 246	0	109.1
106				
## 205	-1	volvo 264gl	1	109.1
114				
##	price			
## 1	13495.00			
## 2	16500.00			
## 3	16500.00			
## 4	13950.00			
## 5	17450.00			
## 6	15250.00			
## 7	17710.00			
## 8	18920.00			
## 9	23875.00			
## 10	17859.17			
## 11	16430.00			
## 12	16925.00			
## 13	20970.00			
## 14	21105.00			
## 15	24565.00			
## 16	30760.00			
## 17	41315.00			
## 18	36880.00			
## 19	5151.00			

## 20	6295.00
## 21	6575.00
## 22	5572.00
## 23	6377.00
## 24	7957.00
## 25	6229.00
## 26	6692.00
## 27	7609.00
## 28	8558.00
## 29	8921.00
## 30	12964.00
## 31	6479.00
## 32	6855.00
## 33	5399.00
## 34	6529.00
## 35	7129.00
## 36	7295.00
## 37	7295.00
## 38	7895.00
## 39	9095.00
## 40	8845.00
## 41	10295.00
## 42	12945.00
## 43	10345.00
## 44	6785.00
## 45	8916.50
## 46	8916.50
## 47	11048.00
## 48	32250.00
## 49	35550.00
## 50	36000.00
## 51	5195.00
## 52	6095.00
## 53	6795.00
## 54	6695.00
## 55	7395.00
## 56	10945.00
## 57	11845.00
## 58	13645.00
## 59	15645.00
## 60	8845.00
## 61	8495.00
## 62	10595.00
## 63	10245.00
## 64	10795.00
## 65	11245.00
## 66	18280.00
## 67	18344.00
## 68	25552.00
## 69	28248.00

##	70	28176.00
##	71	31600.00
##	72	34184.00
##	73	35056.00
##	74	40960.00
##	75	45400.00
##	76	16503.00
##	77	5389.00
##	78	6189.00
##	79	6669.00
##	80	7689.00
##	81	9959.00
##	82	8499.00
##	83	12629.00
##	84	14869.00
##	85	14489.00
##	86	6989.00
##	87	8189.00
##	88	9279.00
##	89	9279.00
##	90	5499.00
##	91	7099.00
##	92	6649.00
##	93	6849.00
##	94	7349.00
##	95	7299.00
##	96	7799.00
##	97	7499.00
##	98	7999.00
##	99	8249.00
##	100	8949.00
##	101	9549.00
##	102	13499.00
##	103	14399.00
##	104	13499.00
##	105	17199.00
##	106	19699.00
##	107	18399.00
##	108	11900.00
##	109	13200.00
##	110	12440.00
##	111	13860.00
##	112	15580.00
##	113	16900.00
##	114	16695.00
##	115	17075.00
##	116	16630.00
##	117	17950.00
##	118	18150.00
##	119	5572.00

##	120	7957.00
##	121	6229.00
##	122	6692.00
##	123	7609.00
##	124	8921.00
##	125	12764.00
##	126	22018.00
##	127	32528.00
##	128	34028.00
##	129	37028.00
##	130	31400.50
##	131	9295.00
##	132	9895.00
##	133	11850.00
##	134	12170.00
##	135	15040.00
##	136	15510.00
##	137	18150.00
##	138	18620.00
##	139	5118.00
##	140	7053.00
##	141	7603.00
##	142	7126.00
##	143	7775.00
##	144	9960.00
##	145	9233.00
##	146	11259.00
##	147	7463.00
##	148	10198.00
##	149	8013.00
##	150	11694.00
##	151	5348.00
##	152	6338.00
##	153	6488.00
##	154	6918.00
##	155	7898.00
##	156	8778.00
##	157	6938.00
##	158	7198.00
##	159	7898.00
##	160	7788.00
##	161	7738.00
##	162	8358.00
##	163	9258.00
##	164	8058.00
##	165	8238.00
##	166	9298.00
##	167	9538.00
##	168	8449.00
##	169	9639.00

```
## 170 9989.00
## 171 11199.00
## 172 11549.00
## 173 17669.00
## 174 8948.00
## 175 10698.00
## 176 9988.00
## 177 10898.00
## 178 11248.00
## 179 16558.00
## 180 15998.00
## 181 15690.00
## 182 15750.00
## 183 7775.00
## 184 7975.00
## 185 7995.00
## 186 8195.00
## 187 8495.00
## 188 9495.00
## 189 9995.00
## 190 11595.00
## 191 9980.00
## 192 13295.00
## 193 13845.00
## 194 12290.00
## 195 12940.00
## 196 13415.00
## 197 15985.00
## 198 16515.00
## 199 18420.00
## 200 18950.00
## 201 16845.00
## 202 19045.00
## 203 21485.00
## 204 22470.00
## 205 22625.00
```

