LinearRegression_Part1

January 2, 2022

0.0.1 Regresión lineal simple

[1]:
```
# Importamos las librerías a emplear
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

# Temas de Jupyter para fondo negro
#from jupyterthemes import jtplot
#jtplot.style(theme='onedork')

# Por si no se nos autocompleta el código
%config IPCompleter.greedy=True
```

[2]:
```
# Cargamos el archivo .csv
data = pd.read_csv(r"D:
↪\Curso-Jupyter-Notebook\GitHub\python-ml-course\datasets\ads\Advertising.
↪csv")
data.head() # Visualizamos los primeros 5 datos
```

[2]:

	TV	Radio	Newspaper	Sales
0	230.1	37.8	69.2	22.1
1	44.5	39.3	45.1	10.4
2	17.2	45.9	69.3	9.3
3	151.5	41.3	58.5	18.5
4	180.8	10.8	58.4	12.9

[3]:
```
# Creamos un modelo lineal
import statsmodels.formula.api as smf
```

[4]:
```
# Creamos el modelo lineal
lm = smf.ols(formula = "Sales~TV", data = data).fit()
```

[5]:
```
lm.params # Parámetros de nuestro modelo
# Se concluye lo siguiente:
# Un incremento en 100 unidades de publicidad en TV implica una 4.7 ventas␣
↪adicionales
```

[5]: Intercept   7.032594
TV   0.047537
dtype: float64

Modelo predictivo: 7.032594 + 0.047537xTV

[6]:
```
# Hallamos los p-valores (F-statistic)
lm.pvalues
# Si el p-valor es menor que el nivel de significación, rechazamos la hipótesis␣
 ↪nula
# y aceptamos que existe una relación lineal entre nuestras variables
```

[6]:
```
Intercept    1.406300e-35
TV           1.467390e-42
dtype: float64
```

[7]:
```
# Hallamos el R^2 (suma de los cuadrados totales) - eficacia del modelo
lm.rsquared
```

[7]: 0.611875050850071

[8]:
```
# Hallamos el R^2 ajustado
lm.rsquared_adj
```

[8]: 0.6099148238341623

[9]:
```
# Visión general del modelo lineal creado
lm.summary()
```

[9]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  Sales   R-squared:                       0.612
Model:                            OLS   Adj. R-squared:                  0.610
Method:                 Least Squares   F-statistic:                     312.1
Date:                Sun, 02 Jan 2022   Prob (F-statistic):           1.47e-42
Time:                        01:13:05   Log-Likelihood:                -519.05
No. Observations:                 200   AIC:                             1042.
Df Residuals:                     198   BIC:                             1049.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      7.0326      0.458     15.360      0.000       6.130       7.935
TV             0.0475      0.003     17.668      0.000       0.042       0.053
==============================================================================
```

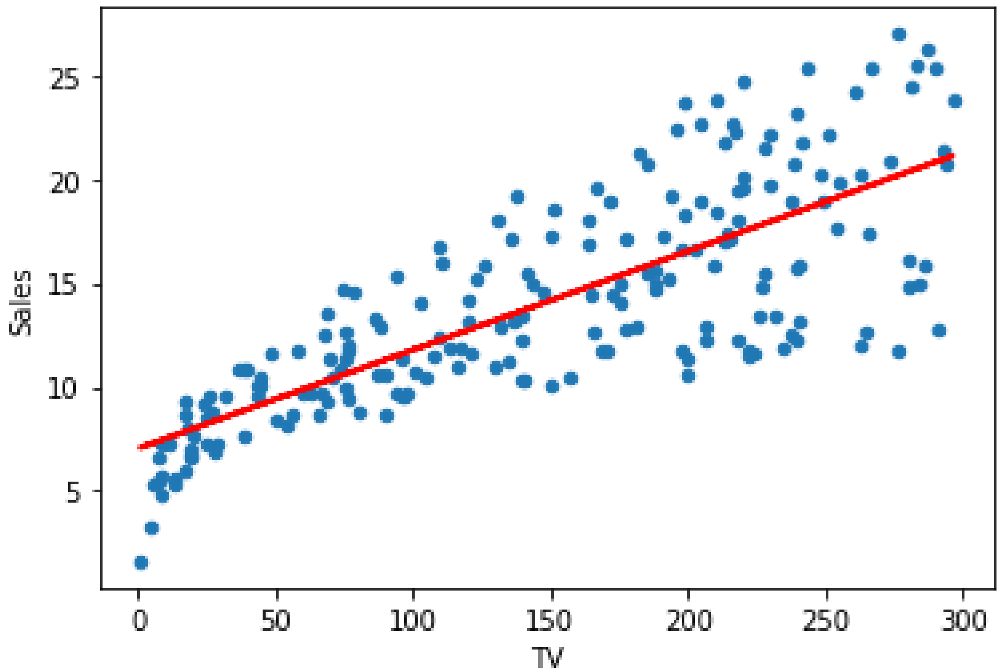
```
Omnibus:                        0.531   Durbin-Watson:                   1.935
Prob(Omnibus):                  0.767   Jarque-Bera (JB):                0.669
Skew:                          -0.089   Prob(JB):                        0.716
Kurtosis:                       2.779   Cond. No.                         338.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
"""
```

[10]:
```python
# Generamos un dataframe con una columna del dataframe anterior
sales_pred = lm.predict(pd.DataFrame(data["TV"]))
sales_pred # Valores predictivos
```

[10]:
```
0      17.970775
1       9.147974
2       7.850224
3      14.234395
4      15.627218
         …
195     8.848493
196    11.510545
197    15.446579
198    20.513985
199    18.065848
Length: 200, dtype: float64
```

[11]:
```python
# Evaluación de nuestro modelo predictivo
%matplotlib inline
data.plot(kind = "scatter", x = "TV", y = "Sales") # scatter -> nube de puntos
plt.plot(pd.DataFrame(data["TV"]), sales_pred, c = "red", linewidth = 2)
```

[11]:
```
[<matplotlib.lines.Line2D at 0x1f107e2db08>]
```



[12]:
```
# Modelo de regresión lineal
data["sales_pred"] = 7.032594 + 0.047537*data["TV"]
```

[13]:
```
# RSE -> Error estándar residual
data["RSE"] = (data["Sales"] - data["sales_pred"])**2

