TFM_Preprocesado_Transformacion

February 27, 2024

1 Objetivo y dataset

El objetivo principal consiste en, a partir del uso de los datos adecuados, facilitar una herramienta y un conjunto de técnicas provenientes del proceso de Minería de Datos que permita predecir y determinar el precio de un determinado vehículo en Australia a cualquier posible comprador.

2 Información general del data set

[1]:
```python
# Importamos las librerías necesarias y adaptamos las configuraciones␣
↪pertinentes.
import pandas as pd
import numpy as np
import seaborn as sns
from datetime import datetime # Necesario para la obtención de la variable de␣
↪salida.
import matplotlib.pyplot as plt
import matplotlib.mlab as mlab
import matplotlib
plt.style.use('ggplot')
from matplotlib.pyplot import figure

%matplotlib inline
matplotlib.rcParams['figure.figsize'] = (12,8)

pd.options.mode.chained_assignment = None
```

A continuación se importan los tres datasets involucrados

[2]:
```python
# Fuente interna. Datos de precios de coches.
car = pd.read_csv('Australian Vehicle Prices.csv')
```

[3]:
```python
car[car['FuelConsumption'] == '0 L / 100 km']['FuelType'].value_counts()
```

[3]:
```
Diesel      198
Electric    105
Unleaded     57
Premium      14
```

```
Leaded        2
Hybrid        1
Name: FuelType, dtype: int64
```

[4]:
```
car['FuelType'].value_counts()
```

[4]:
```
Unleaded    6985
Diesel      4905
Premium     3377
Hybrid       652
-            637
Electric     115
Other         42
LPG           15
Leaded         5
Name: FuelType, dtype: int64
```

[5]:
```
# Índices de precio
pr = pd.read_excel('Price_Index_Australia.xlsx')
```

[6]:
```
# Cambio de moneda
coin = pd.read_csv('euro-daily-hist_1999_2022.csv')
```

3 Unificación de datasets

El siguiente paso consiste en unificar toda la información de cara a facilitar la comprensión del ejercicio. Es decir, se calcula el cambio de moneda medio anual del dólar australiano al euro y el índice de precio medio anual, añadiéndose así dichas columnas en el dataset car, realizando cada unión a partir del año de fabricación de cada vehículo y el año del valor medio de cambio de moneda o del índice de precio.

[7]:
```
# Se añade la columna Year en los datasets coin y pr, que no tienen Missing
coin[coin.columns[0]] = pd.to_datetime(coin[coin.columns[0]])
pr[pr.columns[0]] = pd.to_datetime(pr[pr.columns[0]])
coin['Year'] = coin[coin.columns[0]].dt.year
pr['Year'] = pr[pr.columns[0]].dt.year
print(pd.isnull(coin['Year']).any(), pd.isnull(pr['Year']).any())
```

```
False False
```

[8]:
```
# Se identifican los Missing Values del dólar australiana (definidos por un␣
 ↪guion) y se imputan por el método fill
ad = coin.columns[1]
ip = pr.columns[1]
aux = []
for i in coin[ad]:
  if str(i) == '-':
```

```
    aux.append(None)
  else :
    aux.append(float(i))

coin[ad] = aux
coin[ad].fillna(method='ffill', inplace=True)

# Se comprueba que el índice de precio no tiene Missing Values y se convierte a␣
 ↪numérico
print('Missing Values del índice de precio: ', pr[ip].isnull().sum(), '\n')
pr[ip]= pr[ip].astype('float64')
print('¿Tiene Missing Values el cambio de moneda? ', pd.isnull(coin[ad]).any(),␣
 ↪'\n')
```

```
Missing Values del índice de precio:  0

¿Tiene Missing Values el cambio de moneda?  False
```

[9]:

```
# Se obtiene el valor medio anual del cambio de dólar australiano a euro y del␣
 ↪índice del precio
coinGroup = coin.groupby(['Year']).mean()[ad]
priceGroup = pr.groupby(['Year']).mean()[ip]
```

```
<ipython-input-9-1b46c6dc792e>:2: FutureWarning: The default value of
numeric_only in DataFrameGroupBy.mean is deprecated. In a future version,
numeric_only will default to False. Either specify numeric_only or select only
columns which should be valid for the function.
  coinGroup = coin.groupby(['Year']).mean()[ad]
<ipython-input-9-1b46c6dc792e>:3: FutureWarning: The default value of
numeric_only in DataFrameGroupBy.mean is deprecated. In a future version,
numeric_only will default to False. Either specify numeric_only or select only
columns which should be valid for the function.
  priceGroup = pr.groupby(['Year']).mean()[ip]
```

[10]:

```
# Se imputa el único Missing Value en el año de fabricación del dataset car␣
 ↪(método fill) y se convierte a entera la columna
print('Missing values de Year en el datset car: ', car['Year'].isnull().sum())
car['Year'].fillna(method='ffill', inplace=True)
print('Missing values de Year en el datset car: ', car['Year'].isnull().sum())
car['Year'] = car['Year'].astype('Int64')
```

```
Missing values de Year en el datset car:  1
Missing values de Year en el datset car:  0
```

[11]:

```
# Se añade en car el valor medio anual del cambio de moneda entre dólar␣
 ↪australiano y el índice de precio medio anual
aux1 = []
```

```
aux2 = []
for i in car['Year']:
  if i in coinGroup.index:
    aux1.append(float(coinGroup[i]))
  else:
    aux1.append(None)
  if i in priceGroup.index:
    aux2.append(float(priceGroup[i]))
  else:
    aux2.append(None)

car['DollarAustralian'] = aux1
car['PriceIndex'] = aux2
```

De esta forma, ya se dispone de toda la información centralizada en el dataset car, cuyo resumen es el siguiente

[12]:
```
print('El dataset contiene', car.shape[0], 'filas y', car.shape[1], 'columnas.')
print('Las columnas, con sus correspondientes tipos, son las siguientes:\n',␣
 ↪car.dtypes)
```

```
El dataset contiene 16734 filas y 21 columnas.
Las columnas, con sus correspondientes tipos, son las siguientes:
 Brand                  object
Year                    Int64
Model                  object
Car/Suv                object
Title                  object
UsedOrNew              object
Transmission           object
Engine                 object
DriveType              object
FuelType               object
FuelConsumption        object
Kilometres             object
ColourExtInt           object
Location               object
CylindersinEngine      object
BodyType               object
Doors                  object
Seats                  object
Price                  object
DollarAustralian      float64
PriceIndex            float64
dtype: object
```

4 Transformación de los datos

Adecuación de tipos de variables.

[13]:
```
# Adecuación de tipos y comprobación si son enteros.

#Variable Engine
l = []
for i in car['Engine']:
  aux1 = str(i).find(',') # Devuelve -1 si no lo encuentra.
  aux2 = str(i).find('L') # Devuelve -1 si no lo encuentra.
  if aux1 != -1 and aux2 != -1:
    l.append(float(i[aux1+2:aux2-1]))
  elif i == '0 L' or i == '2 L':
    l.append(float(i[0]))
  elif i == '-' or pd.isna(i) or i == '4 cyl':
    l.append(None)
  else:
    print("Si se pinta esta línea hay un valor en Engine con formato no␣
 ↪identificado.")

car['Engine'] = l


# Variable CylindersinEngine -> Cylinders
l = []
for i in car['CylindersinEngine']:
  aux = str(i).find('c')
  if aux != -1:
    l.append(int(i[0:aux]))
  elif i == '0 L' or i == '2 L' or i == '-' or pd.isna(i):
    l.append(None)
  else:
    print("Si se pinta esta línea hay un valor en CylindersinEngine con formato␣
 ↪no identificado.")

car['CylindersinEngine'] = l
car.rename(columns = {list(car)[14]:'Cylinders'}, inplace=True)
car['Cylinders'] = car['Cylinders'].astype('Int64')

# Variable FuelConsumption
l = []
for i in car['FuelConsumption']:
  aux = str(i).find('L')
  if aux != -1:
    l.append(float(i[0:aux]))
  elif i =='-' or pd.isna(i) :
```

```
    l.append(None)
  else:
    print("Si se pinta esta línea hay un valor en FuelConsumption con formato␣
 ↪no identificado.")

car['FuelConsumption'] = l

# Variable Doors

l = []
for i in car['Doors']:
  aux1 = str(i).find('D')
  aux2 = str(i).find('S')
  if aux1 != -1:
    l.append(int(i[0:aux1]))
  elif  i =='-' or pd.isna(i) or aux2 != -1:
    l.append(None)
  else:
    print("Si se pinta esta línea hay un valor en Doors con formato no␣
 ↪identificado.")

car['Doors']=l
car['Doors'] = car['Doors'].astype('Int64')

# Variable Seats

l = []
for i in car['Seats']:
  aux = str(i).find('S')
  if aux != -1:
    l.append(int(i[0:aux]))
  elif  i =='-' or pd.isna(i) :
    l.append(None)
  else:
    print("Si se pinta esta línea hay un valor en Seats con formato no␣
 ↪identificado.")

car['Seats'] = l
car['Seats'] = car['Seats'].astype('Int64')

# Variable kilometres
l = []
for i in car['Kilometres']:
  if str(i).isnumeric():
    l.append(float(i))
  elif  i =='-' or pd.isna(i) or i == '- / -':
    l.append(None)
```

```
  else:
    print("Si se pinta esta línea hay un valor en Kilometres con formato no␣
 ↪identificado.")

car['Kilometres'] = l

# Variable Price
l = []
for i in car['Price']:
  if str(i).isnumeric():
    l.append(float(i))
  elif  i =='-' or pd.isna(i) or i == 'POA':
    l.append(None)
  else:
    print("Si se pinta esta línea hay un valor en Price con formato no␣
 ↪identificado.")

car['Price'] = l
```

[14]:
```
print('Las columnas, con sus correspondientes tipos, son las siguientes:\n',␣
 ↪car.dtypes)
```

```
Las columnas, con sus correspondientes tipos, son las siguientes:
 Brand                object
Year                  Int64
Model                object
Car/Suv              object
Title                object
UsedOrNew            object
Transmission         object
Engine              float64
DriveType            object
FuelType             object
FuelConsumption     float64
Kilometres          float64
ColourExtInt         object
Location             object
Cylinders             Int64
BodyType             object
Doors                 Int64
Seats                 Int64
Price               float64
DollarAustralian    float64
PriceIndex          float64
dtype: object
```

A continuación se determinan las columnas a eliminar por tener un número excesivo de categorías.

[15]:
```
# Columnas a eliminar por tener un número excesivo de categorías.
cols_to_drop = ['Brand', 'Model', 'Car/Suv', 'Title', 'ColourExtInt',␣
 ↪'Location']
for i in cols_to_drop:
  print(i, ":")
  print(car[i].value_counts())
  print("\n")
```

```
Brand :
Toyota         2784
Hyundai        1239
Mazda          1179
Holden         1087
Ford           1055
               …
Proton            1
Daewoo            1
Hummer            1
Rolls-Royce       1
Packard           1
Name: Brand, Length: 76, dtype: int64


Model :
Hilux          430
Corolla        405
Ranger         398
Landcruiser    370
I30            366
              …
Celerio          1
R-Class          1
Vectra           1
ES300            1
120              1
Name: Model, Length: 781, dtype: int64


Car/Suv :
SUV                                5921
Hatchback                          2365
Ute / Tray                         2068
Sedan                              1898
Wagon                               577
                                   …
Werribee Hyundai                      1
Bay City Holden Used.                 1
Auto Mega Warehouse Brisbane          1
```

```
Consign-A-Car P/L (Kedron)         1
Australian Vehicle Locators        1
Name: Car/Suv, Length: 618, dtype: int64


Title :
2019 Hyundai I30 Active                             60
2020 Kia Cerato S                                   52
2020 Hyundai Kona Active (fwd)                      38
2020 Hyundai I30 Active                             35
2021 Toyota Corolla Ascent Sport Hybrid             28
                                                    ..
2016 Porsche Cayenne Diesel Platinum Edition         1
2014 Ford Falcon XR6                                 1
2011 Toyota Kluger KX-S (4X4)                        1
2020 Toyota C-HR Koba                                1
2021 Mercedes-Benz C200                              1
Name: Title, Length: 8804, dtype: int64


ColourExtInt :
White / -               2846
White / Black           1701
Silver / -              1117
Grey / -                 941
Black / -                905
                        …
Green / Black & Grey       1
- / 44Lb20                 1
Blue / 74La20              1
White / 2015/05            1
Red / Blue/Black           1
Name: ColourExtInt, Length: 834, dtype: int64


Location :
Minchinbury, NSW          544
Blacktown, NSW            295
Liverpool, NSW            254
Hoppers Crossing, VIC     227
Ringwood, VIC             215
                         …
West Lakes, SA              1
Eight Mile Plains, QLD      1
Goodwood, SA                1
Mudgeeraba, QLD             1
East Toowoomba, QLD         1
Name: Location, Length: 618, dtype: int64
```

[16]:
```
# Eliminación
cols_to_drop = ['Brand', 'Model', 'Car/Suv', 'Title', 'ColourExtInt',␣
↪'Location']
car = car.drop(cols_to_drop, axis=1)
```

Seguidamete, se intenta reducir las categorías de las variables categóricas.

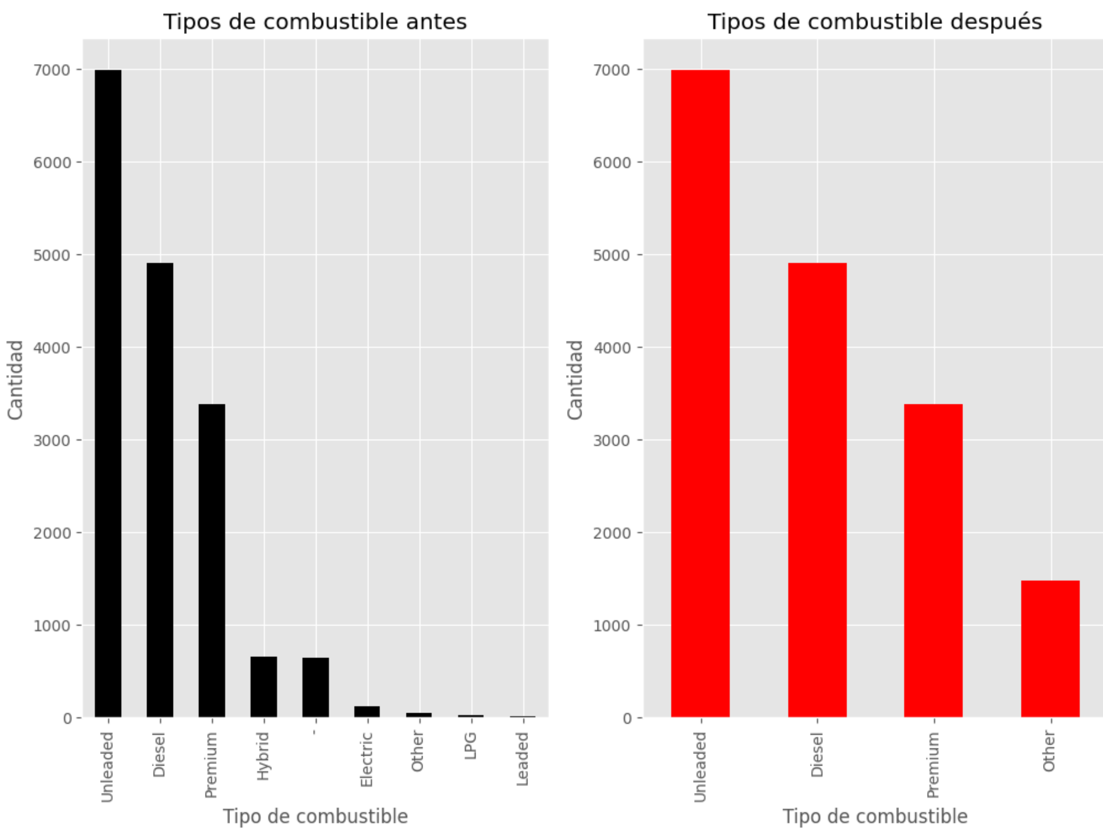
[17]:
```
# Transformación
cols_to_reduce = ['UsedOrNew', 'Transmission', 'DriveType', 'FuelType',␣
↪'BodyType']
for i in cols_to_reduce:
  print(i, ":")
  print(car[i].value_counts())
  print("\n")
```

```
UsedOrNew :
USED    14994
NEW      1227
DEMO      512
Name: UsedOrNew, dtype: int64


Transmission :
Automatic    14530
Manual        1952
-              251
Name: Transmission, dtype: int64


DriveType :
Front    6978
4WD      3143
AWD      3113
Rear     2350
Other    1149
Name: DriveType, dtype: int64


FuelType :
Unleaded    6985
Diesel      4905
Premium     3377
Hybrid       652
-            637
Electric     115
```

```
Other          42
LPG            15
Leaded          5
Name: FuelType, dtype: int64


BodyType :
SUV               6907
Hatchback         2697
Ute / Tray        2512
Sedan             1983
Wagon             1232
Commercial         610
Coupe              336
Convertible        131
Other               23
People Mover        21
Name: BodyType, dtype: int64
```

