```
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/data.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, label_leather_interior = label_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 | 1 | 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 | 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 | 1 | 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 | 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 | 1 | 0.185065 | 1.5 | 0.670907 | 4 | 0.000061 | 4 | 4 | 0.922512 | 0.261941 | 308 | 26644 | 0 |

## OUTLIERS

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


# Crear características adicionales basadas en correlaciones y relaciones avanzadas
df2['Mileage_Engine_ratio'] = df2['Mileage'] / (df2['Engine volume'] + 1)
df2['Age'] = 2024 - df2['Prod. year']
df2['Mileage_Age'] = df2['Mileage'] * df2['Age']
df2['Mileage_Engine_Age'] = df2['Mileage'] * df2['Engine volume'] * df2['Age']
df2['Mileage_Age_squared'] = (df2['Mileage'] * df2['Age']) ** 2
df2['log_Mileage'] = np.log1p(df2['Mileage'])
df2['Age_SalesFee'] = df2['Age'] * df2['Sales Fee']
df2['Mileage_Age_Log'] = np.log1p(df2['Mileage_Age'])


# 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)]
    print(col, ' ', outlier.shape[0], ' ', outlier.shape[0]/dataset.shape[0]*100, '%')

cuantificaOutliers(df2)
```

```
Id   0   0.0 %
Category   0   0.0 %
Manufacturer   0   0.0 %
Model   0   0.0 %
Prod. year   824   5.039447128615987 %
Gear box type   0   0.0 %
Leather interior   0   0.0 %
Fuel type   0   0.0 %
Engine volume   1184   7.241147330438505 %
Drive wheels   0   0.0 %
Cylinders   4140   25.31955232095896 %
Mileage   2015   12.323405296312153 %
Doors   763   4.666381261084949 %
```

```
Airbags   0   0.0 %
Wheel   1267   7.7487615436364745 %
Color   0   0.0 %
Sales Fee   136   0.831753409577396 %
price   901   5.510366338450248 %
Turbo   1618   9.89541924041343 %
Mileage_Engine_ratio   2058   12.586386153752063 %
Age   824   5.039447128615987 %
Mileage_Age   2240   13.699467922451225 %
Mileage_Engine_Age   2150   13.149042871995597 %
Mileage_Age_squared   3023   18.488165861415204 %
log_Mileage   2015   12.323405296312153 %
Age_SalesFee   548   3.3514769738853896 %
Mileage_Age_Log   2240   13.699467922451225 %
```

```
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,'Mileage_Engine_ratio')
Modifica_Outliers(df2,'Age')
Modifica_Outliers(df2,'Mileage_Age')
Modifica_Outliers(df2,'Mileage_Engine_Age')
Modifica_Outliers(df2,'Mileage_Age_squared')
Modifica_Outliers(df2,'log_Mileage')
Modifica_Outliers(df2,'Age_SalesFee')
Modifica_Outliers(df2,'Mileage_Age_Log')
cuantificaOutliers(df2)
```

```
Id   0   0.0 %
Category   0   0.0 %
Manufacturer   0   0.0 %
Model   0   0.0 %
Prod. year   0   0.0 %
Gear box type   0   0.0 %
Leather interior   0   0.0 %
Fuel type   0   0.0 %
Engine volume   0   0.0 %