# Suma de los cuadrados de la diferencia
SSD = sum(data["RSE"])

# Error estándar residual
RSE = np.sqrt(SSD/(len(data) - 2))
RSE
```

[13]: 3.258656369238098

[14]:
```
# Promedio de ventas
sales_m = np.mean(data["Sales"])
sales_m
```

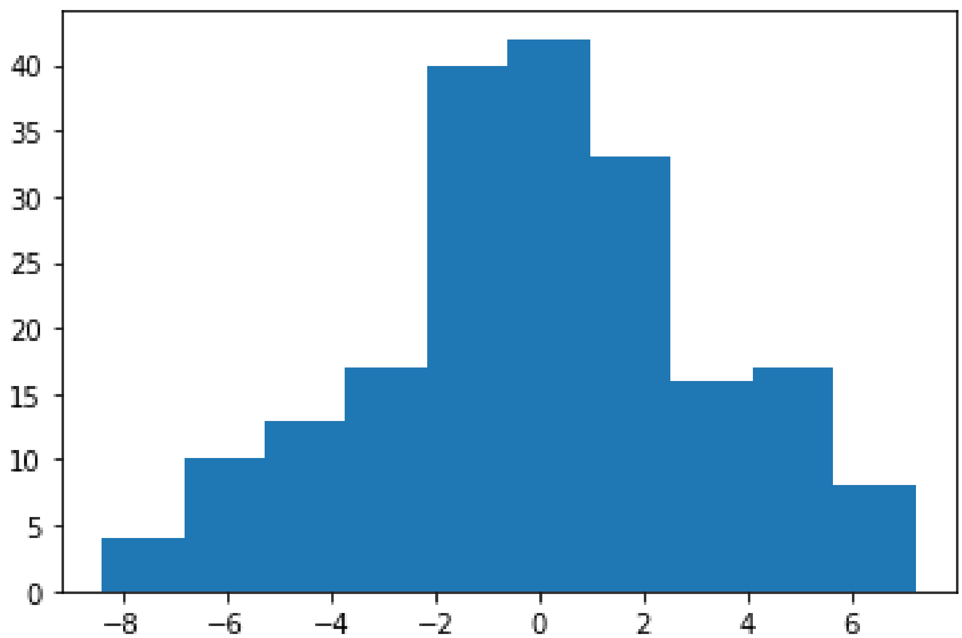
[14]: 14.0225

[15]:
```
# Error promedio
error = RSE/sales_m
error
```

[15]: 0.23238768901680143

[16]:
```python
# Histograma de la distribución de errores respecto al modelo
# Observamos una distribución normal, aproximadamente
plt.hist((data["Sales"] - data["sales_pred"]))
```

[16]:
```
(array([ 4., 10., 13., 17., 40., 42., 33., 16., 17.,  8.]),
 array([-8.3860819 , -6.82624404, -5.26640618, -3.70656832, -2.14673046,
        -0.5868926 ,  0.97294526,  2.53278312,  4.09262098,  5.65245884,
         7.2122967 ]),
 <BarContainer object of 10 artists>)
```



0.0.2 Regresión lineal múltiple

[17]:
```python
# Añadimos el Newspaper al modelo existente
lm2 = smf.ols(formula = "Sales~TV+Newspaper", data = data).fit()
```

[18]:
```python
# Parámetros de nuestro segundo modelo lineal
lm2.params
```

[18]:
```
Intercept    5.774948
TV           0.046901
Newspaper    0.044219
dtype: float64
```

Modelo predictivo: 5.774948 + 0.046901xTV + 0.044219xNewspaper

[19]:
```
# Hallamos los p-valores
lm2.pvalues
```

[19]:
```
Intercept    3.145860e-22
TV           5.507584e-44
Newspaper    2.217084e-05
dtype: float64
```

[20]:
```
# Hallamos el R^2
# Notamos que R^2 a aumentado, eso es bueno
lm2.rsquared
```

[20]:
```
0.6458354938293271
```

[21]:
```
# Hallamos el R^2 ajustado
lm2.rsquared_adj
```

[21]:
```
0.6422399150864777
```

[22]:
```
# Predicciones del modelo creado: ventas respecto a TV y Newspaper
sales_pred = lm2.predict(data[["TV", "Newspaper"]])
sales_pred
```

[22]:
```
0      19.626901
1       9.856348
2       9.646055
3      15.467318
4      16.837102
         …
195     8.176802
196    10.551220
197    14.359467
198    22.003458
199    17.045429
Length: 200, dtype: float64
```

[23]:
```
# Desviación estándar de los residuos
SSD = sum((data["Sales"] - sales_pred)**2)
SSD
```

[23]:
```
1918.5618118968275
```

[24]:
```
# Error estándar residual
RSE = np.sqrt(SSD/(len(data) - 2 - 1))
RSE
```

[24]:
```
3.1207198602528856
```

[25]:
```
# Errorpromedio
error = RSE/sales_m
error
```

[25]:
```
0.22255089037282122
```

[26]:
```
# Visión general del modelo lineal creado
lm2.summary()
```

[26]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  Sales   R-squared:                       0.646
Model:                            OLS   Adj. R-squared:                  0.642
Method:                 Least Squares   F-statistic:                     179.6
