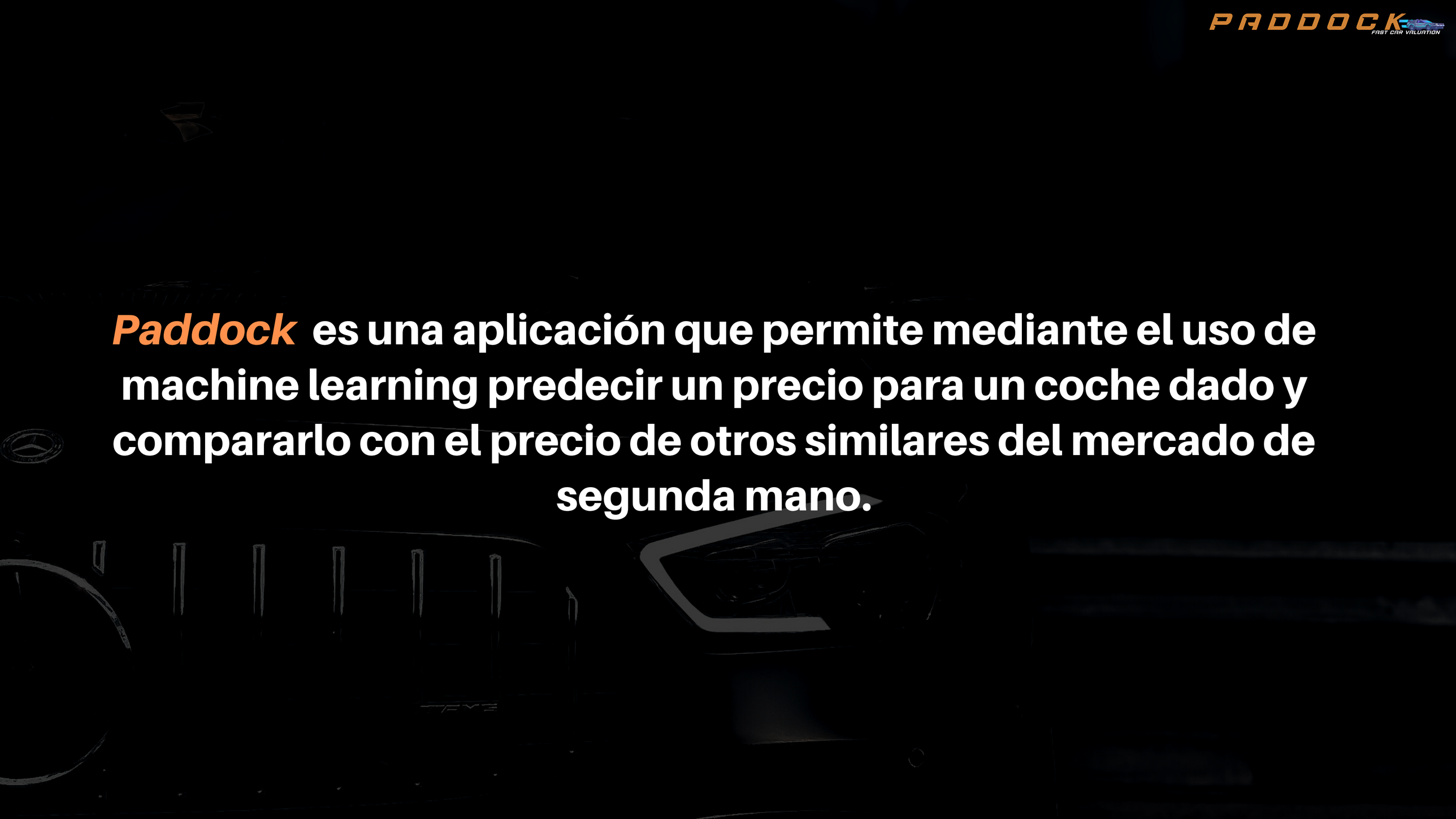
PADDOCK

FAST CAR VALUATION

¿QUÉ ES PADDOCK ?

FAST CAR VALUATION



Paddock **es una aplicación que permite mediante el uso de machine learning predecir un precio para un coche dado y compararlo con el precio de otros similares del mercado de segunda mano.**

PADDOCK
FAST CAR VALUATION

DESARROLLO

DESARROLLO

- Obtención de datos
- Limpieza de datos
- Visualización
- Machine Learning
- Einstein (Chatbot)
- Desarrollo web

Tecnologías usadas

Desarrollo

Lenguajes

PYTHON DART

Entornos

COLAB VISUALSTUDIO ANDROIDSTUDIO

FrontEnd

FLUTTER FIREBASE

BackEnd

GOOGLE-CLOUD DOCKER FLASK MONGODB

Diseño

FIGMA

Control de versiones

GITHUB NOTION

Analisis

NUMPY PANDAS PLOTLY

Machine Learning

TENSORFLOW SCIKIT-LEARN

Scraping

SELENIUM BEATIFULSOUP

Documentación

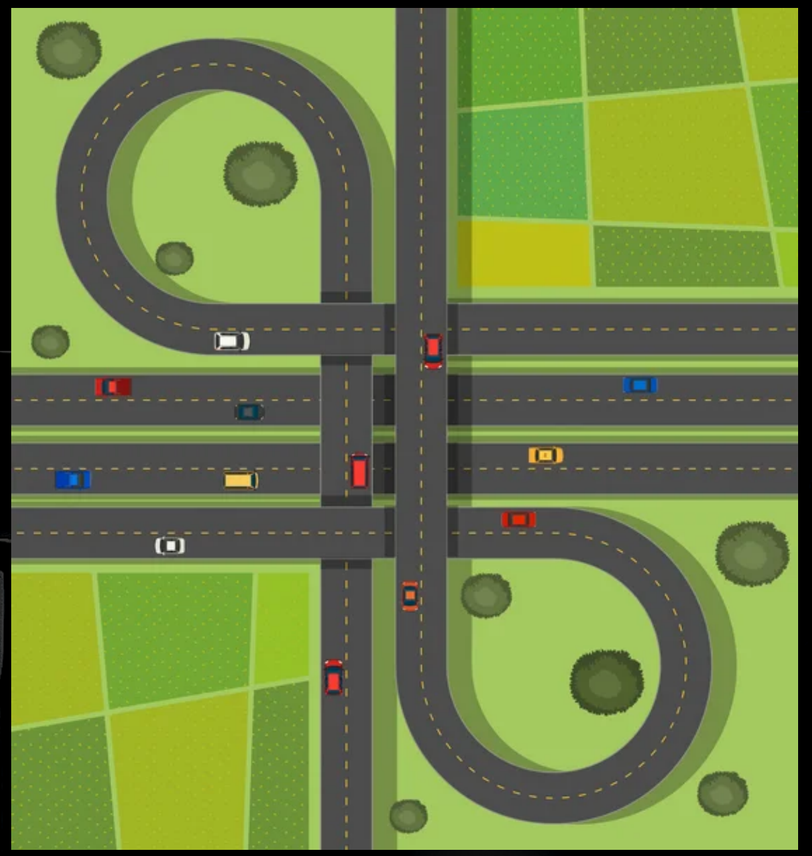
CHATGPT CHATBING STACKOVERFLOW

OBTENCIÓN DE LOS DATOS

SCRAPING

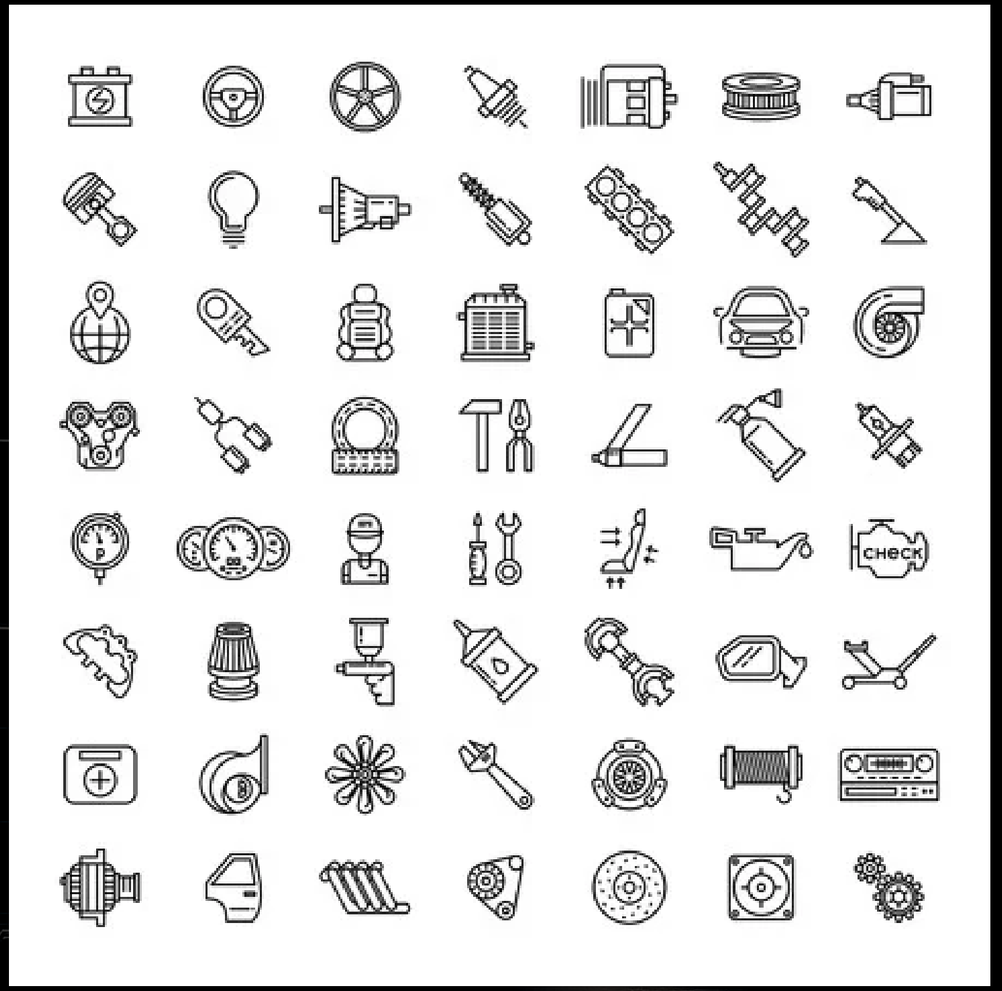
Localizando los objetivos

Multiprocesamiento



Cazando los datos

Creación del dataframe



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FAST CAR VALUATION

LIMPIEZA DE LOS DATOS

PREPROCESADO

Información general

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 179502 entries, 0 to 179501
Data columns (total 35 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   Unnamed: 0    179502 non-null  int64
 1   localidad     179502 non-null  object
 2   marca         179502 non-null  object
 3   modelo        179502 non-null  object
 4   año           179502 non-null  float64
 5   motor (CV)    179502 non-null  float64
 6   motor (KW)    179502 non-null  float64
 7   kilometros    179502 non-null  float64
 8   combustible   179502 non-null  object
 9   puertas       179502 non-null  float64
 10  cambio        179502 non-null  object
 11  emisiones     179502 non-null  float64
 12  color         179502 non-null  object
 13  garantía      179502 non-null  object
 14  vendedor      179502 non-null  object
 15  precio        179502 non-null  float64
 16  maletero      179502 non-null  float64
 17  longitud      179502 non-null  float64
 18  altura        179502 non-null  float64
 19  anchura       179502 non-null  float64
 20  plazas        179502 non-null  float64
 21  deposito      179502 non-null  float64
 22  peso max      179502 non-null  float64
 23  carroceria    179502 non-null  object
 24  vel. maxima   179502 non-null  float64
 25  c. mixto      179502 non-null  float64
 26  c. urbano     179502 non-null  float64
 27  extraurbano   179502 non-null  float64
 28  0-100 km/h    179502 non-null  float64
 29  cilindrada    179502 non-null  float64
 30  cilindros     179502 non-null  float64
 31  transmisión   179502 non-null  object
 32  par maximo    179502 non-null  float64
 33  marchas       179502 non-null  float64
 34  traccion      179502 non-null  object
dtypes: float64(23), int64(1), object(11)
memory usage: 47.9+ MB
```

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Información general

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 11  emisiones     179502 non-null  float64
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dtypes: float64(23), int64(1), object(11)
memory usage: 47.9+ MB
```

Nulos

```
cars.isnull().sum()
```

```
Unnamed: 0      0
localidad       0
marca           0
modelo          0
año             0
motor (CV)      0
motor (KW)      0
kilometros      0
combustible     0
puertas         0
cambio          0
emisiones       0
color           0
garantía        0
vendedor        0
precio          0
maletero        0
longitud        0
altura          0
anchura         0
plazas          0
deposito        0
peso max        0
carroceria      0
vel. maxima     0
c. mixto        0
c. urbano       0
extraurbano     0
0-100 km/h      0
cilindrada      0
cilindros       0
transmisión     0
par maximo      0
marchas         0
traccion        0
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```
Unnamed: 0      0
localidad       0
marca           0
modelo          0
año             0
motor (CV)      0
motor (KW)      0
kilometros      0
combustible     0
puertas         0
cambio          0
emisiones       0
color           0
garantía        0
vendedor        0
precio          0
maletero        0
longitud        0
altura          0
anchura         0
plazas          0
deposito        0
peso max        0
carroceria      0
vel. maxima     0
c. mixto        0
c. urbano       0
extraurbano     0
0-100 km/h      0
cilindrada      0
cilindros       0
transmisión     0
par maximo      0
marchas         0
traccion        0
dtype: int64
```

Datos de interes

	count	mean	std	min	25%	50%	75%	max
Unnamed: 0	179502.0	4456.412987	3645.833011	0.0	1347.00	3565.50	6802.750	15547.0
año	179502.0	2016.842046	3.841619	1993.0	2015.00	2018.00	2019.000	2023.0
motor (CV)	179502.0	147.338215	74.697602	1.0	110.00	130.00	150.000	887.0
motor (KW)	179502.0	108.396413	55.132019	9.0	81.00	96.00	110.000	817.0
kilometros	179502.0	81811.256900	56117.663986	0.0	40000.00	74498.00	114000.000	2890000.0
puertas	179502.0	4.708109	0.735979	0.0	5.00	5.00	5.000	5.0
emisiones	179502.0	114.994368	48.185070	0.0	103.00	115.00	134.000	495.0
precio	179502.0	23926.384798	32034.218607	1.0	13850.00	18990.00	26450.000	1799700.0
maletero	179502.0	1007.807924	582.970727	0.0	470.00	1122.00	1478.000	6000.0
longitud	179502.0	438.542675	32.171825	224.5	420.40	438.00	462.400	616.5
altura	179502.0	153.986220	11.083085	103.6	145.50	151.00	162.300	223.5
anchura	179502.0	181.004077	7.393938	123.7	177.00	180.70	184.200	224.4
plazas	179502.0	4.965181	0.585251	2.0	5.00	5.00	5.000	9.0
deposito	179502.0	52.278442	14.298763	0.0	45.00	51.00	60.000	121.0
peso max	179502.0	2.638252	25.286031	0.0	1.75	1.92	2.125	975.0
vel. maxima	179502.0	190.620322	43.072073	0.0	180.00	192.00	210.000	350.0
c. mixto	179502.0	4.739973	2.034619	0.0	4.10	4.70	5.500	22.0
c. urbano	179502.0	5.752468	2.805384	0.0	4.70	5.70	6.700	31.0
extraurbano	179502.0	4.087472	1.647663	0.0	3.60	4.10	4.800	17.0
0-100 km/h	179502.0	9.868147	2.725705	0.0	8.60	10.20	11.400	62.0
cilindrada	179502.0	1697.397221	638.232397	0.0	1368.00	1598.00	1995.000	8300.0
cilindros	179502.0	3.921750	0.974608	0.0	4.00	4.00	4.000	12.0
par maximo	179502.0	277.381892	121.722770	0.0	200.00	260.00	340.000	973.0
marchas	179502.0	5.934558	1.482954	0.0	5.00	6.00	6.000	10.0