Drive wheels   0   0.0 %
Cylinders   4140   25.31955232095896 %
Mileage   0   0.0 %
Doors   763   4.666381261084949 %
Airbags   0   0.0 %
Wheel   1267   7.7487615436364745 %
Color   0   0.0 %
Sales Fee   0   0.0 %
```

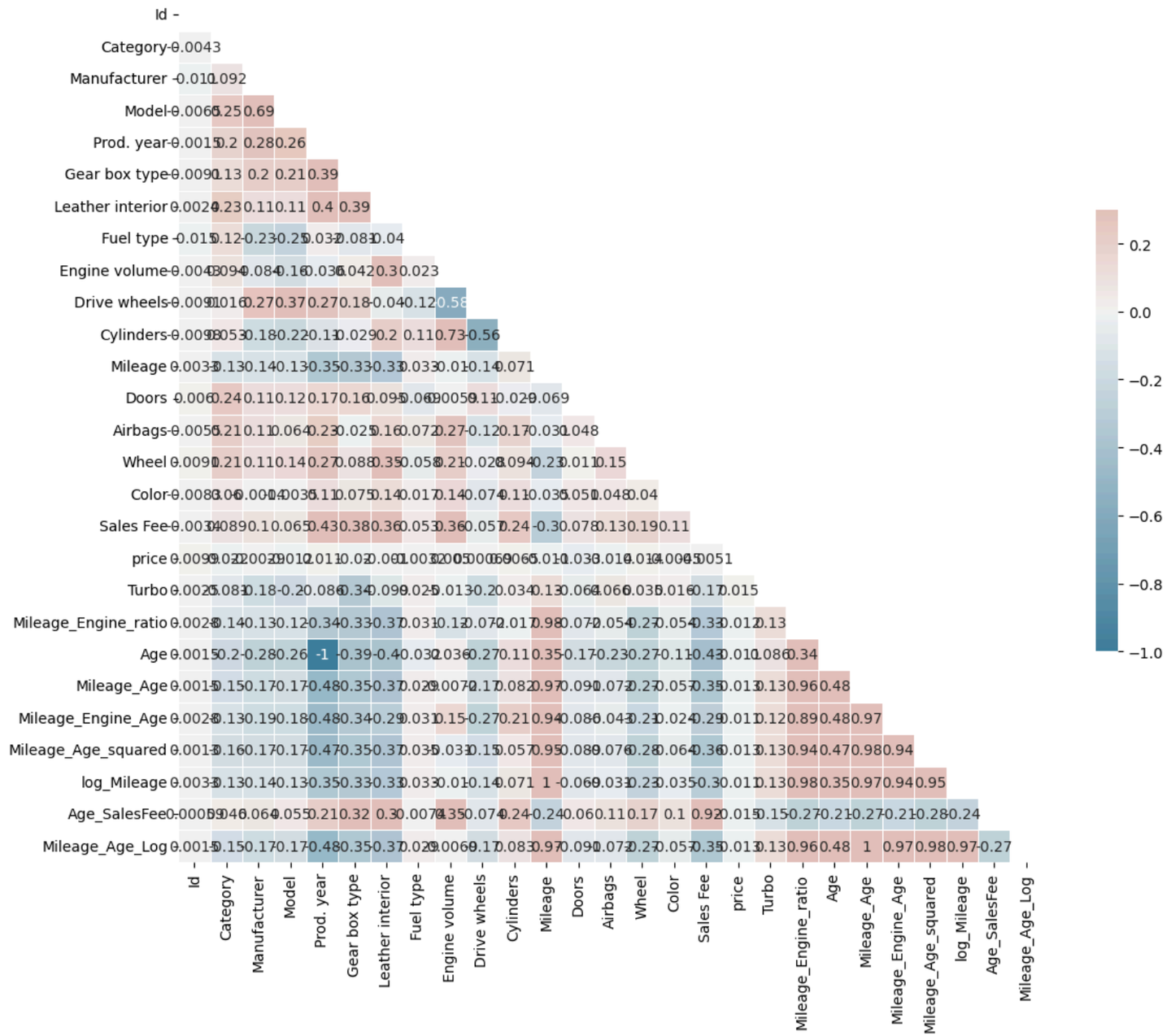
```
price   901   5.510366338450248 %
Turbo   1618   9.89541924041343 %
Mileage_Engine_ratio   0   0.0 %
Age   0   0.0 %
Mileage_Age   0   0.0 %
Mileage_Engine_Age   0   0.0 %
Mileage_Age_squared   0   0.0 %
log_Mileage   0   0.0 %
Age_SalesFee   0   0.0 %
Mileage_Age_Log   0   0.0 %
```

## 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: >


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
Mileage_Engine_ratio
Age
Mileage_Age
Mileage_Engine_Age
Mileage_Age_squared
log_Mileage
Age_SalesFee
Mileage_Age_Log
0.2
0.0
−0.2
−0.4
−0.6
−0.8
−1.0

```
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
Gear box type           0.020325
Turbo                   0.015388
Age_SalesFee            0.014557
Wheel                   0.013929
Airbags                 0.013830
Mileage_Age_Log         0.013287
Mileage_Age             0.013278
Mileage_Age_squared     0.013014
Mileage_Engine_ratio    0.012200
Model                   0.012108
Mileage_Engine_Age      0.011147
Prod. year              0.010756
Age                     0.010756
log_Mileage             0.010523
Mileage                 0.010522
Id                      0.009915
Cylinders               0.006525
Sales Fee               0.005070
Engine volume           0.005026
Color                   0.004539
Fuel type               0.003239
Manufacturer            0.002938
Leather interior        0.000998
Drive wheels            0.000685
Name: price, dtype: float64
```

## VARIABLES

```
df3 = df2
df3 = df3.drop('Cylinders', axis=1)
df3 = df3.drop('Sales Fee', axis=1)
df3 = df3.drop('Color', axis=1)
df3 = df3.drop('Mileage', 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 | Engine volume | Doors | Airbags | Wheel | price | Turbo | Mileage_Engine_ratio | Age | Mileage_Age | Mileage_Engine_Age | Mileage_Age_squared | log_Mileage | Age_SalesFee | Mileage_Age_Log |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 2680 | 0.287567 | 0.022567 | 2014.0 | 0.702832 | 2.5 | 4 | 4 | 0.922512 | 22433 | 0 | 0.000017 | 10.0 | 0.000612 | 0.001529 | 3.740342e-07 | 0.000061 | 7770.0 | 0.000611 |
| **1** | 5960 | 0.453183 | 0.000428 | 2002.0 | 0.702832 | 1.8 | 4 | 2 | 0.922512 | 7500 | 0 | 0.001028 | 22.0 | 0.043055 | 0.099920 | 7.853073e-04 | 0.003270 | 0.0 | 0.042667 |
| **2** | 2185 | 0.287567 | 0.027521 | 2014.0 | 0.702832 | 2.0 | 4 | 4 | 0.922512 | 27284 | 0 | 0.000041 | 10.0 | 0.001223 | 0.002446 | 1.496137e-06 | 0.000122 | 6390.0 | 0.001222 |
| **3** | 15905 | 0.453183 | 0.000061 | 2000.0 | 0.096875 | 2.6 | 4 | 4 | 0.922512 | 3450 | 0 | 0.001028 | 24.0 | 0.043055 | 0.099920 | 7.853073e-04 | 0.003270 | 0.0 | 0.042667 |