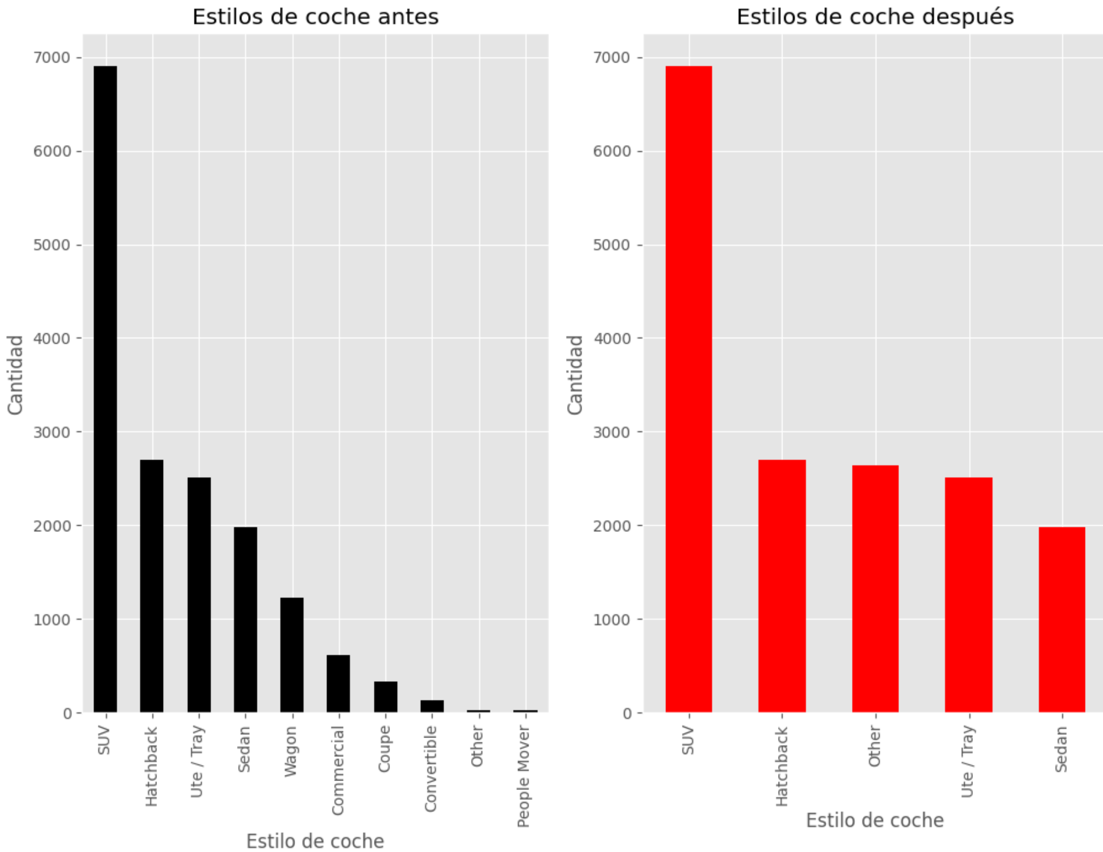
[18]:
```
l = []
for i in car['FuelType']:
  if i != 'Unleaded' and i != 'Diesel' and i != 'Premium':
    l.append('Other')
  else :
    l.append(i)

s = pd.Series(l)
plt.subplot(1, 2, 1)
car['FuelType'].value_counts().plot.bar(color = 'black')
plt.xlabel('Tipo de combustible')
plt.ylabel('Cantidad')
plt.title('Tipos de combustible antes')

plt.subplot(1, 2, 2)
s.value_counts().plot.bar(color = 'red')
plt.xlabel('Tipo de combustible')
plt.ylabel('Cantidad')
plt.title('Tipos de combustible después')
```

[18]:
```
Text(0.5, 1.0, 'Tipos de combustible después')
```



[19]:
```python
l = []
for i in car['BodyType']:
  if i != 'SUV' and i != 'Hatchback' and i != 'Ute / Tray' and i != 'Sedan':
    l.append('Other')
  else :
    l.append(i)

s = pd.Series(l)
plt.subplot(1, 2, 1)
car['BodyType'].value_counts().plot.bar(color = 'black')
plt.xlabel('Estilo de coche')
plt.ylabel('Cantidad')
plt.title('Estilos de coche antes')

plt.subplot(1, 2, 2)
s.value_counts().plot.bar(color = 'red')
plt.xlabel('Estilo de coche')
plt.ylabel('Cantidad')
plt.title('Estilos de coche después')
```

[19]:
```
Text(0.5, 1.0, 'Estilos de coche después')
```



Se ve conveniente reducir las categorías de las variables del tipo de combustible y el estilo del coche, obteneiendo los resultados de los gráficos en rojo anteriores.

[20]:
```
# Transformación
l = []
for i in car['FuelType']:
  if i != 'Unleaded' and i != 'Diesel' and i != 'Premium':
    l.append('Other')
  else :
    l.append(i)

car['FuelType'] = l

l = []
for i in car['BodyType']:
  if i != 'SUV' and i != 'Hatchback' and i != 'Ute / Tray' and i != 'Sedan':
    l.append('Other')
  else :
    l.append(i)
```

```
car['BodyType'] = 1
```

5 Missing Values

[21]:
```
# Listado por porcentajes.
for col in car.columns:
    pct_missing = np.mean(car[col].isnull())
    print('{} - {}%'.format(col, round(pct_missing*100, 2)))
```

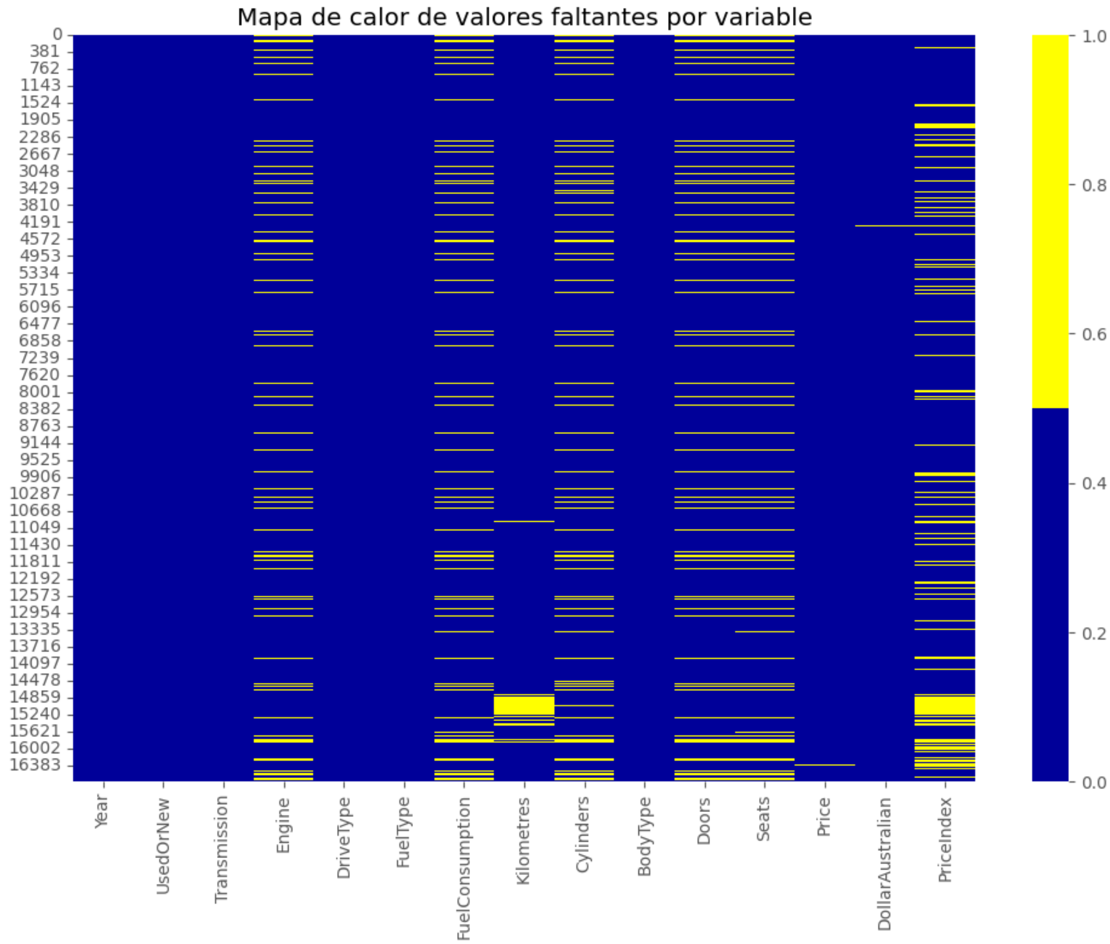
```
Year - 0.0%
UsedOrNew - 0.01%
Transmission - 0.01%
Engine - 10.02%
DriveType - 0.01%
FuelType - 0.0%
FuelConsumption - 10.15%
Kilometres - 3.54%
Cylinders - 10.65%
BodyType - 0.0%
Doors - 10.01%
Seats - 10.19%
Price - 0.32%
DollarAustralian - 0.54%
PriceIndex - 17.4%
```

[22]:
```
car['DriveType'].value_counts()
```

[22]:
```
Front     6978
4WD       3143
AWD       3113
Rear      2350
Other     1149
Name: DriveType, dtype: int64
```

[23]:
```
# Mapa de calor de Missing Values.
cols = car.columns
colours = ['#000099', '#ffff00'] # especificamos los colores - amarillo es␣
 ↪missing. Azul no es missing.
sns.heatmap(car[cols].isnull(), cmap=sns.color_palette(colours))
plt.title('Mapa de calor de valores faltantes por variable')
```

[23]:
```
Text(0.5, 1.0, 'Mapa de calor de valores faltantes por variable')
```



[24]:
```
# Categóricas
# UsedOrNew -> Lo añadimos a USED
# Transmission -> Lo añadimos a automatic
col_top = ['UsedOrNew', 'Transmission']

for col in col_top:
    missing = car[col].isnull()
    num_missing = np.sum(missing)
    if num_missing > 0:  # only do the imputation for the columns that have␣
 ↪missing values.
        top = car[col].describe()['top'] # impute with the most frequent value.
        car[col] = car[col].fillna(top)

# Transmission "-"" a Automatic
l = []
for i in car['Transmission']:
  if i == '-':
```

```
    l.append('Automatic')
  else :
    l.append(i)

car['Transmission'] = l
# DriveType a Other
l = []
for i in car['DriveType']:
  if pd.isna(i):
    l.append('Other')
  else :
    l.append(i)

car['DriveType'] = l
```

[25]:
```
# Numéricas
# impute the missing values and create the missing value indicator variables␣
↪for each numeric column.
num_mi_col = ['Engine', 'FuelConsumption', 'Kilometres', 'Cylinders', 'Doors',␣
↪'Seats', 'DollarAustralian', 'PriceIndex', 'Price']
for col in num_mi_col:
    missing = car[col].isnull()
    num_missing = np.sum(missing)
    print('imputing missing values for: {}'.format(col))
    med = car[col].median()
    if col in ('Cylinders', 'Doors', 'Seats'):
      med = int(med)
    car[col] = car[col].fillna(med)

# Comprobamos que los  campos ya no presentan missing values.
for col in num_mi_col:
  print('Missing values en', col, car[col].isnull().sum())
```

```
imputing missing values for: Engine
imputing missing values for: FuelConsumption
imputing missing values for: Kilometres
imputing missing values for: Cylinders
imputing missing values for: Doors
imputing missing values for: Seats
imputing missing values for: DollarAustralian
imputing missing values for: PriceIndex
imputing missing values for: Price
Missing values en Engine 0
Missing values en FuelConsumption 0
Missing values en Kilometres 0
Missing values en Cylinders 0
Missing values en Doors 0
Missing values en Seats 0
```

```
Missing values en DollarAustralian 0
Missing values en PriceIndex 0
Missing values en Price 0
```

[26]:
```
print('El dataset contiene', car.shape[0], 'filas y', car.shape[1], 'columnas.')
print('Las columnas, con sus correspondientes tipos, son las siguientes:\n',␣
↪car.dtypes)
```

```
El dataset contiene 16734 filas y 15 columnas.
Las columnas, con sus correspondientes tipos, son las siguientes:
 Year                 Int64
UsedOrNew           object
Transmission        object
Engine             float64
DriveType           object
FuelType            object
FuelConsumption    float64
Kilometres         float64
Cylinders            Int64
BodyType            object
Doors                Int64
Seats                Int64
Price              float64
DollarAustralian   float64
PriceIndex         float64
dtype: object
```

6 Selección de características

No hay variables de entrada excesivamente correlacionadas. Aunque Seats y Doors parece que no están relacionadas con Price, las dejamos por si existe otra relación que no sea lineal. Se justificará su uso o no después en el futuro modelo lineal generalizado.