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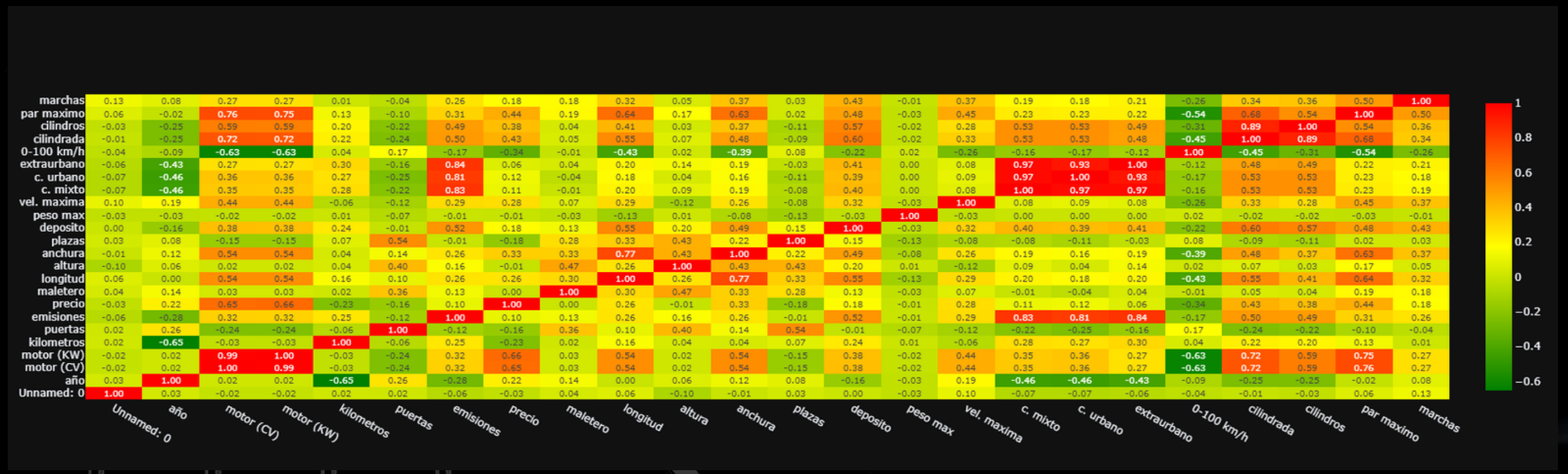
Datos de interes

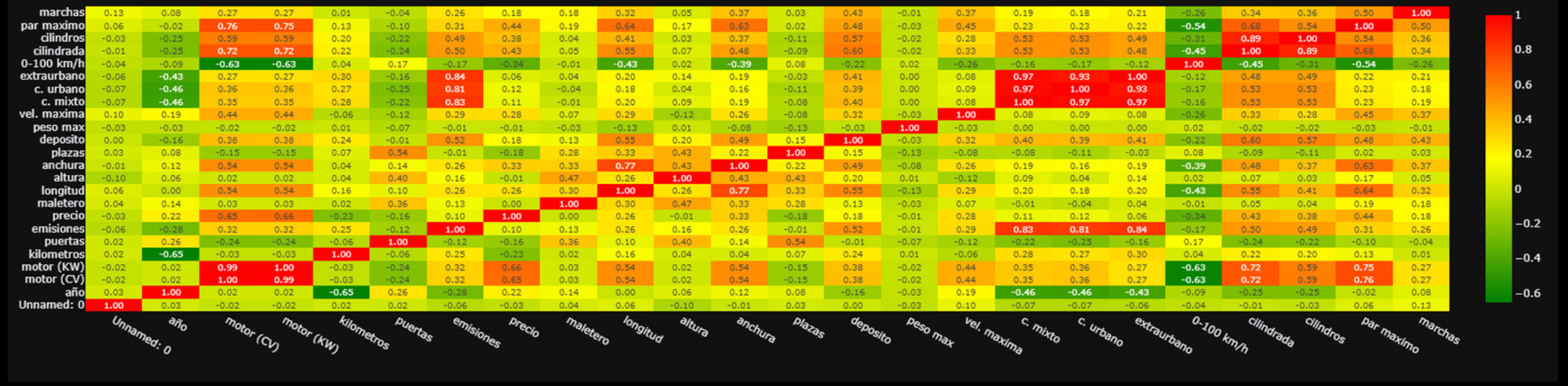
	count	mean	std	min	25%	50%	75%	max
Unnamed: 0	179502.0	4456.412987	3645.833011	0.0	1347.00	3565.50	6802.750	15547.0
año	179502.0	2016.842046	3.841619	1993.0	2015.00	2018.00	2019.000	2023.0
motor (CV)	179502.0	147.338215	74.697602	1.0	110.00	130.00	150.000	887.0
motor (KW)	179502.0	108.396413	55.132019	9.0	81.00	96.00	110.000	817.0
kilometros	179502.0	81811.256900	56117.663986	0.0	40000.00	74498.00	114000.000	2890000.0
puertas	179502.0	4.708109	0.735979	0.0	5.00	5.00	5.000	5.0
emisiones	179502.0	114.994368	48.185070	0.0	103.00	115.00	134.000	495.0
precio	179502.0	23926.384798	32034.218607	1.0	13850.00	18990.00	26450.000	1799700.0
maletero	179502.0	1007.807924	582.970727	0.0	470.00	1122.00	1478.000	6000.0
longitud	179502.0	438.542675	32.171825	224.5	420.40	438.00	462.400	616.5
altura	179502.0	153.986220	11.083085	103.6	145.50	151.00	162.300	223.5
anchura	179502.0	181.004077	7.393938	123.7	177.00	180.70	184.200	224.4
plazas	179502.0	4.965181	0.585251	2.0	5.00	5.00	5.000	9.0
deposito	179502.0	52.278442	14.298763	0.0	45.00	51.00	60.000	121.0
peso max	179502.0	2.638252	25.286031	0.0	1.75	1.92	2.125	975.0
vel. maxima	179502.0	190.620322	43.072073	0.0	180.00	192.00	210.000	350.0
c. mixto	179502.0	4.739973	2.034619	0.0	4.10	4.70	5.500	22.0
c. urbano	179502.0	5.752468	2.805384	0.0	4.70	5.70	6.700	31.0
extraurbano	179502.0	4.087472	1.647663	0.0	3.60	4.10	4.800	17.0
0-100 km/h	179502.0	9.868147	2.725705	0.0	8.60	10.20	11.400	62.0
cilindrada	179502.0	1697.397221	638.232397	0.0	1368.00	1598.00	1995.000	8300.0
cilindros	179502.0	3.921750	0.974608	0.0	4.00	4.00	4.000	12.0
par maximo	179502.0	277.381892	121.722770	0.0	200.00	260.00	340.000	973.0
marchas	179502.0	5.934558	1.482954	0.0	5.00	6.00	6.000	10.0

Correlaciones

Correlaciones generales



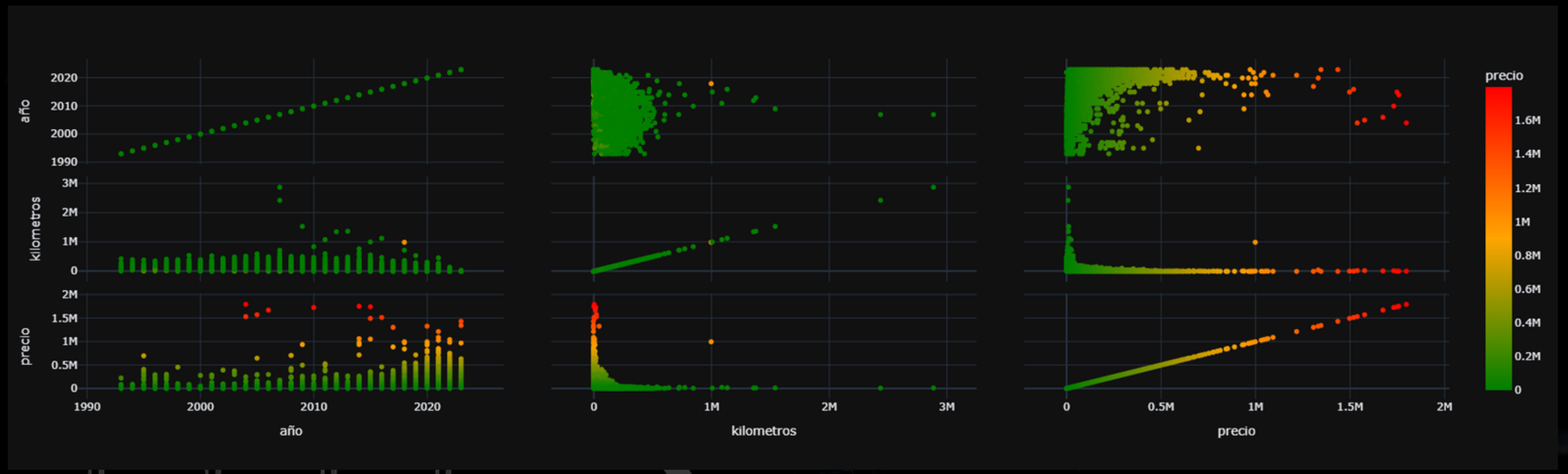
Correlaciones generales



Correlaciones sobre el precio

PADDOCK FAST CAR VALUATION

Graficas de correlaciones



Outlier


kilometros=0.999999M
precio=0.999999M
precio=999999
0
0.5M
1M
1.5M
2M
2.5M
3M

Código

PADDOCK
FAST CAR VALUATION

Eliminación de columnas

```
cars_pre = cars.drop(['Unnamed: 0', 'puertas', 'maletero', 'longitud', 'altura', 'anchura', 'peso max', 'vel. maxima', 'c. mixto', 'c. urbano', 'extraurbano', 'cilindros', 'par maximo', 'color', 'garantía', 'vendedor', 'transmisión', 'carroceria', 'traccion'], axis=1)
```

Función para transformar valores

```python
# Función para transformar los valores categoricos a numericos
def parseador(dataset, marca_data, model_data, combustible_data, cambio_data, locate_car):

  for index, model in enumerate(tqdm(marca_data)):
    dataset.loc[dataset['marca'] == model, 'marca_id'] = index
    car_list_marca.append((index, model))

  for index, model in enumerate(tqdm(model_data)):
    dataset.loc[dataset['modelo'] == model, 'modelo_id'] = index
    car_list_model.append((index, model))

  for index, model in enumerate(tqdm(combustible_data)):
    dataset.loc[dataset['combustible'] == model, 'combustible_id'] = index
    car_list_combustible_data.append((index, model))

  for index, model in enumerate(tqdm(cambio_data)):
    dataset.loc[dataset['cambio'] == model, 'cambio_id'] = index
    car_list_cambio_data.append((index, model))

  for index, model in enumerate(tqdm(locate_car)):
    dataset.loc[dataset['localidad'] == model, 'localidad_id'] = index
    car_list_locate.append((index, model))
```

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Resultados

Origen

	count	mean	std	min	25%	50%	75%	max
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motor (KW)	179502.0	108.396413	55.132019	9.0	81.00	96.00	110.000	817.0
kilometros	179502.0	81811.256900	56117.663986	0.0	40000.00	74498.00	114000.000	2890000.0
puertas	179502.0	4.708109	0.735979	0.0	5.00	5.00	5.000	5.0
emisiones	179502.0	114.994368	48.185070	0.0	103.00	115.00	134.000	495.0
precio	179502.0	23926.384798	32034.218607	1.0	13850.00	18990.00	26450.000	1799700.0
maletero	179502.0	1007.807924	582.970727	0.0	470.00	1122.00	1478.000	6000.0
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vel. maxima	179502.0	190.620322	43.072073	0.0	180.00	192.00	210.000	350.0
c. mixto	179502.0	4.739973	2.034619	0.0	4.10	4.70	5.500	22.0
c. urbano	179502.0	5.752468	2.805384	0.0	4.70	5.70	6.700	31.0
extraurbano	179502.0	4.087472	1.647663	0.0	3.60	4.10	4.800	17.0
0-100 km/h	179502.0	9.868147	2.725705	0.0	8.60	10.20	11.400	62.0
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par maximo	179502.0	277.381892	121.722770	0.0	200.00	260.00	340.000	973.0
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puertas	179502.0	4.708109	0.735979	0.0	5.00	5.00	5.000	5.0
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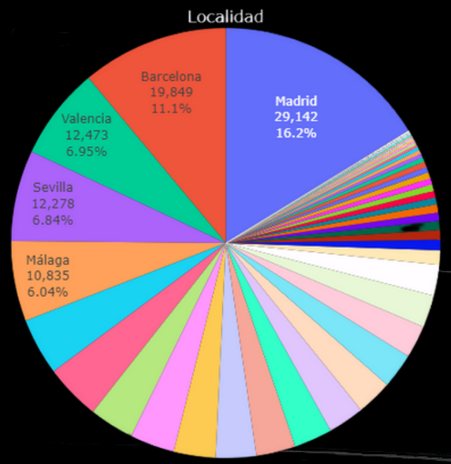
maletero	179502.0	1007.807924	582.970727	0.0	470.00	1122.00	1478.000	6000.0
longitud	179502.0	438.542675	32.171825	224.5	420.40	438.00	462.400	616.5
altura	179502.0	153.986220	11.083085	103.6	145.50	151.00	162.300	223.5
anchura	179502.0	181.004077	7.393938	123.7	177.00	180.70	184.200	224.4
plazas	179502.0	4.965181	0.585251	2.0	5.00	5.00	5.000	9.0
deposito	179502.0	52.278442	14.298763	0.0	45.00	51.00	60.000	121.0
peso max	179502.0	2.638252	25.286031	0.0	1.75	1.92	2.125	975.0
vel. maxima	179502.0	190.620322	43.072073	0.0	180.00	192.00	210.000	350.0
c. mixto	179502.0	4.739973	2.034619	0.0	4.10	4.70	5.500	22.0
c. urbano	179502.0	5.752468	2.805384	0.0	4.70	5.70	6.700	31.0
extraurbano	179502.0	4.087472	1.647663	0.0	3.60	4.10	4.800	17.0
0-100 km/h	179502.0	9.868147	2.725705	0.0	8.60	10.20	11.400	62.0
cilindrada	179502.0	1697.397221	638.232397	0.0	1368.00	1598.00	1995.000	8300.0
cilindros	179502.0	3.921750	0.974608	0.0	4.00	4.00	4.000	12.0
par maximo	179502.0	277.381892	121.722770	0.0	200.00	260.00	340.000	973.0
marchas	179502.0	5.934558	1.482954	0.0	5.00	6.00	6.000	10.0