| **4** | 15337 | 0.018592 | 0.022690 | 2015.0 | 0.702832 | 1.5 | 4 | 4 | 0.922512 | 26644 | 0 | 0.000024 | 9.0 | 0.000550 | 0.000826 | 3.029677e-07 | 0.000061 | 2772.0 | 0.000550 |

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

## MODELO

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error

# Separar Dataset en Training y Testing Sets
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)

# Definir función para calcular el RMSE
def root_mean_squared_error(y_true, y_pred):
    return np.sqrt(mean_squared_error(y_true, y_pred))

# Función de evaluación para Random Forest
def random_forest_evaluate(max_depth, n_estimators, max_features, min_samples_split, min_samples_leaf):
    model = RandomForestRegressor(
        max_depth=int(max_depth),
        n_estimators=int(n_estimators),
        max_features=max_features,
        min_samples_split=int(min_samples_split),
        min_samples_leaf=int(min_samples_leaf),
        random_state=42,
        n_jobs=-1  # Usar todos los procesadores disponibles
    )
    model.fit(x_train, y_train)
    y_val_pred = model.predict(x_test)
    return -root_mean_squared_error(y_test, y_val_pred)

# Definir límites para los parámetros de optimización
param_bounds = {
    'max_depth': (5, 15),
    'n_estimators': (100, 1000),
    'max_features': (0.1, 0.9),
    'min_samples_split': (2, 10),
    'min_samples_leaf': (1, 5)
}
```

```
# Ejecutar optimización bayesiana
optimizer = BayesianOptimization(f=random_forest_evaluate, pbounds=param_bounds, random_state=42, verbose=2)
optimizer.maximize(init_points=10, n_iter=25)

# Obtener los mejores parámetros
best_params = optimizer.max['params']
best_params['max_depth'] = int(best_params['max_depth'])
best_params['n_estimators'] = int(best_params['n_estimators'])
best_params['min_samples_split'] = int(best_params['min_samples_split'])
best_params['min_samples_leaf'] = int(best_params['min_samples_leaf'])

print("Mejores parámetros encontrados:")
print(best_params)

# Inicializar y entrenar el modelo con los mejores parámetros
rf_regressor = RandomForestRegressor(**best_params, random_state=42, n_jobs=-1)
rf_regressor.fit(x_train, y_train)

# Hacer predicciones
y_pred = rf_regressor.predict(x_test)

# Calcular y mostrar el RMSE en el conjunto de prueba
test_rmse = root_mean_squared_error(y_test, y_pred)
print("RMSE en el conjunto de prueba:", test_rmse)
```

| iter | target | max_depth | max_fe... | min_sa... | min_sa... | n_esti... |
|---|---|---|---|---|---|---|
| 1 | -4.601e+0 | 8.745 | 0.8606 | 3.928 | 6.789 | 240.4 |
| 2 | -4.601e+0 | 6.56 | 0.1465 | 4.465 | 6.809 | 737.3 |
| 3 | -4.601e+0 | 5.206 | 0.8759 | 4.33 | 3.699 | 263.6 |
| 4 | -4.601e+0 | 6.834 | 0.3434 | 3.099 | 5.456 | 362.1 |
| 5 | -4.601e+0 | 11.12 | 0.2116 | 2.169 | 4.931 | 510.5 |
