Fuente de Datos : https://www.kaggle.com/kyanyoga/sample-sales-data

IMPORTAR LIBRERÍAS Y DATASETS

```
In [ ]:
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import zipfile
import cv2
import tensorflow as tf
from tensorflow.python.keras import Sequential
from tensorflow.keras import layers, optimizers
from tensorflow.keras.applications.resnet50 import ResNet50
from tensorflow.keras.layers import Input, Add, Dense, Activation, ZeroPadding2D, BatchNormalization, Flatten,
from tensorflow.keras.models import Model, load_model
from tensorflow.keras.initializers import glorot_uniform
from tensorflow.keras.utils import plot_model
from tensorflow.keras.callbacks import ReduceLROnPlateau, EarlyStopping, ModelCheckpoint, LearningRateSchedule
from IPython.display import display
from tensorflow.keras import backend as K
from sklearn.preprocessing import StandardScaler, normalize
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE
from sklearn.metrics.pairwise import cosine_similarity
import plotly.express as px
import plotly.graph_objects as go

from google.colab import files #Libreria para cargar ficheros directamente en Colab
%matplotlib inline
```

```
In [ ]:
# Procedemos a montar el disco usando los siguientes comandos:

from google.colab import drive
drive.mount('/content/drive')
```

Mounted at /content/drive

```
In [ ]:
sales_df = pd.read_csv('/content/drive/MyDrive/01_Oriol/01_Machine Learning/07_Masterclass-IA-Moderna/03_Market
```

```
In [ ]:
sales_df
```

Out[ ]:

	ORDERNUMBER	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	ORDERDATE	STATUS	QTR_ID	MONTH_ID	YEAR_ID
0	10107	30	95.70	2	2871.00	2/24/2003 0:00	Shipped	1	2	2003
1	10121	34	81.35	5	2765.90	5/7/2003 0:00	Shipped	2	5	2003
2	10134	41	94.74	2	3884.34	7/1/2003 0:00	Shipped	3	7	2003
3	10145	45	83.26	6	3746.70	8/25/2003 0:00	Shipped	3	8	2003
4	10159	49	100.00	14	5205.27	10/10/2003 0:00	Shipped	4	10	2003
...	...	...	...	...	...	...	...	...	...	...
2818	10350	20	100.00	15	2244.40	12/2/2004 0:00	Shipped	4	12	2004
2819	10373	29	100.00	1	3978.51	1/31/2005 0:00	Shipped	1	1	2005
2820	10386	43	100.00	4	5417.57	3/1/2005 0:00	Resolved	1	3	2005
2821	10397	34	62.24	1	2116.16	3/28/2005 0:00	Shipped	1	3	2005
2822	10414	47	65.52	9	3079.44	5/6/2005 0:00	On Hold	2	5	2005