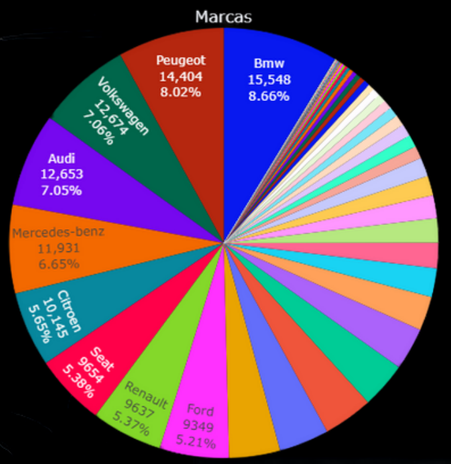
Resultado

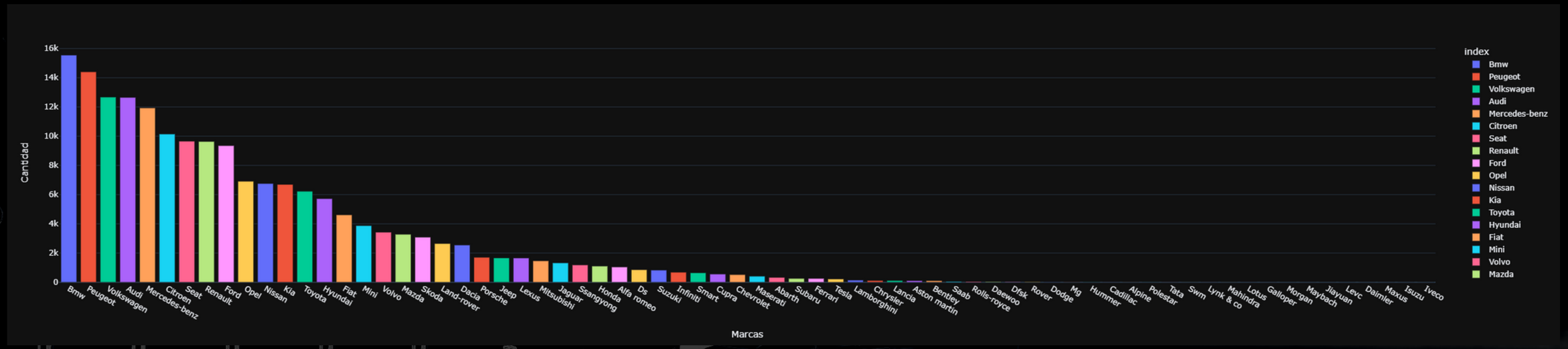
	count	mean	std	min	25%	50%	75%	max
año	179502.0	2016.842046	3.841619	1993.0	2015.0	2018.0	2019.0	2023.0
motor (CV)	179502.0	147.338215	74.697602	1.0	110.0	130.0	150.0	887.0
motor (KW)	179502.0	108.396413	55.132019	9.0	81.0	96.0	110.0	817.0
kilometros	179502.0	81811.256900	56117.663986	0.0	40000.0	74498.0	114000.0	2890000.0
emisiones	179502.0	114.994368	48.185070	0.0	103.0	115.0	134.0	495.0
precio	179502.0	23926.384798	32034.218607	1.0	13850.0	18990.0	26450.0	1799700.0
plazas	179502.0	4.965181	0.585251	2.0	5.0	5.0	5.0	9.0
deposito	179502.0	52.278442	14.298763	0.0	45.0	51.0	60.0	121.0
0-100 km/h	179502.0	9.868147	2.725705	0.0	8.6	10.2	11.4	62.0
cilindrada	179502.0	1697.397221	638.232397	0.0	1368.0	1598.0	1995.0	8300.0
marchas	179502.0	5.934558	1.482954	0.0	5.0	6.0	6.0	10.0
marca_id	179502.0	36.936352	21.835715	0.0	18.0	44.0	54.0	69.0
modelo_id	179502.0	372.703017	214.247216	0.0	186.0	409.0	545.0	718.0
combustible_id	179502.0	1.970446	1.204450	0.0	1.0	1.0	3.0	7.0
cambio_id	179502.0	0.605308	0.488786	0.0	0.0	1.0	1.0	1.0
localidad_id	179502.0	23.404658	14.736913	0.0	8.0	28.0	34.0	49.0

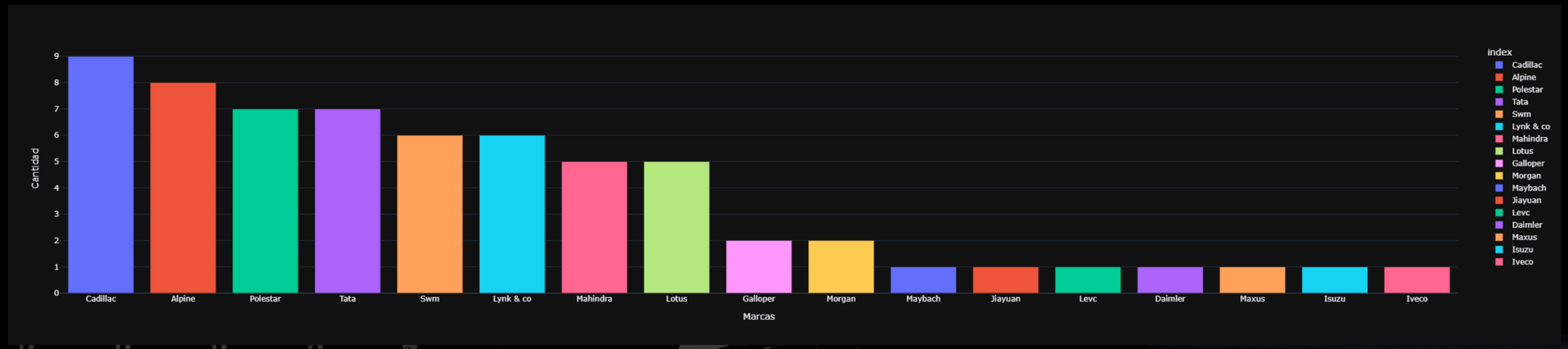
PADDOCK FAST CAR VALUATION

VISUALIZACIÓN

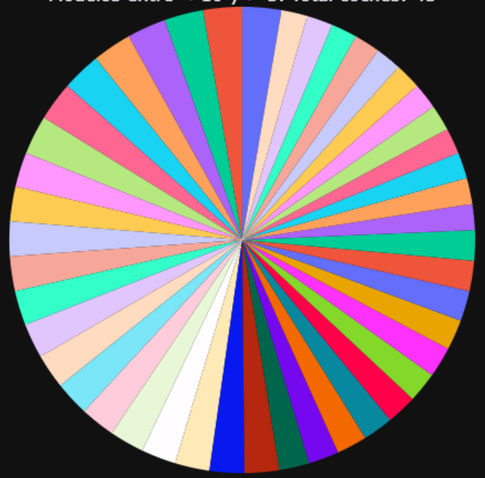

Localidad
Madrid
29,142
16.2%
Barcelona
19,849
11.1%
Valencia
12,473
6.95%
Sevilla
12,278
6.84%
Málaga
10,835
6.04%


Marcas
Bmw
15,548
8.66%
Peugeot
14,404
8.02%
Volkswagen
12,674
7.06%
Audi
12,653
7.05%
Mercedes-benz
11,931
6.65%
Citroen
10,145
5.65%
Seat
9654
5.38%
Renault
9637
5.37%
Ford
9349
5.21%

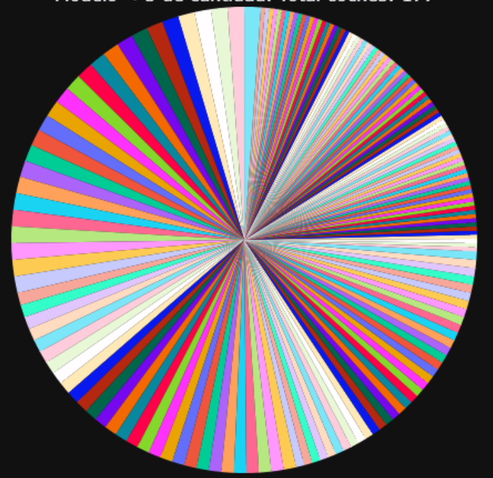

Cantidad
16k
14k
12k
10k
8k
6k
4k
2k
0
Bmw
Peugeot
Volkswagen
Audi
Mercedes-benz
Citroen
Seat
Renault
Ford
Opel
Nissan
Kia
Toyota
Hyundai
Fiat
Mini
Volvo
Mazda
Skoda
Land-rover
Dacia
Porsche
Jeep
Lexus
Mitsubishi
Jaguar
Ssangyong
Honda
Alfa romeo
Ds
Suzuki
Infiniti
Smart
Cupra
Chevrolet
Masarati
Abarth
Subaru
Ferrari
Tesla
Lamborghini
Chrysler
Lancia
Aston martin
Bentley
Saab
Rolls-royce
Daewoo
Dfsk
Rover
Dodge
Mg
Hummer
Cadillac
Alpine
Polestar
Tata
Swm
Lynk & co
Mahindra
Lotus
Galloper
Morgan
Maybach
Jiayuan
Levc
Daimler
Maxus
Tsuzu
Iveco
Marcas
index
Bmw
Peugeot
Volkswagen
Audi
Mercedes-benz
Citroen
Seat
Renault
Ford
Opel
Nissan
Kia
Toyota
Hyundai
Fiat
Mini
Volvo
Mazda


Cantidad
0
1
2
3
4
5
6
7
8
9
Cadillac
Alpine
Polestar
Tata
Swm
Lynk & co
Mahindra
Lotus
Galloper
Morgan
Maybach
Jiayuan
Levc
Daimler
Maxus
Isuzu
Iveco
Marcas
index
Cadillac
Alpine
Polestar
Tata
Swm
Lynk & co
Mahindra
Lotus
Galloper
Morgan
Maybach
Jiayuan
Levc
Daimler
Maxus
Isuzu
Iveco

Modelos entre < 10 y > 5. Total coches: 45



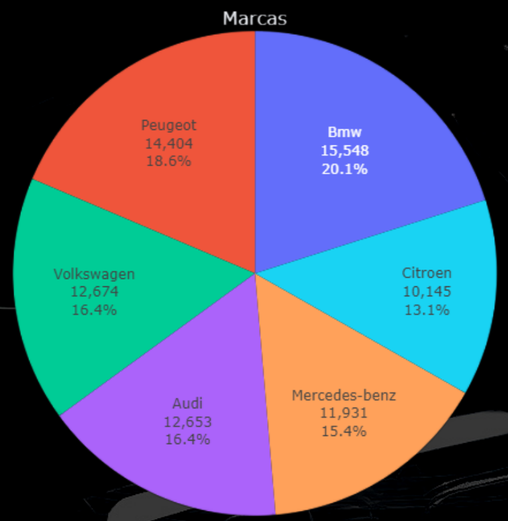
Modelo < 5 de cantidad. Total coches: 177



- Chevrolet Lacetti
- Suzuki Sx4
- Kia Stinger
- Mg Zs suv
- Bmw I4
- Mercedes-benz Slr
- Mercedes-benz Clase sls amg
- Dodge Caliber
- Aston martin Vanquish
- Nissan 370z
- Seat Altea freetrack
- Ferrari Ff
- Renault Mégane scénic
- Alpine A110
- Chevrolet Kalos
- Toyota Camry
- Volvo C70
- Seat Córdoba
- Opel Karl
- Infiniti Qx50
- Rover 75
- Citroen C4 x

