```
import xgboost as xgb
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
from sklearn.metrics import f1_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score
from sklearn.metrics import root_mean_squared_error
from bayes_opt import BayesianOptimization
```

```
#df = pd.read_csv('../data/sample submission.csv')
df = pd.read_csv('../data/data2.csv', sep=';', encoding='latin1')
print(df)
```

```
          Id     Category   Manufacturer     Model  Prod. year Gear box type  \
0       2680         Jeep        HYUNDAI        H1        2014     Automatic   
1       5960        Sedan     MITSUBISHI    Mirage        2002     Automatic   
2       2185         Jeep        HYUNDAI  Santa FE        2014     Automatic   
3      15905        Sedan  MERCEDES-BENZ     E 260        1992        Manual   
4      15337    Universal          HONDA       FIT        2015     Automatic   
...      ...          ...            ...       ...         ...           ...   
16346  19198         Jeep         TOYOTA     RAV 4        2015     Automatic   
16347   3583        Sedan         TOYOTA     Prius        2009     Automatic   
16348  18497         Jeep      SSANGYONG    REXTON        2015     Automatic   
16349   4565  Goods wagon           OPEL     Combo        2011        Manual   
16350  11586        Sedan           FORD    Fusion        2013     Automatic   

      Leather interior Fuel type Engine volume Drive wheels  Cylinders  \
0                  Yes    Diesel           2.5        Front          4   
1                   No    Petrol           1.8        Front          4   
2                  Yes    Diesel             2        Front          4   
3                   No       CNG           2.6         Rear          6   
4                  Yes    Hybrid           1.5        Front          4   
...                ...       ...           ...          ...        ...   
16346              Yes    Petrol           2.5          4x4          4   
16347              Yes    Hybrid           1.5        Front          4   
16348              Yes    Diesel             2        Front          4   
16349               No    Diesel     1.3 Turbo        Front          4   
16350              Yes    Hybrid             2        Front          4   

         Mileage Doors  Airbags       Wheel   Color Sales Fee  price  
0       74210 km     4        4  Left wheel  Silver       777  22433  
1      160000 km     4        2  Left wheel   White         -   7500  
2       51106 km     4        4  Left wheel   White       639  27284  
3           0 km     4        4  Left wheel   Beige         -   3450  
4       35624 km     4        4  Left wheel   Black       308  26644  
...          ...   ...      ...         ...     ...       ...    ...  
16346  149019 km     4        0  Left wheel    Grey       934  28225  
16347  142426 km     4       12  Left wheel   White       746   1882  
16348  123303 km     4        4  Left wheel   Black       765  36219  
16349   95000 km     4        4  Left wheel   White       490   9408  
```

```
16350  174619 km     4        0  Left wheel    Grey       640   1646

[16351 rows x 18 columns]
```

DATOS FALTANTES

```
# verificar datos faltantes
for col in df.columns.to_list():
  calc = (df[col].isna().sum()/df.shape[0])*100
  print(f'{col} missing Values: {calc}%')
```

```
Id missing Values: 0.0%
Category missing Values: 0.0%
Manufacturer missing Values: 0.0%
Model missing Values: 0.0%
Prod. year missing Values: 0.0%
Gear box type missing Values: 0.0%
Leather interior missing Values: 0.0%
Fuel type missing Values: 0.0%
Engine volume missing Values: 0.0%
Drive wheels missing Values: 0.0%
Cylinders missing Values: 0.0%
Mileage missing Values: 0.0%
Doors missing Values: 0.0%
Airbags missing Values: 0.0%
Wheel missing Values: 0.0%
Color missing Values: 0.0%
Sales Fee missing Values: 0.0%
price missing Values: 0.0%
```

VARIABLES CATEGÓRICAS

ENCODING

```
def label_encoding(dataset, column_name):
    label_encoder = LabelEncoder()
    dataset[column_name] = label_encoder.fit_transform(dataset[column_name])
    return dataset, label_encoder

def frequency_encoding(dataset, col):
    freq = dataset[col].value_counts(normalize=True)
    dataset[col] = dataset[col].map(freq)
    return dataset, freq
```

```
df2 = df
def to_zero(n):
  if n == '-': return 0
  return n
```

```
def mileage_km(n):
  return n.replace(' km', '')

def turbo(n):
  if 'Turbo' in n: return 1
  return 0

def engine_volume(n):
  return n.replace(' Turbo', '')

def doors(n):
  if n == '>5': return 6
  return n


df2['Turbo'] = df2['Engine volume'].map(turbo)



df2['Sales Fee'] = df2['Sales Fee'].map(to_zero)
df2['Mileage'] = df2['Mileage'].map(mileage_km)
df2['Engine volume'] = df2['Engine volume'].map(engine_volume)
df2['Doors'] = df2['Doors'].map(doors)

df2.head(20)
```