Date:                Sun, 02 Jan 2022   Prob (F-statistic):           3.95e-45
Time:                        01:13:08   Log-Likelihood:                -509.89
No. Observations:                 200   AIC:                             1026.
Df Residuals:                     197   BIC:                             1036.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      5.7749      0.525     10.993      0.000       4.739       6.811
TV             0.0469      0.003     18.173      0.000       0.042       0.052
Newspaper      0.0442      0.010      4.346      0.000       0.024       0.064
==============================================================================
Omnibus:                        0.658   Durbin-Watson:                   1.969
Prob(Omnibus):                  0.720   Jarque-Bera (JB):                0.415
Skew:                          -0.093   Prob(JB):                        0.813
Kurtosis:                       3.122   Cond. No.                         410.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
"""
```

[27]:
```
# Ahora probamos añandiendo la radio al modelo existente
lm3 = smf.ols(formula = "Sales~TV+Radio", data = data).fit()
```

[28]:
```
# Visión general del modelo lineal creado
lm3.summary()
```

[28]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  Sales   R-squared:                       0.897
Model:                            OLS   Adj. R-squared:                  0.896
Method:                 Least Squares   F-statistic:                     859.6
Date:                Sun, 02 Jan 2022   Prob (F-statistic):           4.83e-98
Time:                        01:13:09   Log-Likelihood:                -386.20
No. Observations:                 200   AIC:                             778.4
Df Residuals:                     197   BIC:                             788.3
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      2.9211      0.294      9.919      0.000       2.340       3.502
TV             0.0458      0.001     32.909      0.000       0.043       0.048
Radio          0.1880      0.008     23.382      0.000       0.172       0.204
==============================================================================
Omnibus:                       60.022   Durbin-Watson:                   2.081
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              148.679
Skew:                          -1.323   Prob(JB):                     5.19e-33
Kurtosis:                       6.292   Cond. No.                         425.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
"""
```

[29]:
```
# Predicciones del modelo creado: ventas respecto a TV y Radio
sales_pred = lm3.predict(data[["TV", "Radio"]])