2823 rows × 25 columns

```
In [ ]:
# Veamos los tipos de datos
sales_df.dtypes
```

```
Out[ ]:
ORDERNUMBER           int64
QUANTITYORDERED       int64
PRICEEACH           float64
ORDERLINENUMBER       int64
SALES               float64
ORDERDATE            object
STATUS               object
QTR_ID                int64
MONTH_ID              int64
YEAR_ID               int64
PRODUCTLINE          object
MSRP                  int64
PRODUCTCODE          object
CUSTOMERNAME         object
PHONE                object
ADDRESSLINE1         object
ADDRESSLINE2         object
CITY                 object
STATE                object
POSTALCODE           object
COUNTRY              object
TERRITORY            object
CONTACTLASTNAME      object
CONTACTFIRSTNAME     object
DEALSIZE             object
dtype: object
```

```
In [ ]:
# Convertir la fecha del pedido en formato de fecha y hora
sales_df['ORDERDATE'] = pd.to_datetime(sales_df['ORDERDATE'])
# Comprobar el tipo de datos
sales_df.dtypes
```

```
Out[ ]:
ORDERNUMBER                    int64
QUANTITYORDERED                int64
PRICEEACH                    float64
ORDERLINENUMBER                int64
SALES                        float64
ORDERDATE             datetime64[ns]
STATUS                        object
QTR_ID                         int64
MONTH_ID                       int64
YEAR_ID                        int64
PRODUCTLINE                   object
MSRP                           int64
PRODUCTCODE                   object
CUSTOMERNAME                  object
PHONE                         object
ADDRESSLINE1                  object
ADDRESSLINE2                  object
CITY                          object
STATE                         object
POSTALCODE                    object
COUNTRY                       object
TERRITORY                     object
CONTACTLASTNAME               object
CONTACTFIRSTNAME              object
DEALSIZE                      object
dtype: object
```

```
In [ ]:
# Comprobar el número de elementos no nulos del data frame
sales_df.info()

# Comprobar el número de elementos nulos del data frame
sales_df.isnull().sum()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2823 entries, 0 to 2822
Data columns (total 25 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   ORDERNUMBER       2823 non-null   int64
 1   QUANTITYORDERED   2823 non-null   int64
 2   PRICEEACH         2823 non-null   float64
 3   ORDERLINENUMBER   2823 non-null   int64
 4   SALES             2823 non-null   float64
 5   ORDERDATE         2823 non-null   datetime64[ns]
 6   STATUS            2823 non-null   object
 7   QTR_ID            2823 non-null   int64
 8   MONTH_ID          2823 non-null   int64
 9   YEAR_ID           2823 non-null   int64
 10  PRODUCTLINE       2823 non-null   object
 11  MSRP              2823 non-null   int64
 12  PRODUCTCODE       2823 non-null   object
 13  CUSTOMERNAME      2823 non-null   object
 14  PHONE             2823 non-null   object
 15  ADDRESSLINE1      2823 non-null   object
 16  ADDRESSLINE2      302 non-null    object
 17  CITY              2823 non-null   object
 18  STATE             1337 non-null   object
 19  POSTALCODE        2747 non-null   object
 20  COUNTRY           2823 non-null   object
 21  TERRITORY         1749 non-null   object
 22  CONTACTLASTNAME   2823 non-null   object
 23  CONTACTFIRSTNAME  2823 non-null   object
 24  DEALSIZE          2823 non-null   object
dtypes: datetime64[ns](1), float64(2), int64(7), object(15)
memory usage: 551.5+ KB
```

```
Out[ ]:
ORDERNUMBER            0
QUANTITYORDERED        0
PRICEEACH              0
ORDERLINENUMBER        0
SALES                  0
ORDERDATE              0
STATUS                 0
QTR_ID                 0
MONTH_ID               0
YEAR_ID                0
PRODUCTLINE            0
MSRP                   0
PRODUCTCODE            0
CUSTOMERNAME           0
PHONE                  0
ADDRESSLINE1           0
ADDRESSLINE2        2521
CITY                   0
STATE               1486
POSTALCODE            76
COUNTRY                0
TERRITORY           1074
CONTACTLASTNAME        0
CONTACTFIRSTNAME       0
DEALSIZE               0
dtype: int64
```

```
In [ ]:
# Dado que hay muchos valores nulos en 'addressline2', 'state', 'postal code' y 'territory', podemos eliminar
# Country representa la información geográfica del pedido.
# También podemos eliminar la ciudad, la dirección1, el número de teléfono, el nombre del contacto, el apellido

df_drop  = ['ADDRESSLINE1', 'ADDRESSLINE2', 'POSTALCODE', 'CITY', 'TERRITORY', 'PHONE', 'STATE', 'CONTACTFIRSTN
sales_df = sales_df.drop(df_drop, axis = 1)
sales_df.head()
```

Out[ ]:

	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	ORDERDATE	STATUS	QTR_ID	MONTH_ID	YEAR_ID	PRODUCTLINE	MSRP
0	30	95.70	2	2871.00	2003-02-24	Shipped	1	2	2003	Motorcycles	95
1	34	81.35	5	2765.90	2003-05-07	Shipped	2	5	2003	Motorcycles	95
2	41	94.74	2	3884.34	2003-07-01	Shipped	3	7	2003	Motorcycles	95
3	45	83.26	6	3746.70	2003-08-25	Shipped	3	8	2003	Motorcycles	95
4	49	100.00	14	5205.27	2003-10-10	Shipped	4	10	2003	Motorcycles	95

```
In [ ]:
sales_df.isnull().sum()
```

```
Out[ ]:
QUANTITYORDERED    0
PRICEEACH          0
ORDERLINENUMBER    0
SALES              0
ORDERDATE          0
STATUS             0
QTR_ID             0
MONTH_ID           0
YEAR_ID            0
PRODUCTLINE        0
MSRP               0
PRODUCTCODE        0
COUNTRY            0
DEALSIZE           0
dtype: int64
```

```
In [ ]:
# Obtener las observaciones únicas de cada columna
sales_df.nunique()
```

```
Out[ ]:
QUANTITYORDERED      58
PRICEEACH          1016
ORDERLINENUMBER      18
SALES              2763
ORDERDATE           252
STATUS                6
QTR_ID                4
MONTH_ID             12
YEAR_ID               3
PRODUCTLINE           7
MSRP                 80
PRODUCTCODE         109
COUNTRY              19
DEALSIZE              3
dtype: int64
```