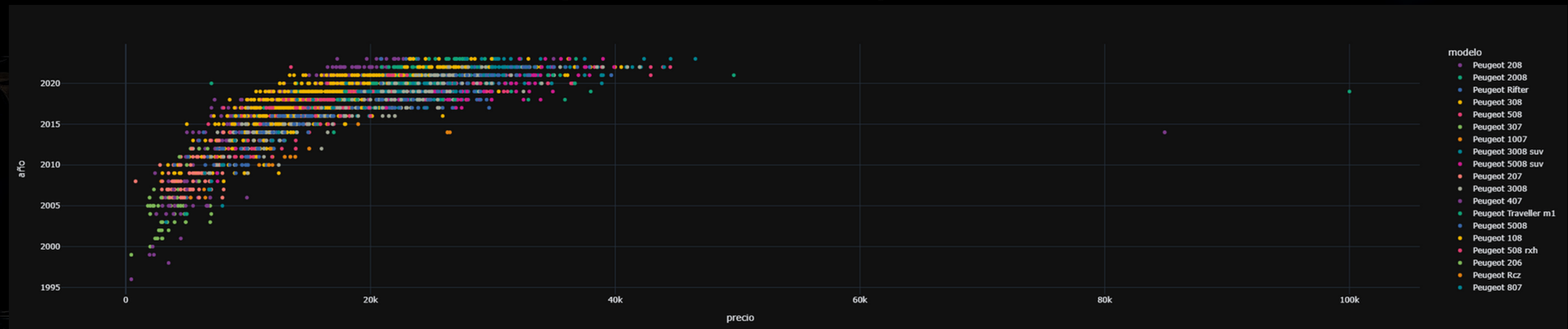
Aplicando filtrado

Marcas + 10.000 coches

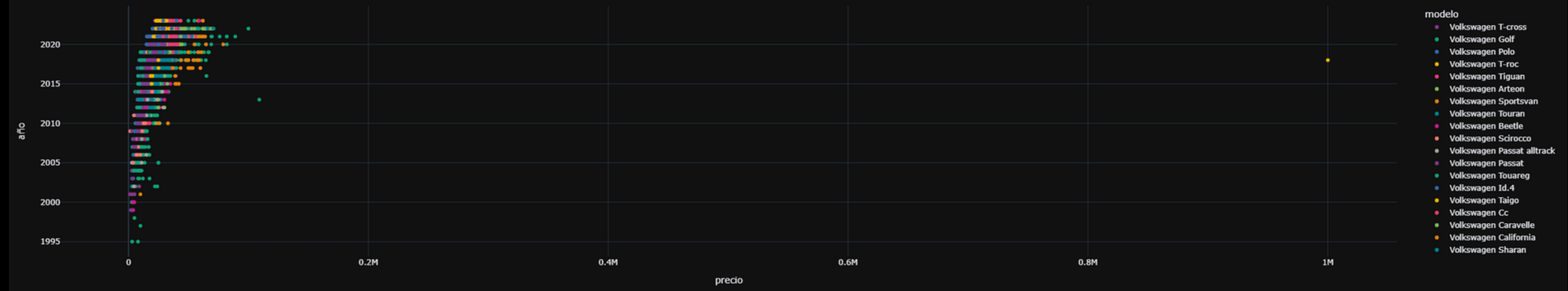


Explorando los datos precio/año

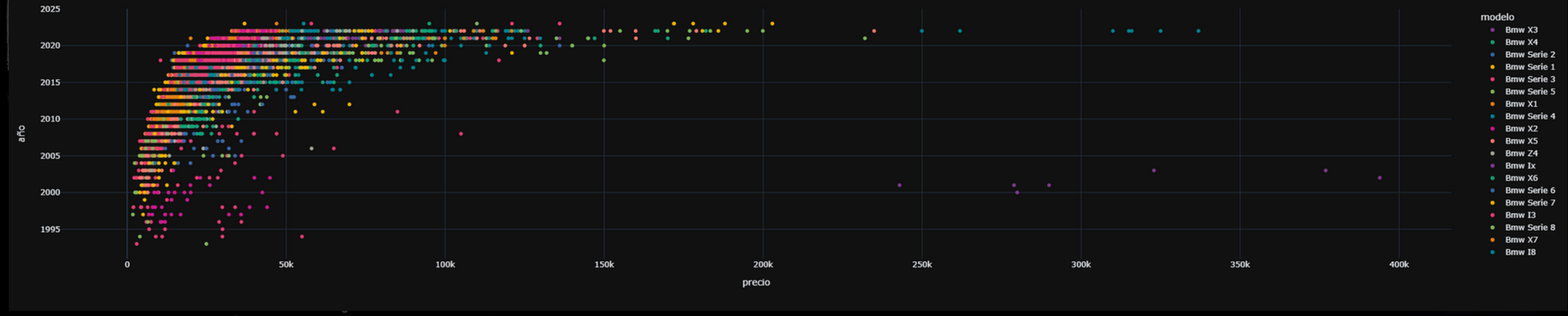
Peugeot



VW

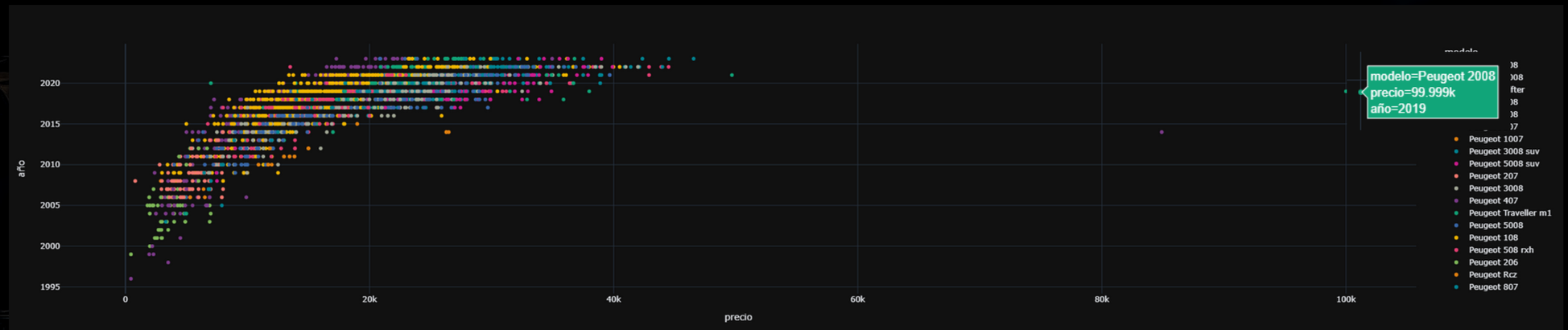


BMW



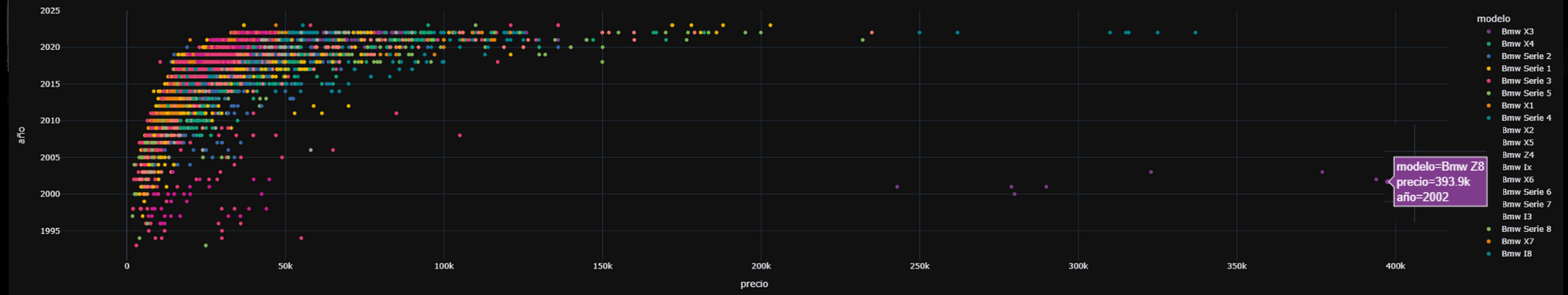
PADDOCK
FAST CAR VALUATION

Peugeot

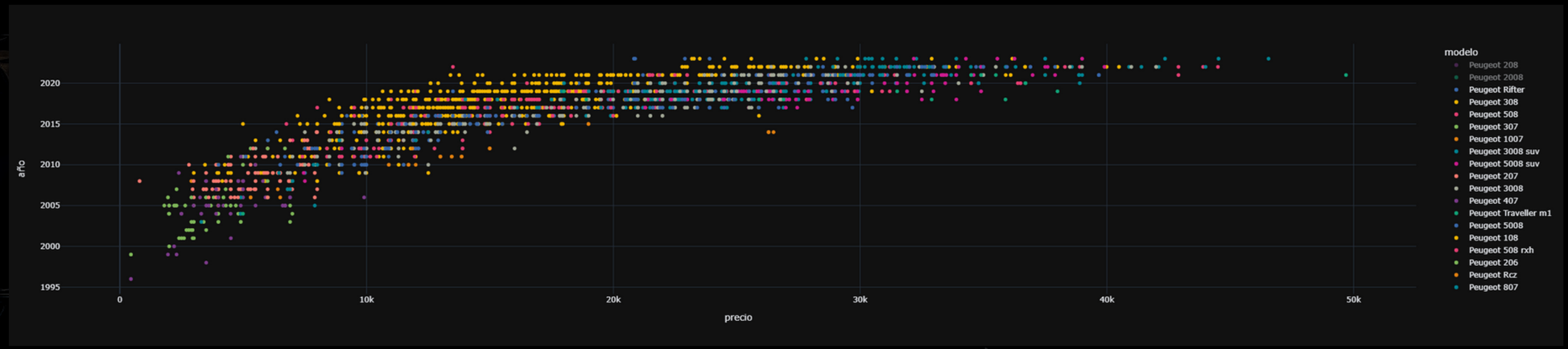


VW

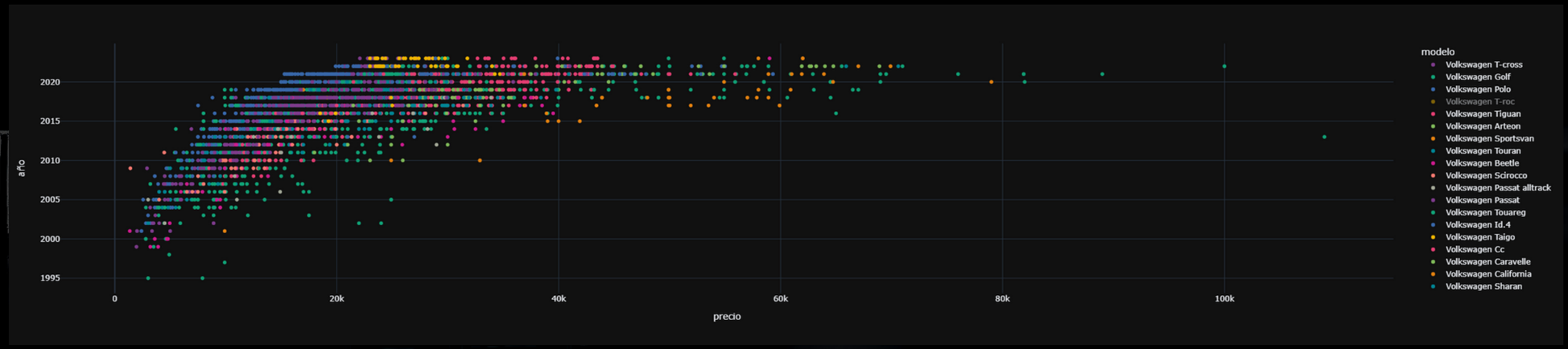
BMW



Peugeot


año
precio
0
10k
20k
30k
40k
50k
1995
2000
2005
2010
2015
2020
modelo
Peugeot 208
Peugeot 2008
Peugeot Rifter
Peugeot 308
Peugeot 508
Peugeot 307
Peugeot 1007
Peugeot 3008 suv
Peugeot 5008 suv
Peugeot 207
Peugeot 3008
Peugeot 407
Peugeot Traveller m1
Peugeot 5008
Peugeot 108
Peugeot 508 rxh
Peugeot 206
Peugeot Rcz
Peugeot 807

VW

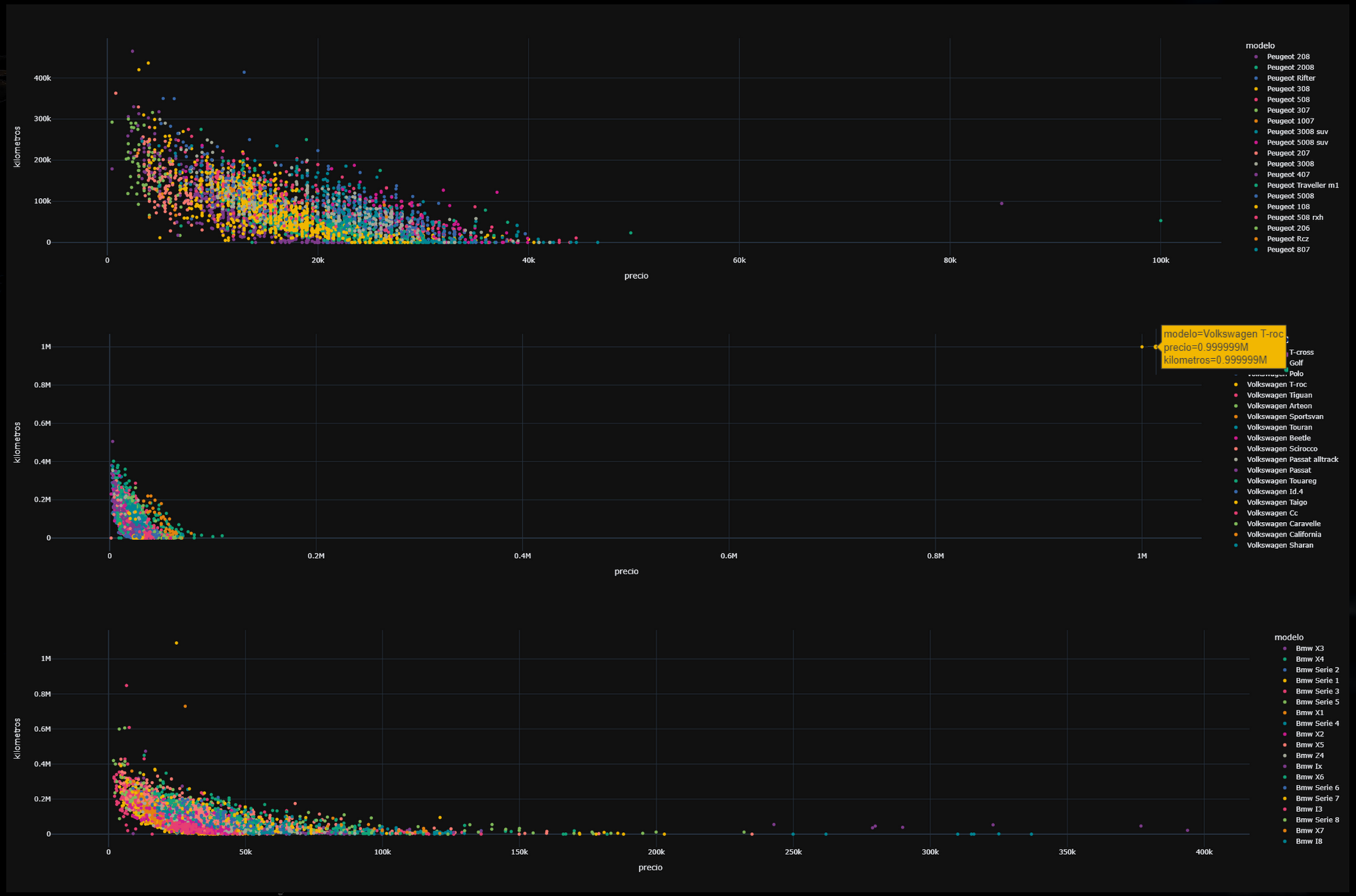

año
precio
0
20k
40k
60k
80k
100k
1995
2000
2005
2010
2015
2020
modelo
Volkswagen T-cross
Volkswagen Golf
Volkswagen Polo
Volkswagen T-roc
Volkswagen Tiguan
Volkswagen Arteon
Volkswagen Sportsvan
Volkswagen Touran
Volkswagen Beetle
Volkswagen Scirocco
Volkswagen Passat alltrack
Volkswagen Passat
Volkswagen Touareg
Volkswagen Id.4
Volkswagen Taigo
Volkswagen Cc
Volkswagen Caravelle
Volkswagen California
Volkswagen Sharan