Exploracion de los datos

Medias estadísticas del modelo

```
cat("Datos sobre fueltype", "\n")

## Datos sobre fueltype

table(group_data$fueltype)

##
## 0 1
## 20 185

cat("\n", "Datos sobre horsepower: ", "\n")
```

```
##
## Datos sobre horsepower:

summary(group_data$horsepower)

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      48.0   70.0   95.0  104.1  116.0   288.0

cat("\n", "Datos sobre wheelbase", "\n")

##
## Datos sobre wheelbase

summary(group_data$wheelbase)

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      86.60   94.50   97.00   98.76  102.40  120.90

cat("Correlacion entre los datos de gas", "\n", "\n")

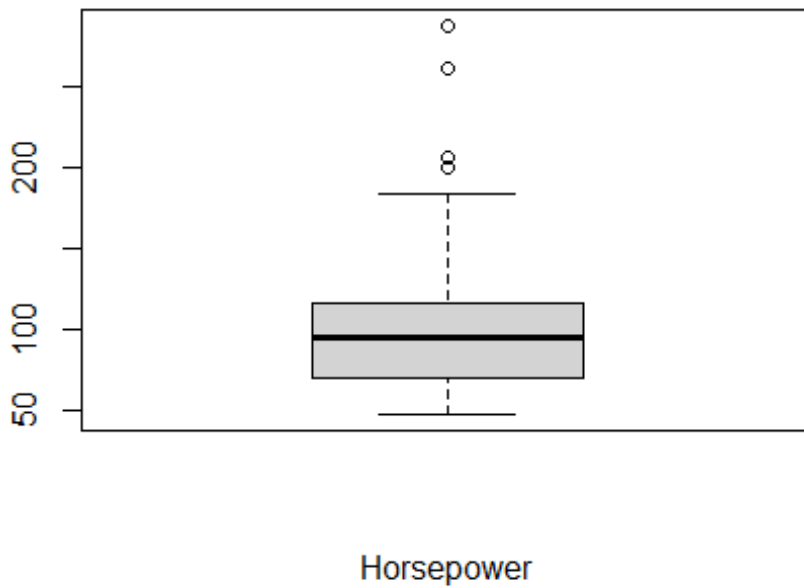
## Correlacion entre los datos de gas
##

numeric_data = subset(group_data, select = c("symboling", "wheelbase",
"horsepower", "price"))

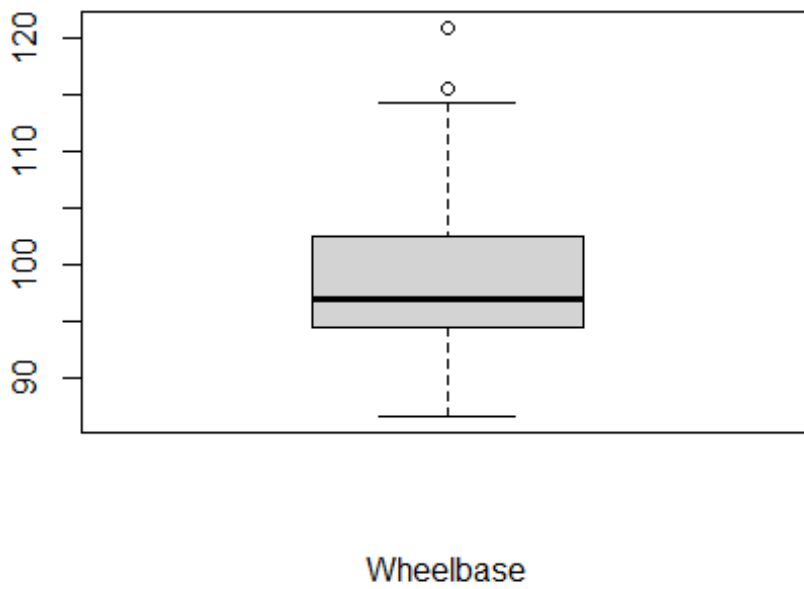
cor(numeric_data, use = "complete.obs")

##           symboling wheelbase horsepower      price
## symboling  1.00000000 -0.5319537  0.07087272 -0.07997822
## wheelbase -0.53195368  1.00000000  0.35329448  0.57781560
## horsepower 0.07087272  0.3532945  1.00000000  0.80813882
## price      -0.07997822  0.5778156  0.80813882  1.00000000

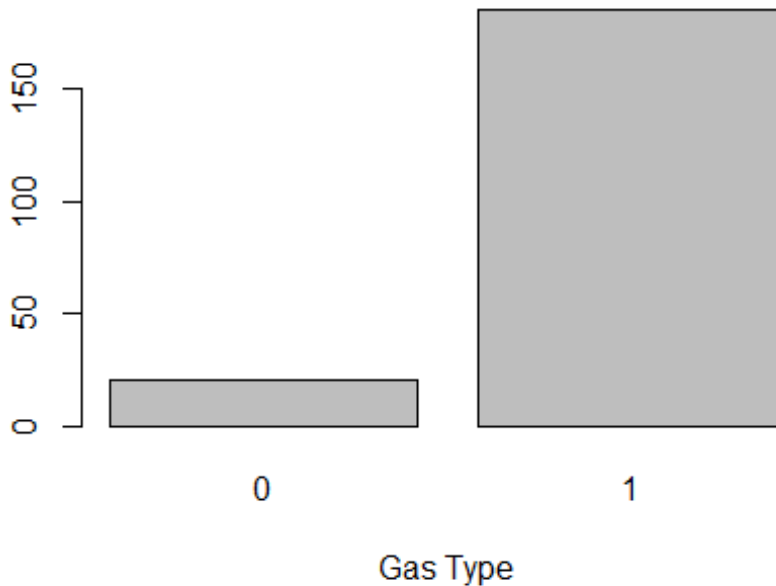
boxplot(group_data$horsepower, xlab = "Horsepower")
```



```
boxplot(group_data$wheelbase, xlab = "Wheelbase")
```



```
barplot(table(group_data$fueltype), xlab = "Gas Type")
```



Modelacion y Verificacion del Modelo

```
M1 = lm(price ~ horsepower * fueltype, data = group_data)
M2 = lm(price ~ wheelbase * horsepower, data = group_data)
```

Analisis del Modelo 1

```
#valor frontera del modelo
abs( qt(0.04/2,(length(M1))))

## [1] 2.302722
```

Hipotesis

$vf = 2.30$ $h_0 < vf$ El modelo no es significativo $h_1 \geq vf$ El modelo es significativo

summary(M1)

```
##
## Call:
## lm(formula = price ~ horsepower * fueltype, data = group_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -11904.3  -1776.2   -381.8   1458.9  19435.5
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
```



```
## (Intercept)          -7731.37      3298.65  -2.344  0.02006 *
## horsepower           279.09       37.42   7.459 2.56e-12 ***
## fueltype             3016.83      3414.35   0.884  0.37798
## horsepower:fueltype  -112.36       38.21  -2.940  0.00366 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4234 on 201 degrees of freedom
## Multiple R-squared:  0.7233, Adjusted R-squared:  0.7191
## F-statistic: 175.1 on 3 and 201 DF,  p-value: < 2.2e-16
```

`anova(M1)`

```
## Analysis of Variance Table
##
## Response: price
##              Df      Sum Sq   Mean Sq  F value    Pr(>F)
## horsepower     1 8502974873 8502974873 474.3725 < 2.2e-16 ***
## fueltype       1  758833988  758833988  42.3346 5.993e-10 ***
## horsepower:fueltype 1 154969609 154969609   8.6456 0.003663 **
## Residuals     201 3602860891  17924681
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Se rechaza h_0 porque al menos un valor f sobrepasa nuestro alfa.

Significancia de B_i

$h_0 < \alpha$ $h_1 > \alpha$

`summary(M1)$coefficients`