[27]:
```
# Variables numéricas relacionadas
corr_matrix = car.corr()
corr_matrix
```

```
<ipython-input-27-0c54bf6cecfa>:2: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  corr_matrix = car.corr()
```

[27]:

	Year	Engine	FuelConsumption	Kilometres	Cylinders	\
Year	1.000000	-0.182471	-0.258235	-0.696667	-0.172040	
Engine	-0.182471	1.000000	0.557007	0.232809	0.804203	
FuelConsumption	-0.258235	0.557007	1.000000	0.218492	0.509391	
Kilometres	-0.696667	0.232809	0.218492	1.000000	0.140161	

```
Cylinders        -0.172040  0.804203          0.509391    0.140161   1.000000
Doors             0.066991 -0.315065         -0.169453   -0.112854  -0.238393
Seats             0.014712  0.038717          0.076615    0.001587   0.016651
Price             0.351451  0.255675          0.021749   -0.347778   0.334112
DollarAustralian  0.123917  0.012041         -0.026594   -0.179824   0.000717
PriceIndex        0.746127 -0.150460         -0.243990   -0.578763  -0.147121

                     Doors     Seats     Price  DollarAustralian  PriceIndex
Year              0.066991  0.014712  0.351451          0.123917    0.746127
Engine           -0.315065  0.038717  0.255675          0.012041   -0.150460
FuelConsumption  -0.169453  0.076615  0.021749         -0.026594   -0.243990
Kilometres       -0.112854  0.001587 -0.347778         -0.179824   -0.578763
Cylinders        -0.238393  0.016651  0.334112          0.000717   -0.147121
Doors             1.000000  0.369554 -0.177394         -0.011402    0.058987
Seats             0.369554  1.000000 -0.041135          0.008452    0.024777
Price            -0.177394 -0.041135  1.000000          0.149495    0.278544
DollarAustralian -0.011402  0.008452  0.149495          1.000000    0.110870
PriceIndex        0.058987  0.024777  0.278544          0.110870    1.000000
```

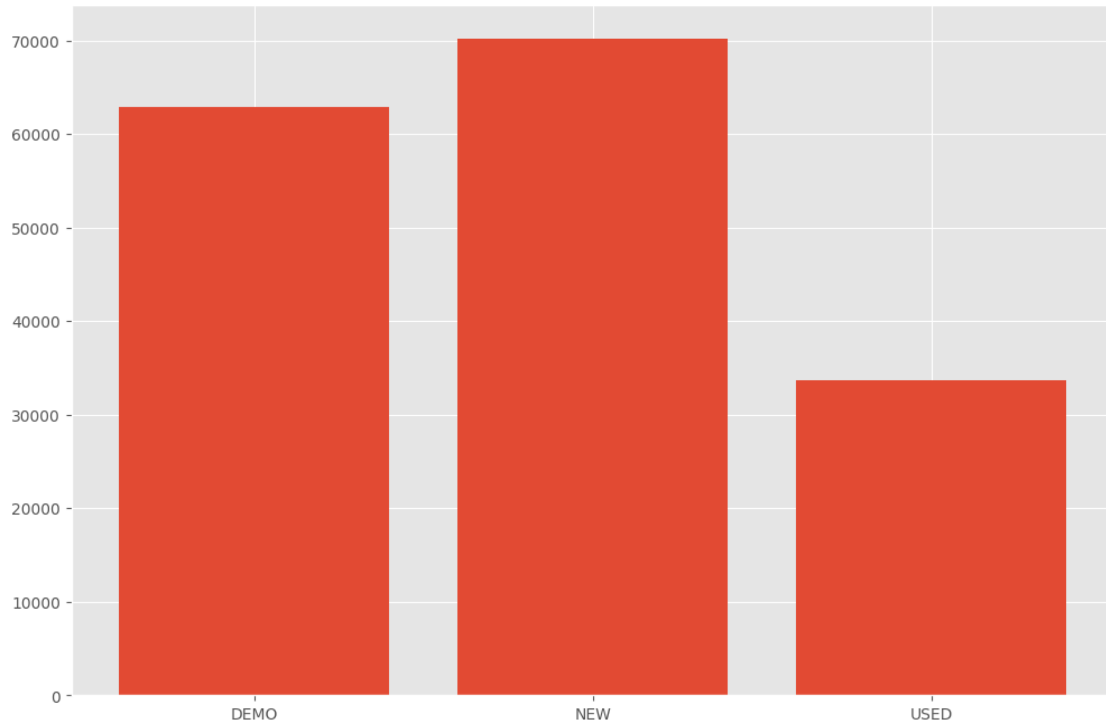
[28]:
```python
corr_matrix[(corr_matrix > 0.6) | (corr_matrix < -0.6)]
```

[28]:
```
                      Year    Engine  FuelConsumption  Kilometres  Cylinders  \
Year              1.000000       NaN              NaN   -0.696667        NaN
Engine                 NaN  1.000000              NaN         NaN   0.804203
FuelConsumption        NaN       NaN              1.0         NaN        NaN
Kilometres       -0.696667       NaN              NaN    1.000000        NaN
Cylinders              NaN  0.804203              NaN         NaN   1.000000
Doors                  NaN       NaN              NaN         NaN        NaN
Seats                  NaN       NaN              NaN         NaN        NaN
Price                  NaN       NaN              NaN         NaN        NaN
DollarAustralian       NaN       NaN              NaN         NaN        NaN
PriceIndex        0.746127       NaN              NaN         NaN        NaN

                  Doors  Seats  Price  DollarAustralian  PriceIndex
Year                NaN    NaN    NaN               NaN    0.746127
Engine              NaN    NaN    NaN               NaN         NaN
FuelConsumption     NaN    NaN    NaN               NaN         NaN
Kilometres          NaN    NaN    NaN               NaN         NaN
Cylinders           NaN    NaN    NaN               NaN         NaN
Doors               1.0    NaN    NaN               NaN         NaN
Seats               NaN    1.0    NaN               NaN         NaN
Price               NaN    NaN    1.0               NaN         NaN
DollarAustralian    NaN    NaN    NaN               1.0         NaN
PriceIndex          NaN    NaN    NaN               NaN    1.000000
```

[29]:
```python
# Varibales categóricas
```

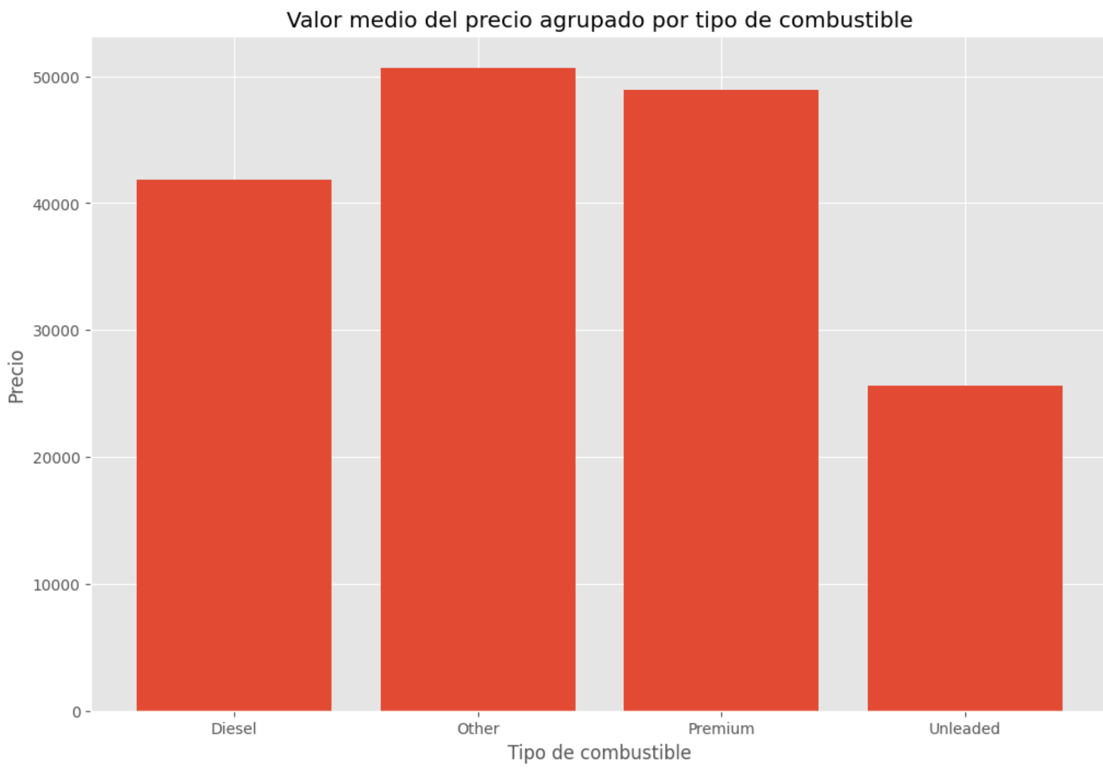
```
UsedOrNew_grouped = car[['UsedOrNew', 'Price']].groupby('UsedOrNew').mean().
  ↪reset_index()
# Creating a bar chart
plt.bar(UsedOrNew_grouped ['UsedOrNew'], UsedOrNew_grouped['Price'])
```

[29]: <BarContainer object of 3 artists>



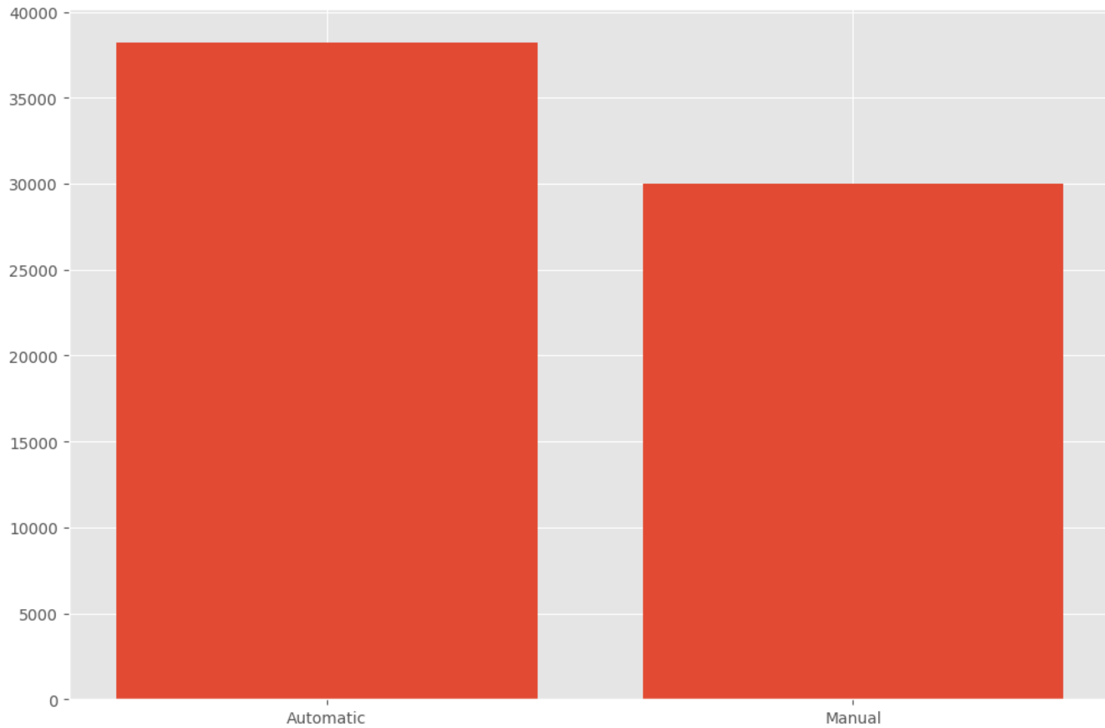
[30]:
```
# Varibales categóricas
FuelType_grouped = car[['FuelType', 'Price']].groupby('FuelType').mean().
  ↪reset_index()
# Creating a bar chart
plt.bar(FuelType_grouped ['FuelType'], FuelType_grouped['Price'])
plt.title('Valor medio del precio agrupado por tipo de combustible')
plt.xlabel('Tipo de combustible')
plt.ylabel('Precio')
```

[30]: Text(0, 0.5, 'Precio')

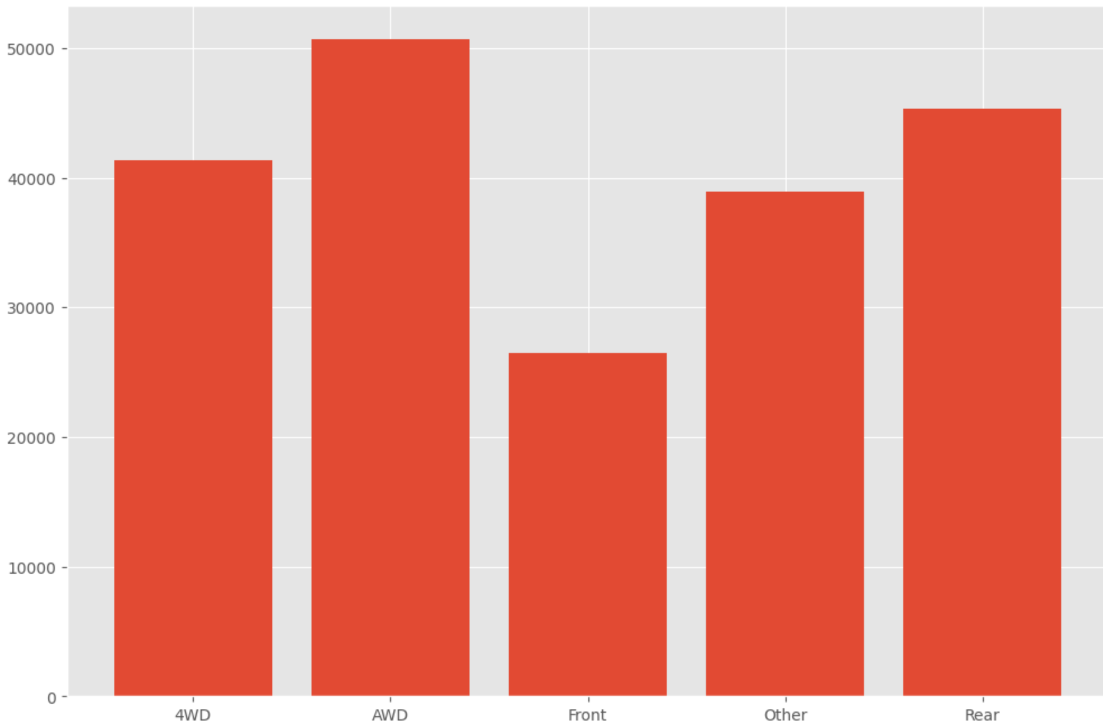



```
[31]: # Varibales categóricas
      Transmission_grouped = car[['Transmission', 'Price']].groupby('Transmission').
       ↪mean().reset_index()
      # Creating a bar chart
      plt.bar(Transmission_grouped ['Transmission'], Transmission_grouped['Price'])
```

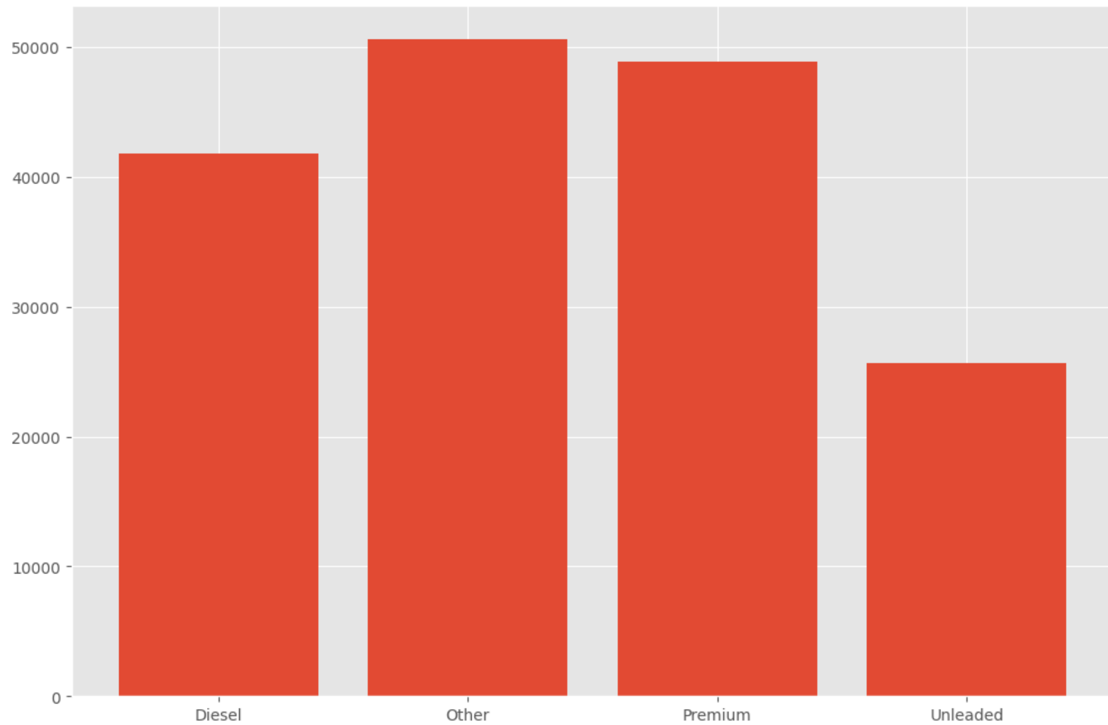
```
[31]: <BarContainer object of 2 artists>
```