Explorando los datos precio/kilometros

Peugeot

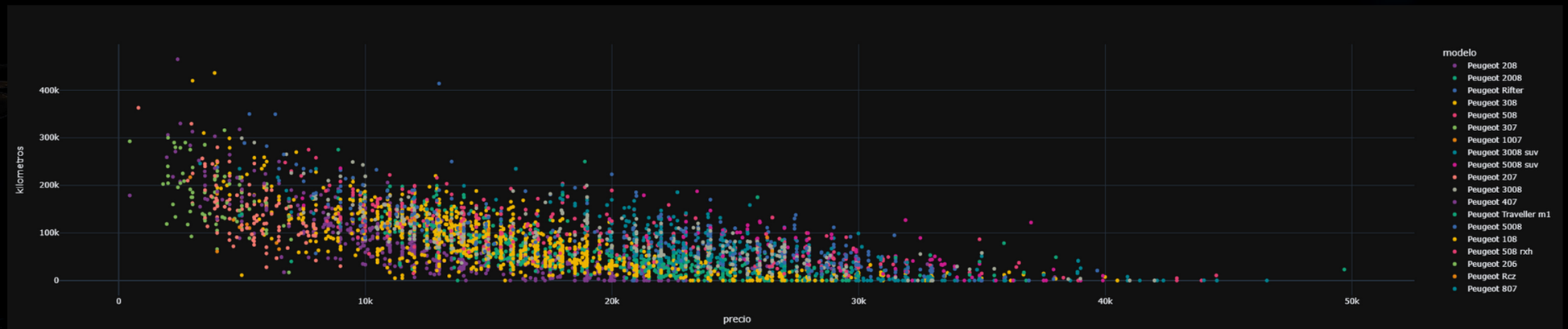
VW

BMW

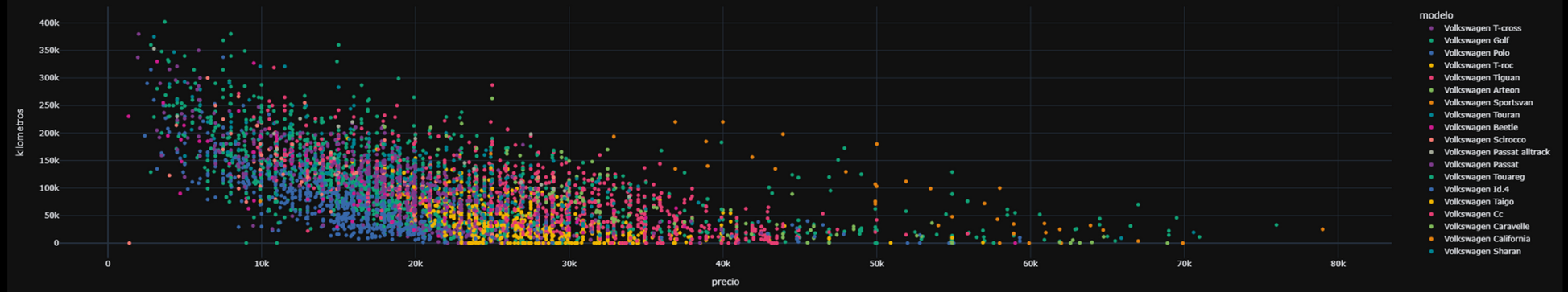


PADDOCK
FAST CAR VALUATION

Peugeot



VW



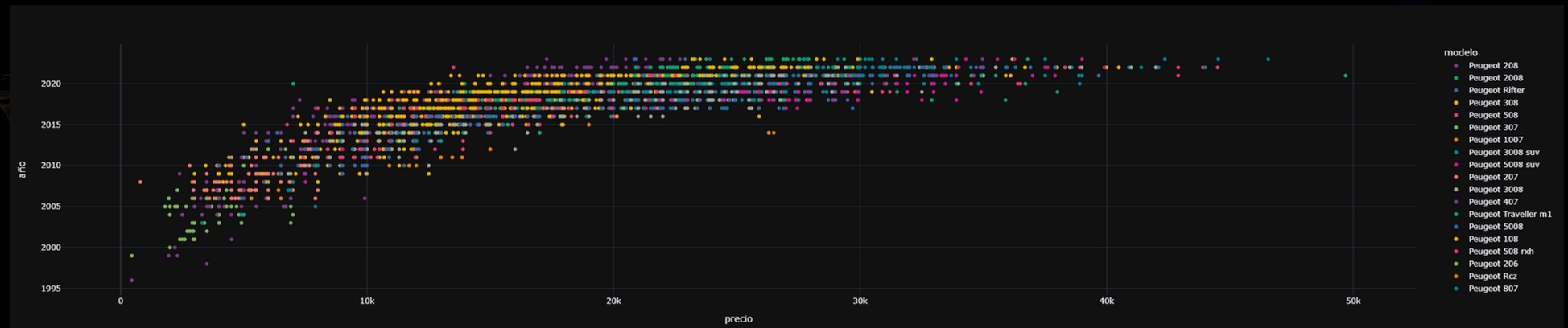
BMW

Explorando los datos precio/año

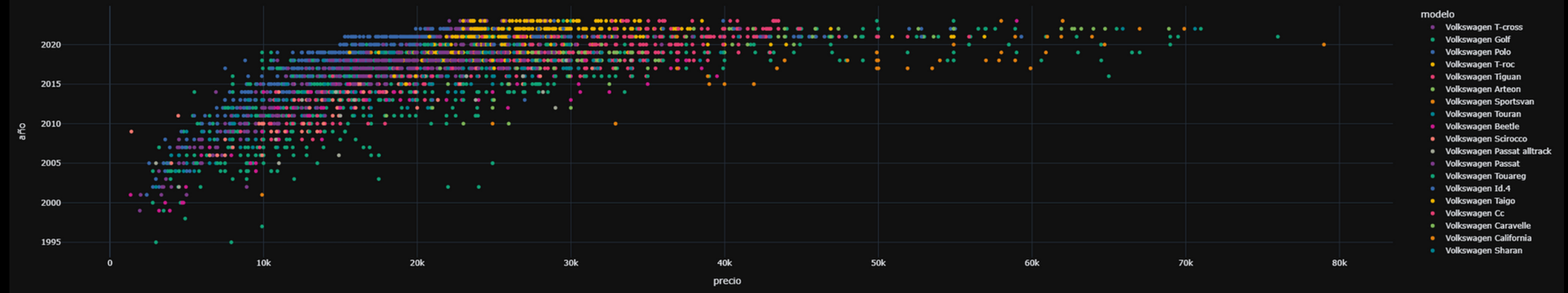
Precio = 80.000€
Kilometros = 500.000km

PADDOCK
FAST CAR VALUATION

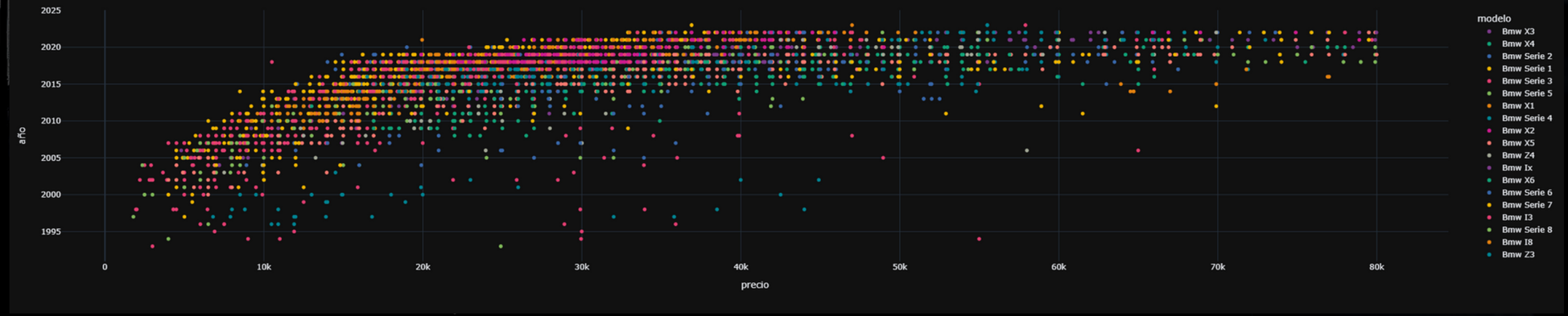
Peugeot



VW



BMW



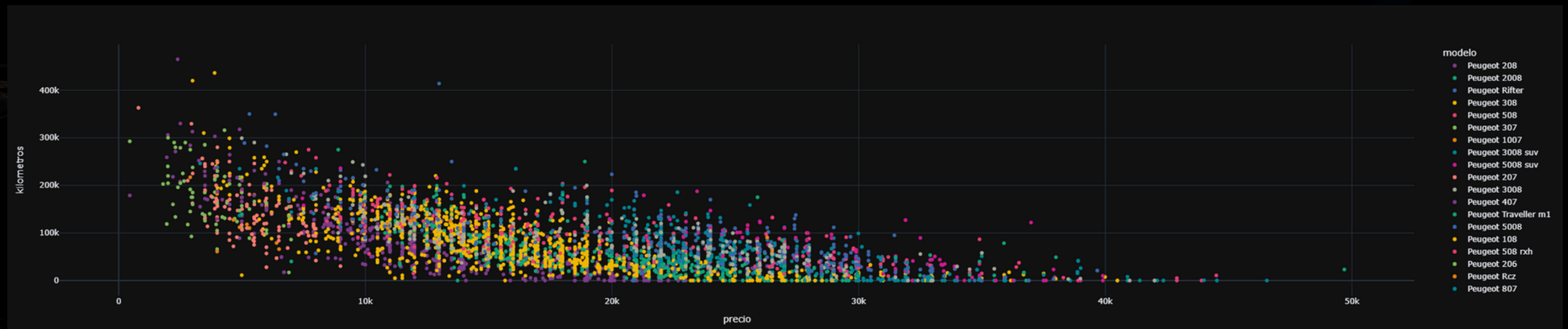
PADDOCK
FAST CAR VALUATION

Explorando los datos precio/kilometros

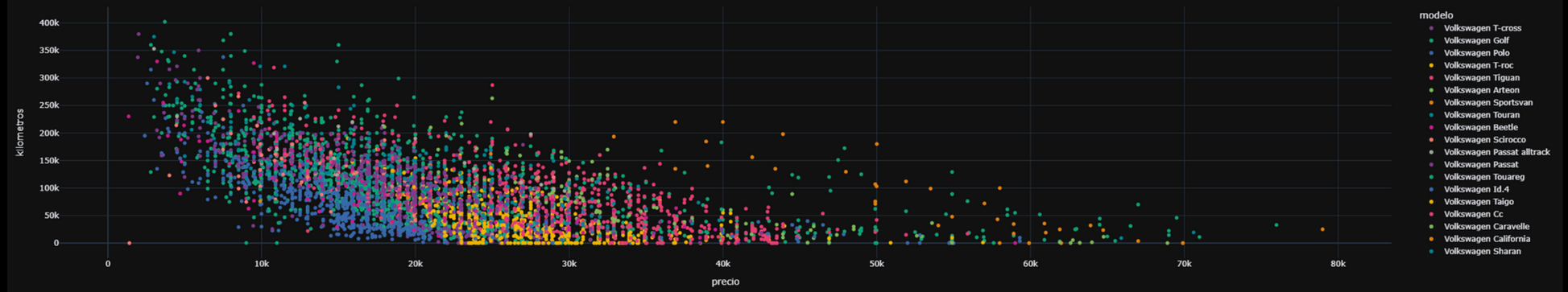
Precio = 80.000€
Kilometros = 500.000km

PADDOCK
FAST CAR VALUATION

Peugeot



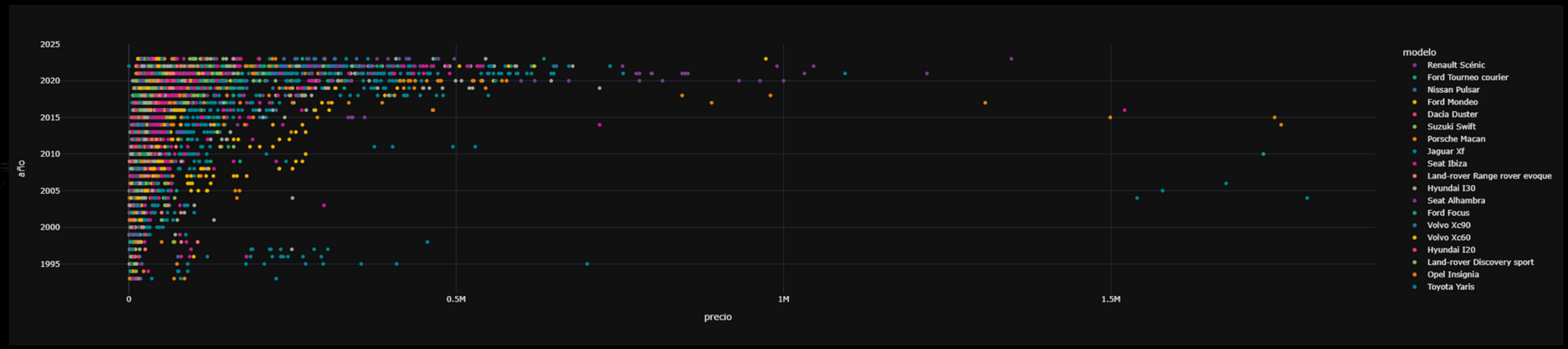
VW



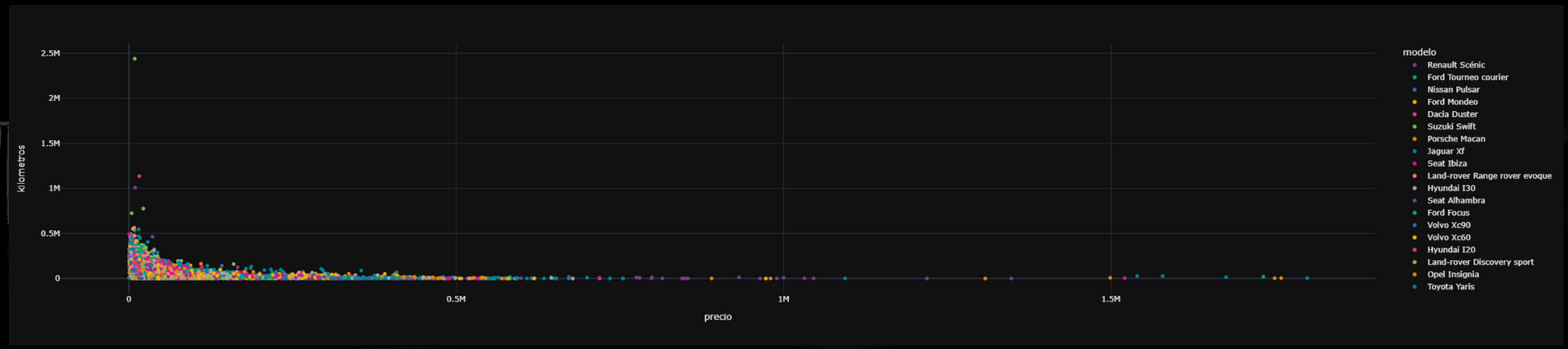
BMW

Resto de coches

Año



Kilometros

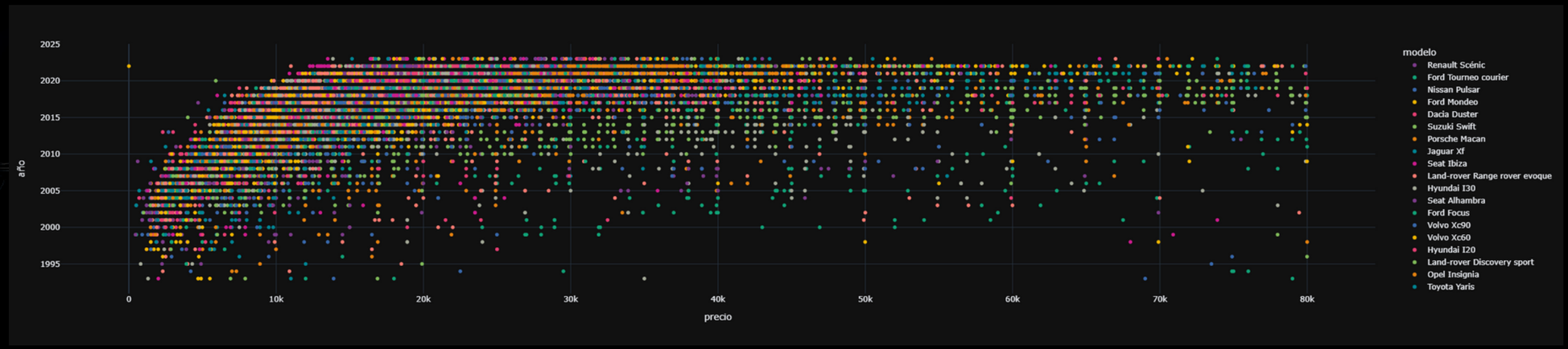


Resto de coches

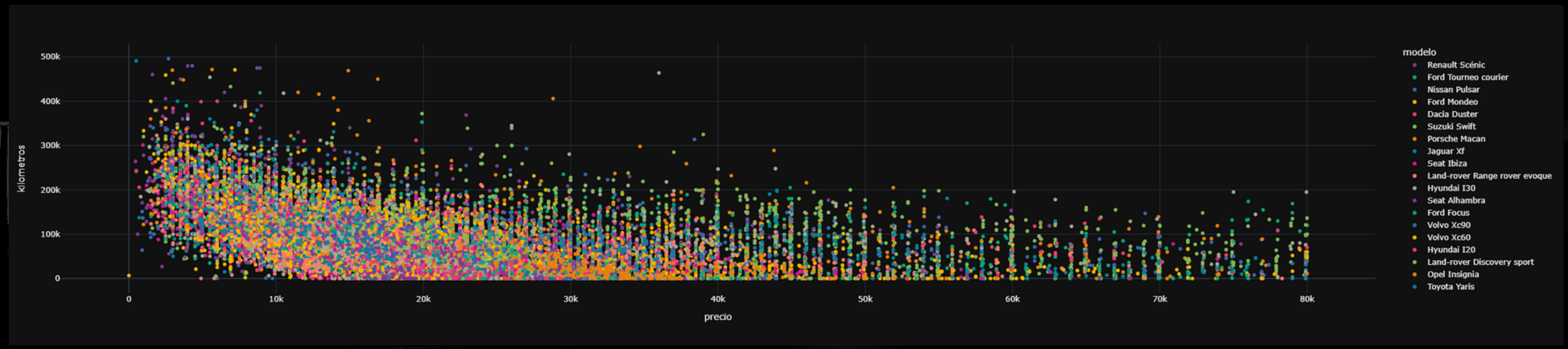
Precio = 80.000€
Kilometros = 500.000km

PADDOCK
FAST CAR VALUATION

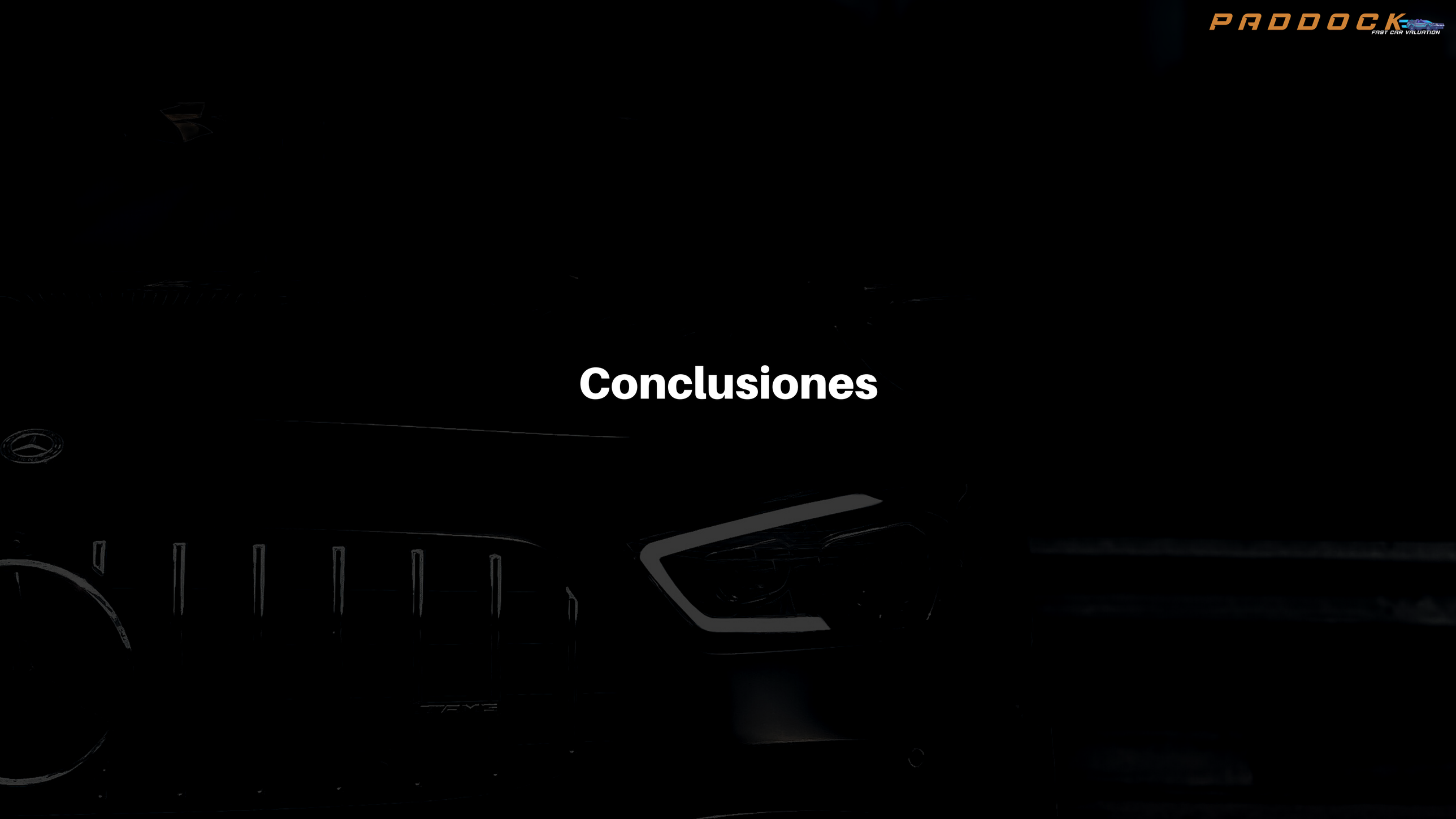
Año



Kilometros



Conclusiones



Limitar las filas donde los kilómetros sea <500.000km

Limitar las filas donde el precio sea <80.000€

Eliminar las marcas con menos de 10 coches

Eliminar los modelos con menos de 5 coches

Eliminar columnas inecesarias

PADDOCK
FAST CAR VALUATION

MACHINE LEARNING

DataFrames

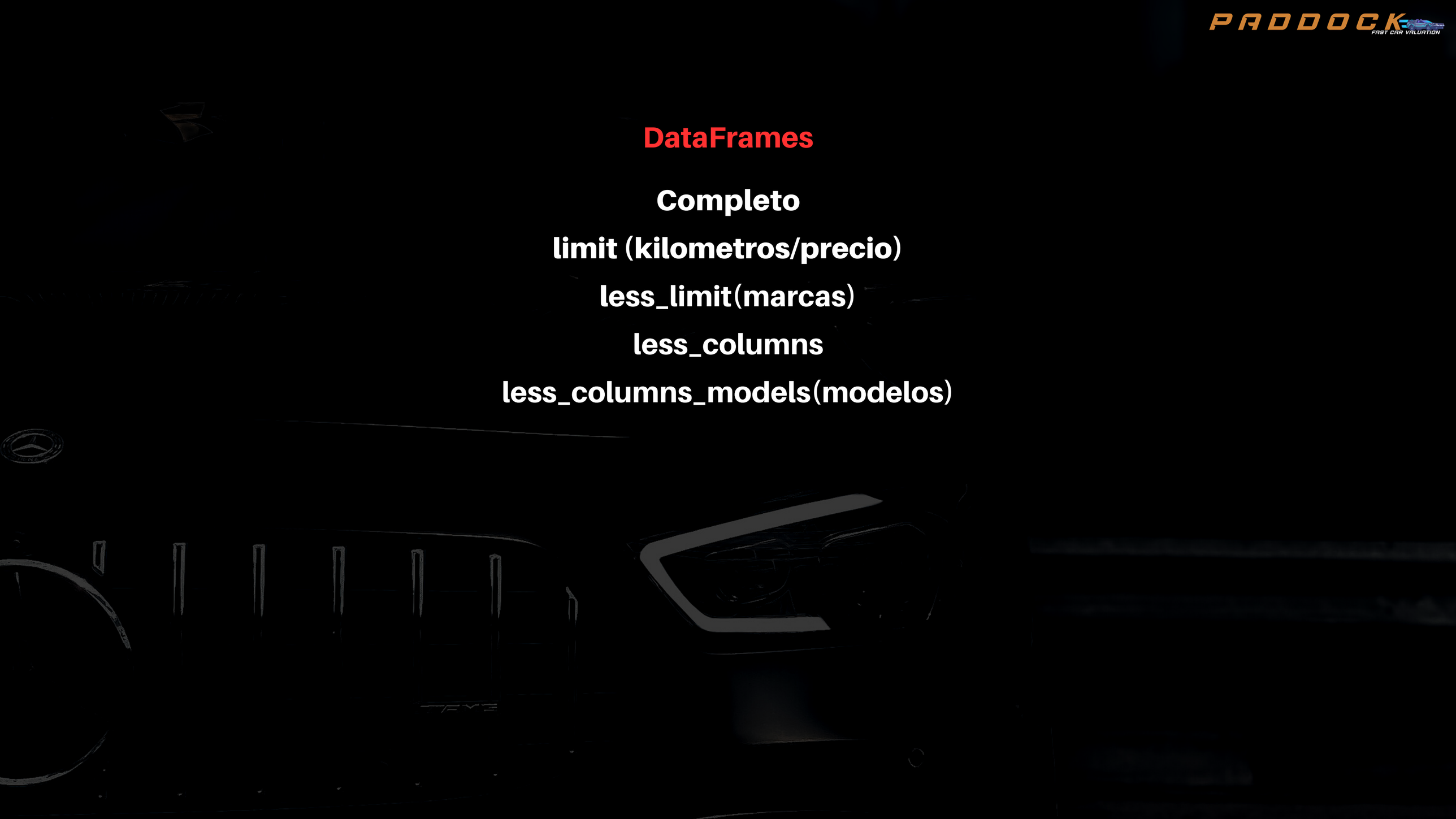
Completo

limit (kilometros/precio)

less_limit(marcas)

less_columns

less_columns_models(modelos)



Clase Prepare

```python
# Preparador de Dataframes
def prepare_dataframes(self, df_selector, input_dataframe, df_droppig):

    # Sección de tipo de dataframe a preparar
    if df_selector == 'complete':
      print(f'Mostrando total filas y columnas:\n{input_dataframe.shape}', '\n')
      # Función que quita columnas
      dropping_data = self.dropping(input_dataframe, df_droppig)

      return dropping_data

    elif df_selector == 'limit':
      # Filtra las lineas del datraframe
      input_dataframe = self.limit(input_dataframe)
      print(f'Mostrando total filas y columnas:\n{input_dataframe.shape}', '\n')
      # Elimina las columnas del datraframe
      dropping = self.dropping(input_dataframe, df_droppig)
      return dropping

    elif df_selector == 'less_limit':
      # Filtra las lineas del datraframe
      input_dataframe = self.limit(input_dataframe)
      # Filtra las marcas con cantidad de coches inferior a 10
      input_dataframe = self.limit_less(input_dataframe)
      # Elimino las columnas
      dropping_data = self.dropping(input_dataframe, df_droppig)

      return dropping_data

    elif df_selector == 'less_columns':
      # Filtra las lineas del datraframe
      input_dataframe = self.limit(input_dataframe)
      # Filtra las marcas con cantidad de coches inferior a 10
      input_dataframe = self.limit_less(input_dataframe)
      # Elimino las columnas
      dropping_data = self.dropping(input_dataframe, df_droppig)
      # Elimino columnas extras
      input_dataframe = self.reducer(dropping_data, df_droppig)
      print(f'Mostrando reducción del total filas y columnas:\n{input_dataframe.shape)\n')

      return input_dataframe

    elif df_selector == 'less_columns_models':
      # Filtra las lineas del datraframe
      input_dataframe = self.limit(input_dataframe)
      # Filtra las marcas con cantidad de coches inferior a 10
      input_dataframe = self.limit_less(input_dataframe)
      # Filtra los modelos con cantidad de coches inferior a 5
      input_dataframe = self.limit_less_model(input_dataframe)
      # Elimino las columnas
      dropping_data = self.dropping(input_dataframe, df_droppig)
      # Elimino columnas extras
      input_dataframe = self.reducer(dropping_data, df_droppig)
      print(f'Mostrando reducción del total filas y columnas:\n{input_dataframe.shape)\n')

      return input_dataframe

  # Metodos para elimnar columnas
  def dropping(self, input_dataframe, df_droppig):

    if df_droppig == 'tensorflow':
      dropping = input_dataframe.drop(['id_car', 'car_brand_id', 'model_id',
                                       'fuel_id', 'gearbox_id',
                                       'localidad_id'], axis = 1)
      print(f'Listado de columnas despues del dropping: {dropping.columns}')
      return dropping

    elif df_droppig == 'sklearn':
      dropping = input_dataframe.drop(['id_car', 'locate', 'car_brand', 'model',
                                       'fuel', 'gearbox'], axis = 1)
      print(f'Listado de columnas despues del dropping: {dropping.columns}')
      return dropping

  # Metodo para eliminar columnas extras.
  def reducer(self, input_dataframe, df_droppig):

      if df_droppig == 'tensorflow':
        print('Reduciendo columnas...', '\n')
        dropping = input_dataframe.drop(['locate', 'engine_power',
                                         'CO2', 'places', 'deposit',
                                         '0_100km'], axis = 1)

        print('Columnas reducidas', '\n')
        print(f'Listado de columnas despues del dropping: {dropping.columns}', '\n')

        return dropping

      elif df_droppig == 'sklearn':
        print('Reduciendo columnas...', '\n')
        dropping = input_dataframe.drop(['engine_power','CO2', 'places',
                                         'deposit','0_100km', 'localidad_id'], axis = 1)

        print('Columnas reducidas', '\n')
        print(f'Listado de columnas despues del dropping: {dropping.columns}', '\n')

        return dropping

  # Metodos para quitar filas
  def limit(self, input_dataframe):

    input_dataframe = input_dataframe[(input_dataframe['price'] <= 80000) & (input_dataframe['km'] < 500000)]
    print(f"Mostrando el precio y los kilometros maximos:\n{input_dataframe[['price', 'km']].max()}", '\n')

    return input_dataframe

  # Metodo para seleccionar las marcas con cantidad de coches inferior a 10
  def limit_less(self, input_dataframe):

      # Cantidad de marcas
      marks = input_dataframe['car_brand'].value_counts()

      # Guardo las marcas que tienen menos de coches
      cars_ten = marks[marks.values < 10]
      print(f'Coches de marcas con catidad < que 10: {sum(cars_ten.values)}', '\n')

      # Apilco la mascara anterior al dataframe con ~ delante indico que los valores True son False y viceversa para el isin()
      input_dataframe = input_dataframe[~input_dataframe['car_brand'].isin(cars_ten.index)]