ANALISIS EXPLORATORIO DE LOS DATOS Y LIMPIEZA

```
In [ ]:
sales_df['COUNTRY'].value_counts().index
```

```
Out[ ]:
Index(['USA', 'Spain', 'France', 'Australia', 'UK', 'Italy', 'Finland',
       'Norway', 'Singapore', 'Canada', 'Denmark', 'Germany', 'Sweden',
       'Austria', 'Japan', 'Belgium', 'Switzerland', 'Philippines', 'Ireland'],
      dtype='object')
```

```
In [ ]:
sales_df['COUNTRY'].value_counts()
```

```
Out[ ]:
USA            1004
Spain           342
France          314
Australia       185
UK              144
Italy           113
Finland          92
Norway           85
Singapore        79
Canada           70
Denmark          63
Germany          62
Sweden           57
Austria          55
Japan            52
Belgium          33
Switzerland      31
Philippines      26
Ireland          16
Name: COUNTRY, dtype: int64
```

```
In [ ]:
# Visualizar el recuento de elementos en una columna determinada

def barplot_visualization(x):
  fig = plt.Figure(figsize = (12, 6))
  fig = px.bar(x = sales_df[x].value_counts().index, y = sales_df[x].value_counts(), color = sales_df[x].value_
  fig.show()
```

```
In [ ]:
# Llamamos a esta función para cualquier columna determinada, como 'COUNTRY'
barplot_visualization('COUNTRY')
```

```
In [ ]:
barplot_visualization('STATUS')
```

```
In [ ]:
sales_df.drop(columns= ['STATUS'], inplace = True)
sales_df
```

Out[ ]:

	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	ORDERDATE	QTR_ID	MONTH_ID	YEAR_ID	PRODUCTLINE	MSRP	PRO
0	30	95.70	2	2871.00	2003-02-24	1	2	2003	Motorcycles	95	
1	34	81.35	5	2765.90	2003-05-07	2	5	2003	Motorcycles	95	
2	41	94.74	2	3884.34	2003-07-01	3	7	2003	Motorcycles	95	
3	45	83.26	6	3746.70	2003-08-25	3	8	2003	Motorcycles	95	
4	49	100.00	14	5205.27	2003-10-10	4	10	2003	Motorcycles	95	
...	...	...	...	...	...	...	...	...	...	...	
2818	20	100.00	15	2244.40	2004-12-02	4	12	2004	Ships	54	
2819	29	100.00	1	3978.51	2005-01-31	1	1	2005	Ships	54	
2820	43	100.00	4	5417.57	2005-03-01	1	3	2005	Ships	54	
2821	34	62.24	1	2116.16	2005-03-28	1	3	2005	Ships	54	
2822	47	65.52	9	3079.44	2005-05-06	2	5	2005	Ships	54	

2823 rows × 13 columns

```
In [ ]:
barplot_visualization('PRODUCTLINE')
```

```
In [ ]:
barplot_visualization('DEALSIZE')
```

```
In [ ]:
# Agregar variables ficticias para reemplazar variables categóricas

def dummies(x):
  dummy = pd.get_dummies(sales_df[x])
  sales_df.drop(columns = x , inplace = True)
  return pd.concat([sales_df, dummy], axis = 1)
```

```
In [ ]:
# Obtenemos variables ficticias para la columna 'PAIS'
sales_df = dummies('COUNTRY')
sales_df
```

Out[ ]:

	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	ORDERDATE	QTR_ID	MONTH_ID	YEAR_ID	PRODUCTLINE	MSRP	PRO
0	30	95.70	2	2871.00	2003-02-24	1	2	2003	Motorcycles	95	
1	34	81.35	5	2765.90	2003-05-07	2	5	2003	Motorcycles	95	
2	41	94.74	2	3884.34	2003-07-01	3	7	2003	Motorcycles	95	
3	45	83.26	6	3746.70	2003-08-25	3	8	2003	Motorcycles	95	
4	49	100.00	14	5205.27	2003-10-10	4	10	2003	Motorcycles	95	
...	...	...	...	...	...	...	...	...	...	...	
2818	20	100.00	15	2244.40	2004-12-02	4	12	2004	Ships	54	
2819	29	100.00	1	3978.51	2005-01-31	1	1	2005	Ships	54	
2820	43	100.00	4	5417.57	2005-03-01	1	3	2005	Ships	54	
2821	34	62.24	1	2116.16	2005-03-28	1	3	2005	Ships	54	
2822	47	65.52	9	3079.44	2005-05-06	2	5	2005	Ships	54	

2823 rows × 31 columns

```
In [ ]:
sales_df = dummies('PRODUCTLINE')
```

```
In [ ]:
sales_df
```

Out[ ]:

	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	ORDERDATE	QTR_ID	MONTH_ID	YEAR_ID	MSRP	PRODUCTCODE	DEA
0	30	95.70	2	2871.00	2003-02-24	1	2	2003	95	S10_1678	
1	34	81.35	5	2765.90	2003-05-07	2	5	2003	95	S10_1678	
2	41	94.74	2	3884.34	2003-07-01	3	7	2003	95	S10_1678	M
3	45	83.26	6	3746.70	2003-08-25	3	8	2003	95	S10_1678	M
4	49	100.00	14	5205.27	2003-10-10	4	10	2003	95	S10_1678	M
...	...	...	...	...	...	...	...	...	...	...	
2818	20	100.00	15	2244.40	2004-12-02	4	12	2004	54	S72_3212	
2819	29	100.00	1	3978.51	2005-01-31	1	1	2005	54	S72_3212	M
2820	43	100.00	4	5417.57	2005-03-01	1	3	2005	54	S72_3212	M
2821	34	62.24	1	2116.16	2005-03-28	1	3	2005	54	S72_3212	
2822	47	65.52	9	3079.44	2005-05-06	2	5	2005	54	S72_3212	M

2823 rows × 37 columns

```
In [ ]:
sales_df = dummies('DEALSIZE')
sales_df
```

Out[ ]:

	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	ORDERDATE	QTR_ID	MONTH_ID	YEAR_ID	MSRP	PRODUCTCODE	Aus
0	30	95.70	2	2871.00	2003-02-24	1	2	2003	95	S10_1678	
1	34	81.35	5	2765.90	2003-05-07	2	5	2003	95	S10_1678	
2	41	94.74	2	3884.34	2003-07-01	3	7	2003	95	S10_1678	
3	45	83.26	6	3746.70	2003-08-25	3	8	2003	95	S10_1678	
4	49	100.00	14	5205.27	2003-10-10	4	10	2003	95	S10_1678	
...	...	...	...	...	...	...	...	...	...	...	
2818	20	100.00	15	2244.40	2004-12-02	4	12	2004	54	S72_3212	
2819	29	100.00	1	3978.51	2005-01-31	1	1	2005	54	S72_3212	
2820	43	100.00	4	5417.57	2005-03-01	1	3	2005	54	S72_3212	
2821	34	62.24	1	2116.16	2005-03-28	1	3	2005	54	S72_3212	
2822	47	65.52	9	3079.44	2005-05-06	2	5	2005	54	S72_3212	

2823 rows × 39 columns

```
In [ ]:
y = pd.Categorical(sales_df['PRODUCTCODE'])
y
```

```
Out[ ]:
['S10_1678', 'S10_1678', 'S10_1678', 'S10_1678', 'S10_1678', ..., 'S72_3212', 'S72_3212', 'S72_3212', 'S72_321
2', 'S72_3212']
Length: 2823
Categories (109, object): ['S10_1678', 'S10_1949', 'S10_2016', 'S10_4698', ..., 'S700_3962',
                           'S700_4002', 'S72_1253', 'S72_3212']
```

```
In [ ]:
y = pd.Categorical(sales_df['PRODUCTCODE']).codes
y
```

```
Out[ ]:
array([  0,   0,   0, ..., 108, 108, 108], dtype=int8)
```

```
In [ ]:
# Dado que el número de código de producto tiene 109 valores únicos, si agregamos variables one-hot,
# serían 109 columnas adicionales, podemos evitarlo usando la codificación categórica

sales_df['PRODUCTCODE'] = pd.Categorical(sales_df['PRODUCTCODE']).codes
```

```
In [ ]:
sales_df
```