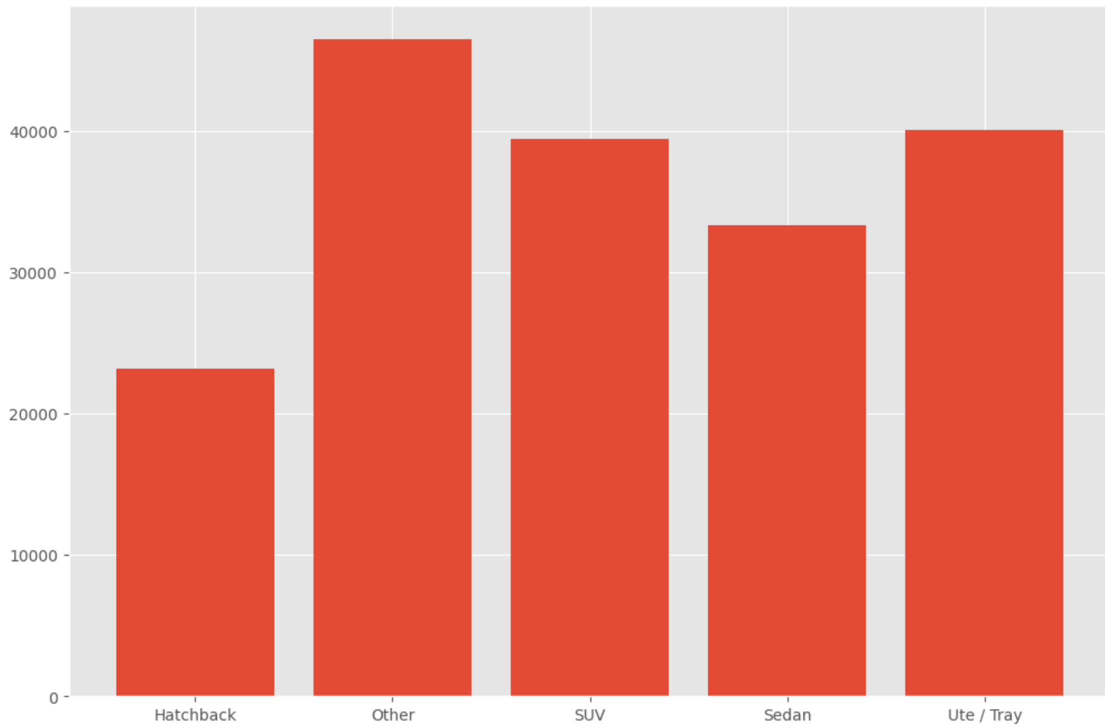
[32]:
```
# Varibales categóricas
DriveType_grouped = car[['DriveType', 'Price']].groupby('DriveType').mean().
  ↪reset_index()
# Creating a bar chart
plt.bar(DriveType_grouped ['DriveType'], DriveType_grouped['Price'])
# Juntamos  4WD con Other
l = []
for i in car['DriveType']:
  if i == '4WD':
    l.append('Other')
  else :
    l.append(i)
car['DriveType'] = l
```



[33]:
```
# Varibales categóricas
FuelType_grouped = car[['FuelType', 'Price']].groupby('FuelType').mean().
  ↪reset_index()
# Creating a bar chart
plt.bar(FuelType_grouped ['FuelType'], FuelType_grouped['Price'])
# Juntamos Diesel/Premium
l = []
for i in car['FuelType']:
  if i == 'Premium':
    l.append('Other')
  else :
    l.append(i)
car['FuelType'] = l
```



[34]:
```
# Varibales categóricas
BodyType_grouped = car[['BodyType', 'Price']].groupby('BodyType').mean().
 ↪reset_index()
# Creating a bar chart
plt.bar(BodyType_grouped ['BodyType'], BodyType_grouped['Price'])
# Juntamos Ute/Tray con SUV
l = []
for i in car['BodyType']:
  if i == 'SUV' or i == 'Ute / Tray':
    l.append('SUV/Ute/Tray')
  else :
    l.append(i)
car['BodyType'] = l
```

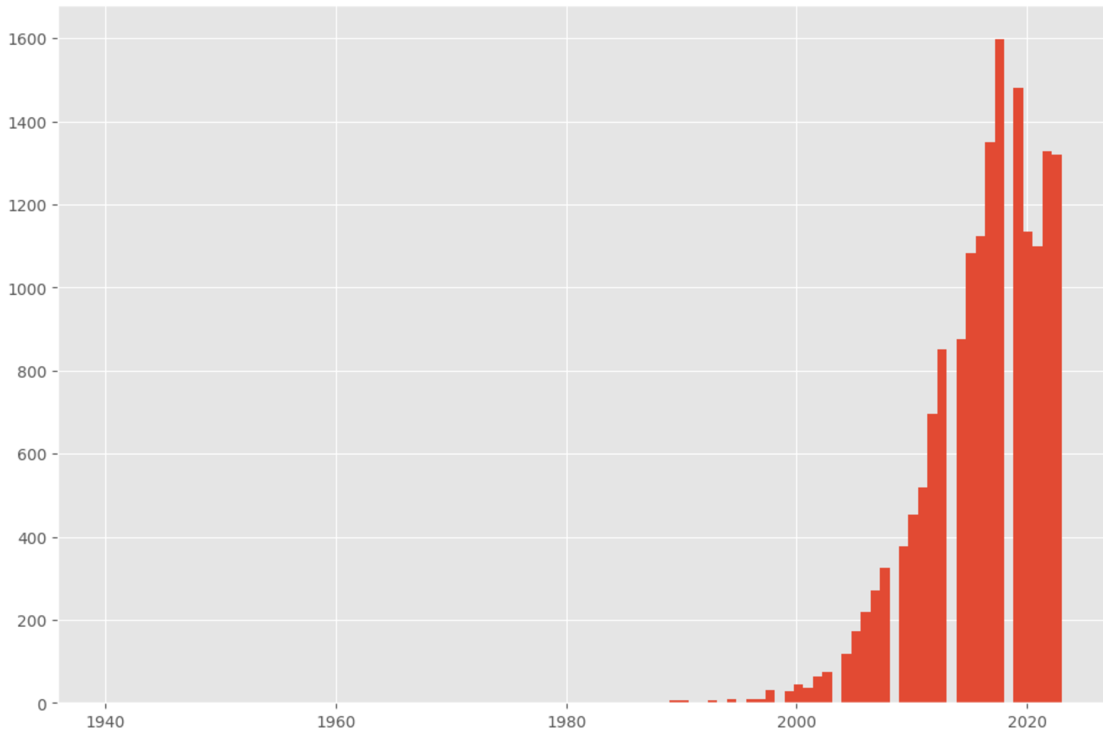


7 Outliers por columna

[35]:
```
# Year
print('Year:')
car['Year'].hist(bins=100)
```

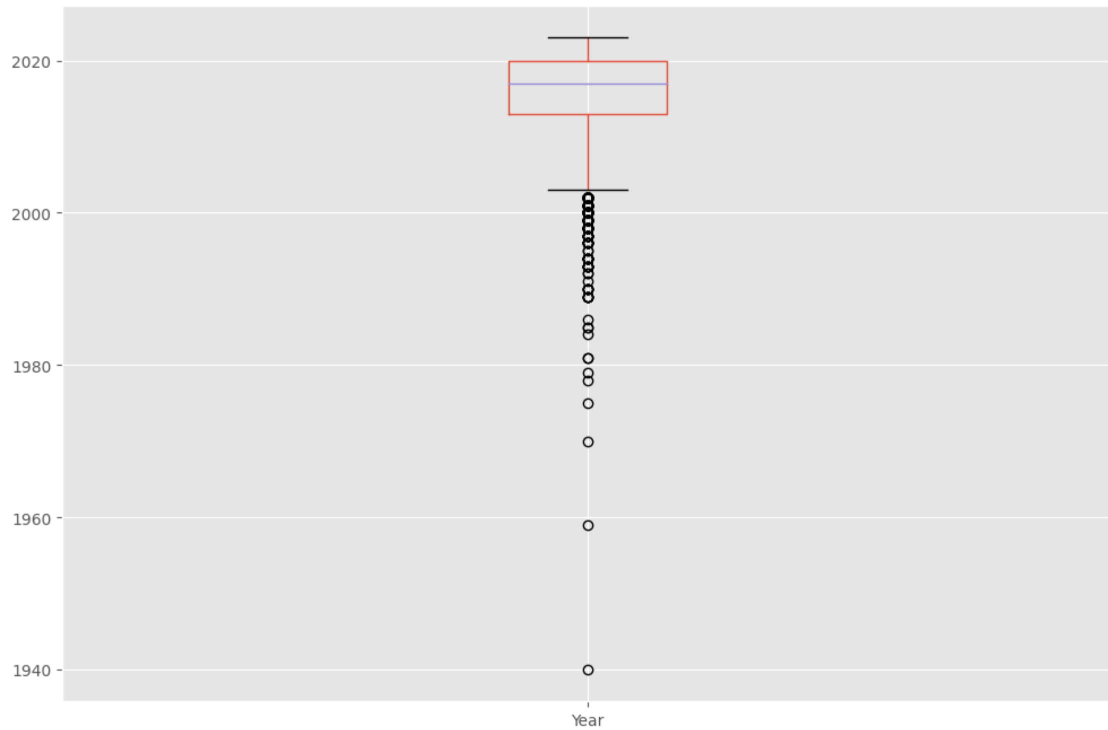
Year:

[35]: <Axes: >



[36]:
```
# box plot.
car.boxplot(column=['Year'])
```

[36]: <Axes: >



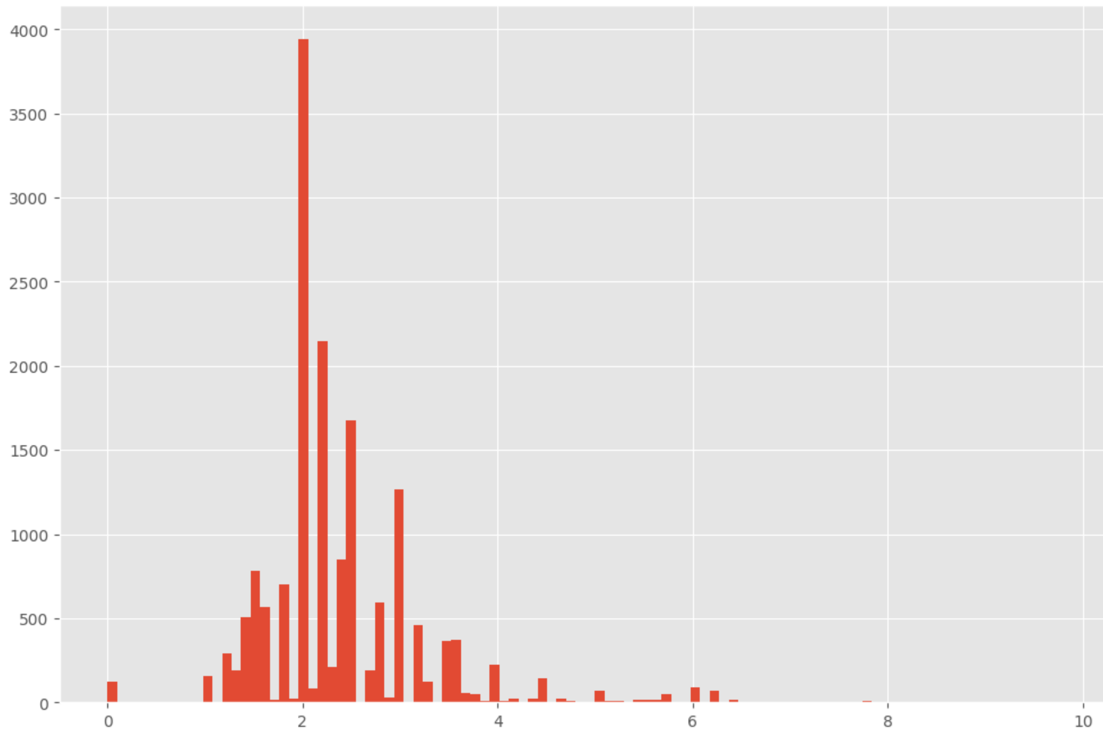
[37]:
```
# Eliminamos los registros con año de fabricación previo al 2002
print('Registros con Year < 2000:', car[car['Year'] < 2000].shape[0])
car.drop(car[car['Year'] < 2000].index, inplace = True)
car.reset_index(drop = True, inplace = True)
```

```
Registros con Year < 2000: 119
```