      print(f'Mostrando total filas y columnas:\n{input_dataframe.shape}', '\n')

      return input_dataframe

  def limit_less_model(self, input_dataframe):

      # Cantidad de modelos
      models = input_dataframe['model'].value_counts()

      # Guardo las marcas que tienen menos de coches
      model_five = models[models.values < 5]
      print(f'Modelos con catidad < que 5: {sum(model_five.values)}', '\n')

      # Apilco la mascara anterior al dataframe con ~ delante indico que los valores True son False y viceversa para el isin()
      input_dataframe = input_dataframe[~input_dataframe['model'].isin(model_five.index)]
      print(f'Mostrando total filas y columnas:\n{input_dataframe.shape}', '\n')

      return input_dataframe
```

Metodo preparador

```python
# Preparador de DataFrames
def prepare_dataframes(self, df_selector, input_dataframe, df_droppig):

  # Sección de tipo de dataframe a preparar
  if df_selector == 'complete':
    print(f'Mostrando total filas y columnas:\n{input_dataframe.shape}', '\n')
    # Función que quita columnas
    dropping_data = self.dropping(input_dataframe, df_droppig)

    return dropping_data

  elif df_selector == 'limit':
    # Filtra las lineas del datraframe
    input_dataframe = self.limit(input_dataframe)
    print(f'Mostrando total filas y columnas:\n{input_dataframe.shape}', '\n')
    # Elimina las columnas del datraframe
    dropping = self.dropping(input_dataframe, df_droppig)
    return dropping

  elif df_selector == 'less_limit':
    # Filtra las lineas del datraframe
    input_dataframe = self.limit(input_dataframe)
    # Filtra las marcas con cantidad de coches inferior a 10
    input_dataframe = self.limit_less(input_dataframe)
    # Elimino las columnas
    dropping_data = self.dropping(input_dataframe, df_droppig)

    return dropping_data

  elif df_selector == 'less_columns':
    # Filtra las lineas del datraframe
    input_dataframe = self.limit(input_dataframe)
    # Filtra las marcas con cantidad de coches inferior a 10
    input_dataframe = self.limit_less(input_dataframe)
    # Elimino las columnas
    dropping_data = self.dropping(input_dataframe, df_droppig)
    # Elimino columnas extras
    input_dataframe = self.reducer(dropping_data, df_droppig)
    print(f'Mostrando reducción del total filas y columnas:\n{input_dataframe.shape}\n')

    return input_dataframe

  elif df_selector == 'less_columns_models':
    # Filtra las lineas del datraframe
    input_dataframe = self.limit(input_dataframe)
    # Filtra las marcas con cantidad de coches inferior a 10
    input_dataframe = self.limit_less(input_dataframe)
    # Filtra los modelos con cantidad de coches inferior a 5
    input_dataframe = self.limit_less_model(input_dataframe)
    # Elimino las columnas
    dropping_data = self.dropping(input_dataframe, df_droppig)
    # Elimino columnas extras
    input_dataframe = self.reducer(dropping_data, df_droppig)
    print(f'Mostrando reducción del total filas y columnas:\n{input_dataframe.shape}\n')

    return input_dataframe
```

PADDOCK
FAST CAR VALUATION

Metodos de eliminación

```python
# Metodos para elimnar columnas
def dropping(self, input_dataframe, df_droppig):

  if df_droppig == 'tensorflow':
    dropping = input_dataframe.drop(['id_car', 'card_brand_id', 'model_id',
                                     'fuel_id', 'gearbox_id',
                                     'localidad_id'], axis = 1)
    print(f'Listado de columnas despues del dropping: {dropping.columns}')
    return dropping

  elif df_droppig == 'sklearn':
    dropping = input_dataframe.drop(['id_car', 'locate', 'car_brand', 'model',
                                     'fuel', 'gearbox'], axis = 1)
    print(f'Listado de columnas despues del dropping: {dropping.columns}')
    return dropping

# Metodo para eliminar columnas extras.
def reducer(self, input_dataframe, df_droppig):

    if df_droppig == 'tensorflow':
      print('Reduciendo columnas...', '\n')
      dropping = input_dataframe.drop(['locate', 'engine_power',
                                       'CO2', 'places', 'deposit',
                                       '0_100km'], axis = 1)
      print('Columnas reducidas', '\n')
      print(f'Listado de columnas despues del dropping: {dropping.columns}', '\n')

      return dropping

    elif df_droppig == 'sklearn':
      print('Reduciendo columnas...', '\n')
      dropping = input_dataframe.drop(['engine_power','CO2', 'places',
                                       'deposit','0_100km', 'localidad_id'], axis = 1)
      print('Columnas reducidas', '\n')
      print(f'Listado de columnas despues del dropping: {dropping.columns}', '\n')

      return dropping
```

Metodos de limitación

```python
# Metodos para quitar filas
def limit(self, input_dataframe):

  input_dataframe = input_dataframe[(input_dataframe['price'] <= 80000) & (input_dataframe['km'] < 500000)]
  print(f"Mostrando el precio y los kilometros maximos:\n{input_dataframe[['price', 'km']].max()}", '\n')

  return input_dataframe

# Metodo para seleccionar las marcas con cantidad de coches inferior a 10
def limit_less(self, input_dataframe):

    # Cantidad de marcas
    marks = input_dataframe['car_brand'].value_counts()

    # Guardo las marcas que tienen menos de coches
    cars_ten = marks[marks.values < 10]
    print(f'Coches de marcas con catidad < que 10: {sum(cars_ten.values)}', '\n')

    # Aplico la mascara anterior al dataframe con ~ delante indico que los valores True son False y viceversa para el isin()
    input_dataframe = input_dataframe[~input_dataframe['car_brand'].isin(cars_ten.index)]
    print(f'Mostrando total filas y columnas:\n{input_dataframe.shape}', '\n')

    return input_dataframe

def limit_less_model(self, input_dataframe):

    # Cantidad de modelos
    models = input_dataframe['model'].value_counts()

    # Guardo las marcas que tienen menos de coches
    model_five = models[models.values < 5]
    print(f'Modelos con catidad < que 5: {sum(model_five.values)}', '\n')

    # Aplico la mascara anterior al dataframe con ~ delante indico que los valores True son False y viceversa para el isin()
    input_dataframe = input_dataframe[~input_dataframe['model'].isin(model_five.index)]
    print(f'Mostrando total filas y columnas:\n{input_dataframe.shape}', '\n')

    return input_dataframe
```