# Desviación estándar de los residuos
SSD = sum((data["Sales"] - sales_pred)**2)

# Error estándar residual
RSE = np.sqrt(SSD/(len(data) - 2 - 1))
RSE
```

[29]:
```
1.6813609125080007
```

[30]:
```
# Error promedio
error = RSE/sales_m
error
```

[30]:
```
0.11990450436855059
```

[31]:
```
# Finalmente evaluamos un modelo lineal múltiple que incluya todos los factores
lm4 = smf.ols(formula = "Sales~TV+Radio+Newspaper", data = data).fit()
```

[32]:
```
# Visión general del modelo lineal creado
lm4.summary()
```

[32]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  Sales   R-squared:                       0.897
Model:                            OLS   Adj. R-squared:                  0.896
Method:                 Least Squares   F-statistic:                     570.3
Date:                Sun, 02 Jan 2022   Prob (F-statistic):           1.58e-96
Time:                        01:13:09   Log-Likelihood:                -386.18
No. Observations:                 200   AIC:                             780.4
Df Residuals:                     196   BIC:                             793.6
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      2.9389      0.312      9.422      0.000       2.324       3.554
TV             0.0458      0.001     32.809      0.000       0.043       0.049
Radio          0.1885      0.009     21.893      0.000       0.172       0.206
Newspaper     -0.0010      0.006     -0.177      0.860      -0.013       0.011
==============================================================================
Omnibus:                       60.414   Durbin-Watson:                   2.084
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              151.241
Skew:                          -1.327   Prob(JB):                     1.44e-33
Kurtosis:                       6.332   Cond. No.                         454.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
"""
```

[33]:
```
# Predicciones del modelo creado: ventas respecto a TV, Radio y Newspaper
sales_pred = lm4.predict(data[["TV", "Radio", "Newspaper"]])

# Desviación estándar de los residuos
SSD = sum((data["Sales"] - sales_pred)**2)

# Error estándar residual
```

```
RSE = np.sqrt(SSD/(len(data) - 3 - 1))
RSE
```

[33]: 1.6855103734147439

[34]:
```
# Error promedio
error = RSE/sales_m
error
```

[34]: 0.12020041885646238

0.0.3 Multicolinealidad

Factor inflación de la varianza - VIF = 1: Las variables no están correlacionadas - VIF < 5: Las variables tienen una correlación moderada y pueden quedarse en el modelo - VIF > 5: Las variables están altísimamente correlacionadas y deben desaparecer del modelo

[35]:
```
# Newspaper ~ TV + Radio -> R^2 | VIF = 1/(1-R^2)
lm_n = smf.ols(formula = "Newspaper~TV+Radio", data = data).fit()
rsquared_n = lm_n.rsquared
VIF = 1/(1 - rsquared_n)
VIF
```

[35]: 1.1451873787239286

[36]:
```
# TV ~ Newspaper + Radio -> R^2 | VIF = 1/(1-R^2)
lm_n = smf.ols(formula = "TV~Newspaper+Radio", data = data).fit()
rsquared_n = lm_n.rsquared
VIF = 1/(1 - rsquared_n)
VIF
# Conclusión: TV no está correlacionada con los demás factores
```

[36]: 1.00461078493965

[37]:
```
# Radio ~ TV + Newspaper -> R^2 | VIF = 1/(1-R^2)
lm_n = smf.ols(formula = "Radio~TV+Newspaper", data = data).fit()
rsquared_n = lm_n.rsquared
VIF = 1/(1 - rsquared_n)
VIF
# Podemos observar que Radio y Newspaper tienen prácticamente el mismo VIF
# significa que ambas están correlacionadas, sin incluir la TV
# Sin embargo el modelo realizado con TV y Radio es superior a los demás modelos
# El modelo con las 3 variables predictorias no mejora
```

[37]: 1.1449519171055353

[38]:
```
lm3.summary()
```

[38]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  Sales   R-squared:                       0.897
Model:                            OLS   Adj. R-squared:                  0.896
Method:                 Least Squares   F-statistic:                     859.6
Date:                Sun, 02 Jan 2022   Prob (F-statistic):           4.83e-98
Time:                        01:13:11   Log-Likelihood:                -386.20
No. Observations:                 200   AIC:                             778.4
Df Residuals:                     197   BIC:                             788.3
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      2.9211      0.294      9.919      0.000       2.340       3.502
TV             0.0458      0.001     32.909      0.000       0.043       0.048
Radio          0.1880      0.008     23.382      0.000       0.172       0.204
==============================================================================
Omnibus:                       60.022   Durbin-Watson:                   2.081
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              148.679
Skew:                          -1.323   Prob(JB):                     5.19e-33
Kurtosis:                       6.292   Cond. No.                         425.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
"""
```