Out[ ]:

	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	ORDERDATE	QTR_ID	MONTH_ID	YEAR_ID	MSRP	PRODUCTCODE	Aus
0	30	95.70	2	2871.00	2003-02-24	1	2	2003	95	0	
1	34	81.35	5	2765.90	2003-05-07	2	5	2003	95	0	
2	41	94.74	2	3884.34	2003-07-01	3	7	2003	95	0	
3	45	83.26	6	3746.70	2003-08-25	3	8	2003	95	0	
4	49	100.00	14	5205.27	2003-10-10	4	10	2003	95	0	
...	...	...	...	...	...	...	...	...	...	...	
2818	20	100.00	15	2244.40	2004-12-02	4	12	2004	54	108	
2819	29	100.00	1	3978.51	2005-01-31	1	1	2005	54	108	
2820	43	100.00	4	5417.57	2005-03-01	1	3	2005	54	108	
2821	34	62.24	1	2116.16	2005-03-28	1	3	2005	54	108	
2822	47	65.52	9	3079.44	2005-05-06	2	5	2005	54	108	

2823 rows × 39 columns

```
In [ ]:
# Agrupamos los datos según la fecha del pedido
sales_df_group = sales_df.groupby(by = "ORDERDATE").sum()
sales_df_group
```

Out[ ]:

	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	QTR_ID	MONTH_ID	YEAR_ID	MSRP	PRODUCTCODE	Australia
ORDERDATE										
2003-01-06	151	288.78	10	12133.25	4	4	8012	363	174.0	0
2003-01-09	142	284.96	10	11432.34	4	4	8012	372	181.0	0
2003-01-10	80	150.14	3	6864.05	2	2	4006	155	37.0	0
2003-01-29	541	1417.54	136	54702.00	16	16	32048	1695	723.0	0
2003-01-31	443	1061.89	91	44621.96	13	13	26039	1365	720.0	0
...	...	...	...	...	...	...	...	...	...	...
2005-05-13	259	561.18	21	31821.90	12	30	12030	728	101.0	0
2005-05-17	509	1269.43	105	59475.10	28	70	28070	1669	462.0	0
2005-05-29	607	1148.40	94	51233.18	30	75	30075	1328	797.0	13
2005-05-30	187	542.16	18	14578.75	14	35	14035	618	265.0	0
2005-05-31	696	1561.40	112	78918.03	38	95	38095	2065	899.0	0