Creación de los dataframe

```
df_selector = ['complete', 'limit', 'less_limit', 'less_columns', 'less_columns_models']
df_droppig = ['tensorflow', 'sklearn']
```

```
# Bucles para ejecutar la clase y almacenar los resultados en el diccionario del bloque anterior.
for i in range(len(df_selector)):
  for x in range(len(df_droppig)):

    if x == 0:
      cars_tf = P.prepare_dataframes(df_selector[i], cars, df_droppig[x])
    elif x == 1:
      cars_sk = P.prepare_dataframes(df_selector[i], cars, df_droppig[x])

  dict_dataframes['tensorflow'][df_selector[i]] = cars_tf
  dict_dataframes['sklearn'][df_selector[i]] = cars_sk
```

PADDOCK
FAST CAR VALUATION

Comprobaciones Dataframe TensorFlow

dict_dataframes['tensorflow']['less_columns_models']

```
less_columns_models tensorflow

Mostrando el precio y los kilometros maximos:
price     80000.0
km       496000.0
dtype: float64

Coches de marcas con catidad < que 10: 60

Mostrando total filas y columnas:
(176492, 22)

Modelos con catidad < que 5: 285

Mostrando total filas y columnas:
(176207, 22)

Listado de columnas despues del dropping: Index(['locate', 'car_brand', 'model', 'year', 'horses', 'engine_power', 'km',
       'fuel', 'gearbox', 'CO2', 'price', 'places', 'deposit', '0_100km',
       'displ_engine', 'marches'],
      dtype='object')
Reduciendo columnas...

Columnas reducidas

Listado de columnas despues del dropping: Index(['car_brand', 'model', 'year', 'horses', 'km', 'fuel', 'gearbox',
       'price', 'displ_engine', 'marches'],
      dtype='object')

Mostrando reducción del total filas y columnas:
(176207, 10)
```

PADDOCK
FAST CAR VALUATION

Comprobaciones Dataframe Sklearn

dict_dataframes['sklearn']['less_columns_models']

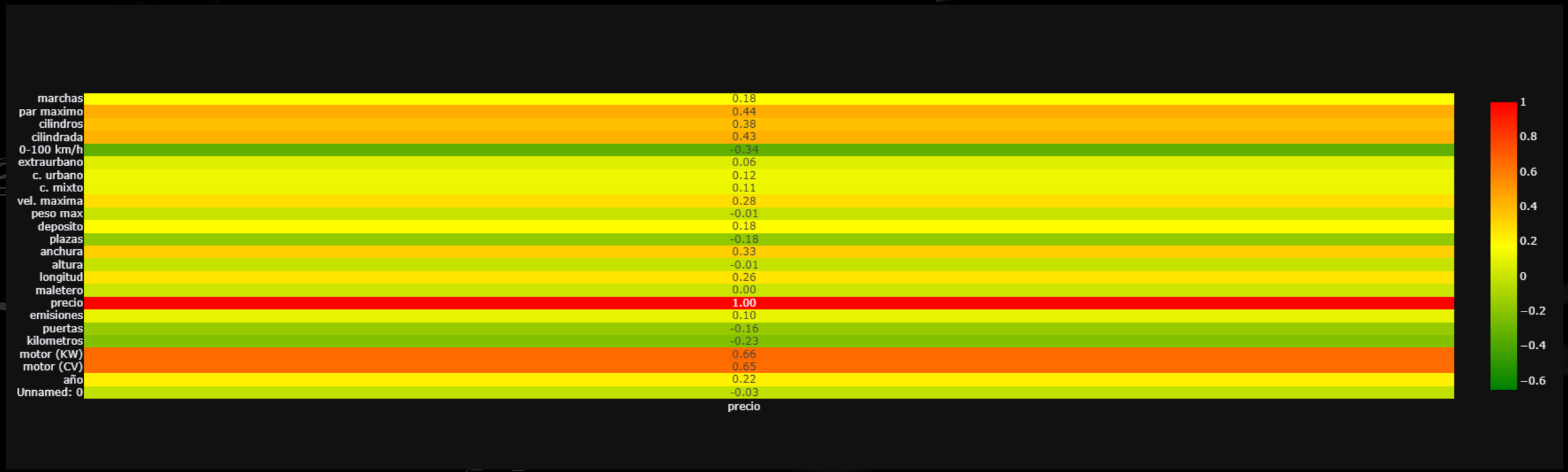
```
less_columns_models sklearn

Mostrando el precio y los kilometros maximos:
price     80000.0
km       496000.0
dtype: float64

Coches de marcas con catidad < que 10: 60

Mostrando total filas y columnas:
(176492, 22)

Modelos con catidad < que 5: 285

Mostrando total filas y columnas:
(176207, 22)

Listado de columnas despues del dropping: Index(['year', 'horses', 'engine_power', 'km', 'CO2', 'price', 'places',
       'deposit', '0_100km', 'displ_engine', 'marches', 'car_brand_id',
       'model_id', 'fuel_id', 'gearbox_id', 'localidad_id'],
      dtype='object')
Reduciendo columnas...

Columnas reducidas

Listado de columnas despues del dropping: Index(['year', 'horses', 'km', 'price', 'displ_engine', 'marches',
       'car_brand_id', 'model_id', 'fuel_id', 'gearbox_id'],
      dtype='object')

Mostrando reducción del total filas y columnas:
(176207, 10)
```

Elección del algoritmo

Arboles de decisión

Arboles de decisión

¿Por que?



PADDOCK
FAST CAR VALUATION

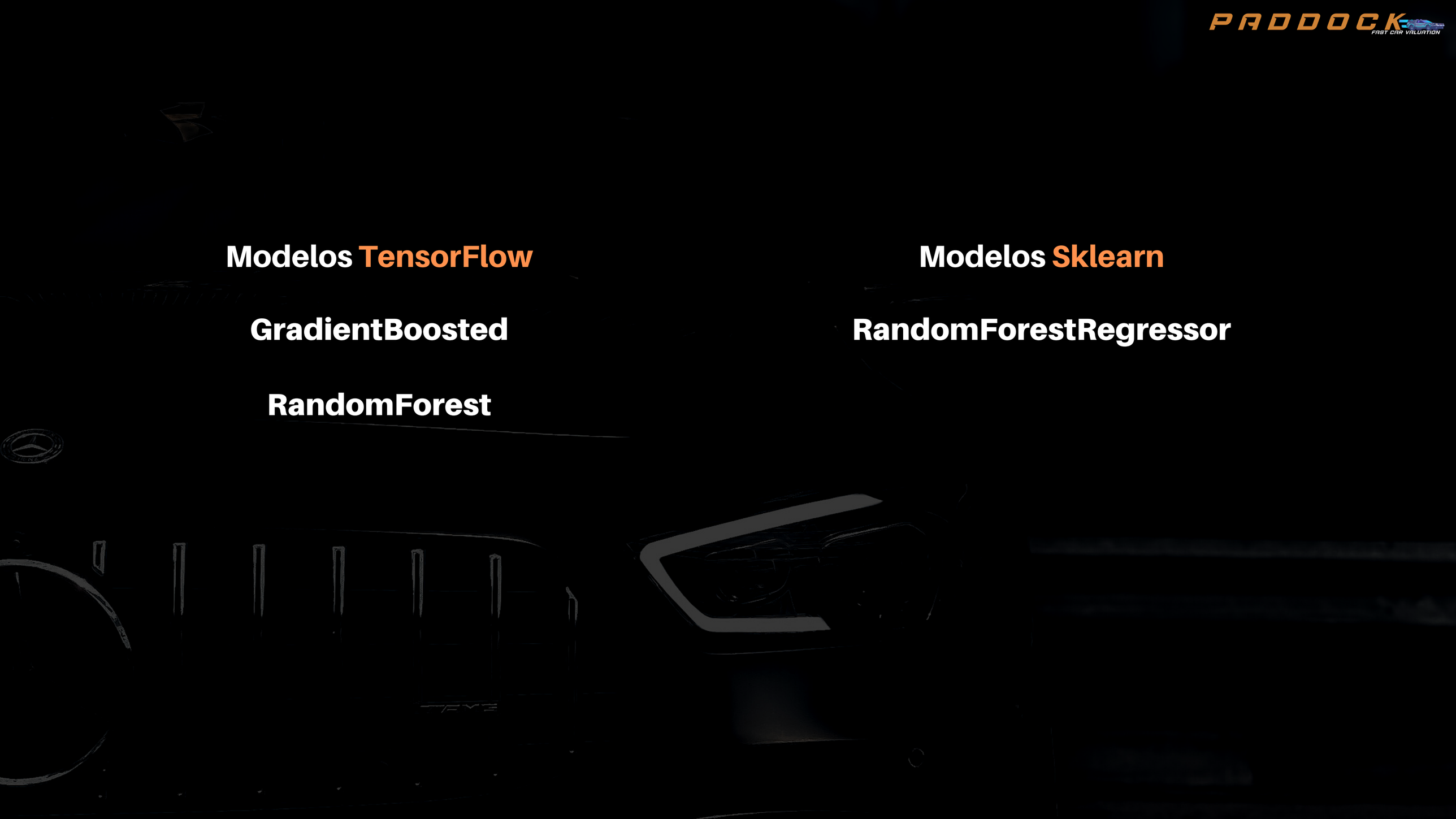
Modelos TensorFlow

GradientBoosted

RandomForest

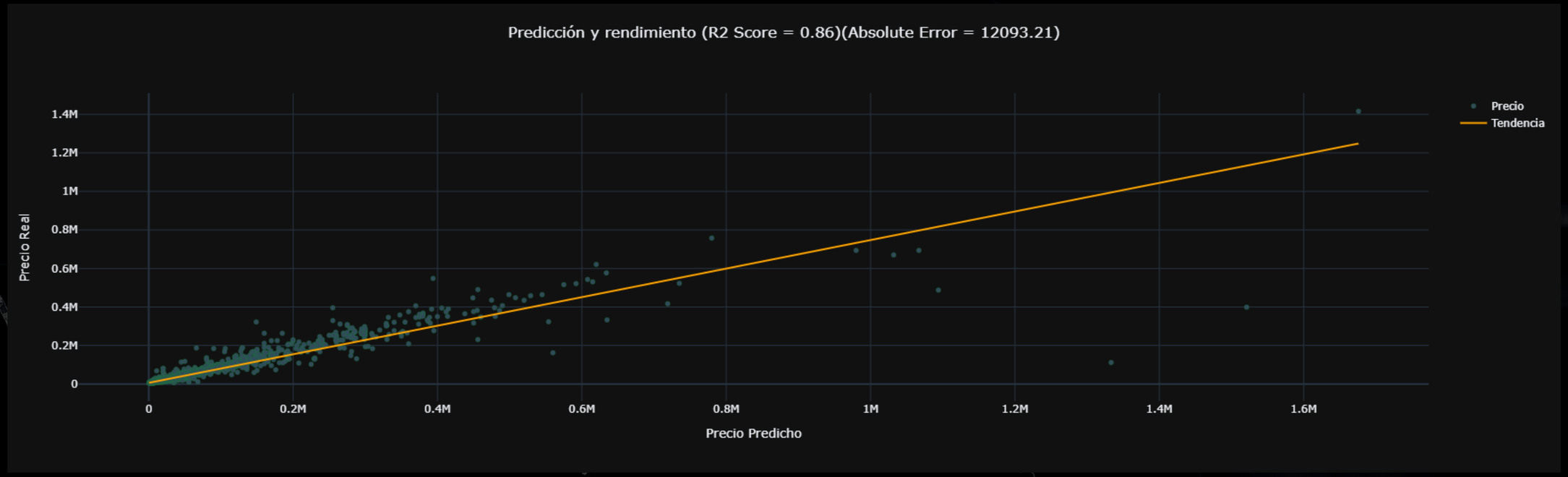
Modelos Sklearn

RandomForestRegressor



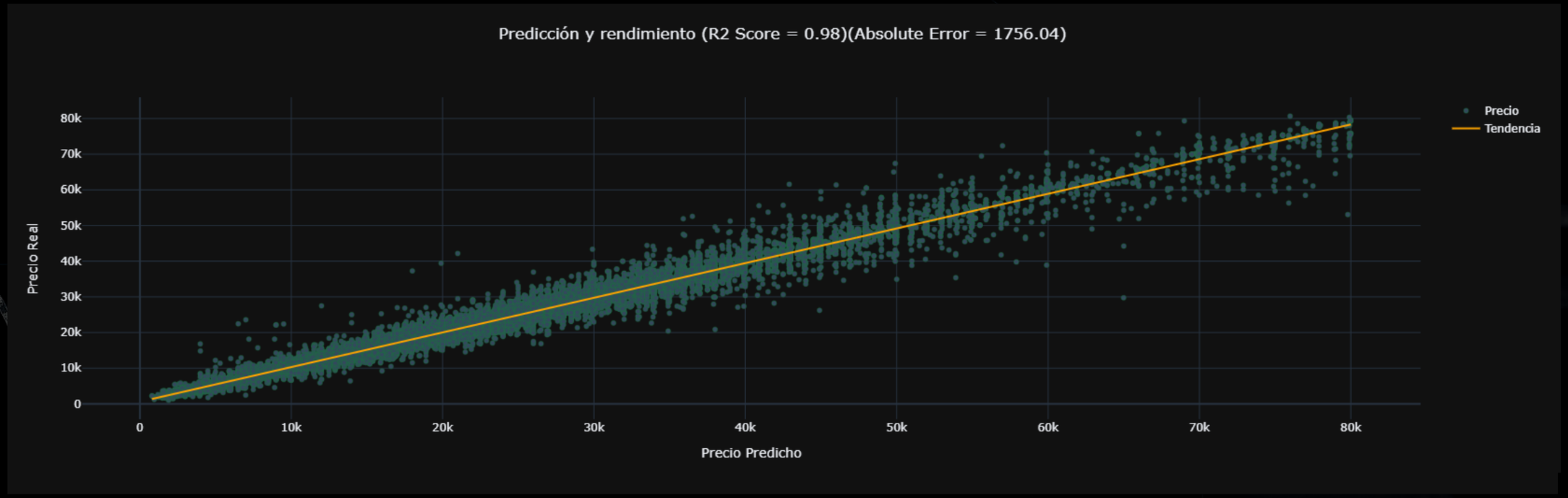
DataFrame 'Complete'

```
36/36 [==============================] - 1s 14ms/step
Error cuadrático medio: 12093.21
Coeficiente de determinación para 'complete': 0.86
10890.00     12174.65          1284.65
23490.00     21817.99          1672.01
37800.00     35141.57          2658.43
23500.00     22326.94          1173.06
12430.00     14483.66          2053.66
9020.00     11132.07          2112.07
23890.00     26358.06          2468.06
11299.00     12262.75           963.75
31000.00     28375.96          2624.04
53000.00     54085.22          1085.22
```



DataFrame 'less_columns_models'

```
Error cuadrático medio: 1756.04
Coeficiente de determinación para 'less_columns_models': 0.98
38850.00     40085.57          1235.57
3490.00      2614.31           875.69
34490.00     36892.32          2402.32
41900.00     37487.47          4412.53
18390.00     18178.66           211.34
39000.00     38705.52           294.48
26900.00     27806.16           906.16
20995.00     19156.58          1838.42
21990.00     23512.63          1522.63
28900.00     28593.37           306.63
```