	Id	Category	Manufacturer	Model	Prod. year	Gear box type	Leather interior	Fuel type	Engine volume	Drive wheels	Cylinders	Mileage	Doors	Airbags	Wheel	Color	Sales Fee	price	Turbo
0	2680	Jeep	HYUNDAI	H1	2014	Automatic	Yes	Diesel	2.5	Front	4	74210	4	4	Left wheel	Silver	777	22433	0
1	5960	Sedan	MITSUBISHI	Mirage	2002	Automatic	No	Petrol	1.8	Front	4	160000	4	2	Left wheel	White	0	7500	0
2	2185	Jeep	HYUNDAI	Santa FE	2014	Automatic	Yes	Diesel	2	Front	4	51106	4	4	Left wheel	White	639	27284	0
3	15905	Sedan	MERCEDES-BENZ	E 260	1992	Manual	No	CNG	2.6	Rear	6	0	4	4	Left wheel	Beige	0	3450	0
4	15337	Universal	HONDA	FIT	2015	Automatic	Yes	Hybrid	1.5	Front	4	35624	4	4	Left wheel	Black	308	26644	0
5	13792	Hatchback	HONDA	FIT	2014	Automatic	Yes	Petrol	1.5	Front	4	78000	4	4	Left wheel	White	501	25638	0
6	12015	Microbus	FORD	Transit	2007	Manual	No	Diesel	2.4	Rear	4	165000	4	2	Left wheel	Blue	0	17249	0
7	307	Sedan	TOYOTA	Camry	2015	Automatic	Yes	Hybrid	2.5	Front	4	35000	4	10	Left wheel	Grey	456	39201	0
8	1054	Sedan	TOYOTA	Camry	2012	Automatic	Yes	Hybrid	2.5	Front	4	156518	4	12	Left wheel	White	781	3607	0
9	7945	Sedan	HYUNDAI	Elantra	2012	Automatic	Yes	Petrol	1.6	Front	4	165294	4	4	Left wheel	Silver	531	16308	0
10	15234	Minivan	MERCEDES-BENZ	Vito	2007	Tiptronic	Yes	Diesel	3.0	Rear	6	250000	4	4	Left wheel	Black	0	30640	1
11	2277	Jeep	LEXUS	RX 450	2010	Automatic	Yes	Hybrid	3.5	4x4	6	167222	4	12	Left wheel	Black	1399	5018	0
12	1660	Sedan	HYUNDAI	Sonata	2016	Automatic	Yes	LPG	2	Front	4	287140	4	4	Left wheel	White	891	18817	0
13	15966	Sedan	FORD	F150	2016	Automatic	Yes	Petrol	3.5	Front	4	33543	4	4	Left wheel	White	1493	126322	0
14	11541	Coupe	HYUNDAI	Genesis	2010	Automatic	Yes	Petrol	3.8	Front	4	151977	4	4	Left wheel	Blue	1511	16621	0
15	1579	Jeep	TOYOTA	RAV 4	2010	Variator	Yes	Petrol	2	4x4	4	167300	6	8	Left wheel	Blue	0	23207	0
16	3011	Jeep	HYUNDAI	Tucson	2016	Automatic	Yes	Diesel	2	Front	4	27243	4	4	Left wheel	Grey	891	29633	0
17	4573	Jeep	MERCEDES-BENZ	ML 350	2009	Automatic	Yes	Diesel	3.5	4x4	6	274088	4	12	Left wheel	Black	1624	6272	0
18	6342	Jeep	MERCEDES-BENZ	GL 450	2006	Automatic	Yes	LPG	4.5	4x4	6	181000	4	6	Left wheel	Black	0	21000	1
19	15558	Sedan	HYUNDAI	Sonata	2015	Automatic	Yes	Petrol	2	Front	4	59150	4	4	Left wheel	Grey	765	42692	0

```
df2, freq_category = frequency_encoding(df2, 'Category')
df2, freq_manufacturer = frequency_encoding(df2, 'Manufacturer')
df2, freq_model = frequency_encoding(df2, 'Model')
# Prod. Year
df2, freq_gear_box_type = frequency_encoding(df2, 'Gear box type')
df2, freq_leather_interior = frequency_encoding(df2, 'Leather interior')
df2, freq_fuel_type = frequency_encoding(df2, 'Fuel type')
# Engine volume: quitar el turbo y crear variable aparte
df2, freq_drive_wheels = frequency_encoding(df2, 'Drive wheels')
# Cylinders
df2, freq_mileage = frequency_encoding(df2, 'Mileage') # quitar km
# Doors: cambiar >5 por 4
# Airbags
df2, freq_wheel = frequency_encoding(df2, 'Wheel')
df2, freq_color = frequency_encoding(df2, 'Color')
# Sales Fee: cambiar '-' por '0'
df2.head()
```

	Id	Category	Manufacturer	Model	Prod. year	Gear box type	Leather interior	Fuel type	Engine volume	Drive wheels	Cylinders	Mileage	Doors	Airbags	Wheel	Color	Sales Fee	price	Turbo
0	2680	0.287567	0.196869	0.022567	2014	0.702832	0.725216	0.211363	2.5	0.670907	4	0.000061	4	4	0.922512	0.195951	777	22433	0
1	5960	0.453183	0.015106	0.000428	2002	0.702832	0.274784	0.528286	1.8	0.670907	4	0.006483	4	2	0.922512	0.233380	0	7500	0
2	2185	0.287567	0.196869	0.027521	2014	0.702832	0.725216	0.211363	2	0.670907	4	0.000122	4	4	0.922512	0.233380	639	27284	0
3	15905	0.453183	0.105315	0.000061	1992	0.096875	0.274784	0.024524	2.6	0.118097	6	0.036817	4	4	0.922512	0.006850	0	3450	0
4	15337	0.018592	0.050028	0.022690	2015	0.702832	0.725216	0.185065	1.5	0.670907	4	0.000061	4	4	0.922512	0.261941	308	26644	0

```
for col in df2.columns:
    df2[col] = pd.to_numeric(df2[col])


# Interaction terms
df2['Doors_Category'] = df2['Doors'] * df2['Category']
df2['Engine_volume_Cylinders'] = df2['Engine volume'] * df2['Cylinders']
df2['Prod_year_Mileage'] = df2['Prod. year'] * df2['Mileage']

# Additional interaction terms
df2['Doors_ProdYear'] = df2['Doors'] * df2['Prod. year']
df2['Mileage_SalesFee'] = df2['Mileage'] * df2['Sales Fee']
df2['Category_Turbo'] = df2['Category'] * df2['Turbo']

# Polynomial terms
df2['Mileage_Squared'] = df2['Mileage'] ** 2
df2['EngineVolume_Squared'] = df2['Engine volume'] ** 2

# Ratios
df2['EngineVolume_per_Cylinder'] = df2['Engine volume'] / df2['Cylinders']
df2['Mileage_per_Door'] = df2['Mileage'] / df2['Doors']

# Age feature
df2['Car_Age'] = 2024 - df2['Prod. year']

# Interaction with age
df2['Age_Mileage'] = df2['Car_Age'] * df2['Mileage']
df2['Age_SalesFee'] = df2['Car_Age'] * df2['Sales Fee']

# Log transformations (to handle skewness)
df2['Log_Mileage'] = np.log1p(df2['Mileage'])
df2['Log_EngineVolume'] = np.log1p(df2['Engine volume'])
df2['Log_SalesFee'] = np.log1p(df2['Sales Fee'])
```