| 6 | -4.601e+0 | 12.85 | 0.2597 | 3.057 | 6.739 | 141.8 |
| 7 | -4.601e+0 | 11.08 | 0.2364 | 1.26 | 9.591 | 969.1 |
| 8 | -4.601e+0 | 13.08 | 0.3437 | 1.391 | 7.474 | 496.1 |
| 9 | -4.601e+0 | 6.22 | 0.4961 | 1.138 | 9.275 | 332.9 |
| 10 | -4.601e+0 | 11.63 | 0.3494 | 3.08 | 6.374 | 266.4 |
| 11 | -4.601e+0 | 11.05 | 0.2764 | 3.503 | 6.573 | 266.4 |
| 12 | -4.601e+0 | 14.87 | 0.7261 | 1.361 | 4.612 | 495.9 |
| 13 | -4.601e+0 | 14.71 | 0.2404 | 1.547 | 5.789 | 501.8 |
| 14 | -4.601e+0 | 8.23 | 0.3864 | 2.127 | 2.612 | 498.4 |
| 15 | -4.601e+0 | 14.34 | 0.8615 | 1.6 | 6.094 | 490.2 |
| 16 | -4.601e+0 | 14.38 | 0.8503 | 1.659 | 3.413 | 272.7 |
| 17 | -4.601e+0 | 14.32 | 0.6006 | 1.615 | 7.967 | 279.9 |
| 18 | -4.601e+0 | 13.2 | 0.6028 | 2.253 | 7.493 | 479.9 |
| 19 | -4.601e+0 | 14.93 | 0.4714 | 2.764 | 2.425 | 289.5 |
| 20 | -4.601e+0 | 5.733 | 0.8643 | 1.271 | 8.721 | 292.4 |
| 21 | -4.601e+0 | 5.025 | 0.6269 | 2.882 | 8.5 | 485.1 |
| 22 | -4.601e+0 | 14.67 | 0.7356 | 4.133 | 9.235 | 270.9 |
| 23 | -4.601e+0 | 14.55 | 0.4547 | 4.173 | 5.08 | 470.9 |
| 24 | -4.601e+0 | 14.25 | 0.892 | 1.846 | 2.107 | 279.8 |
| 25 | -4.601e+0 | 5.998 | 0.2655 | 1.775 | 9.047 | 954.1 |
| 26 | -4.601e+0 | 14.32 | 0.1754 | 2.706 | 8.978 | 981.9 |
| 27 | -4.601e+0 | 7.429 | 0.5572 | 4.829 | 3.663 | 127.3 |
| 28 | -4.601e+0 | 11.84 | 0.7307 | 2.57 | 5.942 | 156.8 |

```
| 29        | -4.601e+0 | 5.759     | 0.6549    | 4.144     | 8.155     | 164.4     |
| 30        | -4.601e+0 | 14.62     | 0.1541    | 1.435     | 8.571     | 151.0     |
| 31        | -4.601e+0 | 7.281     | 0.5995    | 4.723     | 2.116     | 149.8     |
| 32        | -4.601e+0 | 14.82     | 0.1892    | 2.43      | 2.058     | 482.9     |
| 33        | -4.601e+0 | 8.5       | 0.2491    | 4.917     | 3.892     | 278.1     |
| 34        | -4.601e+0 | 14.99     | 0.7239    | 1.94      | 2.672     | 156.9     |
| 35        | -4.602e+0 | 5.935     | 0.1465    | 3.373     | 2.353     | 976.9     |
=============================================================================
Mejores parámetros encontrados:
{'max_depth': 14, 'max_features': 0.8919926731764096, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 279}
RMSE en el conjunto de prueba: 460062.11229749117
```

## EVALUACIÓN

```
from sklearn.metrics import mean_squared_error, r2_score

mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)

print("Root Mean Squared Error (RMSE):", rmse)
print("R^2 Score:", r2)
```

```
Root Mean Squared Error (RMSE): 460062.11229749117
R^2 Score: 0.00018140426903967555
```

```
from sklearn.model_selection import cross_val_score

#  cross-validation
cv_scores = cross_val_score(rf_regressor, x, y, cv=5, scoring='neg_mean_squared_error')
cv_rmse = np.sqrt(-cv_scores)

print("Cross-Validated RMSE:", cv_rmse.mean())
```

```
Cross-Validated RMSE: 139738.48538999498
```