[38]:
```
# Engine
# Year
print('Engine')
car['Engine'].hist(bins=100)
```

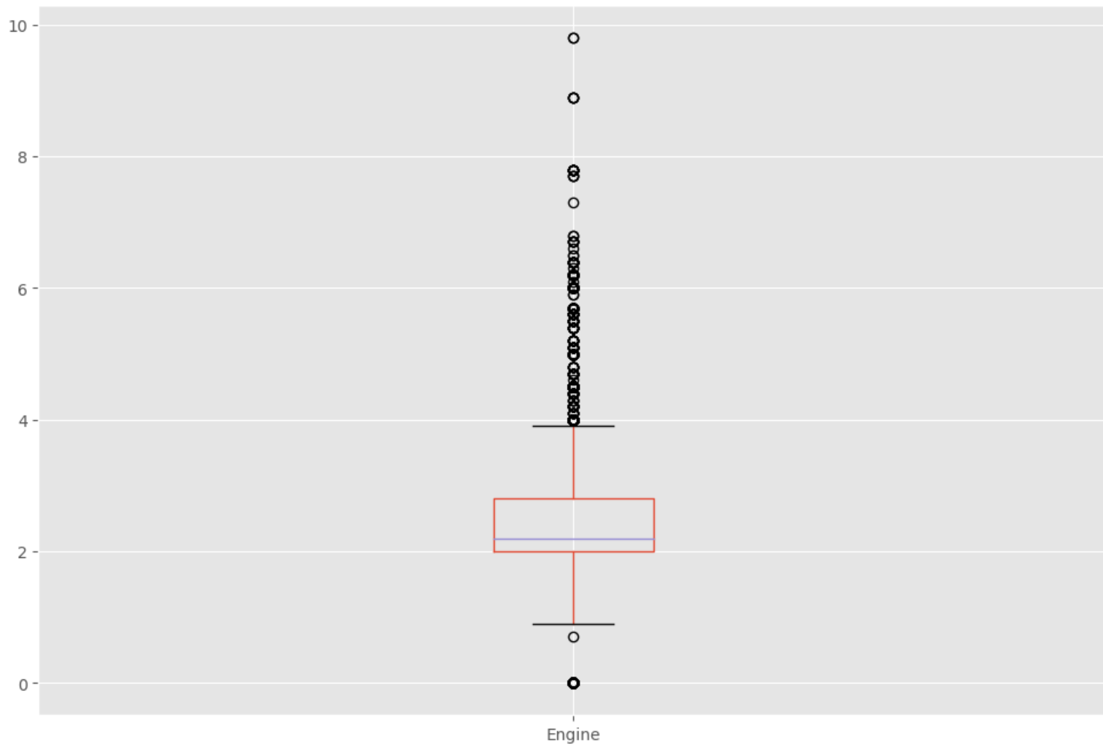
```
Engine
```

[38]:
```
<Axes: >
```



[39]:
```
# box plot.
car.boxplot(column=['Engine'])
```

[39]: <Axes: >



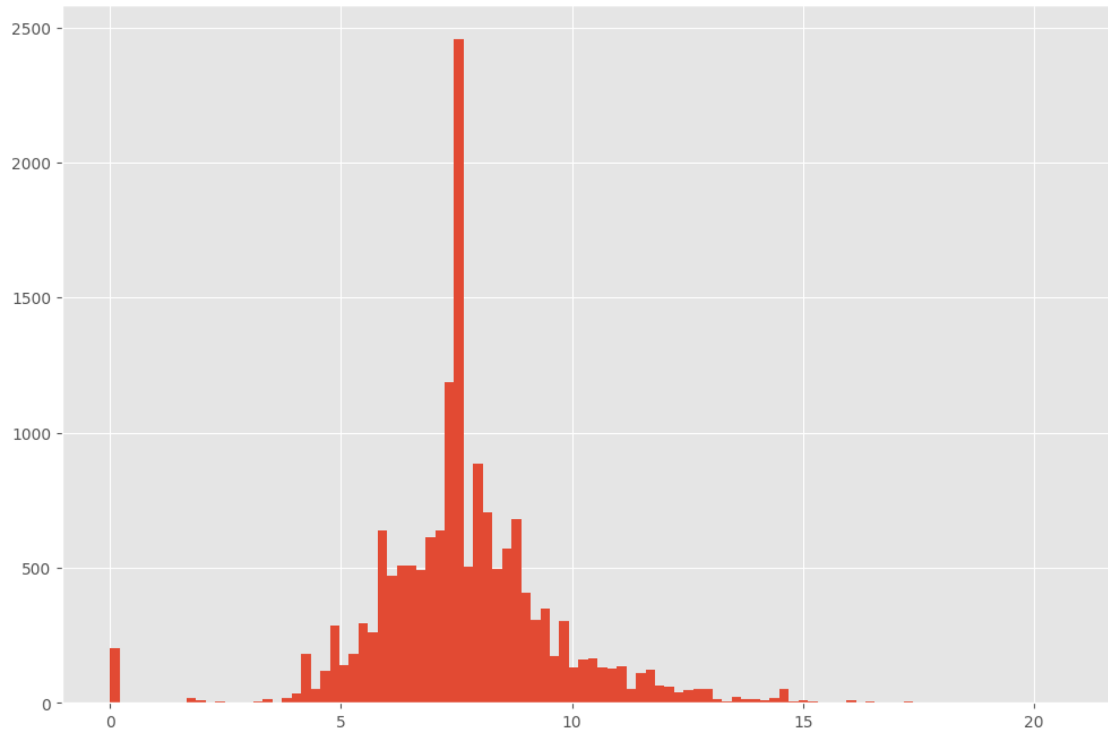
[40]:
```
# Eliminamos los registros con año de fabricación previo al 2002
print('Registros con Engine > 6:', car[car['Engine'] > 6].shape[0])
print('Registros con Engine < 1:', car[car['Engine'] < 1].shape[0])
car.drop(car[car['Engine'] > 6].index, inplace = True)
car.drop(car[car['Engine'] < 1].index, inplace = True)
car.reset_index(drop = True, inplace = True)
```

```
Registros con Engine > 6: 116
Registros con Engine < 1: 124
```

[41]:
```
# FuelConsumption
# Year
print('FuelConsumption')
car['FuelConsumption'].hist(bins=100)
```

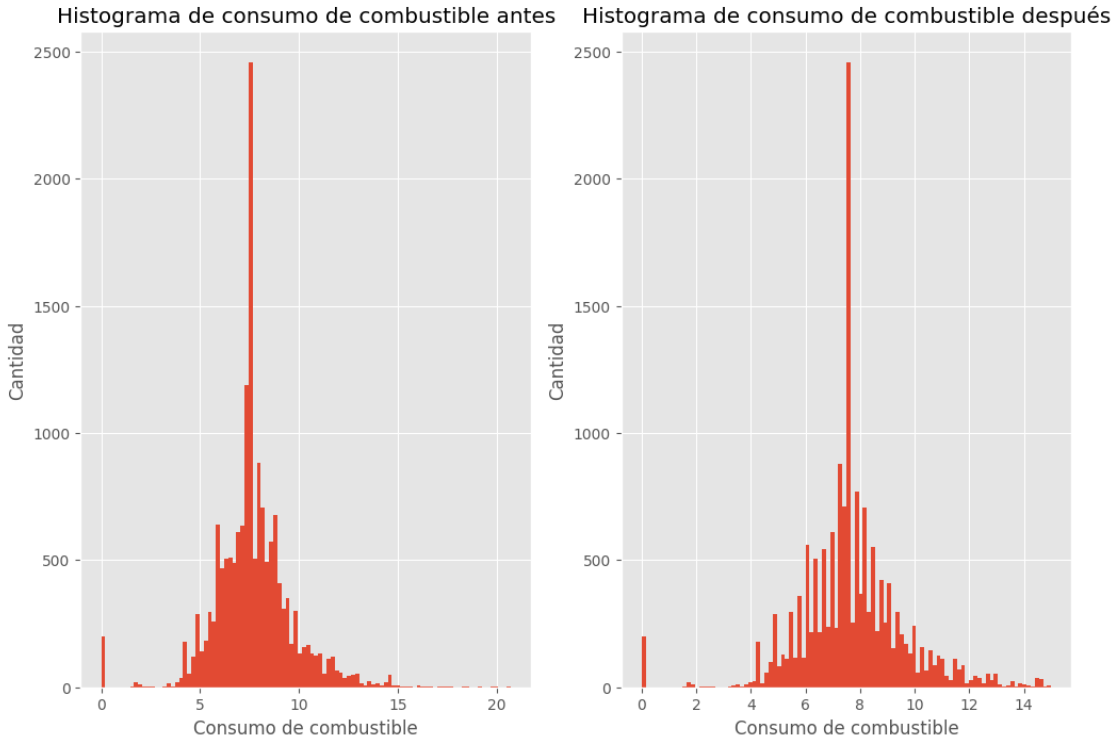
```
FuelConsumption
```

[41]: <Axes: >



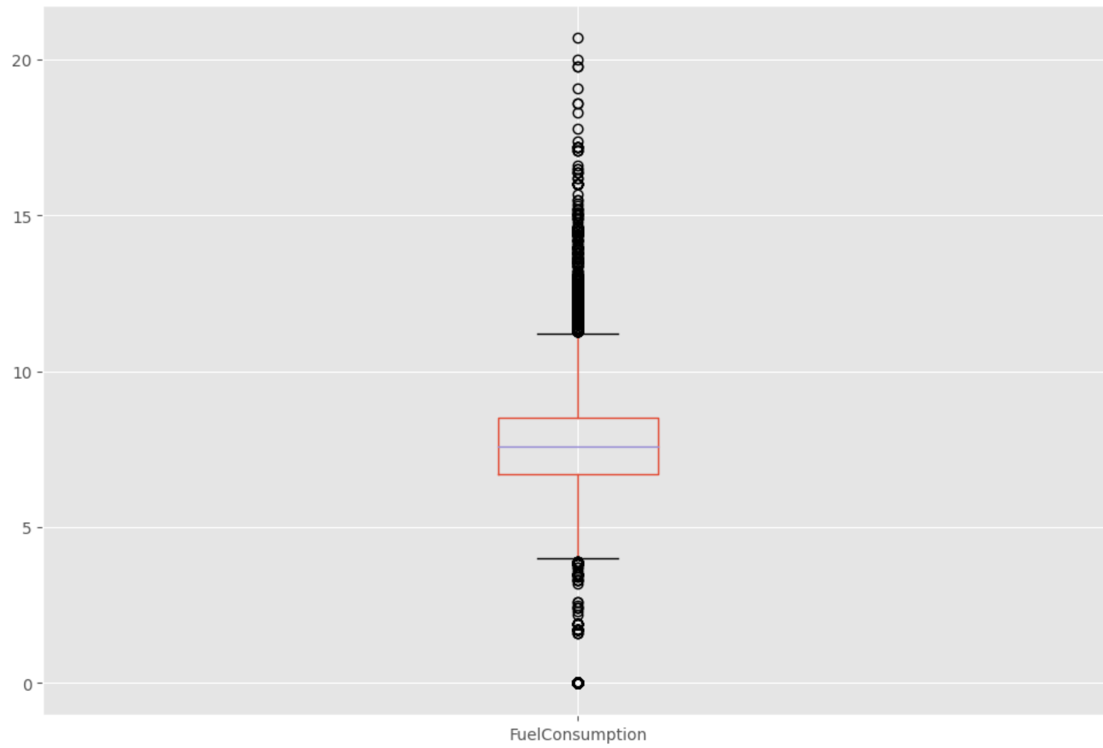
[42]:
```
l = []
for i in car['FuelConsumption']:
  if i <= 15:
    l.append(i)

s = pd.Series(l)

plt.subplot(1, 2, 1)

car['FuelConsumption'].hist(bins=100)
plt.xlabel('Consumo de combustible')
plt.ylabel('Cantidad')
plt.title('Histograma de consumo de combustible antes')

plt.subplot(1, 2, 2)
s.hist(bins=100)
plt.xlabel('Consumo de combustible')
plt.ylabel('Cantidad')
plt.title('Histograma de consumo de combustible después')
```

[42]:
```
Text(0.5, 1.0, 'Histograma de consumo de combustible después')
```



[43]:
```
# box plot.
car.boxplot(column=['FuelConsumption'])
```

[43]: <Axes: >



[44]:
```
# Eliminamos los registros con año de fabricación previo al 2002
print('Registros con Fuel Consumption > 15:', car[car['FuelConsumption'] > 15].
 ↪shape[0])
car.drop(car[car['FuelConsumption'] > 15].index, inplace = True)
#car.drop(car[car['Engine'] < 1].index, inplace = True)
car.reset_index(drop = True, inplace = True)
```

```
Registros con Fuel Consumption > 15: 47
```

[45]:
```
car[car['FuelConsumption']==0]['FuelType'].value_counts()
```

[45]:
```
Diesel      146
Unleaded     44
Other        12
Name: FuelType, dtype: int64
```

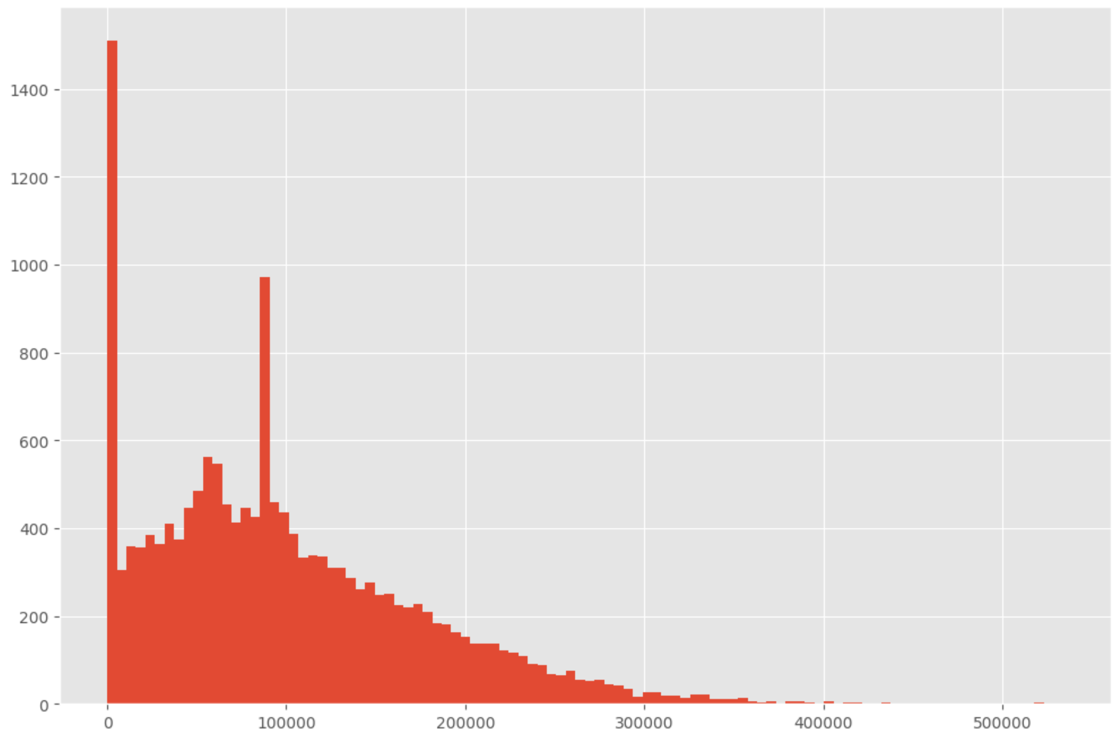
[46]:
```
car['FuelType'].value_counts()
```

[46]:
```
Unleaded    6894
Diesel      4846
Other       4588
Name: FuelType, dtype: int64
```

[47]:
```
# FuelConsumption
# Year
print('Kilometres')
car['Kilometres'].hist(bins=100)
```