OUTLIERS

```
# Tratar con outliers
def cuantificaOutliers(dataset):
  for col in dataset.columns:
    q1, q3 = np.percentile(dataset[col],[25,75])
```

```
    iqr = q3-q1
    lower_bound = q1 - (1.5*iqr)
    upper_bound = q3 + (1.5*iqr)
    outlier = dataset[(dataset[col]<lower_bound)|(dataset[col]>upper_bound)]
    if (outlier.shape[0] > 0):
      print(col, ' ', outlier.shape[0], ' ', outlier.shape[0]/dataset.shape[0]*100, '%')

cuantificaOutliers(df2)
```

```
Prod. year   824   5.039447128615987 %
Engine volume   1184   7.241147330438505 %
Cylinders   4140   25.31955232095896 %
Mileage   2015   12.323405296312153 %
Doors   763   4.666381261084949 %
Wheel   1267   7.7487615436364745 %
Sales Fee   136   0.831753409577396 %
price   901   5.510366338450248 %
Turbo   1618   9.89541924041343 %
Engine_volume_Cylinders   3426   20.952846920677633 %
Prod_year_Mileage   2014   12.3172894624182 %
Doors_ProdYear   1424   8.708947464986851 %
Mileage_SalesFee   2533   15.491407253378997 %
Category_Turbo   1618   9.89541924041343 %
Mileage_Squared   2750   16.81854320836646 %
EngineVolume_Squared   2373   14.512873830346768 %
EngineVolume_per_Cylinder   198   1.2109351110023852 %
Mileage_per_Door   1994   12.194972784539173 %
Car_Age   824   5.039447128615987 %
Age_Mileage   2240   13.699467922451225 %
Age_SalesFee   548   3.3514769738853896 %
Log_Mileage   2015   12.323405296312153 %
Log_EngineVolume   1089   6.660143110513118 %
```

```
def Modifica_Outliers (dataset,columna):
  q1, q3 = np.percentile(dataset[columna], [25, 75])
  # Calculate the interquartile range
  iqr = q3 - q1
  # Calculate the lower and upper bounds
  lower_limit = q1 - (1.5 * iqr)
  upper_limit = q3 + (1.5 * iqr)

  dataset[columna] = np.where(dataset[columna]>upper_limit,upper_limit,np.where(dataset[columna]<lower_limit,lower_limit,dataset[columna]))
  return (dataset)

Modifica_Outliers(df2,'Engine volume')
Modifica_Outliers(df2,'Prod. year')
Modifica_Outliers(df2,'Mileage')
Modifica_Outliers(df2,'Sales Fee')
Modifica_Outliers(df2,'Engine_volume_Cylinders')
Modifica_Outliers(df2,'Prod_year_Mileage')
Modifica_Outliers(df2,'Doors_ProdYear')
Modifica_Outliers(df2,'Mileage_SalesFee')
Modifica_Outliers(df2,'Age_SalesFee')
Modifica_Outliers(df2,'Log_Mileage')
Modifica_Outliers(df2,'Log_EngineVolume')
Modifica_Outliers(df2,'Car_Age')
```

```
Modifica_Outliers(df2,'Age_Mileage')
Modifica_Outliers(df2,'Mileage_per_Door')
Modifica_Outliers(df2,'Mileage_Squared')
Modifica_Outliers(df2,'EngineVolume_Squared')
Modifica_Outliers(df2,'EngineVolume_per_Cylinder')
cuantificaOutliers(df2)
```