252 rows × 38 columns

```
In [ ]:
fig = px.line(x = sales_df_group.index, y = sales_df_group.SALES, title = 'Sales')
fig.show()
```

```
In [ ]:
# Podemos eliminar 'ORDERDATE' y quedarnos con el resto de datos relacionados con la fecha como 'MONTH'
sales_df.drop("ORDERDATE", axis = 1, inplace = True)
sales_df.shape
```

```
Out[ ]:
(2823, 38)
```

```
In [ ]:
plt.figure(figsize = (15, 15))
corr_matrix = sales_df.iloc[:, :9].corr()
sns.heatmap(corr_matrix, annot = True, cbar = False)
```

```
Out[ ]:
<matplotlib.axes._subplots.AxesSubplot at 0x7f91b57184e0>
```


```
In [ ]:
# Parece que el ID del trimestre y los ID del mes están altamente correlacionados
# Dejemos 'QTR_ID' (o 'MONTH_ID')
sales_df.drop("QTR_ID", axis = 1, inplace = True)
sales_df.shape
```

```
Out[ ]:
(2823, 37)
```

```
In [ ]:
# Representar las distribuciones
# Distplot muestra el (1) histograma, (2) kde plot y (3) rug plot.
# (1) Histograma: es una visualización gráfica de datos que usa barras con varias alturas. Cada barra agrupa lo
# (2) Densidad: la estimación de la función de densidad se utiliza para visualizar la densidad de probabilidad
# (3) Gráfico de alfombra: gráfico de datos para una única variable cuantitativa, que se muestra como marcas a

import plotly.figure_factory as ff

plt.figure(figsize = (10, 10))

for i in range(8):
  if sales_df.columns[i] != 'ORDERLINENUMBER':
    col_name = sales_df.columns[i]
    fig = ff.create_distplot([sales_df[col_name].apply(lambda x: float(x))], ['distplot'])
    fig.update_layout(title_text = col_name)
    fig.show()
```

```
Epoch 1/500
Epoch 2/500
Epoch 3/500
Epoch 4/500
Epoch 5/500
Epoch 6/500
Epoch 7/500
Epoch 8/500
Epoch 9/500
Epoch 10/500
Epoch 11/500
Epoch 12/500
Epoch 13/500
Epoch 14/500
Epoch 15/500
Epoch 16/500
Epoch 17/500
Epoch 18/500
Epoch 19/500
Epoch 20/500
Epoch 21/500
Epoch 22/500
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Epoch 32/500
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Epoch 72/500
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Epoch 79/500
Epoch 80/500
Epoch 81/500
Epoch 82/500
Epoch 83/500
Epoch 84/500
Epoch 85/500
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Out[ ]: <tensorflow.python.keras.callbacks.History at 0x7f91b88ae668>

In [ ]:
```
autoencoder.save_weights('autoencoder_1.h5')
```

In [ ]:
```
pred = encoder.predict(sales_df_scaled)
```

In [ ]:
```
pred
```

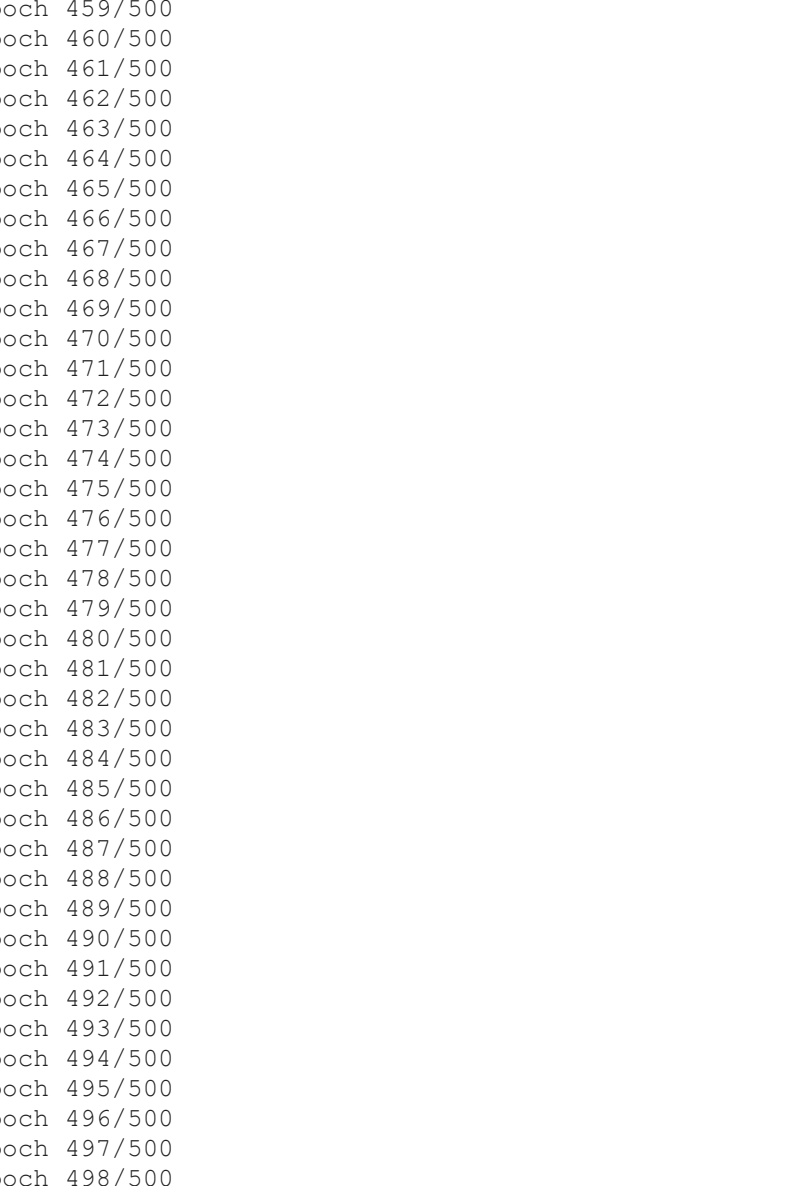
Out[ ]:
```
array([[ 0.        ,  0.9572773 ,  2.052799  , ...,  2.8538415 ,
         5.177384  ,  3.7766817 ],
       [ 0.        ,  1.474308  ,  3.2650466 , ...,  1.1344082 ,
         4.54118   ,  6.102257  ],
       [ 0.        ,  1.8946625 ,  6.611377  , ...,  1.6915857 ,
         7.6524625 ,  6.197023  ],
       ...,
       [ 0.        ,  5.2380247 ,  1.7845033 , ...,  8.191807  ,
         2.2916932 ,  4.8318996 ],
       [ 0.        ,  8.066888  ,  2.925734  , ...,  3.8033655 ,
         7.006839  , 14.542607  ],
       [ 0.        ,  5.8996243 ,  0.51634616, ...,  7.410111  ,
         4.386255  ,  3.2716434 ]], dtype=float32)
```

In [ ]:
```
scores = []