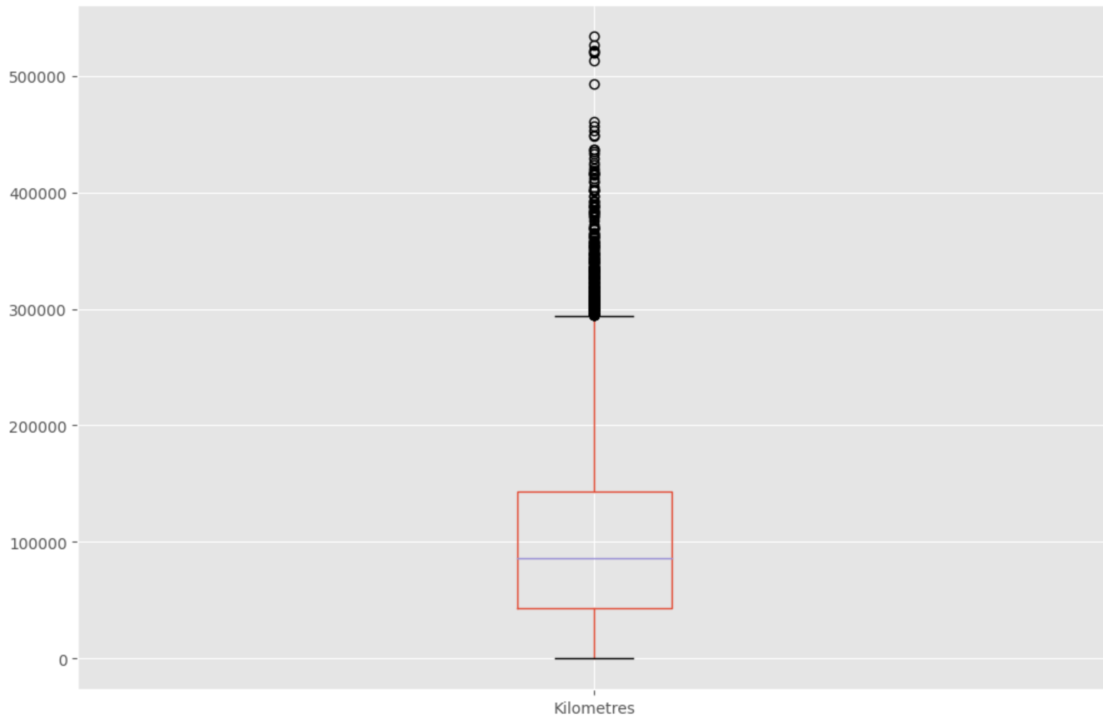
```
Kilometres
```

[47]:
```
<Axes: >
```



[48]:
```
# box plot.
car.boxplot(column=['Kilometres'])
```

[48]:
```
<Axes: >
```



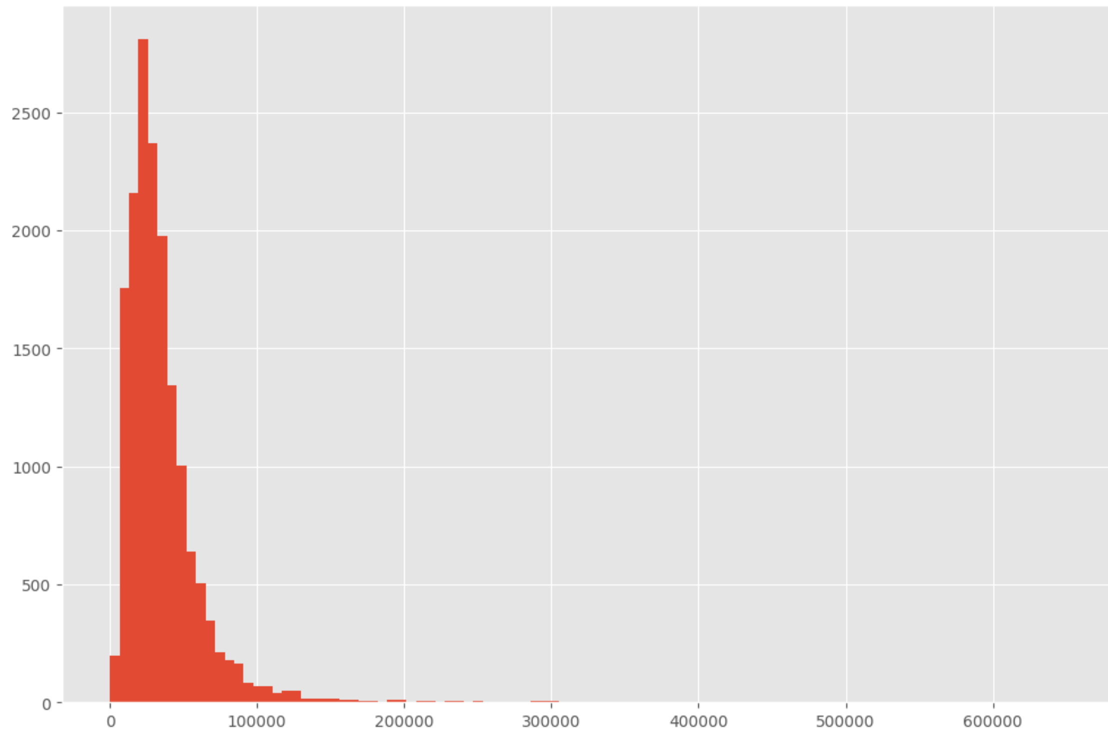
[49]:
```
# Eliminamos los registros con año de fabricación previo al 2002
print('Registros Kilometres > 350000:', car[car['Kilometres'] > 350000].
  ↪shape[0])
car.drop(car[car['Kilometres'] > 350000].index, inplace = True)
#car.drop(car[car['Engine'] < 1].index, inplace = True)
car.reset_index(drop = True, inplace = True)
```

```
Registros Kilometres > 350000: 87
```

[50]:
```
# FuelConsumption
# Year
print('Price')
car['Price'].hist(bins=100)
```

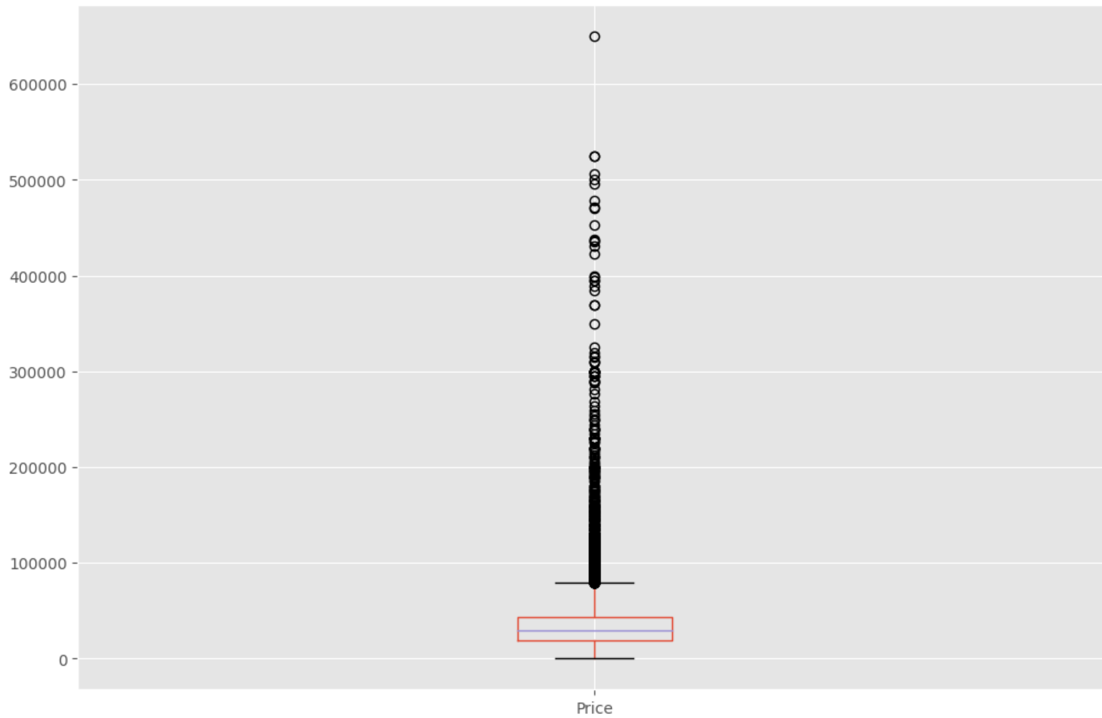
```
Price
```

[50]: `<Axes: >`



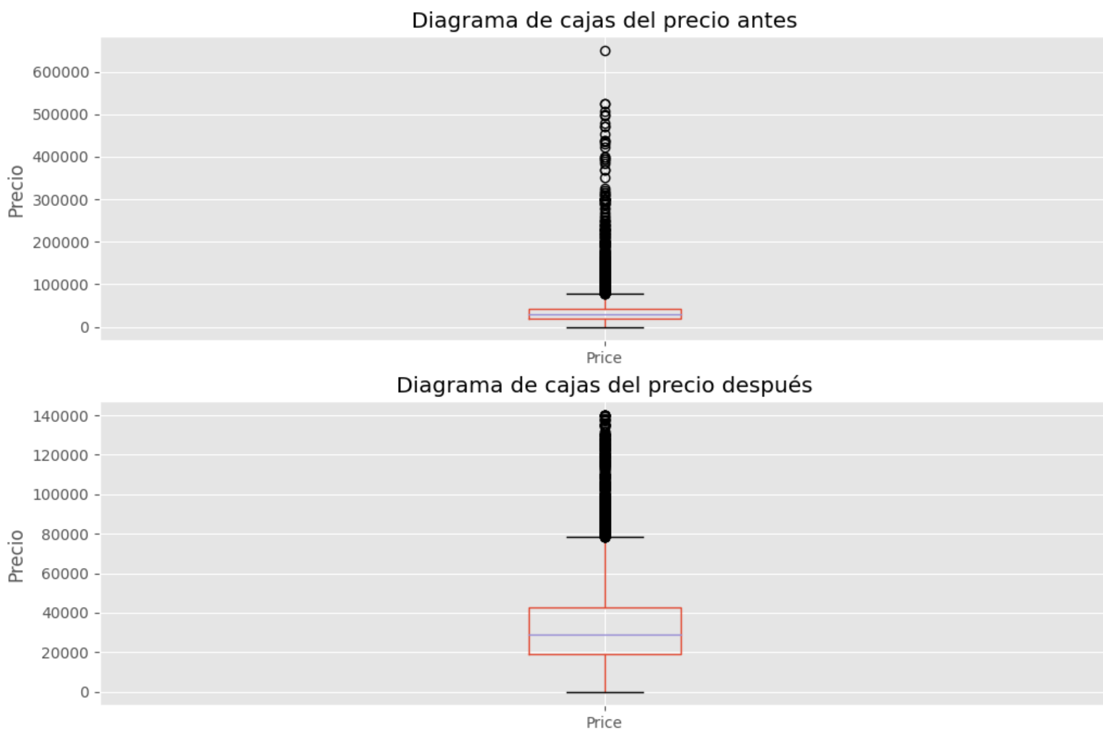
[51]:
```
# box plot.
car.boxplot(column=['Price'])
```

[51]: `<Axes: >`



[52]:
```
l = []
p = pd.DataFrame()
for i in car['Price']:
  if i <= 140000:
    l.append(i)

s = pd.Series(l)
p['Price'] = s

plt.subplot(2, 1, 1)

car.boxplot(column=['Price'])
plt.ylabel('Precio')
plt.title('Diagrama de cajas del precio antes')

plt.subplot(2, 1, 2)
p.boxplot(column=['Price'])
plt.ylabel('Precio')
plt.title('Diagrama de cajas del precio después')
```

[52]:
```
Text(0.5, 1.0, 'Diagrama de cajas del precio después')
```



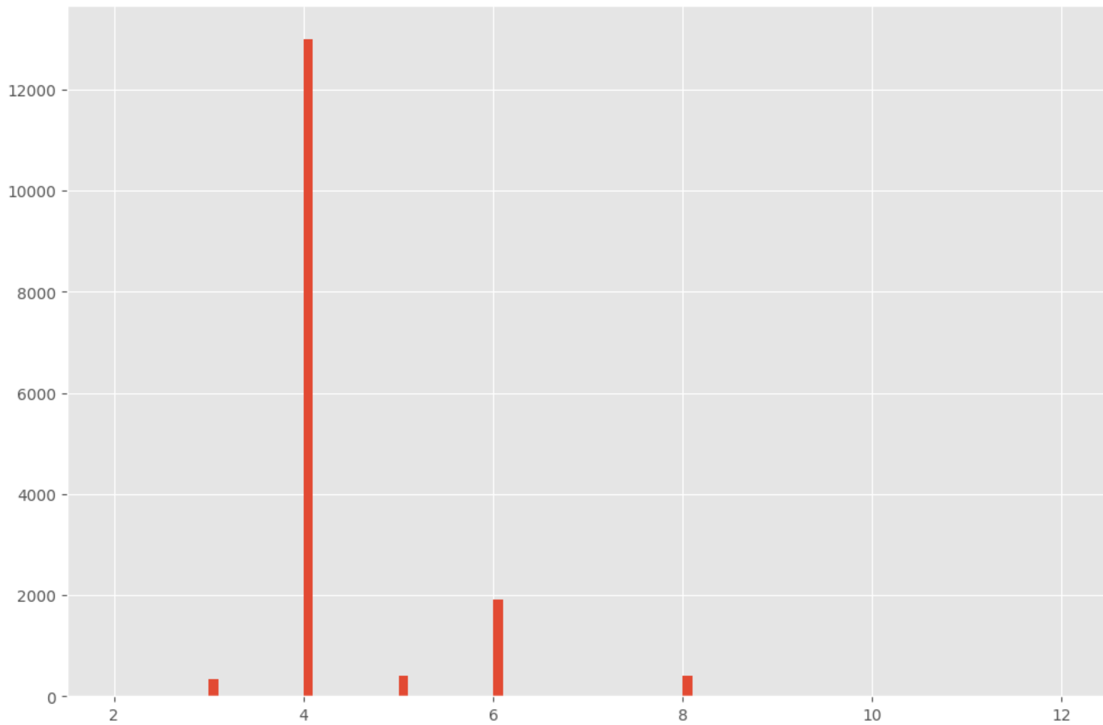
[53]:
```python
# Eliminamos los registros que tienen un Time_Affect superior a 4000.
print('Registros:', car[car['Price'] > 140000].shape[0])
#print('Registros:', car[car['Price'] < 1000].shape[0])
car.drop(car[car['Price'] > 140000].index, inplace = True)
#car.drop(car[car['Price'] < 1000].index, inplace = True)
car.reset_index(drop = True, inplace = True)
```

```
Registros: 185
```

[54]:
```python
# FuelConsumption
# Year
print('Cylinders')
car['Cylinders'].hist(bins=100)
```

```
Cylinders
```

[54]: <Axes: >



[55]:
```
car['Cylinders'].describe()
```

[55]:
```
count     16056.0
mean     4.344482
std      0.902389
min           2.0
25%           4.0
50%           4.0
75%           4.0
max          12.0
Name: Cylinders, dtype: Float64
```

[56]:
```
print('Registros:', car[car['Cylinders'] > 8].shape[0])
print('Registros:', car[car['Cylinders'] < 3].shape[0])
car.drop(car[car['Cylinders'] > 8].index, inplace = True)
car.drop(car[car['Cylinders'] < 3].index, inplace = True)
car.reset_index(drop = True, inplace = True)
```

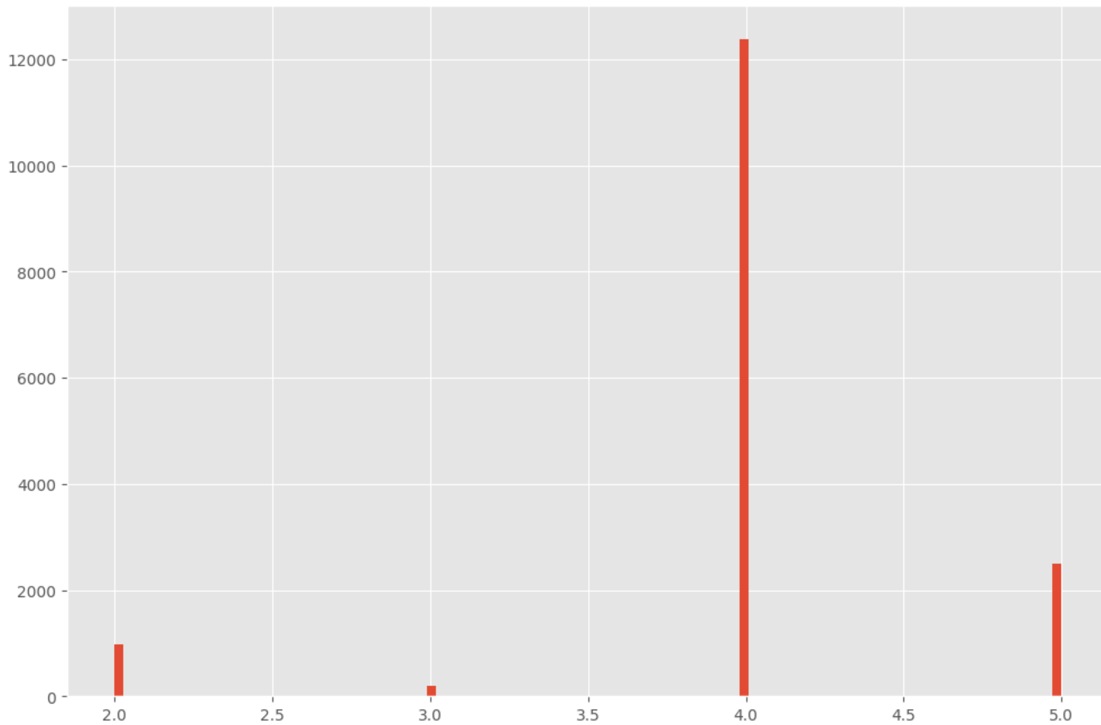
```
Registros: 2
Registros: 1
```

[57]:
```
# FuelConsumption
# Year
print('Doors')
```

```python
car['Doors'].hist(bins=100)
```

Doors

[57]: <Axes: >



[58]:
```python
car['Doors'].describe()
```

[58]:
```
count    16053.0
mean     4.02199
std      0.640114
min          2.0
25%          4.0
50%          4.0
75%          4.0
max          5.0
Name: Doors, dtype: Float64
```

