

# **Lista de ejercicios 3 - Análisis de regresión**

**Ciclo nivelación 2025-2**

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Una empresa de análisis inmobiliario desea modelar el precio de venta de departamentos en una ciudad usando información estructural y comercial. Se construyó una base de datos de 100 propiedades vendidas recientemente.

Variable respuesta: Precio de venta (miles de USD)

Variables explicativas:

- x1: Área construida, en metros cuadrados
- x2: Índice de calidad constructiva (z-score), es un puntaje técnico de materiales y acabados.
- x3: Intensidad de publicidad digital (z-score), es una medida de exposición en portales y anuncios.
- x4: Tiene cochera (0: No, 1: Sí)
- x5: Zona de la ciudad (A = Zona periférica, B = Zona intermedia, C = Zona comercial, D = Zona premium)

Objetivos:

- Identificar leverages, residuales y valores influenciales
- Seleccionar variables
- Reportar el modelo resultante e interpretar sus coeficientes estimados.

1. División del conjunto de datos en entrenamiento y prueba

```
library(readxl)
datos = read_xlsx('Lista3_datos.xlsx')
```

```
library(rsample)
set.seed(12369874)
split_obj = initial_split(datos, prop = 0.75)
train     = training(split_obj)
test      = testing(split_obj)
train |> nrow()
```

```
[1] 375
```

```
test |> nrow()
```

```
[1] 125
```

## 2. Creación del modelo inicial de regresión lineal

```
modelo = lm(y ~ x1 + x2 + x3 + x4 + x5, data = train)
modelo |> summary()
```

Call:

```
lm(formula = y ~ x1 + x2 + x3 + x4 + x5, data = train)
```

Residuals:

Min	1Q	Median	3Q	Max
-11.7807	-1.0193	-0.1207	0.8529	13.9607

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	5.55013	0.42123	13.176	< 2e-16 ***
x1	1.35969	0.04177	32.553	< 2e-16 ***
x2	-0.55100	0.06354	-8.672	< 2e-16 ***
x3	0.02829	0.10227	0.277	0.782246
x41	0.98436	0.20580	4.783	2.51e-06 ***
x5B	0.77653	0.27400	2.834	0.004851 **
x5C	-1.02727	0.26210	-3.919	0.000106 ***
x5D	1.18452	0.32541	3.640	0.000312 ***
---				
Signif. codes:	0 '***'	0.001 '**'	0.01 '*'	0.05 '.'
	0.1 '	0.1 '	'	1

Residual standard error: 1.976 on 367 degrees of freedom

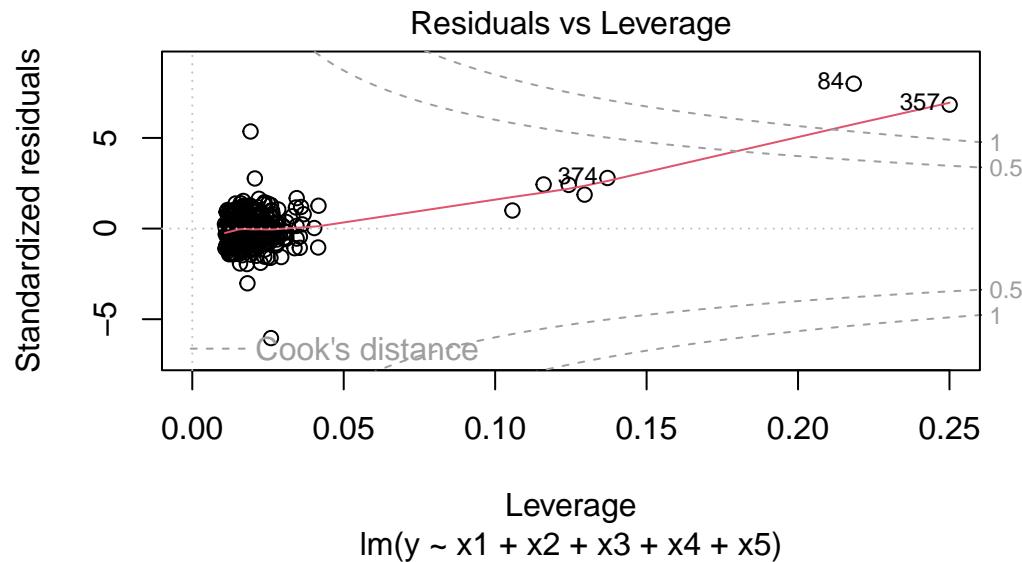
Multiple R-squared: 0.9966, Adjusted R-squared: 0.9965

F-statistic: 1.532e+04 on 7 and 367 DF, p-value: < 2.2e-16

### 3. Detección de leverages

```
modelo |> model.matrix() -> X  
X %*% solve(t(X) %*% X) %*% t(X) -> H  
train |> nrow() -> n  
modelo |> coef() |> length() -> k  
as.vector(which(diag(H) > 2*k/n)) -> leverages
```

```
library(olsrr)  
modelo |> plot(which=5)
```