range_values = range(1, 15)

for i in range_values:
  kmeans = KMeans(n_clusters = i)
  kmeans.fit(pred)
  scores.append(kmeans.inertia_)

plt.plot(range_values, scores, 'bx-')
plt.title('Encontrar el número correcto de clústers')
plt.xlabel('Nº de Clústers')
plt.ylabel('WCSS')
plt.show()
```



In [ ]:
```
kmeans = KMeans(3)
kmeans.fit(pred)
labels = kmeans.labels_
y_kmeans = kmeans.fit_predict(sales_df_scaled)
```

In [ ]:
```
df_cluster_dr = pd.concat([sales_df, pd.DataFrame({'cluster':labels})], axis = 1)
df_cluster_dr.head()
```

Out[ ]:

	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	MONTH_ID	YEAR_ID	MSRP	PRODUCTCODE	Australia	Austria	Belgium
0	30	95.70	2.0	2871.00	2	2003	95	0	0	0	0
1	34	81.35	5.0	2765.90	5	2003	95	0	0	0	0
2	41	94.74	2.0	3884.34	7	2003	95	0	0	0	0
3	45	83.26	6.0	3746.70	8	2003	95	0	0	0	0
4	49	100.00	14.0	5205.27	10	2003	95	0	0	0	0

In [ ]:
```
cluster_centers = pd.DataFrame(data = kmeans.cluster_centers_, columns = [sales_df.columns])
cluster_centers
```

Out[ ]:

	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	MONTH_ID	YEAR_ID	MSRP	PRODUCTCODE	Australia	Austria	B
0	1.245428	0.800220	-0.259579	2.573861	-0.088008	0.136857	1.430265	-0.871802	-0.084647	0.043374	-0.
1	0.293073	0.580208	-0.010805	0.458608	0.003368	-0.012482	0.376634	-0.165542	-0.013717	0.010642	-0.
2	-0.468912	-0.724370	0.043454	-0.810304	0.007142	-0.003285	-0.581757	0.285478	0.025174	-0.016801	0.

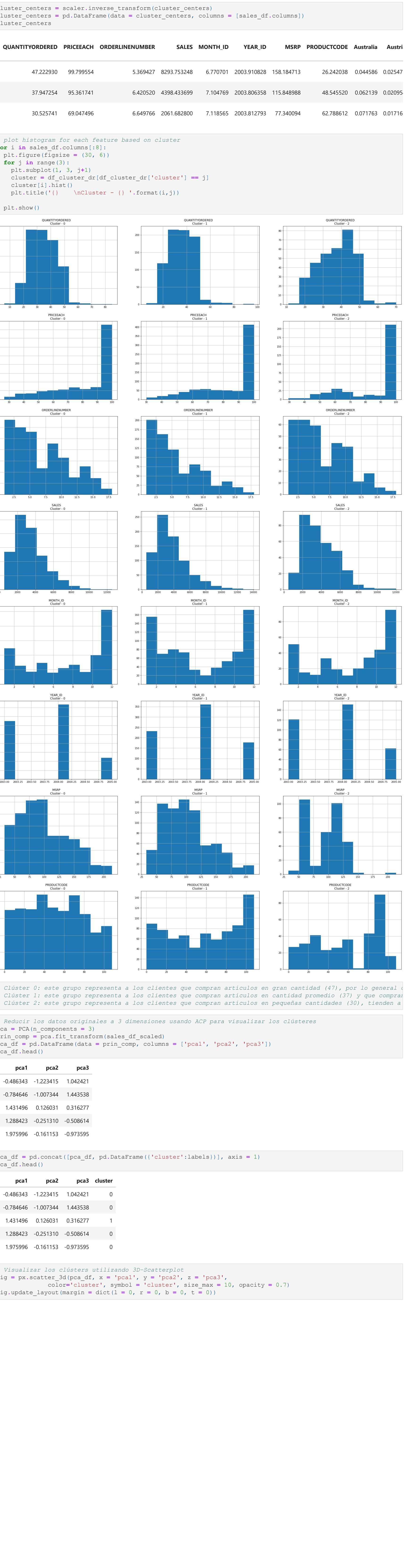
In [ ]:
```
cluster_centers = scaler.inverse_transform(cluster_centers)
cluster_centers = pd.DataFrame(data = cluster_centers, columns = [sales_df.columns])
cluster_centers
```

Out[ ]:

	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	MONTH_ID	YEAR_ID	MSRP	PRODUCTCODE	Australia	Austri
0	47.222930	99.799554	5.369427	8293.753248	6.770701	2003.910828	158.184713	26.242038	0.044586	0.02547
1	37.947254	95.361741	6.420520	4398.433699	7.104769	2003.806358	115.848988	48.545520	0.062139	0.02095
2	30.525741	69.047496	6.649766	2061.682800	7.118565	2003.812793	77.340094	62.788612	0.071763	0.01716

In [ ]:
```
# plot histogram for each feature based on cluster
for i in sales_df.columns[:8]:
  plt.figure(figsize = (30, 6))
  for j in range(3):
    plt.subplot(1, 3, j+1)
    cluster = df_cluster_dr[df_cluster_dr['cluster'] == j]
    cluster[i].hist()
    plt.title('{}    \nCluster - {} '.format(i,j))