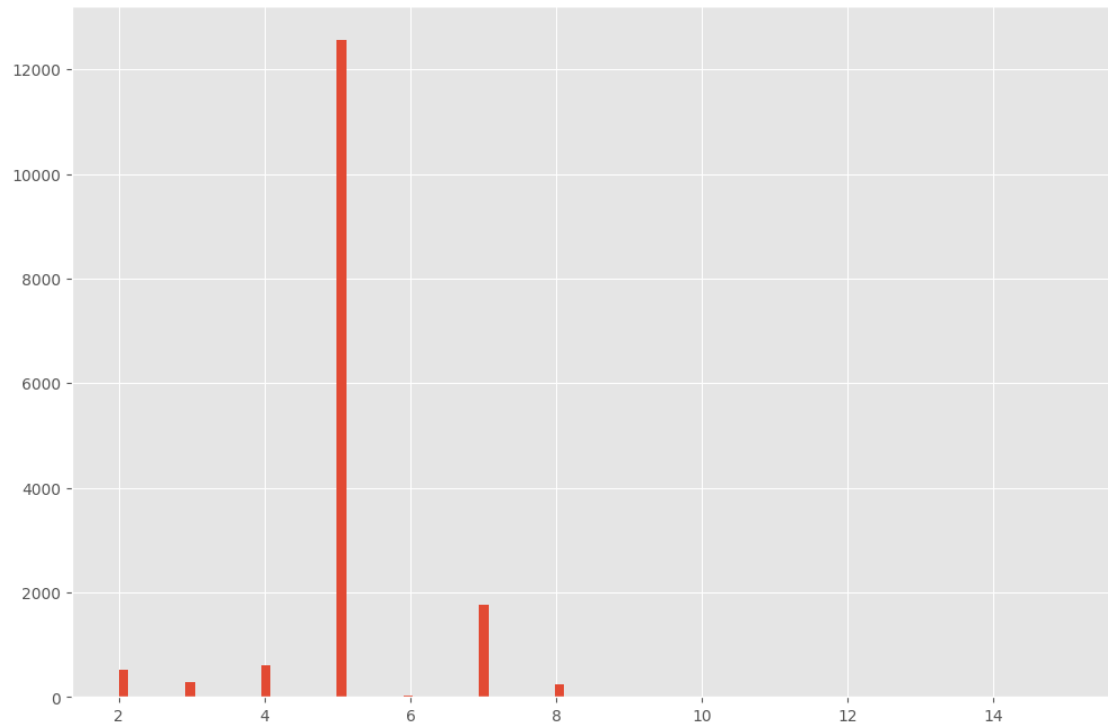
[59]:
```python
print('Registros:', car[car['Doors'] > 4].shape[0])
print('Registros:', car[car['Doors'] < 3].shape[0])
car.reset_index(drop = True, inplace = True)
```

```
Registros: 2496
Registros: 973
```

```
[60]: # FuelConsumption
      # Year
      print('Seats')
      car['Seats'].hist(bins=100)
```

```
Seats
```

```
[60]: <Axes: >
```




```
[61]: car['Seats'].describe()
```

```
[61]: count     16053.0
      mean     5.103532
      std        1.0268
      min           2.0
      25%           5.0
      50%           5.0
      75%           5.0
      max          15.0
      Name: Seats, dtype: Float64
```

```
[62]: print('Registros:', car[car['Seats'] > 8].shape[0])
      car.drop(car[car['Seats'] > 8].index, inplace = True)
      car.reset_index(drop = True, inplace = True)
```

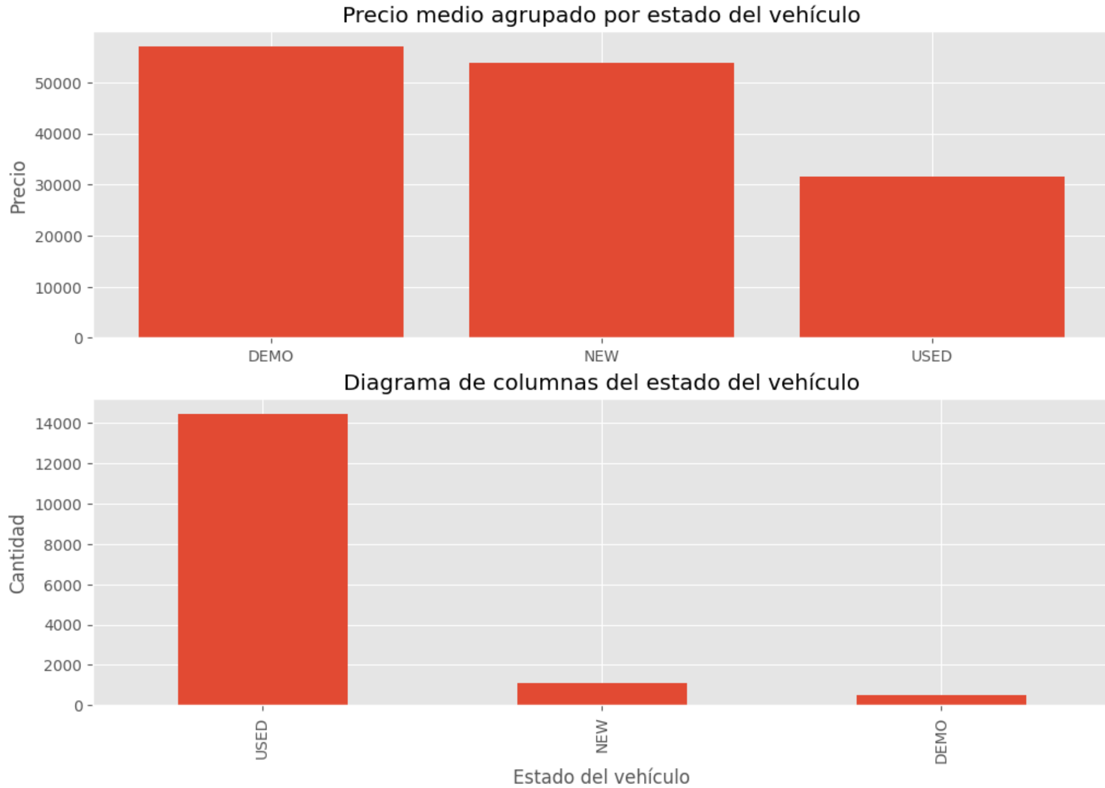
```
Registros: 20
```

[63]:
```
# Variables categóricas
print('El dataset contiene', car.shape[0], 'filas y', car.shape[1], 'columnas.')
print('Las columnas, con sus correspondientes tipos, son las siguientes:\n',␣
↪car.dtypes)
```

```
El dataset contiene 16033 filas y 15 columnas.
Las columnas, con sus correspondientes tipos, son las siguientes:
 Year                   Int64
UsedOrNew             object
Transmission          object
Engine               float64
DriveType             object
FuelType              object
FuelConsumption      float64
Kilometres           float64
Cylinders              Int64
BodyType              object
Doors                  Int64
Seats                  Int64
Price                float64
DollarAustralian     float64
PriceIndex           float64
dtype: object
```

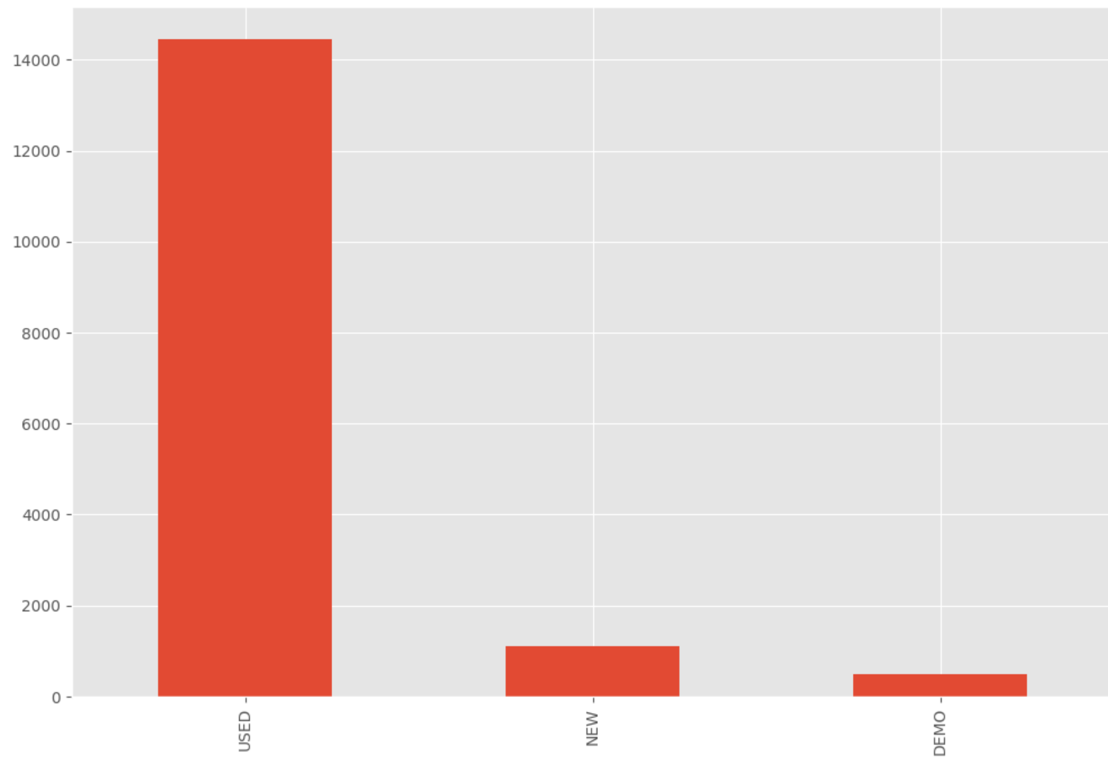
[64]:
```
plt.subplot(2, 1, 1)
UsedOrNew_grouped = car[['UsedOrNew', 'Price']].groupby('UsedOrNew').mean().
↪reset_index()
plt.bar(UsedOrNew_grouped ['UsedOrNew'], UsedOrNew_grouped['Price'])
plt.ylabel('Precio')
plt.title('Precio medio agrupado por estado del vehículo')



plt.subplot(2, 1, 2)
car['UsedOrNew'].value_counts().plot.bar()
plt.ylabel('Cantidad')
plt.xlabel('Estado del vehículo')
plt.title('Diagrama de columnas del estado del vehículo')
```

[64]:
```
Text(0.5, 1.0, 'Diagrama de columnas del estado del vehículo')
```



[65]:
```
# UsedOrNew.
print(car['UsedOrNew'].value_counts())
car['UsedOrNew'].value_counts().plot.bar()

# Juntamos DEMO con NEW (además tienen precio medio similar), el hecho de que␣
↪solo haya 500 lo refuerza
l = []
for i in car['UsedOrNew']:
  if i == 'DEMO' or i == 'NEW':
    l.append('NOT USED')
  else :
    l.append(i)
car['UsedOrNew'] = l
```

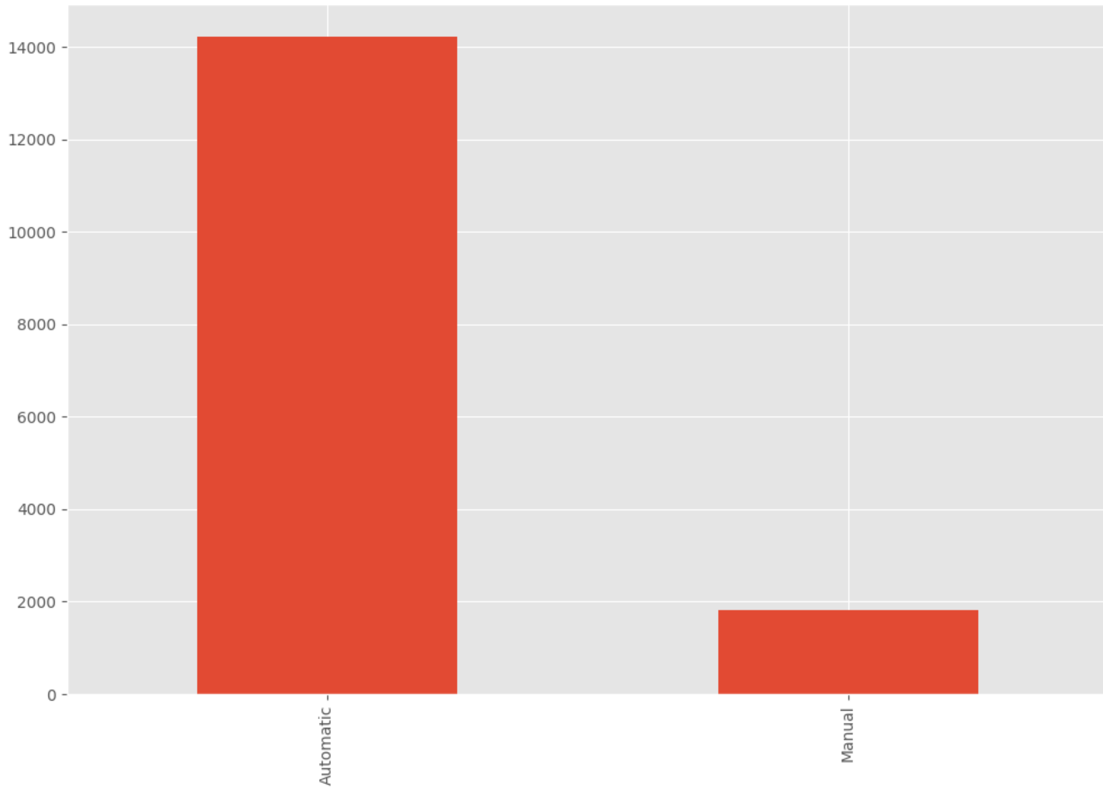
```
USED    14446
NEW      1102
DEMO      485
Name: UsedOrNew, dtype: int64
```



[66]:
```
# Transmission
print(car['Transmission'].value_counts())
car['Transmission'].value_counts().plot.bar()
```

```
Automatic    14212
Manual        1821
Name: Transmission, dtype: int64
```

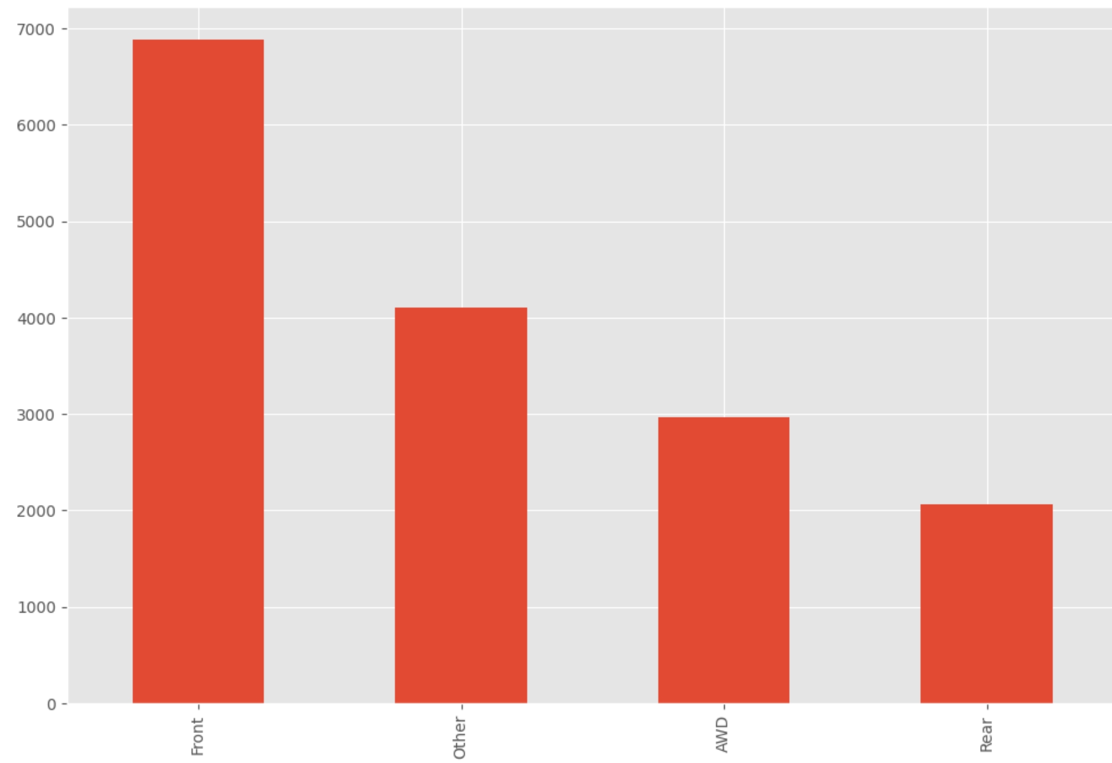
[66]: <Axes: >



[67]:
```
# DriveType
print(car['DriveType'].value_counts())
car['DriveType'].value_counts().plot.bar()
```

```
Front     6883
Other     4110
AWD       2972
Rear      2068
Name: DriveType, dtype: int64
```