```
##              Estimate Std. Error  t value    Pr(>|t|)
## (Intercept)   -7731.3655 3298.64586 -2.3437998 2.006495e-02
## horsepower     279.0943   37.41715  7.4589949 2.564780e-12
## fueltype      3016.8270 3414.34521  0.8835741 3.779818e-01
## horsepower:fueltype -112.3606  38.21346 -2.9403400 3.662756e-03
```

Se acepta h_0 porque todos los valores p de los coeficientes son menores a alfa.

Porcentaje de variación del modelo

`summary(M1)$r.squared`

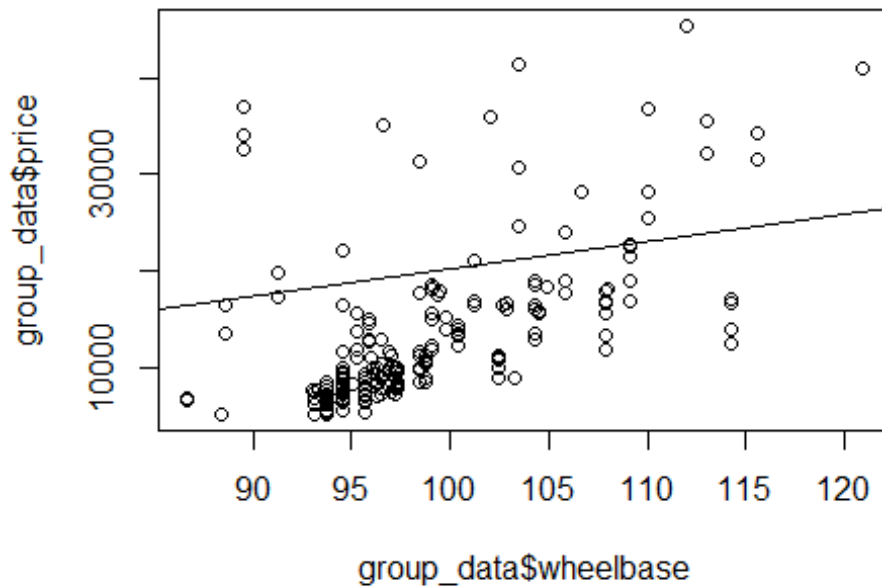
```
## [1] 0.7232749
```

Diagrama de dispersión

```
plot(group_data$wheelbase, group_data$price, main = "Dispersión Wheelbase
vs Price")
abline(M1)
```

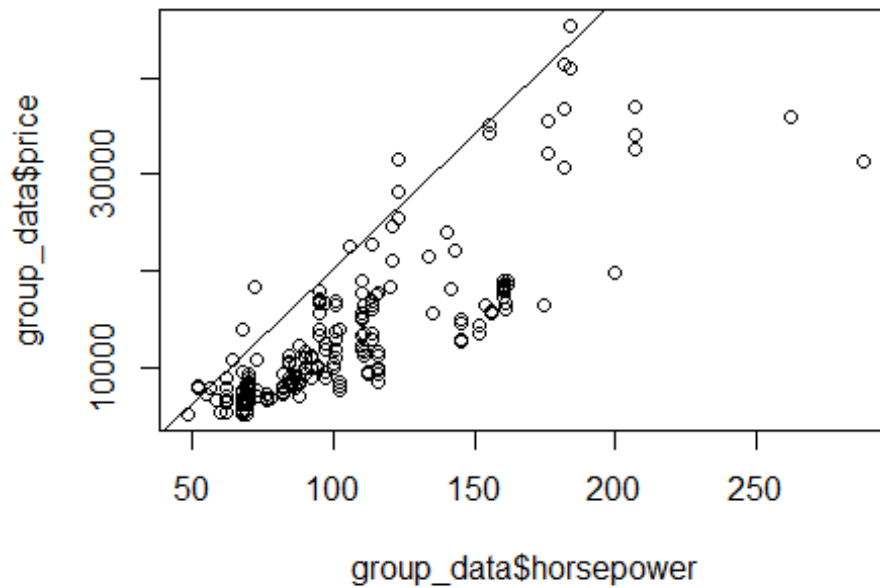
```
## Warning in abline(M1): only using the first two of 4 regression
coefficients
```

Dispersión Wheelbase vs Price



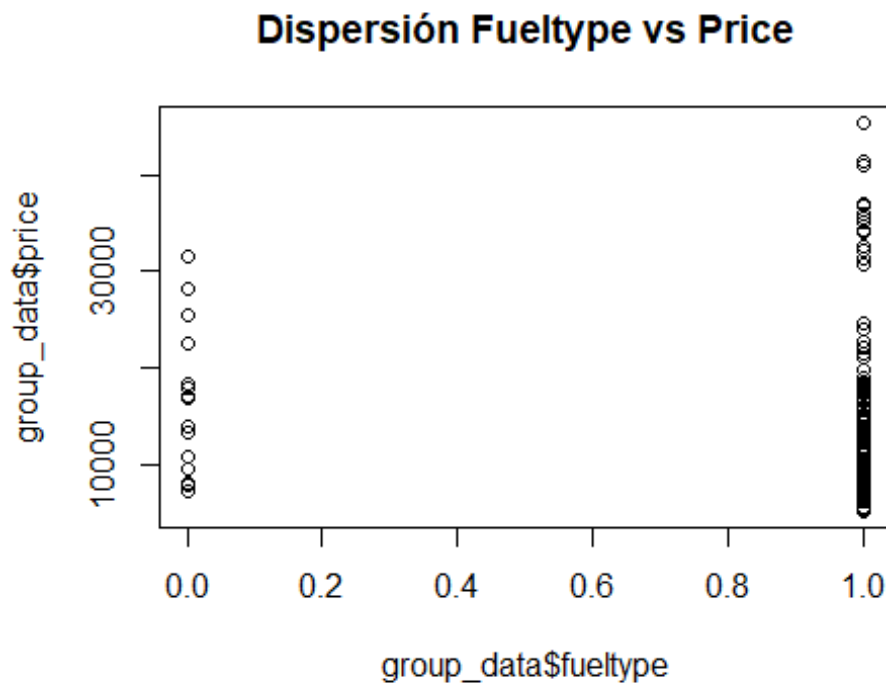
```
plot(group_data$horsepower, group_data$price, main = "Dispersión  
Horsepower vs Price")  
abline(M1)  
  