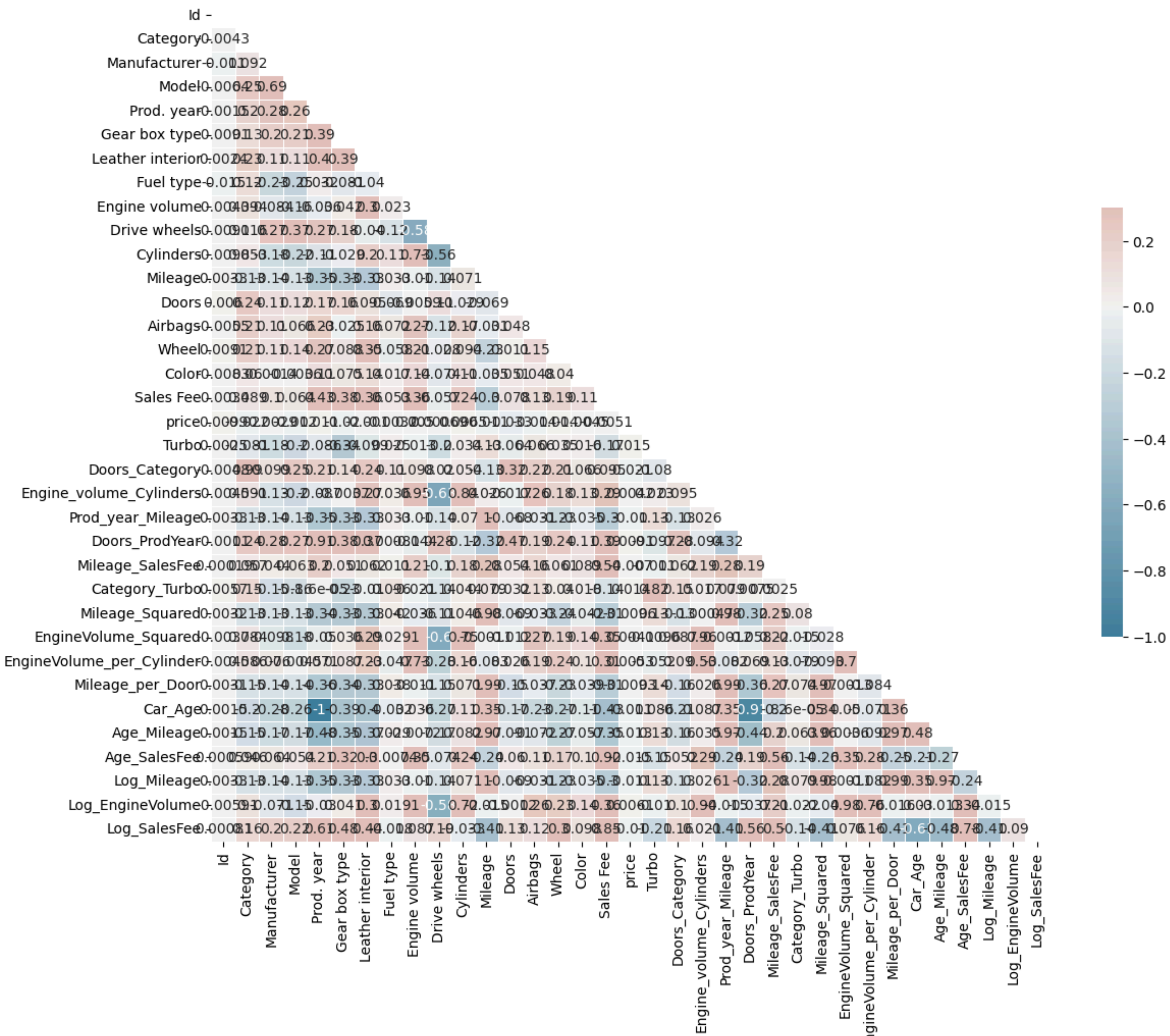
```
Cylinders   4140   25.31955232095896 %
Doors   763   4.666381261084949 %
Wheel   1267   7.7487615436364745 %
price   901   5.510366338450248 %
Turbo   1618   9.89541924041343 %
Category_Turbo   1618   9.89541924041343 %
```

ANÁLISIS DE CORRELACIÓN

```
# Realizar un análisis de correlación
corr = df2.corr(method='pearson')
mask = np.triu(np.ones_like(corr, dtype=bool))
f, ax = plt.subplots(figsize=(11,9))
cmap = sns.diverging_palette(230, 20, as_cmap=True)

plt.tight_layout()
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0, square=True, linewidths=.5, cbar_kws={'shrink':0.5}, annot=True)
```

<Axes: >



```
correlations = df2.corr()['price'].abs().sort_values(ascending=False)
print("Correlación con la variable objetivo (Curado):\n", correlations)
```

```
Correlación con la variable objetivo (Curado):
 price                        1.000000
Doors                        0.032986
Category                     0.021632
Doors_Category               0.021222
Gear box type                0.020325
Turbo                        0.015388
Age_SalesFee                 0.014557
Category_Turbo               0.014314
Wheel                        0.013929
Airbags                      0.013830
Age_Mileage                  0.013278
Model                        0.012115
Prod. year                   0.010756
Car_Age                      0.010756
Log_Mileage                  0.010523
Mileage                      0.010522
Prod_year_Mileage            0.010499
Log_SalesFee                 0.010103
Id                           0.009915
Mileage_Squared              0.009551
Mileage_per_Door             0.009313
Doors_ProdYear               0.009095
Mileage_SalesFee             0.006985
Cylinders                    0.006525
Log_EngineVolume             0.006075
EngineVolume_per_Cylinder    0.005289
Sales Fee                    0.005070
Engine volume                0.005026
Color                        0.004539
Engine_volume_Cylinders      0.004228
EngineVolume_Squared         0.004103
Fuel type                    0.003239
Manufacturer                 0.002938
Leather interior             0.000998
Drive wheels                 0.000685
Name: price, dtype: float64
```