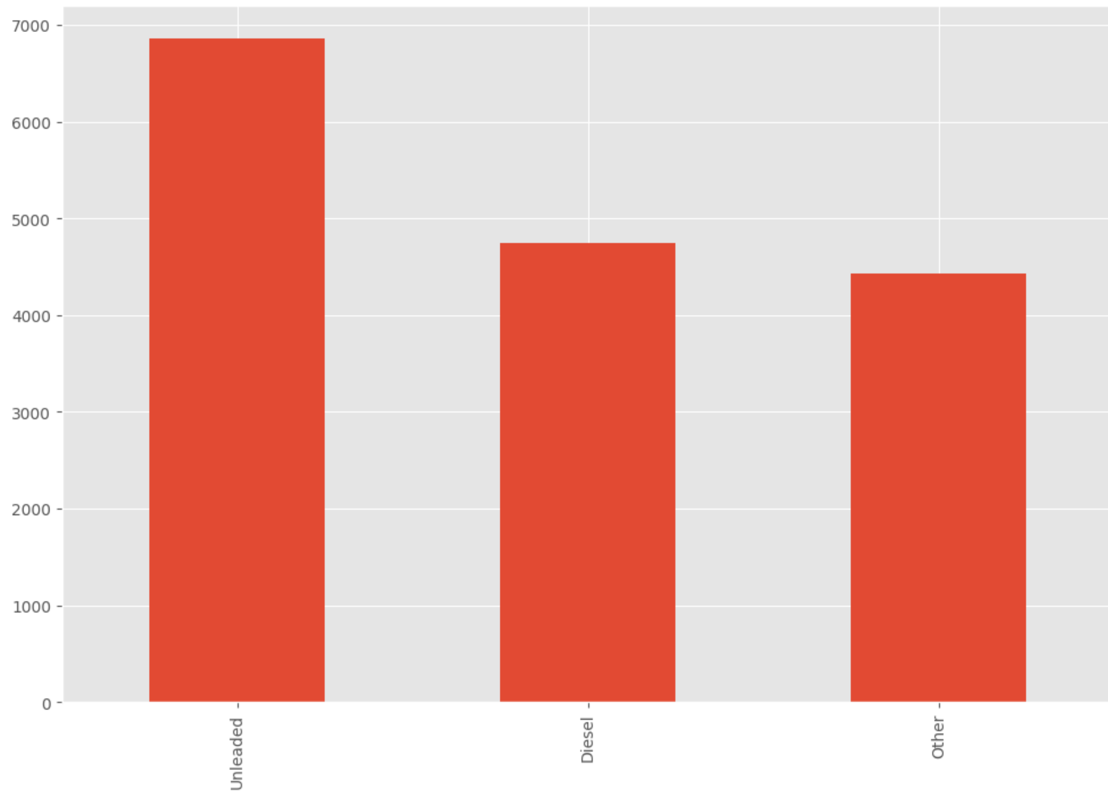
[67]:
```
<Axes: >
```



[68]:
```python
# FuelType
print(car['FuelType'].value_counts())
car['FuelType'].value_counts().plot.bar()
```

```
Unleaded    6855
Diesel      4743
Other       4435
Name: FuelType, dtype: int64
```

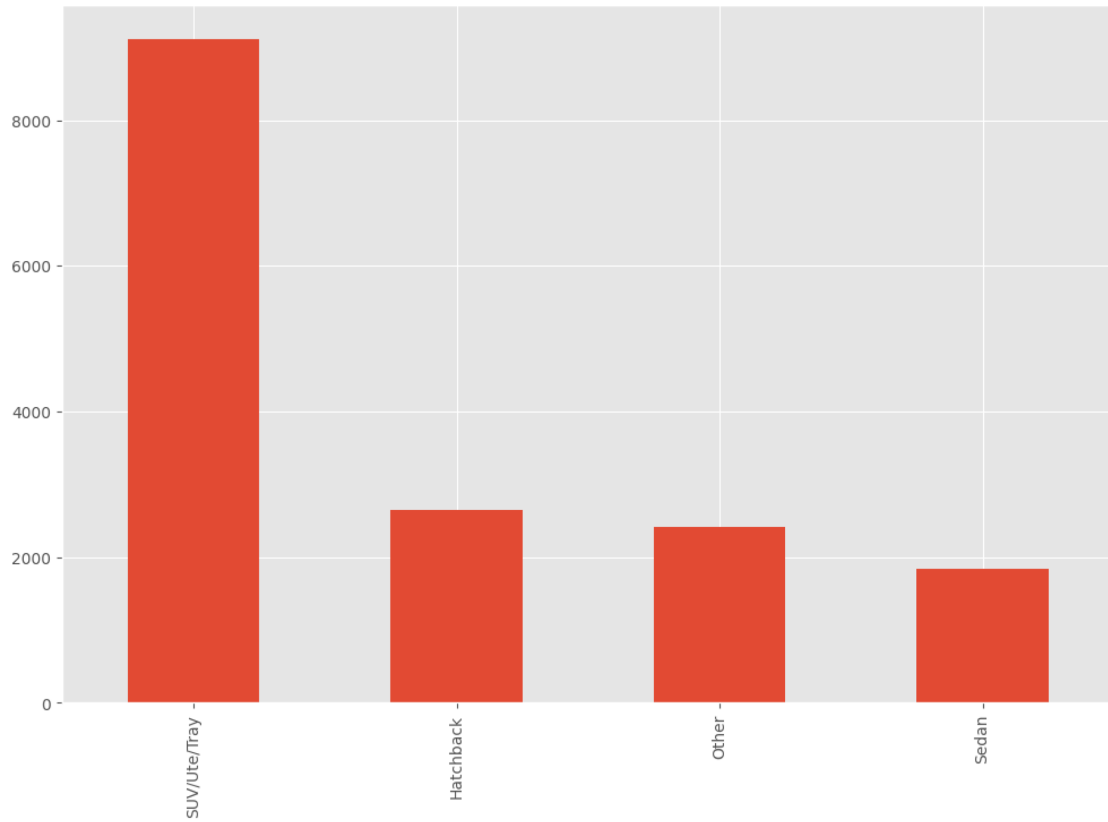
[68]: <Axes: >



[69]:
```
# BodyType
print(car['BodyType'].value_counts())
car['BodyType'].value_counts().plot.bar()
```

```
SUV/Ute/Tray    9119
Hatchback       2655
Other           2416
Sedan           1843
Name: BodyType, dtype: int64
```

[69]: <Axes: >

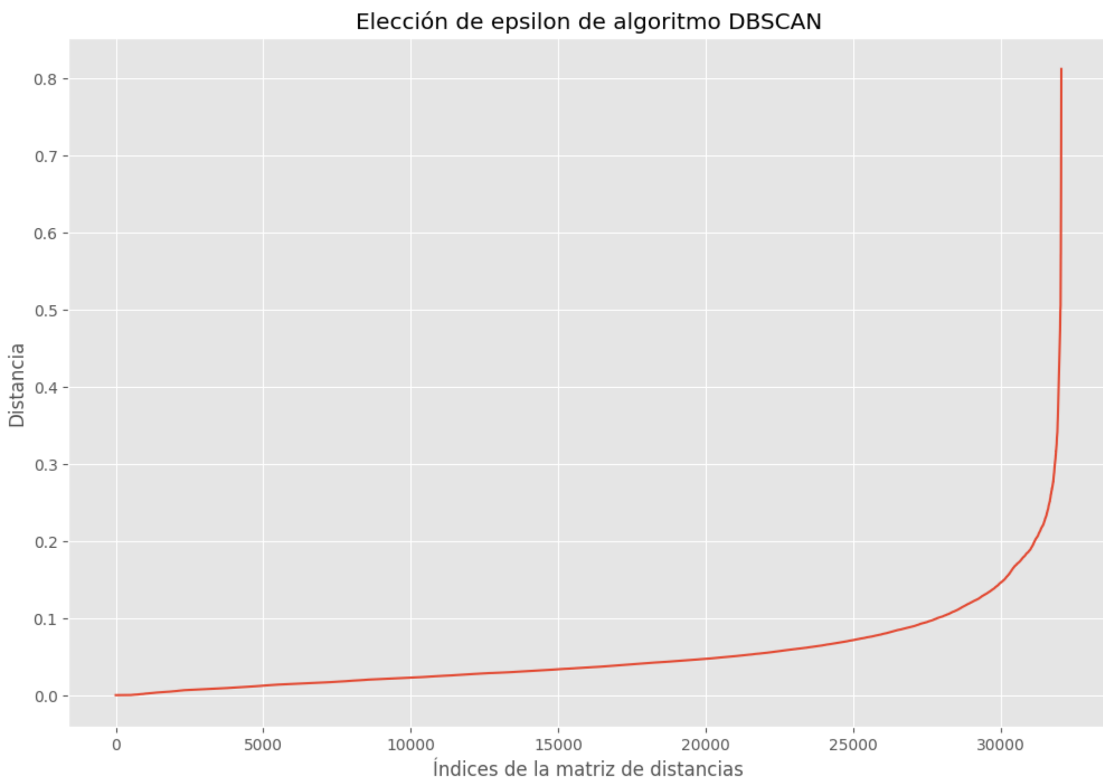


8 Outliers por filas (DBSCAN)

[70]:
```
from sklearn import preprocessing
min_max_scaler = preprocessing.MinMaxScaler()
num_cols = ['Year', 'Engine', 'FuelConsumption', 'Kilometres', 'Cylinders',␣
↪'Doors', 'Seats', 'DollarAustralian', 'PriceIndex', 'Price']
features_norm = min_max_scaler.fit_transform(car[num_cols])

## DBSCAN
from scipy import cluster
import sklearn.metrics
```

[71]:
```
from sklearn import preprocessing
min_max_scaler = preprocessing.MinMaxScaler()
num_cols = ['Year', 'Engine', 'FuelConsumption', 'Kilometres', 'Cylinders',␣
↪'Doors', 'Seats', 'DollarAustralian', 'PriceIndex', 'Price']
features_norm = min_max_scaler.fit_transform(car[num_cols])

## DBSCAN
from scipy import cluster
```

```python
import sklearn.metrics
dist = sklearn.metrics.DistanceMetric.get_metric('euclidean')
matdist= dist.pairwise(features_norm)
minPts=2
from sklearn.neighbors import kneighbors_graph
A = kneighbors_graph(features_norm, minPts, include_self=False)
Ar = A.toarray()

seq = []
for i,s in enumerate(features_norm):
    for j in range(len(features_norm)):
        if Ar[i][j] != 0:
            seq.append(matdist[i][j])

seq.sort()
# establecer intervalo ejes
fig = plt.figure()
ax = fig.gca()
#ax.set_xticks(np.arange(0, 120, 10))
#ax.set_yticks(np.arange(0, 7, 0.5))

plt.plot(seq)
plt.xlabel('Índices de la matriz de distancias')
plt.ylabel('Distancia')
plt.title('Elección de epsilon de algoritmo DBSCAN')

plt.show()
```



[72]:
```
from sklearn.cluster import DBSCAN
print("Para los distintos epsilons, se muestra el número de clústers y outliers␣
 ↪obtenidos con el método DBSCAN:\n")
for eps in np.arange(0.05, 0.45, 0.05):
  db = DBSCAN(eps, min_samples=minPts).fit(features_norm)
  core_samples_mask = np.zeros_like(db.labels_, dtype=bool)
  core_samples_mask[db.core_sample_indices_] = True
  labels = db.labels_
  n_clusters_ = len(set(labels)) - (1 if -1 in labels else 0)
  n_outliers = list(labels).count(-1)
  print ("%6.2f, %d, %d" % (eps, n_clusters_, n_outliers))


#labels
```

```
Para los distintos epsilons, se muestra el número de clústers y outliers
obtenidos con el método DBSCAN:

  0.05, 1395, 4412
  0.10, 722, 1550
  0.15, 427, 674
  0.20, 235, 320
```

```
0.25, 96, 135
0.30, 62, 72
0.35, 36, 41
0.40, 28, 29
```

[73]:
```
# Prescindimos de los 72 registros más extremos, a fin de evitar distorsionar␣
↪los resultados
eps= 0.3
db = DBSCAN(eps, min_samples=minPts).fit(features_norm)
labels = db.labels_
```

[74]:
```
j = 0
l = []
for i in labels:
  if i == -1:
    l.append(j)
  j = j+1

car.drop(l, axis=0, inplace=True)
car.reset_index(drop = True, inplace = True)
```

[75]:
```
print('El dataset contiene', car.shape[0], 'filas y', car.shape[1], 'columnas.')
print('Las columnas, con sus correspondientes tipos, son las siguientes:\n',␣
↪car.dtypes)
```

```
El dataset contiene 15961 filas y 15 columnas.
Las columnas, con sus correspondientes tipos, son las siguientes:
 Year                    Int64
UsedOrNew             object
Transmission          object
Engine               float64
DriveType             object
FuelType              object
FuelConsumption      float64
Kilometres           float64
Cylinders              Int64
BodyType              object
Doors                  Int64
Seats                  Int64
Price                float64
DollarAustralian     float64
PriceIndex           float64
dtype: object
```

9 Datos innecesarios

9.1 Datos desinformativos

[76]:
```
num_rows = len(car.index)
low_information_cols = []

for col in car.columns:
    cnts = car[col].value_counts(dropna=False)
    top_pct = (cnts/num_rows).iloc[0]

    if top_pct > 0.95:
        low_information_cols.append(col)
        print('{0}: {1:.5f}%'.format(col, top_pct*100))
        print(cnts)
        print()
```

9.2 Datos Duplicados

[77]:
```
# we know that column 'id' is unique, but what if we drop it?
car_dedupped = car.drop_duplicates()

# there were duplicate rows
print(car.shape)
print(car_dedupped .shape)

#Dekete duplicates
car.drop_duplicates(inplace = True)
```

```
(15961, 15)
(15891, 15)
```

[78]:
```
print('El dataset contiene', car.shape[0], 'filas y', car.shape[1], 'columnas.')
print('Las columnas, con sus correspondientes tipos, son las siguientes:\n',␣
↪car.dtypes)
```

```
El dataset contiene 15891 filas y 15 columnas.
Las columnas, con sus correspondientes tipos, son las siguientes:
 Year                  Int64
UsedOrNew            object
Transmission         object
Engine              float64
DriveType            object
FuelType             object
FuelConsumption     float64
Kilometres          float64
Cylinders             Int64
BodyType             object
Doors                 Int64
```

```
Seats                 Int64
Price               float64
DollarAustralian    float64
PriceIndex          float64
dtype: object
```

10 Anexo y exportación de resultados

Finalmente, confirmamos que la variable del precio toma valores enteros y exportamos el fichero final listo para la siguiente fase de modelado.

[79]:
```
aux = True
for i in car['Price']: # Recorremos el campo.
  if not(i.is_integer()): # Preguntamos si es real.
    aux = False # Si hay algún número real en este campo aux será falso.
    break

# En caso de que solo haya valores enteros en ambos campos (sin contar los␣
 ↪Missings), aux y aux2 serán True.
print('¿Los valores de Price son enteros?', aux)
```

```
¿Los valores de Price son enteros? True
```

[80]:
```
car.to_csv('Australian vehicle Prices Clean.csv', index = False)
```