## Warning in abline(M1): only using the first two of 4 regression  
coefficients
```

Dispersión Horsepower vs Price



```
plot(group_data$horsepower, group_data$price, main = "Dispersión Horsepower vs Price")
abline(M1)

## Warning in abline(M1): only using the first two of 4 regression
coefficients
```



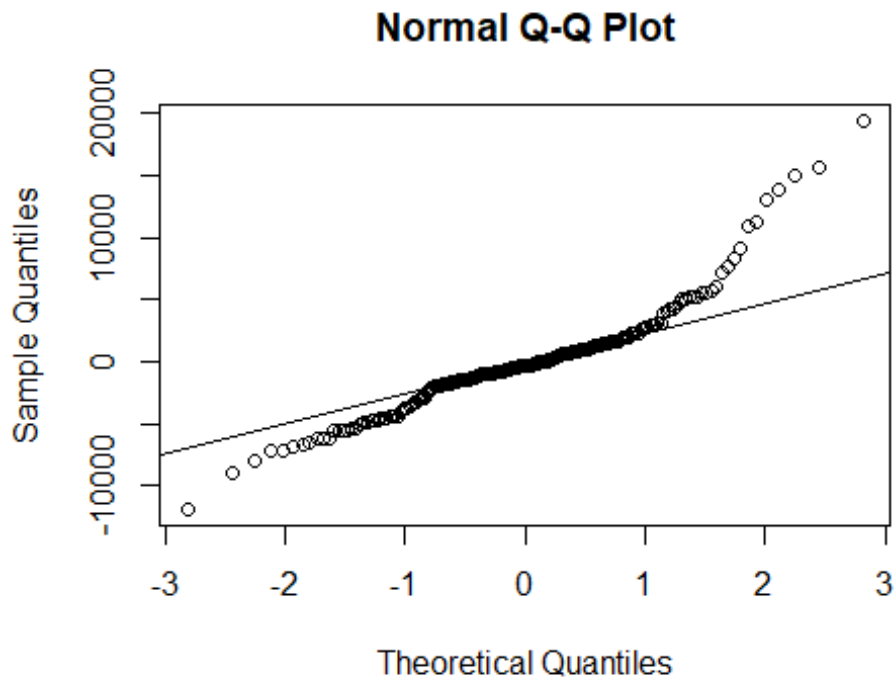
Se analiza la posible relación entre wheelbase y price, horsepower y price, y fueltype y price. Podemos observar que el precio aumenta considerablemente si el fueltype es diesel. De la misma manera con horsepower, mientras este aumenta, de igual manera lo hace el precio, y exactamente el mismo comportamiento sucede con wheelbase.

Validez del modelo propuesto

```
library(nortest)
ad.test(M1$residuals)

##
##  Anderson-Darling normality test
##
## data:  M1$residuals
## A = 4.7325, p-value = 9.266e-12

qqnorm(M1$residuals)
qqline(M1$residuals)
```



Se rechaza h_0

porque el valor p es menor que alfa (0.04).

Verificación de media 0

```
t.test(M1$residuals)
```

```
##
## One Sample t-test
##
## data: M1$residuals
## t = -1.5791e-15, df = 204, p-value = 1
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
## -578.714 578.714
## sample estimates:
## mean of x
## -4.634905e-13
```

Se rechaza h_0 porque el valor p de la media cero no es igual a 0, por lo que se acepta h_1

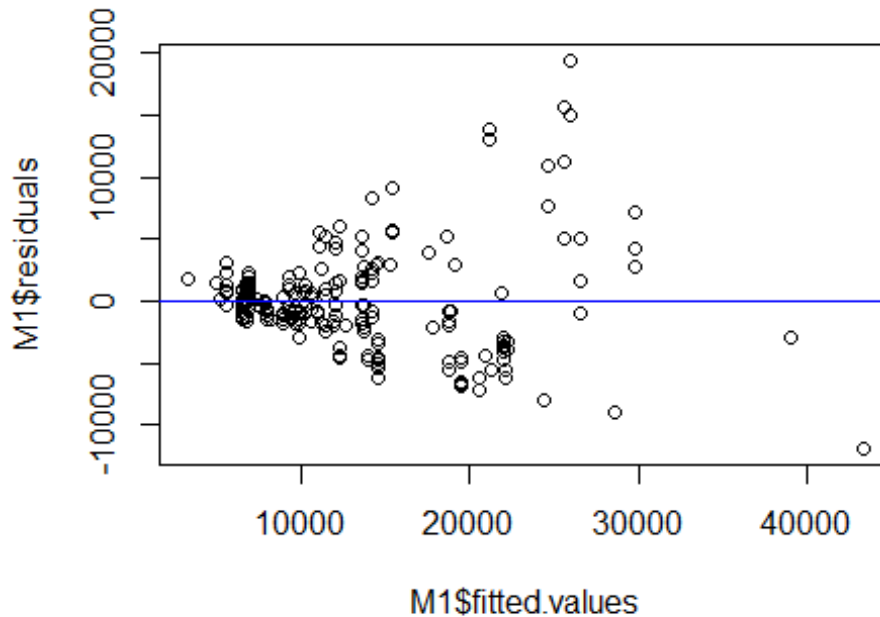
Homocedasticidad

```
library(lmtest)
```

```
## Cargando paquete requerido: zoo
##
## Adjuntando el paquete: 'zoo'
```

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

plot(M1$fitted.values, M1$residuals)
abline(h=0, col="blue")
```



```
bptest(M1)

##
## studentized Breusch-Pagan test
##
## data: M1
## BP = 62.878, df = 3, p-value = 1.426e-13

dwtest(M1)

##
## Durbin-Watson test
##
## data: M1
## DW = 1.0589, p-value = 3.272e-12
## alternative hypothesis: true autocorrelation is greater than 0
```

Se acepta h_0 debido a que el valor p que nos da la prueba de BP es mucho menor a 0.05, por lo que no hay suficiente evidencia de que existe heterocedasticidad.