VARIABLES

```
df3 = df2
"""
Mileage_Squared              0.009551
Mileage_per_Door             0.009313
Doors_ProdYear               0.009095
Mileage_SalesFee             0.006985
Cylinders                    0.006525
Log_EngineVolume             0.006075
EngineVolume_per_Cylinder    0.005289
```

```
Sales Fee                  0.005070
Engine volume              0.005026
Color                      0.004539
Engine_volume_Cylinders    0.004228
EngineVolume_Squared       0.004103
Fuel type                  0.003239
Manufacturer               0.002938
Leather interior           0.000998
Drive wheels               0.000685
"""
df3 = df3.drop('Mileage_Squared', axis=1)
df3 = df3.drop('Mileage_per_Door', axis=1)
df3 = df3.drop('Doors_ProdYear', axis=1)
df3 = df3.drop('Mileage_SalesFee', axis=1)
df3 = df3.drop('Cylinders', axis=1)
df3 = df3.drop('Log_EngineVolume', axis=1)
df3 = df3.drop('EngineVolume_per_Cylinder', axis=1)
df3 = df3.drop('Sales Fee', axis=1)
df3 = df3.drop('Engine volume', axis=1)
df3 = df3.drop('Color', axis=1)
df3 = df3.drop('Engine_volume_Cylinders', axis=1)
df3 = df3.drop('EngineVolume_Squared', axis=1)
df3 = df3.drop('Fuel type', axis=1)
df3 = df3.drop('Manufacturer', axis=1)
df3 = df3.drop('Leather interior', axis=1)
df3 = df3.drop('Drive wheels', axis=1)
df3.head()
```

	Id	Category	Model	Prod. year	Gear box type	Mileage	Doors	Airbags	Wheel	price	Turbo	Doors_Category	Prod_year_Mileage	Category_Turbo	Car_Age	Age_Mileage	Age_SalesFee	Log_Mileage	Log_SalesFee
0	2680	0.287567	0.022567	2014.0	0.702832	0.000061	4	4	0.922512	22433	0	1.150266	0.123173	0.0	10.0	0.000612	7770.0	0.000061	6.656727
1	5960	0.453183	0.000428	2002.0	0.702832	0.003272	4	2	0.922512	7500	0	1.812733	6.582839	0.0	22.0	0.043055	0.0	0.003270	0.000000
2	2185	0.287567	0.027521	2014.0	0.702832	0.000122	4	4	0.922512	27284	0	1.150266	0.246346	0.0	10.0	0.001223	6390.0	0.000122	6.461468
3	15905	0.453183	0.000061	2000.0	0.096875	0.003272	4	4	0.922512	3450	0	1.812733	6.582839	0.0	24.0	0.043055	0.0	0.003270	0.000000
4	15337	0.018592	0.022690	2015.0	0.702832	0.000061	4	4	0.922512	26644	0	0.074369	0.123234	0.0	9.0	0.000550	2772.0	0.000061	5.733341

```
df4 = df3
y = df4['price']
x = df4.drop('price', axis=1)
```