Leverages identificados:

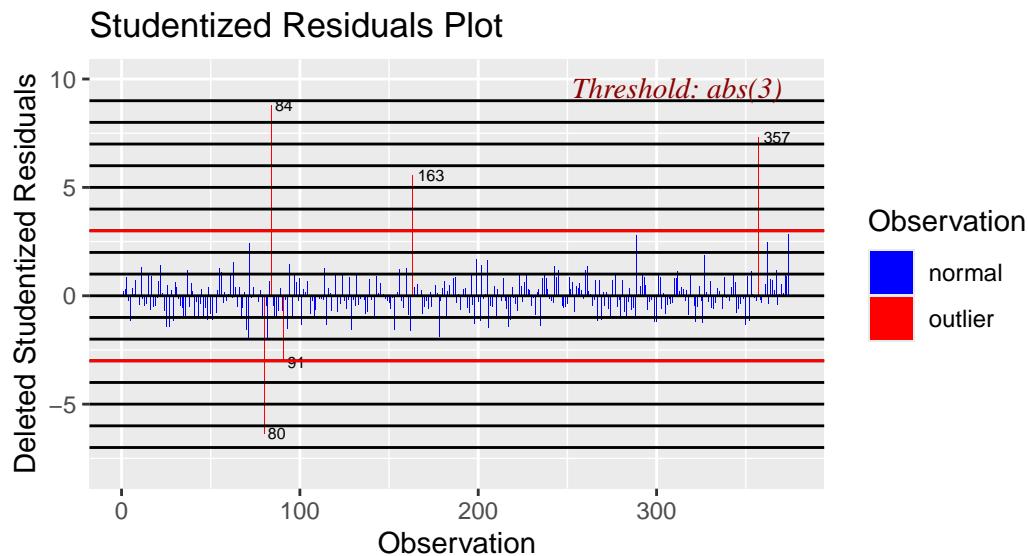
```
leverages
```

```
[1] 72 84 319 327 357 362 374
```

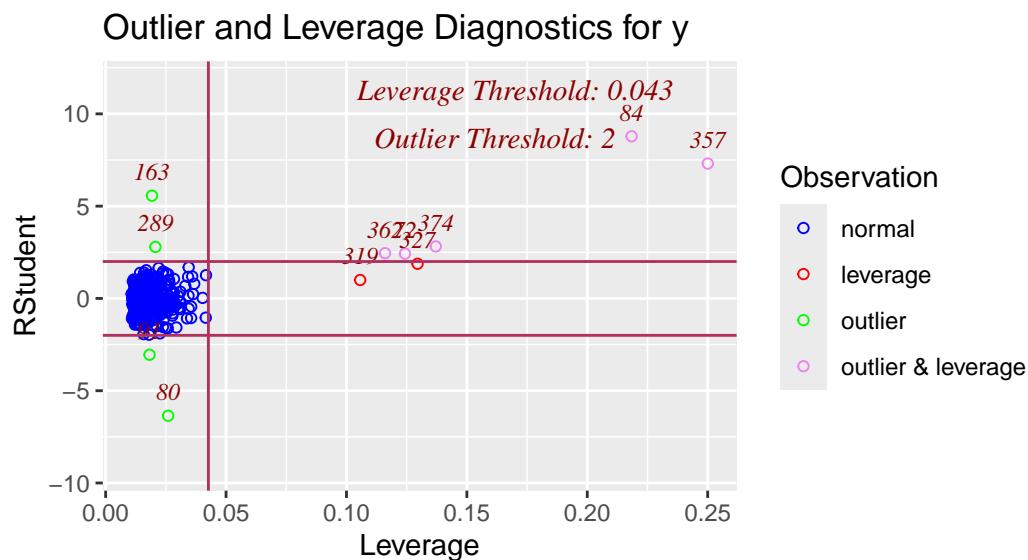
#### 4. Detección de valores atípicos

```
library(MASS)
as.vector(which((modelo |> studres() |> abs()) > 2)) -> outliers

modelo |> ols_plot_resid_stud()
```



```
modelo |> ols_plot_resid_lev()
```