Debido a que el valor de la prueba de Durbin-Watson es cercano a 2, podemos entender que los residuos son independientes, por lo que aceptamos h_0 ya que los errores no están correlacionados.

```
library(lmtest)
bptest(M1)

##
## studentized Breusch-Pagan test
##
## data: M1
## BP = 62.878, df = 3, p-value = 1.426e-13
```

Analisis del Modelo 2

```
#valor frontera del modelo
abs( qt(0.04/2,(length(M2))))

## [1] 2.302722
```

Hipotesis

$vf = 2.30$ $h_0 < vf$ El modelo no es significativo $h_1 \geq vf$ El modelo es significativo

```
summary(M2)

##
## Call:
## lm(formula = price ~ wheelbase * horsepower, data = group_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -8847  -2050   -177    1350   15889
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -17059.574  14377.287  -1.187   0.2368
## wheelbase       155.900    148.256   1.052   0.2943
## horsepower     -89.721    111.777  -0.803   0.4231
## wheelbase:horsepower    2.342     1.140   2.055   0.0412 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3977 on 201 degrees of freedom
## Multiple R-squared:  0.7558, Adjusted R-squared:  0.7522
## F-statistic: 207.4 on 3 and 201 DF, p-value: < 2.2e-16

anova(M2)

## Analysis of Variance Table
##
## Response: price
```

```
##              Df      Sum Sq    Mean Sq  F value Pr(>F)
## wheelbase      1 4346878264 4346878264 274.8574 <2e-16 ***
## horsepower      1 5427172318 5427172318 343.1654 <2e-16 ***
## wheelbase:horsepower 1   66767095   66767095    4.2217 0.0412 *
## Residuals     201 3178821685   15815033
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Se rechaza h_0 porque al menos un valor f sobrepasa nuestro alfa.

Significancia de Bi

$h_0 < \alpha$ $h_1 > \alpha$

```
summary(M2)$coefficients
```

```
##              Estimate Std. Error  t value Pr(>|t|)
## (Intercept) -17059.573669 14377.287334 -1.1865641 0.23680017
## wheelbase    155.899761   148.256466  1.0515545 0.29426654
## horsepower   -89.720766   111.776866 -0.8026774 0.42310928
## wheelbase:horsepower  2.342437    1.140044  2.0546894 0.04120263
```

Se acepta h_0 porque todos los valores p de los coeficientes son menores a alfa.

Porcentaje de variación del modelo

```
summary(M2)$r.squared
```

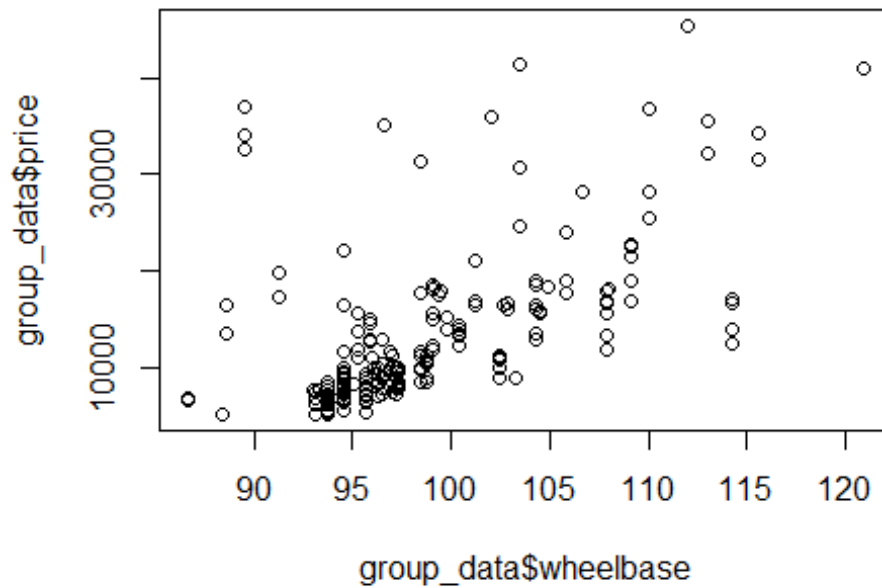
```
## [1] 0.7558441
```

Diagrama de dispersión

```
plot(group_data$wheelbase, group_data$price, main = "Dispersión Wheelbase
vs Price")
abline(M2)
```

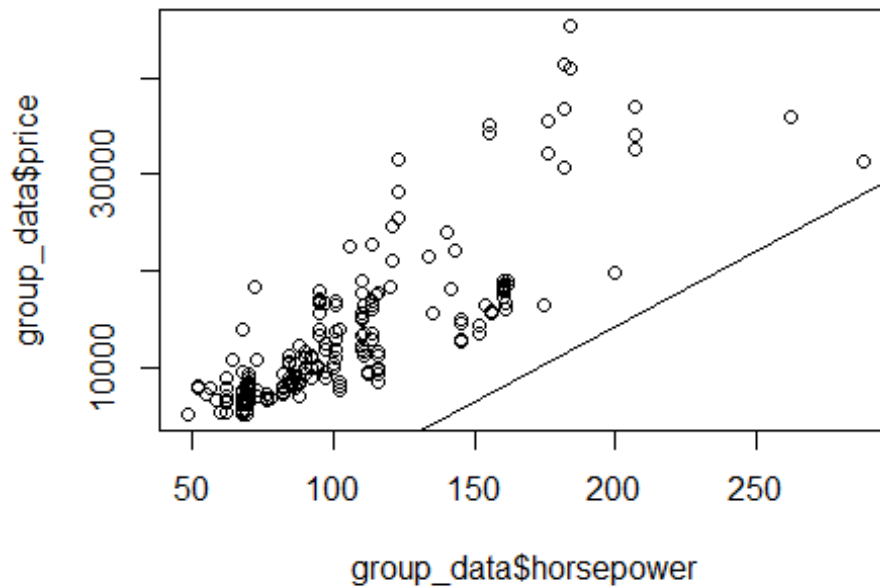
```
## Warning in abline(M2): only using the first two of 4 regression
coefficients
```


Dispersión Wheelbase vs Price



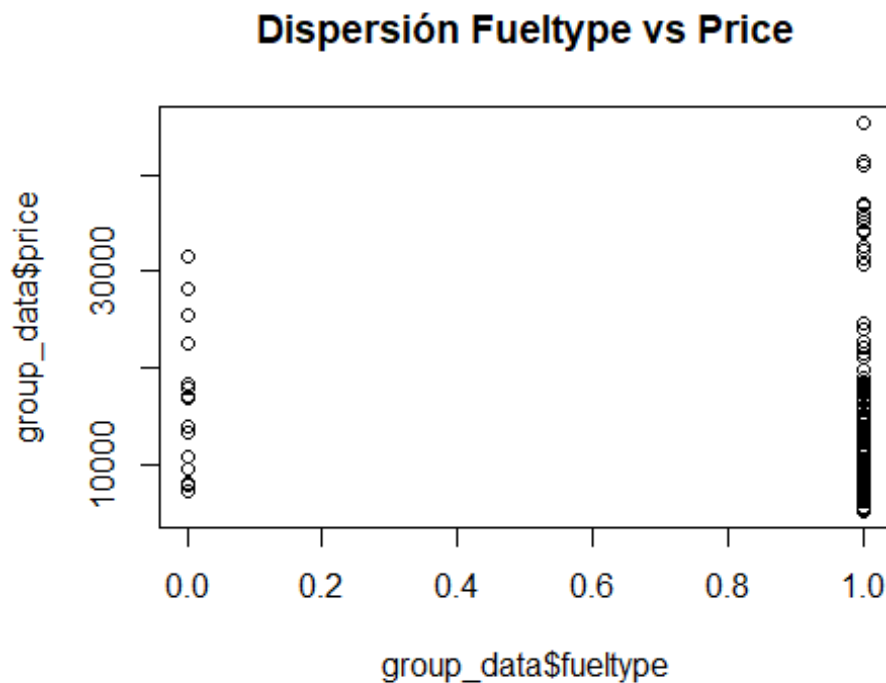
```
plot(group_data$horsepower, group_data$price, main = "Dispersión  
Horsepower vs Price")  
abline(M2)  
  