MODELO

```
from sklearn.metrics import mean_squared_error
from bayes_opt import BayesianOptimization
import xgboost as xgb
from sklearn.model_selection import train_test_split

# Train-test split
```

```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.25, random_state=101)

# Define the objective function for Bayesian optimization
def xgb_evaluate(max_depth, learning_rate, n_estimators, subsample, colsample_bytree):
    params = {
        'objective': 'reg:squarederror',
        'max_depth': int(max_depth),
        'learning_rate': learning_rate,
        'n_estimators': int(n_estimators),
        'subsample': subsample,
        'colsample_bytree': colsample_bytree,
        'random_state': 42
    }
    model = xgb.XGBRegressor(**params)

    # Fit model with early stopping
    model.fit(
        x_train, y_train,
        eval_set=[(x_test, y_test)],
        verbose=False
    )

    # Predict and calculate RMSE
    y_val_pred = model.predict(x_test)
    rmse = mean_squared_error(y_test, y_val_pred)

    # Return negative RMSE for maximization
    return -rmse

# Define parameter bounds for Bayesian optimization
param_bounds = {
    'max_depth': (5, 15),
    'learning_rate': (0.001, 0.05),
    'n_estimators': (1000, 4000),
    'subsample': (0.6, 1.0),
    'colsample_bytree': (0.4, 0.9)
}

# Run Bayesian optimization
optimizer = BayesianOptimization(
    f=xgb_evaluate,
    pbounds=param_bounds,
    random_state=42,
    verbose=2
)
optimizer.maximize(init_points=10, n_iter=25)

# Extract best parameters
best_params = optimizer.max['params']
best_params['max_depth'] = int(best_params['max_depth'])
best_params['n_estimators'] = int(best_params['n_estimators'])

print("Best parameters found:")
print(best_params)
```

```
# Train the final model with best parameters on the entire training set
final_model = xgb.XGBRegressor(objective="reg:squarederror", **best_params)
final_model.fit(
    x_train, y_train,
    eval_set=[(x_test, y_test)],
    verbose=False
)

# Make predictions and evaluate final model
predictions = final_model.predict(x_test)
final_rmse = mean_squared_error(y_test, predictions)
print("Final RMSE on test set:", final_rmse)
```

```
|   iter    |  target   | colsam... | learni... | max_depth | n_esti... | subsample |
-------------------------------------------------------------------------------------
| 1         | -1.694e+1 | 0.5873    | 0.04759   | 12.32     | 2.796e+03 | 0.6624    |
| 2         | -1.693e+1 | 0.478     | 0.003846  | 13.66     | 2.803e+03 | 0.8832    |
| 3         | -1.693e+1 | 0.4103    | 0.04853   | 13.32     | 1.637e+03 | 0.6727    |
| 4         | -1.693e+1 | 0.4917    | 0.01591   | 10.25     | 2.296e+03 | 0.7165    |
| 5         | -1.693e+1 | 0.7059    | 0.007835  | 7.921     | 2.099e+03 | 0.7824    |
| 6         | -1.693e+1 | 0.7926    | 0.01078   | 10.14     | 2.777e+03 | 0.6186    |
| 7         | -1.693e+1 | 0.7038    | 0.009356  | 5.651     | 3.847e+03 | 0.9863    |
| 8         | -1.694e+1 | 0.8042    | 0.01593   | 5.977     | 3.053e+03 | 0.7761    |
| 9         | -1.694e+1 | 0.461     | 0.02526   | 5.344     | 3.728e+03 | 0.7035    |
| 10        | -1.694e+1 | 0.7313    | 0.01627   | 10.2      | 2.64e+03  | 0.6739    |
| 11        | -1.694e+1 | 0.7942    | 0.03268   | 5.286     | 3.846e+03 | 0.9444    |
| 12        | -1.693e+1 | 0.8532    | 0.006162  | 6.473     | 3.776e+03 | 0.9083    |
| 13        | -1.693e+1 | 0.692     | 0.003341  | 5.358     | 1.314e+03 | 0.6933    |
| 14        | -1.694e+1 | 0.6343    | 0.04966   | 14.22     | 2.295e+03 | 0.7262    |
| 15        | -1.693e+1 | 0.8038    | 0.009614  | 8.167     | 1.807e+03 | 0.8904    |
| 16        | -1.693e+1 | 0.6456    | 0.01353   | 12.35     | 2.787e+03 | 0.9192    |
| 17        | -1.693e+1 | 0.4377    | 0.04078   | 9.667     | 1.917e+03 | 0.7195    |
| 18        | -1.693e+1 | 0.4413    | 0.04529   | 10.94     | 3.249e+03 | 0.8992    |
| 19        | -1.694e+1 | 0.7641    | 0.03371   | 14.95     | 2.22e+03  | 0.8155    |
| 20        | -1.694e+1 | 0.4668    | 0.03713   | 8.013     | 1.569e+03 | 0.6907    |
| 21        | -1.694e+1 | 0.5357    | 0.03293   | 5.622     | 3.241e+03 | 0.9837    |
| 22        | -1.694e+1 | 0.4819    | 0.005954  | 7.379     | 3.737e+03 | 0.9181    |
| 23        | -1.694e+1 | 0.7887    | 0.01852   | 13.38     | 3.804e+03 | 0.6652    |
| 24        | -1.694e+1 | 0.6528    | 0.02607   | 12.91     | 1.991e+03 | 0.969     |
| 25        | -1.694e+1 | 0.8319    | 0.02903   | 9.163     | 1.55e+03  | 0.7126    |
| 26        | -1.694e+1 | 0.7124    | 0.03839   | 8.835     | 1.57e+03  | 0.935     |
| 27        | -1.693e+1 | 0.6831    | 0.003556  | 8.642     | 1.49e+03  | 0.662     |
| 28        | -1.694e+1 | 0.668     | 0.04028   | 13.26     | 2.648e+03 | 0.8185    |
| 29        | -1.693e+1 | 0.4343    | 0.004392  | 6.533     | 2.015e+03 | 0.7493    |
| 30        | -1.693e+1 | 0.6183    | 0.008403  | 10.78     | 3.175e+03 | 0.6543    |
| 31        | -1.694e+1 | 0.5179    | 0.03158   | 13.5      | 3.556e+03 | 0.9243    |
| 32        | -1.693e+1 | 0.6158    | 0.04192   | 11.29     | 1.39e+03  | 0.6115    |
| 33        | -1.693e+1 | 0.8921    | 0.01937   | 7.062     | 3.232e+03 | 0.8698    |
| 34        | -1.694e+1 | 0.7253    | 0.04273   | 8.764     | 3.886e+03 | 0.6838    |
| 35        | -1.694e+1 | 0.6317    | 0.0383    | 12.29     | 3.706e+03 | 0.642     |
=====================================================================================
Best parameters found:
{'colsample_bytree': 0.7037724259507192, 'learning_rate': 0.009355682060677287, 'max_depth': 5, 'n_estimators': 3846, 'subsample': 0.9862528132298237}
Final RMSE on test set: 169328417801.86072
```

```
xgb_reg = xgb.XGBRegressor(objective="reg:squarederror", **best_params)
xgb_reg.fit(x_train, y_train)
```

```
predictions = xgb_reg.predict(x_test)
```