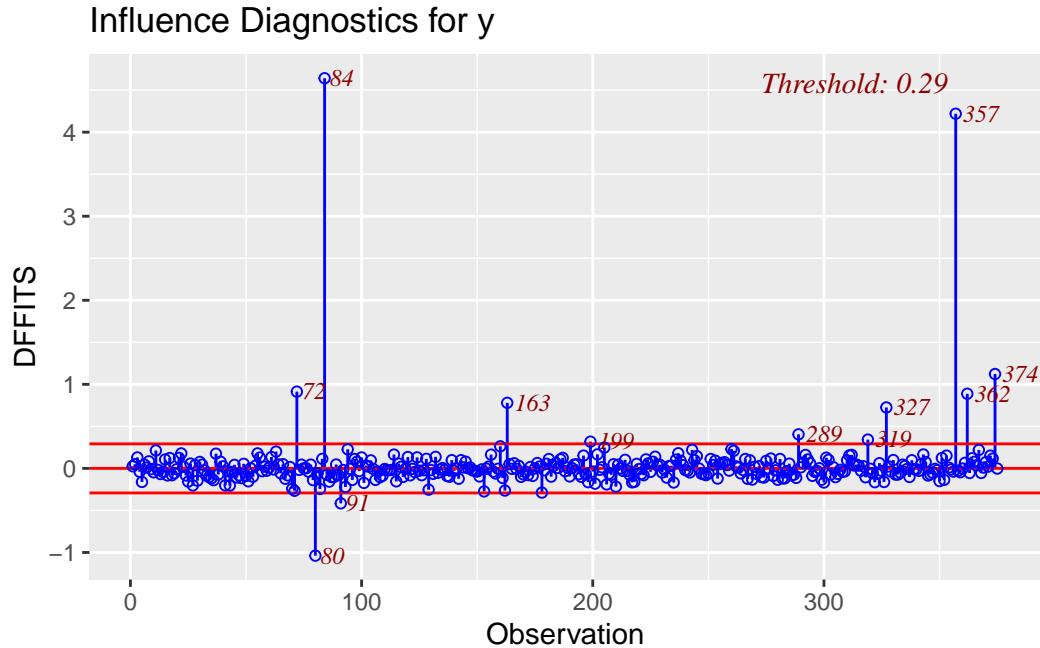
Valores atípicos identificados:

```
outliers
```

```
[1] 72 80 84 91 163 289 357 362 374
```

## 5. Detección de DFFITS

```
modelo |> coef() |> length() -> k  
train |> nrow() -> n  
(abs(modelo |> dffits())) -> dffits  
as.vector(which(dffits >= 2*sqrt(k/n))) -> inf_dffits  
  
modelo |> ols_plot_dffits()
```



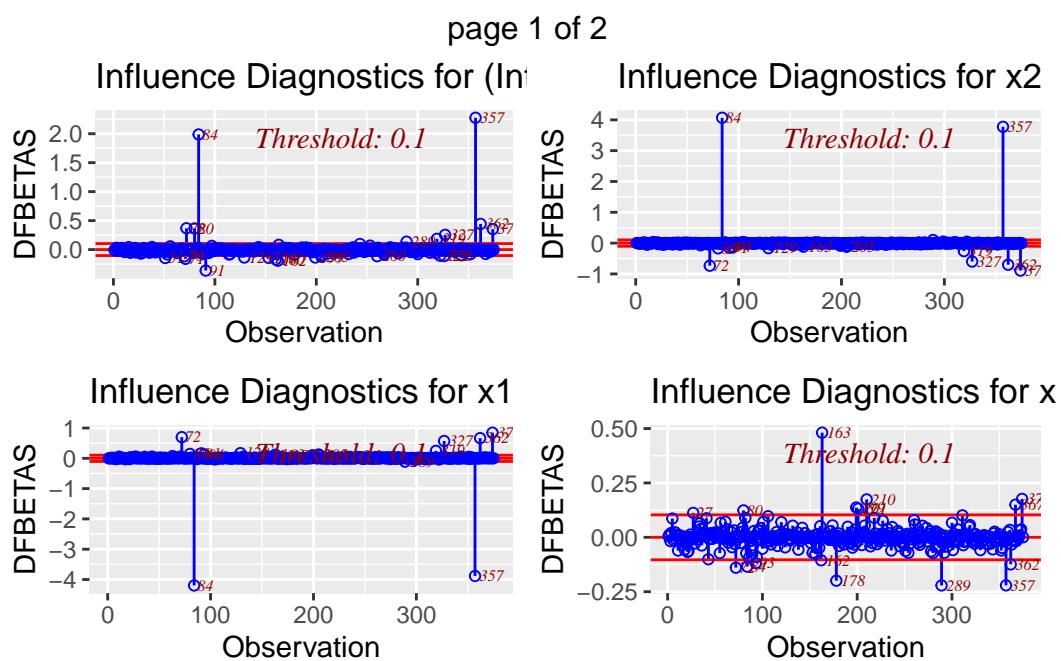
Valores influyentes según DFFITS:

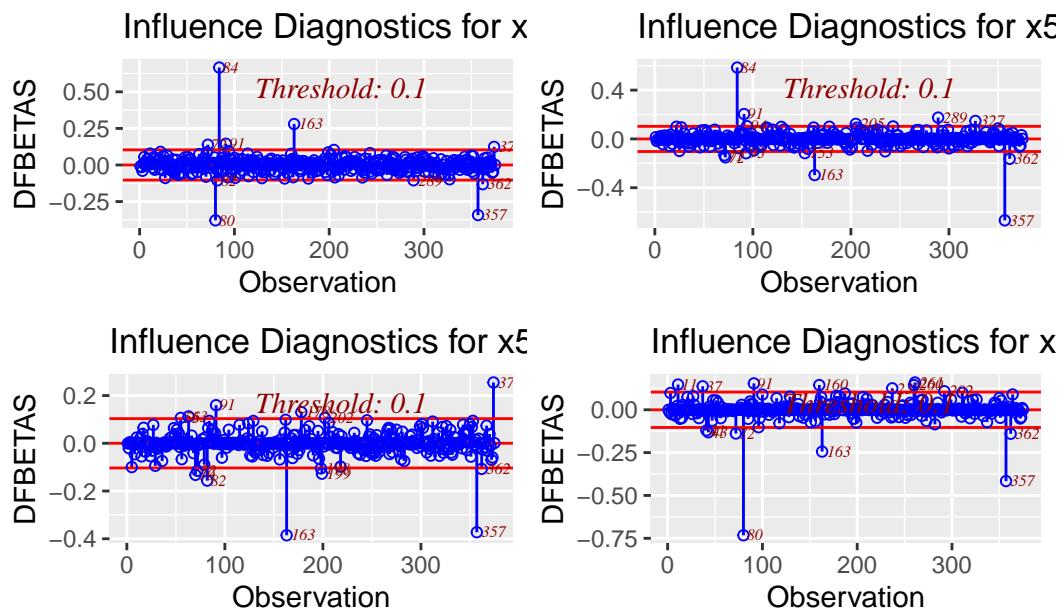
```
inf_dffits  
  
[1] 72 80 84 91 163 199 289 319 327 357 362 374
```

## 6. Detección de DFBETAS

```
(abs(modelo |> dfbetas()) -> dfbetas
as.vector(which(dfbetas[,1] >= 2/sqrt(n))) -> dfbeta0
as.vector(which(dfbetas[,2] >= 2/sqrt(n))) -> dfbeta1
as.vector(which(dfbetas[,3] >= 2/sqrt(n))) -> dfbeta2
as.vector(which(dfbetas[,4] >= 2/sqrt(n))) -> dfbeta3
as.vector(which(dfbetas[,5] >= 2/sqrt(n))) -> dfbeta4
as.vector(which(dfbetas[,6] >= 2/sqrt(n))) -> dfbeta5
as.vector(which(dfbetas[,7] >= 2/sqrt(n))) -> dfbeta6
as.vector(which(dfbetas[,8] >= 2/sqrt(n))) -> dfbeta7

modelo |> ols_plot_dfbetas()
```





Valores influyentes según DFBETAS:

```
dfbeta0
```

```
[1] 51 70 71 72 80 84 91 129 153 160 162 199 205 260 289 319 322 326 327
[20] 357 362 374
```

```
dfbeta1
```

```
[1] 72 80 84 91 94 129 163 205 289 319 327 357 362 374
```

```
dfbeta2
```

```
[1] 72 80 84 91 94 129 163 205 319 327 357 362 374
```

```
dfbeta3
```

```
[1] 27 72 80 84 93 162 163 178 199 201 210 289 357 362 367 374
```

```
dfbeta4
```

```
[1] 72 80 82 84 91 163 289 357 362 374
```

```
dfbeta5
```

```
[1] 55 63 70 72 82 91 163 178 198 199 202 357 362 374
```

```
dfbeta6
```

```
[1] 71 72 84 91 93 94 153 163 205 289 327 357 362
```

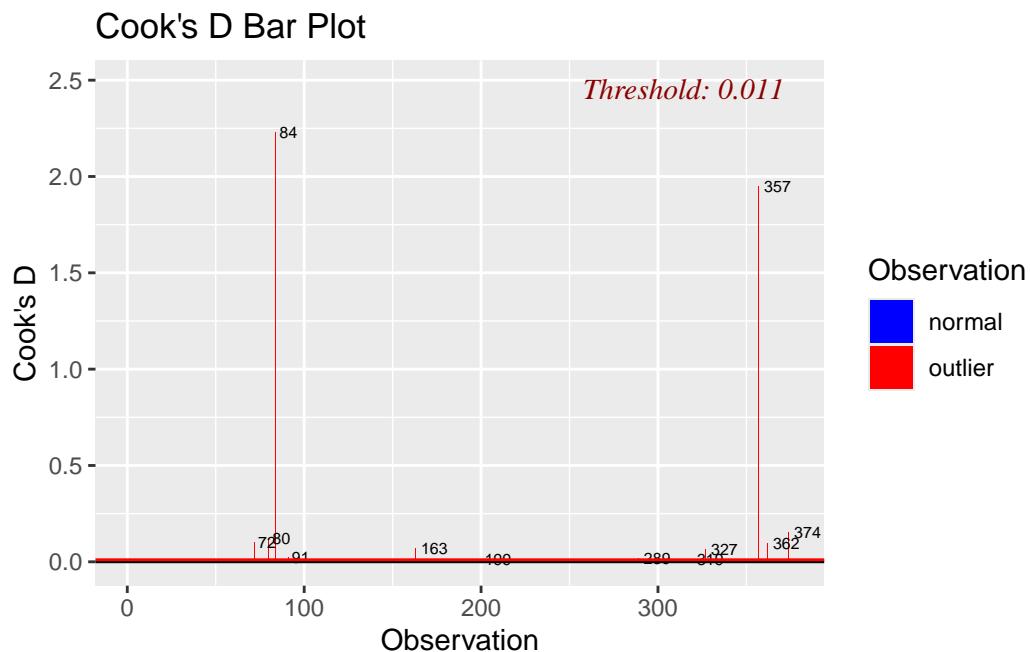
```
dfbeta7
```

```
[1] 11 37 41 43 72 80 91 160 163 237 260 261 292 357 362
```