## Warning in abline(M2): only using the first two of 4 regression  
coefficients
```

Dispersión Horsepower vs Price



```
plot(group_data$horsepower, group_data$price, main = "Dispersión Horsepower vs Price")
abline(M2)

## Warning in abline(M2): only using the first two of 4 regression
coefficients
```



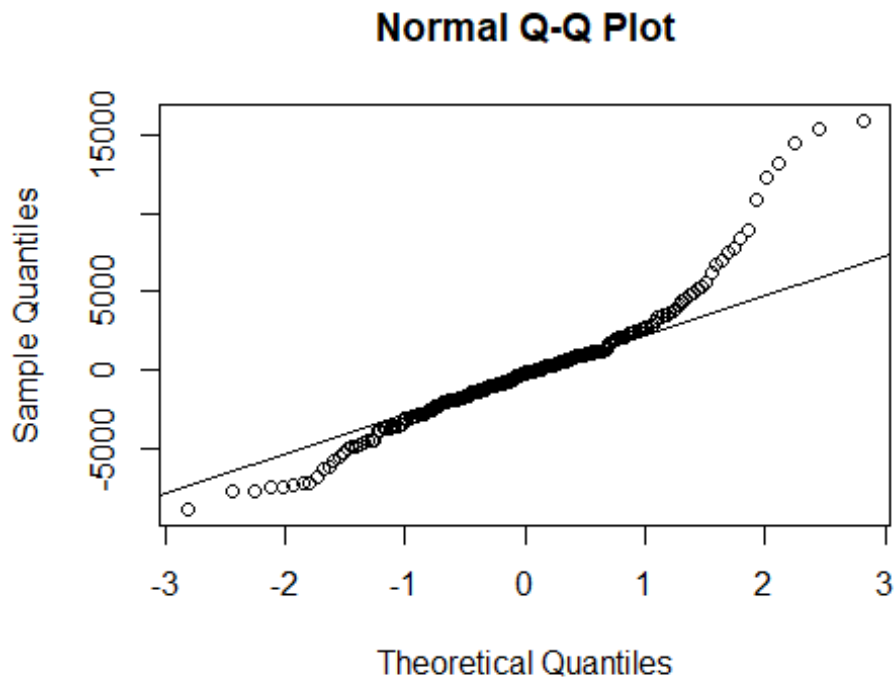
Se analiza la posible relación entre wheelbase y price, horsepower y price, y fueltype y price. Podemos observar que el precio aumenta considerablemente si el fueltype es diesel. De la misma manera con horsepower, mientras este aumenta, de igual manera lo hace el precio, y exactamente el mismo comportamiento sucede con wheelbase.

Validez del modelo propuesto

```
library(nortest)
ad.test(M2$residuals)

##
##  Anderson-Darling normality test
##
## data:  M2$residuals
## A = 3.6742, p-value = 3.374e-09

qqnorm(M2$residuals)
qqline(M2$residuals)
```



Se rechaza h_0

porque el valor p es menor que alfa (0.04).

Verificación de media 0

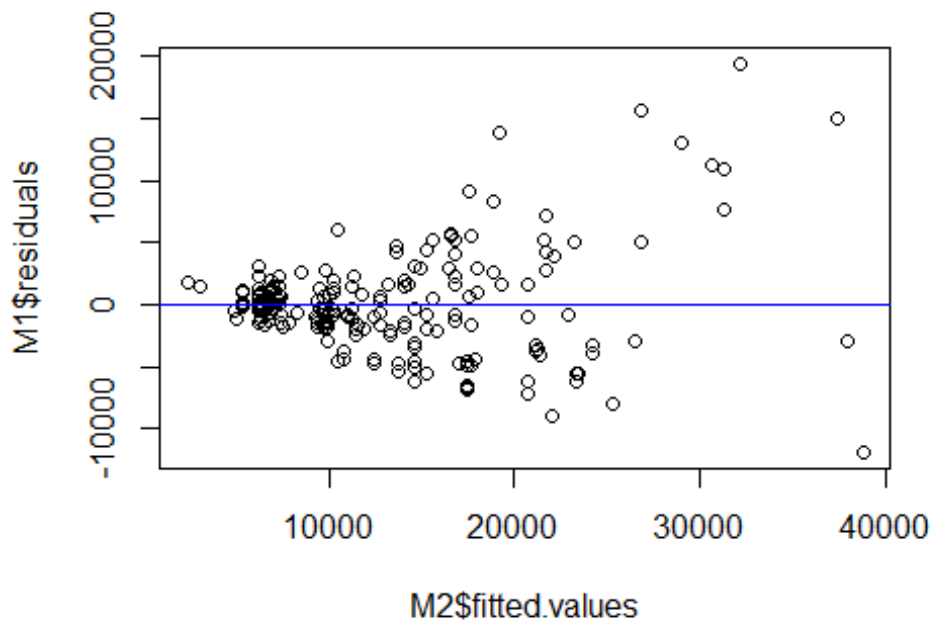
```
t.test(M2$residuals)
```