  plt.show()
```



In [ ]:
```
# Cluster 0: este grupo representa a los clientes que compran artículos en gran cantidad (47), por lo general a
# Cluster 1: este grupo representa a los clientes que compran artículos en cantidad promedio (37) y que compran
# Cluster 2: este grupo representa a los clientes que compran artículos en pequeñas cantidades (30), tienden a
```

In [ ]:
```
# Reducir los datos originales a 3 dimensiones usando ACP para visualizar los clústeres
pca = PCA(n_components = 3)
prin_comp = pca.fit_transform(sales_df_scaled)
pca_df = pd.DataFrame(data = prin_comp, columns = ['pca1', 'pca2', 'pca3'])
pca_df.head()
```

Out[ ]:

	pca1	pca2	pca3
0	-0.486343	-1.223415	1.042421
1	-0.784646	-1.007344	1.443538
2	1.431496	0.126031	0.316277
3	1.288423	-0.251310	-0.508614
4	1.975996	-0.161553	-0.973595

In [ ]:
```
pca_df = pd.concat([pca_df, pd.DataFrame({'cluster':labels})], axis = 1)
pca_df.head()
```

Out[ ]:

	pca1	pca2	pca3	cluster
0	-0.486343	-1.223415	1.042421	0
1	-0.784646	-1.007344	1.443538	0
2	1.431496	0.126031	0.316277	1
3	1.288423	-0.251310	-0.508614	0
4	1.975996	-0.161553	-0.973595	0

In [ ]:
```
# Visualizar los clusters utilizando 3D-Scatterplot
fig = px.scatter_3d(pca_df, x = 'pca1', y = 'pca2', z = 'pca3',
              color='cluster', symbol = 'cluster', size_max = 10, opacity = 0.7)
fig.update_layout(margin = dict(l = 0, r = 0, b = 0, t = 0))
```