## 7. Detección de valores influyentes según distancia de Cook

```
modelo |> cooks.distance() -> cookd  
as.vector(which(cookd > 4/n)) -> inf_cook
```

```
modelo |> ols_plot_cooksd_bar()
```



Valores influyentes según Distancia de Cook:

```
inf_cook
```

```
[1] 72 80 84 91 163 199 289 319 327 357 362 374
```

## 8. Detección de valores influyentes según COVRATIO

```
modelo |> covratio() |> abs() -> covra
as.vector(which(covra > 1+3*k/n)) -> inf_covra1
as.vector(which(covra < 1-3*k/n)) -> inf_covra2
c(inf_covra1, inf_covra2) -> inf_covra
```

Valores influyentes según COVRATIO:

```
inf_covra
```

```
[1] 185 319 327 80 84 91 163 289 357
```

En resumen:

```
lista <- list(leverages,
               outliers,
               inf_dffits,
               dfbeta0,dfbeta1,dfbeta2,dfbeta3,dfbeta4, dfbeta5,dfbeta6,dfbeta7,
               inf_cook,
               inf_covra)

inter <- Reduce(intersect, lista)
inter
```

```
[1] 357
```

## 9. Remoción de los valores leverage, atípicos e influyentes

```
train2 <- train[-c(inter),]
```

## 10. Creación de un nuevo modelo

```
modelo2 = lm(y ~ x1 + x2 + x3 + x4 + x5, data = train2)
```

## 11. Comparación de los reportes del modelo original y el nuevo

```
modelo |> summary()
```

```
Call:  
lm(formula = y ~ x1 + x2 + x3 + x4 + x5, data = train)  
  
Residuals:  
    Min      1Q  Median      3Q     Max  
-11.7807 -1.0193 -0.1207  0.8529 13.9607  
  
Coefficients:  
            Estimate Std. Error t value Pr(>|t|)  
(Intercept) 5.55013   0.42123 13.176 < 2e-16 ***  
x1          1.35969   0.04177 32.553 < 2e-16 ***  
x2         -0.55100   0.06354 -8.672 < 2e-16 ***  
x3          0.02829   0.10227  0.277 0.782246  
x41         0.98436   0.20580  4.783 2.51e-06 ***  
x5B         0.77653   0.27400  2.834 0.004851 **  
x5C        -1.02727   0.26210 -3.919 0.000106 ***  
x5D         1.18452   0.32541  3.640 0.000312 ***  
---  
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 1.976 on 367 degrees of freedom  
Multiple R-squared:  0.9966,    Adjusted R-squared:  0.9965  
F-statistic: 1.532e+04 on 7 and 367 DF,  p-value: < 2.2e-16
```

```
modelo2 |> summary()
```

```
Call:  
lm(formula = y ~ x1 + x2 + x3 + x4 + x5, data = train2)  
  
Residuals:  
    Min      1Q  Median      3Q     Max  
-11.7913 -0.9513 -0.1185  0.8672 17.3718  
  
Coefficients:  
            Estimate Std. Error t value Pr(>|t|)  
(Intercept) 4.65340   0.41271 11.275 < 2e-16 ***  
x1          1.51145   0.04425 34.158 < 2e-16 ***  
x2         -0.77528   0.06690 -11.589 < 2e-16 ***  
x3          0.04942   0.09571  0.516 0.605908  
x41         1.05033   0.19273  5.450 9.29e-08 ***  
x5B         0.87202   0.25665  3.398 0.000754 ***  
x5C        -0.86361   0.24620 -3.508 0.000508 ***  
x5D         1.31120   0.30490  4.300 2.19e-05 ***  
---  
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 1.848 on 366 degrees of freedom  
Multiple R-squared:  0.9969,    Adjusted R-squared:  0.9969  
F-statistic: 1.688e+04 on 7 and 366 DF,  p-value: < 2.2e-16
```