```
##
## One Sample t-test
##
## data: M2$residuals
## t = -5.7484e-17, df = 204, p-value = 1
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
## -543.5923 543.5923
## sample estimates:
## mean of x
## -1.584857e-14
```

Se rechaza h_0 porque el valor p de la media cero no es igual a 0, por lo que se acepta h_1

Homocedasticidad

```
library(lmtest)
plot(M2$fitted.values, M1$residuals)
abline(h=0, col="blue")
```



```
bptest(M2)
```

```
##
## studentized Breusch-Pagan test
##
## data: M2
## BP = 60.863, df = 3, p-value = 3.845e-13
```

```
dwtest(M2)
```

```
##
## Durbin-Watson test
##
## data: M2
## DW = 1.0509, p-value = 1.575e-12
## alternative hypothesis: true autocorrelation is greater than 0
```

Se acepta h_0 debido a que el valor p que nos da la prueba de BP es mucho menor a 0.05, por lo que no hay suficiente evidencia de que existe heterocedasticidad.

Debido a que el valor de la prueba de Durbin-Watson es cercano a 2, podemos entender que los residuos son independientes, por lo que aceptamos h_0 ya que los errores no están correlacionados.

Tras ver los resultados de las pruebas de análisis, podemos concluir que el mejor modelo es el segundo, pues nos ofrece un mejor porcentaje de variación de los datos,

además de esto, los coeficientes de este modelo presentan una mayor significancia para el modelo.

Intervalos de predicción y significancia

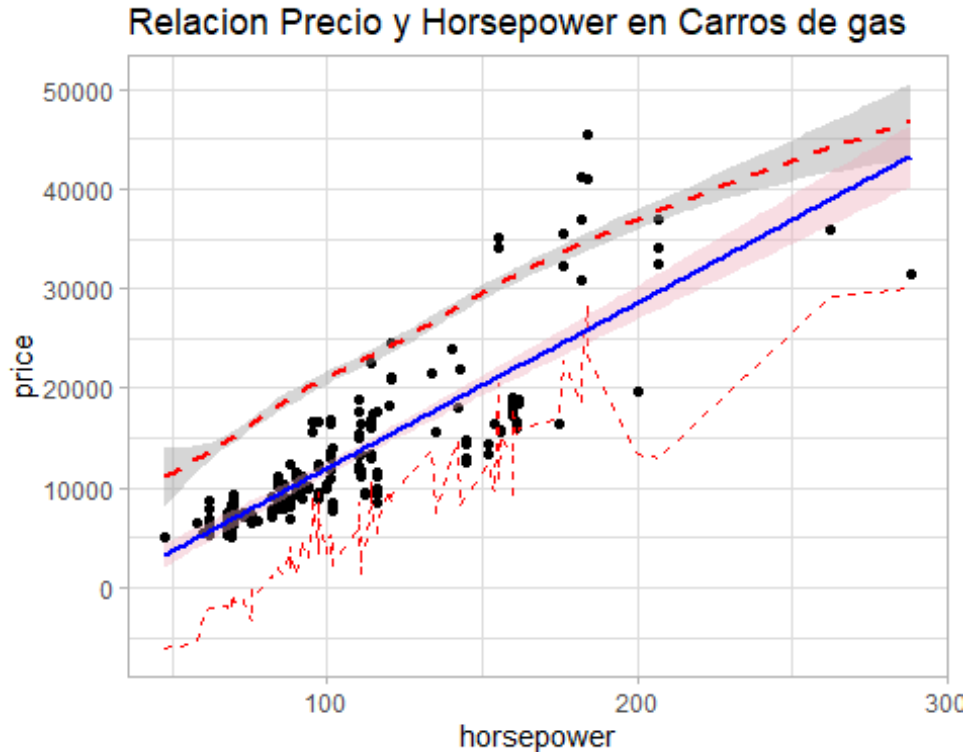
```
A = M2
Ip=predict(object=A,interval="prediction",level=0.96)

## Warning in predict.lm(object = A, interval = "prediction", level =
0.96): predictions on current data refer to _future_ responses

M2=cbind(group_data,Ip)
M2g = subset(M2, fueltype == 1)
M2d = subset(M2, fueltype == 0)

library(ggplot2)
ggplot(M2g,aes(x= horsepower ,y= price))+
  ggtitle("Relacion Precio y Horsepower en Carros de gas")+
  geom_point()+
  geom_line(aes(y=lwr), color="red", linetype="dashed")+
  geom_smooth(aes(y=upr), color="red", linetype="dashed")+
  geom_smooth(method=lm, formula=y~x, se=TRUE, level=0.96, col="blue",
fill="pink2")+
  theme_light()