EVALUACIÓN

```
#print('Accuracy: ', metrics.accuracy_score(y_test,predictions))
print((root_mean_squared_error(predictions, y_test)))
```

```
411495.34359681484
```

```
scores = cross_val_score(xgb_reg, x, y, cv=10, scoring='f1_weighted')
print("Scores de cada fold:", scores)
print("Promedio del F1 score:", scores.mean())
```

```
c:\Python312\Lib\site-packages\sklearn\model_selection\_validation.py:1000: UserWarning: Scoring failed. The score on this train-test partition for these parameters will be set to nan. Details:
Traceback (most recent call last):
  File "c:\Python312\Lib\site-packages\sklearn\metrics\_scorer.py", line 139, in __call__
    score = scorer._score(
            ^^^^^^^^^^^^^^
  File "c:\Python312\Lib\site-packages\sklearn\metrics\_scorer.py", line 376, in _score
    return self._sign * self._score_func(y_true, y_pred, **scoring_kwargs)
                        ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "c:\Python312\Lib\site-packages\sklearn\utils\_param_validation.py", line 213, in wrapper
    return func(*args, **kwargs)
           ^^^^^^^^^^^^^^^^^^^^^
  File "c:\Python312\Lib\site-packages\sklearn\metrics\_classification.py", line 1293, in f1_score
    return fbeta_score(
           ^^^^^^^^^^^^
  File "c:\Python312\Lib\site-packages\sklearn\utils\_param_validation.py", line 186, in wrapper
    return func(*args, **kwargs)
           ^^^^^^^^^^^^^^^^^^^^^
  File "c:\Python312\Lib\site-packages\sklearn\metrics\_classification.py", line 1485, in fbeta_score
    _, _, f, _ = precision_recall_fscore_support(
                 ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "c:\Python312\Lib\site-packages\sklearn\utils\_param_validation.py", line 186, in wrapper
    return func(*args, **kwargs)
           ^^^^^^^^^^^^^^^^^^^^^
  File "c:\Python312\Lib\site-packages\sklearn\metrics\_classification.py", line 1789, in precision_recall_fscore_support
    labels = _check_set_wise_labels(y_true, y_pred, average, labels, pos_label)
             ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "c:\Python312\Lib\site-packages\sklearn\metrics\_classification.py", line 1561, in _check_set_wise_labels
    y_type, y_true, y_pred = _check_targets(y_true, y_pred)
                             ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "c:\Python312\Lib\site-packages\sklearn\metrics\_classification.py", line 112, in _check_targets
    raise ValueError(
ValueError: Classification metrics can't handle a mix of multiclass and continuous targets

  warnings.warn(
c:\Python312\Lib\site-packages\sklearn\model_selection\_validation.py:1000: UserWarning: Scoring failed. The score on this train-test partition for these parameters will be set to nan. Details:
Traceback (most recent call last):
  File "c:\Python312\Lib\site-packages\sklearn\metrics\_scorer.py", line 139, in __call__
    score = scorer._score(
            ^^^^^^^^^^^^^^
  File "c:\Python312\Lib\site-packages\sklearn\metrics\_scorer.py", line 376, in _score
    return self._sign * self._score_func(y_true, y_pred, **scoring_kwargs)
                        ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
```

```
  File "c:\Python312\Lib\site-packages\sklearn\utils\_param_validation.py", line 213, in wrapper
    return func(*args, **kwargs)
           ^^^^^^^^^^^^^^^^^^^^^
  File "c:\Python312\Lib\site-packages\sklearn\metrics\_classification.py", line 1293, in f1_score
    return fbeta_score(
           ^^^^^^^^^^^^
  File "c:\Python312\Lib\site-packages\sklearn\utils\_param_validation.py", line 186, in wrapper
    return func(*args, **kwargs)
           ^^^^^^^^^^^^^^^^^^^^^
  File "c:\Python312\Lib\site-packages\sklearn\metrics\_classification.py", line 1485, in fbeta_score
    _, _, f, _ = precision_recall_fscore_support(
                 ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "c:\Python312\Lib\site-packages\sklearn\utils\_param_validation.py", line 186, in wrapper
    return func(*args, **kwargs)
           ^^^^^^^^^^^^^^^^^^^^^
  File "c:\Python312\Lib\site-packages\sklearn\metrics\_classification.py", line 1789, in precision_recall_fscore_support
```