## 12. Selección de variables según $R^2$ predictivo

```
library(olsrr)
library(dplyr)
ols_step_all_possible(modelo2)$result |> data.frame() -> resultados
resultados |>
  select(n,predrsq,predictors) |>
  arrange(-predrsq) |>
  head()
```

n	predrsq	predictors
1	4	0.9960979 x1 x2 x4 x5
2	5	0.9960822 x1 x2 x3 x4 x5
3	3	0.9958170 x1 x2 x5
4	4	0.9958046 x1 x2 x3 x5
5	3	0.9956196 x1 x2 x4
6	4	0.9956054 x1 x2 x3 x4

Modelo resultante:  $Y = f(x_1, x_5)$

## 13. Selección de variables según AIC

```
resultados |>
  select(n,aic,predictors) |>
  arrange(aic) |>
  head()
```

n	aic	predictors
1	4	1529.078 x1 x2 x4 x5
2	5	1530.806 x1 x2 x3 x4 x5
3	3	1556.697 x1 x2 x5
4	4	1557.986 x1 x2 x3 x5
5	3	1586.814 x1 x2 x4
6	4	1587.844 x1 x2 x3 x4

Modelo resultante:  $Y = f(x_1, x_2, x_4, x_5)$

#### 14. Selección de variables según SBC

```
resultados |>
  select(n,sbc,predictors) |>
  arrange(sbc) |>
  head()
```

n	sbc	predictors
1	4 1560.472	x1 x2 x4 x5
2	5 1566.124	x1 x2 x3 x4 x5
3	3 1584.167	x1 x2 x5
4	4 1589.380	x1 x2 x3 x5
5	3 1606.435	x1 x2 x4
6	4 1611.390	x1 x2 x3 x4

Modelo resultante:  $Y = f(x_1, x_2, x_4, x_5)$

#### 15. Selección de variables según SBIC

```
resultados |>
  select(n,sbic,predictors) |>
  arrange(sbic) |>
  head()
```

n	sbic	predictors
1	4 463.9225	x1 x2 x4 x5
2	5 465.7012	x1 x2 x3 x4 x5
3	3 490.8719	x1 x2 x5
4	4 492.0656	x1 x2 x3 x5
5	3 524.2984	x1 x2 x4
6	4 525.0742	x1 x2 x3 x4

Modelo resultante:  $Y = f(x_1, x_2, x_4, x_5)$

## 16. Selección de variables según Cp de Mallows

```
resultados |>
  select(n,cp,predictors) |>
  mutate(dif = n-cp,.after=cp) |>
  arrange(abs(dif)) |>
  head()

  n      cp      dif      predictors
1 4  6.266637 -2.266637    x1 x2 x4 x5
2 5  8.000000 -3.000000    x1 x2 x3 x4 x5
3 3 34.452883 -31.452883    x1 x2 x5
4 4 35.699554 -31.699554    x1 x2 x3 x5
5 4 69.193442 -65.193442    x1 x2 x3 x4
6 3 68.318519 -65.318519    x1 x2 x4
```

Modelo resultante:  $Y = f(X_1, X_2, X_4, X_5)$

## 17. Selección del modelo según mejores subconjuntos

```
modelo2 |> ols_step_best_subset()
```

```
Best Subsets Regression
-----
Model Index      Predictors
-----
1          x1
2          x1 x2
3          x1 x2 x5
4          x1 x2 x4 x5
5          x1 x2 x3 x4 x5
-----
```

### Subsets Regression Summary

Model	Adj. R-Square	Pred R-Square	C(p)	AIC	SBIC	SBC	MSEP	FPE	HSP	
1	0.9949	0.9948	0.9947	239.6075	1709.6139	646.4032	1721.3867	2094.0560	5.6290	0.0151
2	0.9960	0.9960	0.9953	102.0304	1614.3672	551.6919	1630.0642	1618.9601	4.3635	0.0117
3	0.9967	0.9966	0.9958	34.4529	1556.6974	490.8719	1584.1672	1369.2324	3.7203	0.0100
4	0.9969	0.9969	0.9961	6.2666	1529.0782	463.9225	1560.4723	1268.4153	3.4555	0.0093
5	0.9969	0.9969	0.9961	8.0000	1530.8059	465.7012	1566.1242	1270.9456	3.4715	0.0093

AIC: Akaike Information Criteria

SBIC: Sawa's Bayesian Information Criteria

SBC: Schwarz Bayesian Criteria

MSEP: Estimated error of prediction, assuming multivariate normality

FPE: Final Prediction Error

HSP: Hocking's Sp

APC: Amemiya Prediction Criteria

Modelo resultante:  $Y = f()$

18. Selección del mejor modelo según forward selection

```
modelo2 |> ols_step_forward_p()
```

Stepwise Summary						
Step	Variable	AIC	SBC	SBIC	R2	Adj. R2
0	Base Model	3678.527	3686.375	2613.180	0.00000	0.00000
1	x1	1709.614	1721.387	646.403	0.99486	0.99484
2	x2	1614.367	1630.064	551.692	0.99603	0.99601
3	x4	1586.814	1606.435	524.298	0.99633	0.99631
4	x5	1529.078	1560.472	463.922	0.99691	0.99686