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



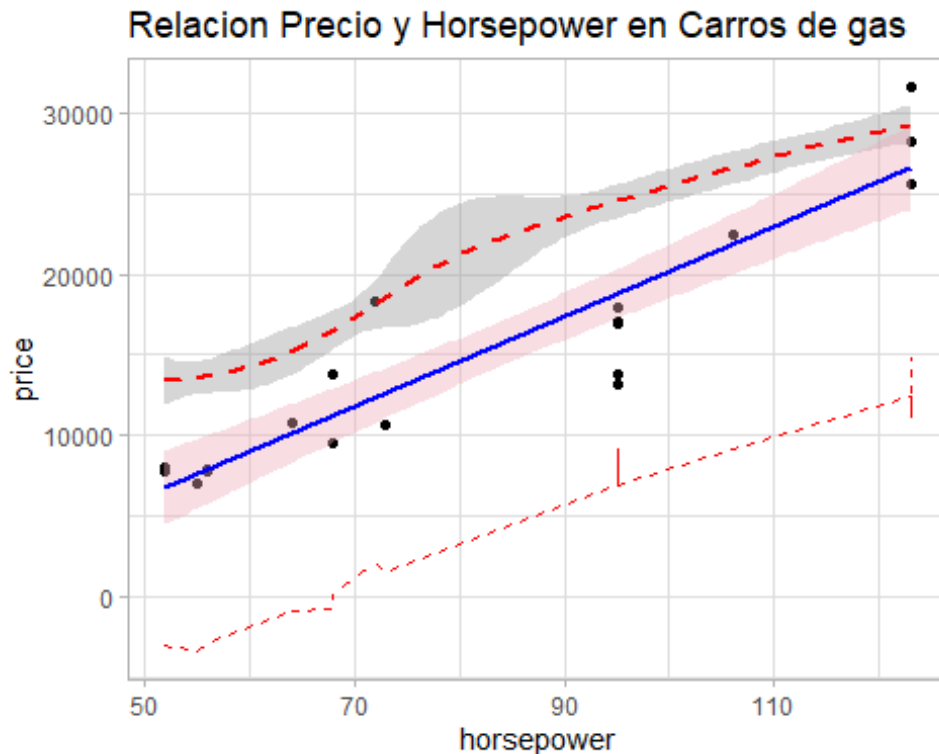
```
library(ggplot2)
ggplot(M2d,aes(x= horsepower ,y= price))+
```

```

ggtitle("Relacion Precio y Horsepower en Carros de gas")+
geom_point()+
geom_line(aes(y=lwr), color="red", linetype="dashed")+
geom_smooth(aes(y=upr), color="red", linetype="dashed")+
geom_smooth(method=lm, formula=y~x, se=TRUE, level=0.96, col="blue",
fill="pink2")+
theme_light()

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

```



Debido a problemas con el paquete de graficas no se pudo hacer unas graficas de prediccion y confianza que explique correctamente el comportamiento de las variables predecidas. Sin embargo, debido al análisis estadístico anterior podemos decir que este Modelo, es el que más nos puede servir para predecir el precio de un automovil, con relacion a las variables de caballos de fuerza y wheelbase. Si bien, no se puede apreciar correctamente los limites, podemos ver que la recta que se genera, atravesza la mayoria de los puntos, lo que confirma nuestra probabilidad de varianza que tiene un valor de 0.75.

Analisis final

```

quantitative_data = data[, c('wheelbase', 'carlength', 'carwidth',
'carheight', 'enginesize',
'stroke', 'compressionratio', 'horsepower',
'peakrpm',
'citympg', 'highwaympg', 'curbweight',

```

```
'price'])
cor(quantitative_data)
```

```
##          wheelbase  carlength  carwidth  carheight
enginesize
## wheelbase      1.0000000  0.8745875  0.7951436  0.58943476
0.56932868
## carlength      0.8745875  1.0000000  0.8411183  0.49102946
0.68335987
## carwidth       0.7951436  0.8411183  1.0000000  0.27921032
0.73543340
## carheight      0.5894348  0.4910295  0.2792103  1.00000000
0.06714874
## enginesize     0.5693287  0.6833599  0.7354334  0.06714874
1.00000000
## stroke         0.1609590  0.1295326  0.1829417 -0.05530667
0.20312859
## compressionratio 0.2497858  0.1584137  0.1811286  0.26121423
0.02897136
## horsepower     0.3532945  0.5526230  0.6407321 -0.10880206
0.80976865
## peakrpm        -0.3604687 -0.2872422 -0.2200123 -0.32041072 -
0.24465983
## citympg         -0.4704136 -0.6709087 -0.6427043 -0.04863963 -
0.65365792
## highwaympg      -0.5440819 -0.7046616 -0.6772179 -0.10735763 -
0.67746991
## curbweight      0.7763863  0.8777285  0.8670325  0.29557173
0.85059407
## price          0.5778156  0.6829200  0.7593253  0.11933623
0.87414480
##          stroke  compressionratio  horsepower  peakrpm
## wheelbase      0.16095905      0.24978585  0.35329448 -0.36046875
## carlength      0.12953261      0.15841371  0.55262297 -0.28724220
## carwidth       0.18294169      0.18112863  0.64073208 -0.22001230
## carheight      -0.05530667      0.26121423 -0.10880206 -0.32041072
## enginesize     0.20312859      0.02897136  0.80976865 -0.24465983
## stroke         1.00000000      0.18611011  0.08093954 -0.06796375
## compressionratio 0.18611011      1.00000000 -0.20432623 -0.43574051
## horsepower     0.08093954      -0.20432623  1.00000000  0.13107251
## peakrpm        -0.06796375      -0.43574051  0.13107251  1.00000000
## citympg         -0.04214475      0.32470142 -0.80145618 -0.11354438
## highwaympg      -0.04393093      0.26520139 -0.77054389 -0.05427481
## curbweight      0.16879004      0.15136174  0.75073925 -0.26624318
## price          0.07944308      0.06798351  0.80813882 -0.08526715
##          citympg  highwaympg  curbweight  price
## wheelbase      -0.47041361 -0.54408192  0.7763863  0.57781560
## carlength       -0.67090866 -0.70466160  0.8777285  0.68292002
## carwidth        -0.64270434 -0.67721792  0.8670325  0.75932530
## carheight       -0.04863963 -0.10735763  0.2955717  0.11933623
```


## enginesize	-0.65365792	-0.67746991	0.8505941	0.87414480
## stroke	-0.04214475	-0.04393093	0.1687900	0.07944308
## compressionratio	0.32470142	0.26520139	0.1513617	0.06798351
## horsepower	-0.80145618	-0.77054389	0.7507393	0.80813882
## peakrpm	-0.11354438	-0.05427481	-0.2662432	-0.08526715
## citympg	1.00000000	0.97133704	-0.7574138	-0.68575134
## highwaympg	0.97133704	1.00000000	-0.7974648	-0.69759909
## curbweight	-0.75741378	-0.79746479	1.0000000	0.83530488
## price	-0.68575134	-0.69759909	0.8353049	1.00000000

Considero que un buen grupo de datos para poder predecir el precio serian horsepower junto con enginesize puesto que entre estas dos variables existe una gran correlación, además de que cada una de ellas tienen una gran correlación con el precio de un auto.