## OUTPUT FILE

```
df_eval = pd.read_csv('../data/Evaluation.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'] = label_leather_interior.transform(df_eval['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])

# Crear características adicionales basadas en correlaciones y relaciones avanzadas
df_eval['Mileage_Engine_ratio'] = df_eval['Mileage'] / (df_eval['Engine volume'] + 1)
df_eval['Age'] = 2024 - df_eval['Prod. year']
df_eval['Mileage_Age'] = df_eval['Mileage'] * df_eval['Age']
df_eval['Mileage_Engine_Age'] = df_eval['Mileage'] * df_eval['Engine volume'] * df_eval['Age']
df_eval['Mileage_Age_squared'] = (df_eval['Mileage'] * df_eval['Age']) ** 2
df_eval['log_Mileage'] = np.log1p(df_eval['Mileage'])
df_eval['Age_SalesFee'] = df_eval['Age'] * df_eval['Sales Fee']
df_eval['Mileage_Age_Log'] = np.log1p(df_eval['Mileage_Age'])

df_eval = df_eval.drop('Cylinders', axis=1)
df_eval = df_eval.drop('Sales Fee', axis=1)
df_eval = df_eval.drop('Color', axis=1)
df_eval = df_eval.drop('Mileage', 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  Engine volume  \
0     15246  0.453183  0.048560        2014       0.702832            1.8
1      5176  0.453183  0.049477        2013       0.702832            2.5
2      3143  0.287567  0.002324        2009       0.702832            2.4
3      3360  0.287567  0.000550        2011       0.096875            3.8
4      3105  0.027093  0.001835        2013       0.702832            0.0
...     ...       ...       ...         ...            ...            ...
2881  17665  0.453183  0.056021        2009       0.702832            1.5
2882   6554  0.287567  0.027521        2015       0.702832            2.4
2883  18661  0.453183  0.017369        2014       0.702832            1.5
2884   6825  0.453183  0.000673        2014       0.702832            3.5
2885  11266  0.015779  0.011009        1996       0.096875            2.5

      Doors  Airbags     Wheel  Turbo  Mileage_Engine_ratio  Age  Mileage_Age  \
0         4        6  0.922512      0              0.000568   10     0.015901
1         4       12  0.922512      0              0.000227   11     0.008746
2         4        4  0.922512      0                   NaN   15          NaN
3         2        2  0.922512      0              0.001108   13     0.069170
4         4       12  0.922512      0              0.000306   11     0.003364
...     ...      ...       ...    ...                   ...  ...          ...
2881      4       12  0.922512      0              0.000098   15     0.003670
2882      4       12  0.922512      0                   NaN    9          NaN
2883      4        0  0.077488      0              0.001321   10     0.033026
```

```
2884      4        4  0.922512      0                NaN   10          NaN
2885      4        2  0.922512      0                NaN   28          NaN
```