Final Model Output

Model Summary

R	0.998	RMSE	1.829
R-Squared	0.997	MSE	3.346
Adj. R-Squared	0.997	Coef. Var	1.456
Pred R-Squared	0.996	AIC	1529.078
MAE	1.178	SBC	1560.472

RMSE: Root Mean Square Error

MSE: Mean Square Error

MAE: Mean Absolute Error

AIC: Akaike Information Criteria

SBC: Schwarz Bayesian Criteria

ANOVA

	Sum of Squares	DF	Mean Square	F	Sig.
Regression	403616.821	6	67269.470	19727.742	0.0000
Residual	1251.430	367	3.410		
Total	404868.252	373			

Parameter Estimates

model	Beta	Std. Error	Std. Beta	t	Sig	lower	upper
(Intercept)	4.646	0.412		11.275	0.000	3.835	5.456
x1	1.511	0.044	1.506	34.192	0.000	1.425	1.598
x2	-0.775	0.067	-0.511	-11.600	0.000	-0.907	-0.644
x41	1.057	0.192	0.016	5.500	0.000	0.679	1.435
x5B	0.883	0.256	0.012	3.454	0.001	0.380	1.385
x5C	-0.872	0.245	-0.012	-3.554	0.000	-1.355	-0.390
x5D	1.300	0.304	0.014	4.279	0.000	0.703	1.898

```
modelo2 |> ols_step_forward_aic()
```

### Stepwise Summary

Step	Variable	AIC	SBC	SBIC	R2	Adj. R2
0	Base Model	3678.527	3686.375	2613.180	0.00000	0.00000
1	x1	1709.614	1721.387	646.403	0.99486	0.99484
2	x2	1614.367	1630.064	551.692	0.99603	0.99601
3	x5	1556.697	1584.167	490.872	0.99665	0.99661
4	x4	1529.078	1560.472	463.922	0.99691	0.99686

### Final Model Output

#### Model Summary

R	0.998	RMSE	1.829
R-Squared	0.997	MSE	3.346
Adj. R-Squared	0.997	Coef. Var	1.456
Pred R-Squared	0.996	AIC	1529.078
MAE	1.178	SBC	1560.472

RMSE: Root Mean Square Error

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MAE: Mean Absolute Error

AIC: Akaike Information Criteria

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#### ANOVA

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x5B	0.883	0.256	0.012	3.454	0.001	0.380	1.385
x5C	-0.872	0.245	-0.012	-3.554	0.000	-1.355	-0.390
x5D	1.300	0.304	0.014	4.279	0.000	0.703	1.898
x41	1.057	0.192	0.016	5.500	0.000	0.679	1.435

Modelo resultante:  $Y = f()$

## 19. Selección del mejor modelo según backward selection

```
modelo2 |> ols_step_backward_p()
```

Stepwise Summary						
Step	Variable	AIC	SBC	SBIC	R2	Adj. R2
0	Full Model	1530.806	1566.124	465.701	0.99691	0.99685
1	x3	1529.078	1560.472	463.922	0.99691	0.99686

Final Model Output

Model Summary

R	0.998	RMSE	1.829
R-Squared	0.997	MSE	3.346
Adj. R-Squared	0.997	Coef. Var	1.456
Pred R-Squared	0.996	AIC	1529.078
MAE	1.178	SBC	1560.472

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ANOVA

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Parameter Estimates

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(Intercept)	4.646	0.412		11.275	0.000	3.835	5.456
x1	1.511	0.044	1.506	34.192	0.000	1.425	1.598
x2	-0.775	0.067	-0.511	-11.600	0.000	-0.907	-0.644
x41	1.057	0.192	0.016	5.500	0.000	0.679	1.435
x5B	0.883	0.256	0.012	3.454	0.001	0.380	1.385
x5C	-0.872	0.245	-0.012	-3.554	0.000	-1.355	-0.390
x5D	1.300	0.304	0.014	4.279	0.000	0.703	1.898

```
modelo2 |> ols_step_backward_aic()
```

Stepwise Summary

Step	Variable	AIC	SBC	SBIC	R2	Adj. R2
0	Full Model	1530.806	1566.124	465.701	0.99691	0.99685
1	x3	1529.078	1560.472	463.902	0.99691	0.99686

Final Model Output

Model Summary

R	0.998	RMSE	1.829
R-Squared	0.997	MSE	3.346
Adj. R-Squared	0.997	Coef. Var	1.456
Pred R-Squared	0.996	AIC	1529.078
MAE	1.178	SBC	1560.472

RMSE: Root Mean Square Error

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ANOVA

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Parameter Estimates

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(Intercept)	4.646	0.412		11.275	0.000	3.835	5.456
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x2	-0.775	0.067	-0.511	-11.600	0.000	-0.907	-0.644
x41	1.057	0.192	0.016	5.500	0.000	0.679	1.435
x5B	0.883	0.256	0.012	3.454	0.001	0.380	1.385
x5C	-0.872	0.245	-0.012	-3.554	0.000	-1.355	-0.390
x5D	1.300	0.304	0.014	4.279	0.000	0.703	1.898