OUTPUT FILE

```
df_eval = pd.read_csv('../data/Evaluation2.csv', sep=';', encoding='latin1')

df_eval['Turbo'] = df_eval['Engine volume'].map(turbo)

df_eval['Sales Fee'] = df_eval['Sales Fee'].map(to_zero)
df_eval['Mileage'] = df_eval['Mileage'].map(mileage_km)
df_eval['Engine volume'] = df_eval['Engine volume'].map(engine_volume)
df_eval['Doors'] = df_eval['Doors'].map(doors)

df_eval['Category'] = df_eval['Category'].map(freq_category).fillna(0)
df_eval['Manufacturer'] = df_eval['Manufacturer'].map(freq_manufacturer)
df_eval['Model'] = df_eval['Model'].map(freq_model)
df_eval['Gear box type'] = df_eval['Gear box type'].map(freq_gear_box_type)
df_eval['Leather interior'] = df_eval['Leather interior'].map(freq_leather_interior)
df_eval['Fuel type'] = df_eval['Fuel type'].map(freq_fuel_type)
df_eval['Drive wheels'] = df_eval['Drive wheels'].map(freq_drive_wheels)
df_eval['Mileage'] = df_eval['Mileage'].map(freq_mileage)
df_eval['Wheel'] = df_eval['Wheel'].map(freq_wheel)
df_eval['Color'] = df_eval['Color'].map(freq_color)

for col in df_eval.columns:
    df_eval[col] = pd.to_numeric(df_eval[col])

# Interaction terms
df_eval['Doors_Category'] = df_eval['Doors'] * df_eval['Category']
df_eval['Engine_volume_Cylinders'] = df_eval['Engine volume'] * df_eval['Cylinders']
df_eval['Prod_year_Mileage'] = df_eval['Prod. year'] * df_eval['Mileage']

# Additional interaction terms
df_eval['Doors_ProdYear'] = df_eval['Doors'] * df_eval['Prod. year']
df_eval['Mileage_SalesFee'] = df_eval['Mileage'] * df_eval['Sales Fee']
df_eval['Category_Turbo'] = df_eval['Category'] * df_eval['Turbo']

# Polynomial terms
```

```
df_eval['Mileage_Squared'] = df_eval['Mileage'] ** 2
df_eval['EngineVolume_Squared'] = df_eval['Engine volume'] ** 2

# Ratios
df_eval['EngineVolume_per_Cylinder'] = df_eval['Engine volume'] / df_eval['Cylinders']
df_eval['Mileage_per_Door'] = df_eval['Mileage'] / df_eval['Doors']

# Age feature
df_eval['Car_Age'] = 2024 - df_eval['Prod. year']

# Interaction with age
df_eval['Age_Mileage'] = df_eval['Car_Age'] * df_eval['Mileage']
df_eval['Age_SalesFee'] = df_eval['Car_Age'] * df_eval['Sales Fee']

# Log transformations (to handle skewness)
df_eval['Log_Mileage'] = np.log1p(df_eval['Mileage'])
df_eval['Log_EngineVolume'] = np.log1p(df_eval['Engine volume'])
df_eval['Log_SalesFee'] = np.log1p(df_eval['Sales Fee'])


df_eval = df_eval.drop('Mileage_Squared', axis=1)
df_eval = df_eval.drop('Mileage_per_Door', axis=1)
df_eval = df_eval.drop('Doors_ProdYear', axis=1)
df_eval = df_eval.drop('Mileage_SalesFee', axis=1)
df_eval = df_eval.drop('Cylinders', axis=1)
df_eval = df_eval.drop('Log_EngineVolume', axis=1)
df_eval = df_eval.drop('EngineVolume_per_Cylinder', axis=1)
df_eval = df_eval.drop('Sales Fee', axis=1)
df_eval = df_eval.drop('Engine volume', axis=1)
df_eval = df_eval.drop('Color', axis=1)
df_eval = df_eval.drop('Engine_volume_Cylinders', axis=1)
df_eval = df_eval.drop('EngineVolume_Squared', axis=1)
df_eval = df_eval.drop('Fuel type', axis=1)
df_eval = df_eval.drop('Manufacturer', axis=1)
df_eval = df_eval.drop('Leather interior', axis=1)
df_eval = df_eval.drop('Drive wheels', axis=1)

print(df_eval)
```

```
         Id  Category     Model  Prod. year  Gear box type   Mileage  Doors  \
0     15246  0.453183  0.048621        2014       0.702832  0.001590      4
1      5176  0.453183  0.049538        2013       0.702832  0.000795      4
2      3143  0.287567  0.002324        2009       0.702832       NaN      4
3      3360  0.287567  0.000550        2011       0.096875  0.005321      2
4      3105  0.027093  0.001835        2013       0.702832  0.000306      4
...     ...       ...       ...         ...            ...       ...    ...
2881  17665  0.453183  0.056205        2009       0.702832  0.000245      4
2882   6554  0.287567  0.027521        2015       0.702832       NaN      4
2883  18661  0.453183  0.017430        2014       0.702832  0.003303      4
2884   6825  0.453183  0.000673        2014       0.702832       NaN      4
2885  11266  0.015779  0.011070        1996       0.096875       NaN      4

      Airbags     Wheel  Turbo  Doors_Category  Prod_year_Mileage  \
0           6  0.922512      0        1.812733           3.202495
1          12  0.922512      0        1.812733           1.600453
2           4  0.922512      0        1.150266                NaN
```

```
3          2  0.922512      0        0.575133         10.700080
4         12  0.922512      0        0.108373          0.615559
...      ...       ...    ...             ...               ...
2881      12  0.922512      0        1.812733          0.491468
2882      12  0.922512      0        1.150266               NaN
2883       0  0.077488      0        1.812733          6.651336
2884       4  0.922512      0        1.812733               NaN
2885       2  0.922512      0        0.063115               NaN

      Category_Turbo  Car_Age  Age_Mileage  Age_SalesFee  Log_Mileage  \
0                0.0       10     0.015901          5840     0.001589
1                0.0       11     0.008746          8569     0.000795
2                0.0       15          NaN         17115          NaN
3                0.0       13     0.069170             0     0.005307
4                0.0       11     0.003364           957     0.000306
...              ...      ...          ...           ...          ...
2881             0.0       15     0.003670         11190     0.000245
2882             0.0        9          NaN          8100          NaN
2883             0.0       10     0.033026             0     0.003297
2884             0.0       10          NaN         10530          NaN
2885             0.0       28          NaN             0          NaN

      Log_SalesFee
0         6.371612
1         6.659294
2         7.040536
3         0.000000
4         4.477337
...            ...
2881      6.616065
2882      6.803505
2883      0.000000
2884      6.960348
2885      0.000000

[2886 rows x 18 columns]
```

```
for col in df_eval.columns:
    if col == 'Id':
        continue
    df_eval[col] = pd.to_numeric(df_eval[col])

print(df_eval)
```

```
         Id  Category     Model  Prod. year  Gear box type   Mileage  Doors  \
0     15246  0.453183  0.048621        2014       0.702832  0.001590      4
1      5176  0.453183  0.049538        2013       0.702832  0.000795      4
2      3143  0.287567  0.002324        2009       0.702832       NaN      4
3      3360  0.287567  0.000550        2011       0.096875  0.005321      2
4      3105  0.027093  0.001835        2013       0.702832  0.000306      4
...     ...       ...       ...         ...            ...       ...    ...
2881  17665  0.453183  0.056205        2009       0.702832  0.000245      4
2882   6554  0.287567  0.027521        2015       0.702832       NaN      4
2883  18661  0.453183  0.017430        2014       0.702832  0.003303      4
2884   6825  0.453183  0.000673        2014       0.702832       NaN      4
2885  11266  0.015779  0.011070        1996       0.096875       NaN      4

      Airbags     Wheel  Turbo  Doors_Category  Prod_year_Mileage  \
0           6  0.922512      0        1.812733           3.202495
```

1	12	0.922512	0	1.812733	1.600453
2	4	0.922512	0	1.150266	NaN
3	2	0.922512	0	0.575133	10.700080
4	12	0.922512	0	0.108373	0.615559
...	...	...	...	...	...
2881	12	0.922512	0	1.812733	0.491468
2882	12	0.922512	0	1.150266	NaN
2883	0	0.077488	0	1.812733	6.651336
2884	4	0.922512	0	1.812733	NaN