Modelo resultante:  $Y = f()$

## 20. Selección del mejor modelo según stepwise selection

```
modelo2 |> ols_step_both_p()
```

Stepwise Summary						
Step	Variable	AIC	SBC	SBIC	R2	Adj. R2
0	Base Model	3678.527	3686.375	2613.180	0.00000	0.00000
1	x1 (+)	1709.614	1721.387	646.403	0.99486	0.99484
2	x2 (+)	1614.367	1630.064	551.692	0.99603	0.99601
3	x4 (+)	1586.814	1606.435	524.298	0.99633	0.99631
4	x5 (+)	1529.078	1560.472	463.922	0.99691	0.99686

Final Model Output

Model Summary

R	0.998	RMSE	1.829
R-Squared	0.997	MSE	3.346
Adj. R-Squared	0.997	Coef. Var	1.456
Pred R-Squared	0.996	AIC	1529.078
MAE	1.178	SBC	1560.472

RMSE: Root Mean Square Error

MSE: Mean Square Error

MAE: Mean Absolute Error

AIC: Akaike Information Criteria

SBC: Schwarz Bayesian Criteria

ANOVA

	Sum of Squares	DF	Mean Square	F	Sig.
Regression	403616.821	6	67269.470	19727.742	0.0000
Residual	1251.430	367	3.410		
Total	404868.252	373			

Parameter Estimates

model	Beta	Std. Error	Std. Beta	t	Sig	lower	upper
(Intercept)	4.646	0.412		11.275	0.000	3.835	5.456
x1	1.511	0.044	1.506	34.192	0.000	1.425	1.598
x2	-0.775	0.067	-0.511	-11.600	0.000	-0.907	-0.644
x41	1.057	0.192	0.016	5.500	0.000	0.679	1.435
x5B	0.883	0.256	0.012	3.454	0.001	0.380	1.385
x5C	-0.872	0.245	-0.012	-3.554	0.000	-1.355	-0.390
x5D	1.300	0.304	0.014	4.279	0.000	0.703	1.898

```
modelo2 |> ols_step_both_aic()
```

### Stepwise Summary

Step	Variable	AIC	SBC	SBIC	R2	Adj. R2
0	Base Model	3678.527	3686.375	2613.180	0.00000	0.00000
1	x1 (+)	1709.614	1721.387	646.403	0.99486	0.99484
2	x2 (+)	1614.367	1630.064	551.692	0.99603	0.99601
3	x5 (+)	1556.697	1584.167	490.872	0.99665	0.99661
4	x4 (+)	1529.078	1560.472	463.922	0.99691	0.99686

### Final Model Output

#### Model Summary

R	0.998	RMSE	1.829
R-Squared	0.997	MSE	3.346
Adj. R-Squared	0.997	Coef. Var	1.456
Pred R-Squared	0.996	AIC	1529.078
MAE	1.178	SBC	1560.472

RMSE: Root Mean Square Error

MSE: Mean Square Error

MAE: Mean Absolute Error

AIC: Akaike Information Criteria

SBC: Schwarz Bayesian Criteria

#### ANOVA

	Sum of Squares	DF	Mean Square	F	Sig.
Regression	403616.821	6	67269.470	19727.742	0.0000
Residual	1251.430	367	3.410		
Total	404868.252	373			

#### Parameter Estimates

model	Beta	Std. Error	Std. Beta	t	Sig	lower	upper
(Intercept)	4.646	0.412		11.275	0.000	3.835	5.456
x1	1.511	0.044	1.506	34.192	0.000	1.425	1.598
x2	-0.775	0.067	-0.511	-11.600	0.000	-0.907	-0.644
x5B	0.883	0.256	0.012	3.454	0.001	0.380	1.385
x5C	-0.872	0.245	-0.012	-3.554	0.000	-1.355	-0.390
x5D	1.300	0.304	0.014	4.279	0.000	0.703	1.898
x41	1.057	0.192	0.016	5.500	0.000	0.679	1.435

Modelo resultante:  $Y = f()$

## 21. Uso del testing

```
pred_train <- predict(modelo2, newdata = train2)
pred_test  <- predict(modelo2, newdata = test)

metricas <- function(y, yhat){
  rmse <- sqrt(mean((y - yhat)^2))
  mae  <- mean(abs(y - yhat))
  r2   <- 1 - sum((y - yhat)^2)/sum((y - mean(y))^2)
  c(RMSE = rmse, MAE = mae, R2 = r2)
}

m_train <- metricas(train2$y, pred_train)
m_test  <- metricas(test$y,  pred_test)

m_train
```

RMSE	MAE	R2
1.8285608	1.1797236	0.9969113

```
m_test
```

RMSE	MAE	R2
2.6046388	1.3963764	0.9931583

## 21. Interpretación de coeficientes del mejor modelo