Clase Mlearn

```python
class Mlearn():

  # Metodo para entrenar un Gradient Boosted
  def tensorflow_bg(self, input_dataframe, train):

      # Definición del modelo
      model_car = tfdf.keras.GradientBoostedTreesModel(
      task=tfdf.keras.Task.REGRESSION,
      validation_ratio = 0.1,
      num_trees = 100,
      max_depth = 10,
      l1_regularization = 0.01,
      l2_regularization = 0.01,
      early_stopping = 'LOSS_INCREASE',
      loss = "SQUARED_ERROR")

      # Entrenamiento del modelo
      model_car.fit(train)

      return model_car

  # Metodo para entrenar un Gradient Boosted
  def tensorflow_rf(self, input_dataframe, train):

      # Definición del modelo
      model_car = tfdf.keras.RandomForestModel(
      task=tfdf.keras.Task.REGRESSION,
      num_trees = 100,
      max_depth = 10,
      split_axis = "AXIS_ALIGNED",
      categorical_algorithm = "CART")

      # Entrenamiento del modelo
      model_car.fit(train)

      return model_car
```

Entrenamiento

```python
dict_tr_ts = {}

for index, df in enumerate(dict_dataframes['tensorflow']):

  data_frame = dict_dataframes['tensorflow'][df]

  # Separo los datos de entrenamiento (train) y los de test (test)
  train, test = train_test_split(data_frame, test_size=0.2, random_state=42)

  # Especificar la columna de la variable de destino (o target)
  target = "price"

  # Convertir el DataFrame de pandas a un conjunto de datos de TensorFlow
  train_cars = tfdf.keras.pd_dataframe_to_tf_dataset(train, label=target, task=tfdf.keras.Task.REGRESSION)
  test_cars = tfdf.keras.pd_dataframe_to_tf_dataset(test, label=target, task=tfdf.keras.Task.REGRESSION)

  # Añado el test_cars al diccionario para poder usarlo despues
  dict_tr_ts.update({df:[test, test_cars]})

  # Entreno el modelo GradientBoosted
  model_car_bg = ML.tensorflow_bg(data_frame, train_cars)

  # Guardo el modelo GradientBoosted en Drive
  model_car_bg.save(f'/content/drive/MyDrive/Colab Notebooks/Curso_IA_BIGDATA/TFM/export_models/Gredient_Boosted_TensowFlow/model_bg_{df}')

  # Entreno el modelo RandomForest
  model_car_rf = ML.tensorflow_rf(data_frame, train_cars)

  # Guardo el modelo RandomForest en Drive
  model_car_rf.save(f'/content/drive/MyDrive/Colab Notebooks/Curso_IA_BIGDATA/TFM/export_models/Random_forest_TensorFlow/model_rf_{df}')
```

Generador de rendimiento y predicciones

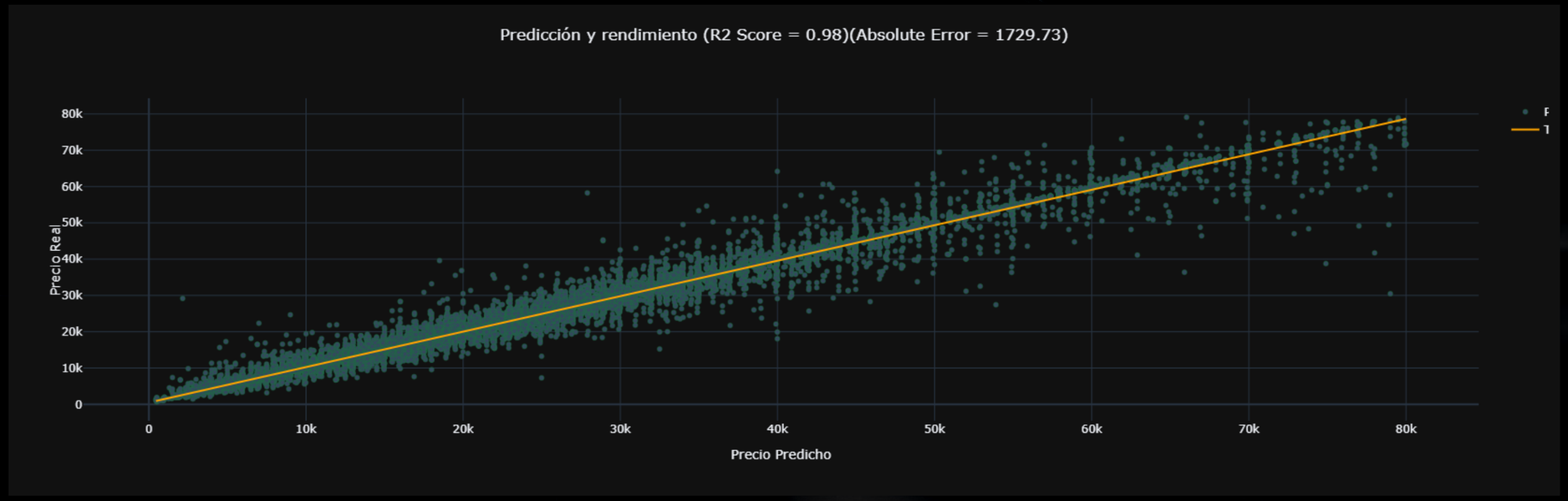
```python
def rendimiento_tensorflow(name_model ,input_model, input_test, imput_test_df):
    predicted_values = input_model.predict(imput_test_df)
    predicted_values = predicted_values.flatten()
    real_values = input_test[target].to_numpy()

    # Error Cuadrativo
    print("Error cuadrático medio: %.2f" % mean_squared_error(real_values, predicted_values, squared=False))
    # Coeficiente de determinación
    print(f"Coeficiente de determinación para '{name_model}': %.2f" % r2_score(real_values, predicted_values))

    mse = mean_squared_error(real_values, predicted_values, squared=False)
    r2 = r2_score(real_values, predicted_values)

    for i in range(10):
      real_price = real_values[i]
      estim_price = predicted_values[i]
      error_abs = abs(real_price - estim_price)
      print(f"{real_price:6.2f} {estim_price:12.2f} {error_abs:16.2f}")

    grafic_predicction(real_values, predicted_values, r2, mse)
```

DataFrame 'Complete'

```
Error cuadrático medio: 11500.59
Coeficiente de determinación para 'complete': 0.87
Sacando predicciones
20680.00     20680.00            0.00
31000.00     31198.64          198.64
37990.00     38864.09          874.09
21199.00     21482.06          283.06
14650.00     15479.75          829.75
5500.00      5938.15           438.15
9990.00      9990.00             0.00
19990.00     20041.30           51.30
14835.00     14835.00            0.00
25900.00     26118.90          218.90
```

DataFrame 'less_columns_models'

```
Error cuadrático medio: 1729.73
Coeficiente de determinación para 'less_columns_models': 0.98
Sacando predicciones
30900.00     31581.30          681.30
20930.00     20930.00            0.00
9190.00      9550.60           360.60
15900.00     15900.00            0.00
25990.00     25575.94          414.06
64990.00     70436.91         5446.91
21950.00     21933.30           16.70
17193.00     17193.00            0.00
19990.00     19990.00            0.00
19995.00     19868.51          126.49
```



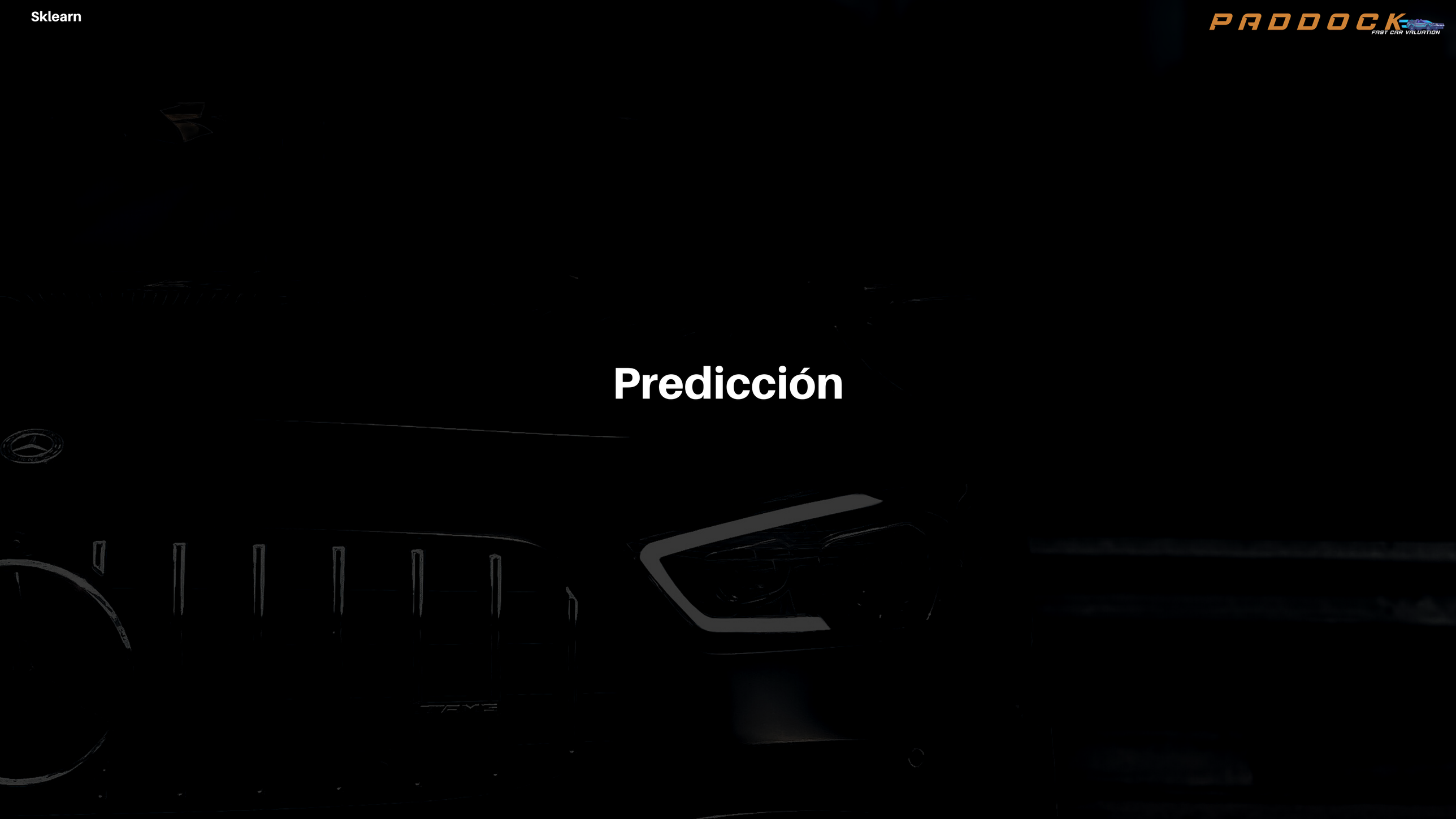
Entrenamiento

```python
dict_sklearn = {}

for index, df in enumerate(dict_dataframes['sklearn']):
  X = dict_dataframes['sklearn'][df].drop(['price'], axis = 1)
  y = dict_dataframes['sklearn'][df]['price']

  X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20)

  dict_sklearn.update({df:[X_test, y_test]})

  rf_model = RandomForestRegressor().fit(X_train.values, y_train.values)
  print(f'Proceso de entrenamiento completado de {df}')

  joblib.dump(rf_model, f'/content/drive/MyDrive/Colab Notebooks/Curso_IA_BIGDATA/TFM/export_models/Sklearn_RF/Sklearn_RF_{df}.pkl', compress=9)
  print(f'Proceso de exportación de Sklearn_RF_{df} completado')
```

Generador de rendimiento y predicciones

```python
def rendimiento_sklearn(name_model ,input_model, input_test, imput_test_df):
    # Predicción con las entradas de test
    predicted_values = input_model.predict(input_test.values)
    # Saco los valores reales de test
    real_values = imput_test_df.values

    # Error Cuadrativo
    print("Error cuadrático medio: %.2f" % mean_squared_error(real_values, predicted_values, squared=False))
    # Coeficiente de determinación
    print(f"Coeficiente de determinación para '{name_model}': %.2f" % r2_score(real_values, predicted_values))

    # Saco predicciones
    print('Sacando predicciones')
    for i in range(10):
      real_price = real_values[i]
      estim_price = predicted_values[i]
      error_abs = abs(real_price - estim_price)
      print(f"{real_price:6.2f} {estim_price:12.2f} {error_abs:16.2f}")
    print('\n')

    # r2_score y mean_squared_error nos permite saber el rendimiento del modelo
    r2 = r2_score(real_values, predicted_values)
    mse = mean_squared_error(real_values, predicted_values, squared=False)

    # Dibujo una gráfica con los resultados
    grafic_predicction(real_values, predicted_values, r2, mse)
```

Predicción



Referencia

	year	horses	km	displ_engine	marches	car_brand_id	model_id	fuel_id	gearbox_id
80462	2009.0	150.0	175000.0	1998.0	6.0	57.0	575.0	3.0	1.0
59424	2006.0	175.0	114378.0	1998.0	5.0	57.0	575.0	3.0	1.0
24172	2006.0	150.0	200000.0	1910.0	6.0	57.0	575.0	1.0	1.0
30789	2006.0	175.0	114378.0	1998.0	5.0	57.0	575.0	3.0	1.0
80645	2009.0	180.0	82000.0	1910.0	6.0	57.0	575.0	1.0	1.0
82213	2000.0	150.0	160656.0	1985.0	5.0	57.0	576.0	3.0	1.0
89967	2006.0	175.0	114378.0	1998.0	5.0	57.0	575.0	3.0	1.0
66875	2010.0	180.0	140000.0	1910.0	6.0	57.0	575.0	1.0	1.0

	car_brand	model	year	horses	km	fuel	gearbox	price	displ_engine	marches
173184	Saab	Saab 9-3	2007.0	150.0	270000.0	Diesel	Manual	3500.0	1910.0	6.0
59424	Saab	Saab 9-3	2006.0	175.0	114378.0	Gasolina	Manual	5900.0	1998.0	5.0
24172	Saab	Saab 9-3	2006.0	150.0	200000.0	Diesel	Manual	4600.0	1910.0	6.0
116728	Saab	Saab 9-3	2006.0	175.0	114378.0	Gasolina	Manual	5900.0	1998.0	5.0
148358	Saab	Saab 9-3	2006.0	175.0	114378.0	Gasolina	Manual	5900.0	1998.0	5.0
11764	Saab	Saab 9-3	2006.0	175.0	114378.0	Gasolina	Manual	5900.0	1998.0	5.0
112518	Saab	Saab 9-5	1999.0	150.0	149000.0	Gasolina	Manual	2990.0	1985.0	5.0
113438	Saab	Saab 9-3	2006.0	175.0	114378.0	Gasolina	Manual	5900.0	1998.0	5.0

Predicción

```
new_car = rf_sk_less_columns.predict([[2005.0, 150.0, 190000.0, 1910.0, 6.0, 57.0, 575.0, 1, 1]])
new_car
```

```
new_car = rf_sk_less_columns.predict([[2005.0, 150.0, 190000.0, 1910.0, 6.0, 57.0, 575.0, 1, 1]])
new_car
```

```
array([5637.63])
```

Resultado

```
array([5637.63])
```

Referencia

	car_brand	model	year	horses	km	fuel	gearbox	price	displ_engine	marches
173184	Saab	Saab 9-3	2007.0	150.0	270000.0	Diesel	Manual	3500.0	1910.0	6.0
59424	Saab	Saab 9-3	2006.0	175.0	114378.0	Gasolina	Manual	5900.0	1998.0	5.0
24172	Saab	Saab 9-3	2006.0	150.0	200000.0	Diesel	Manual	4600.0	1910.0	6.0
116728	Saab	Saab 9-3	2006.0	175.0	114378.0	Gasolina	Manual	5900.0	1998.0	5.0
148358	Saab	Saab 9-3	2006.0	175.0	114378.0	Gasolina	Manual	5900.0	1998.0	5.0
11764	Saab	Saab 9-3	2006.0	175.0	114378.0	Gasolina	Manual	5900.0	1998.0	5.0
112518	Saab	Saab 9-5	1999.0	150.0	149000.0	Gasolina	Manual	2990.0	1985.0	5.0
113438	Saab	Saab 9-3	2006.0	175.0	114378.0	Gasolina	Manual	5900.0	1998.0	5.0

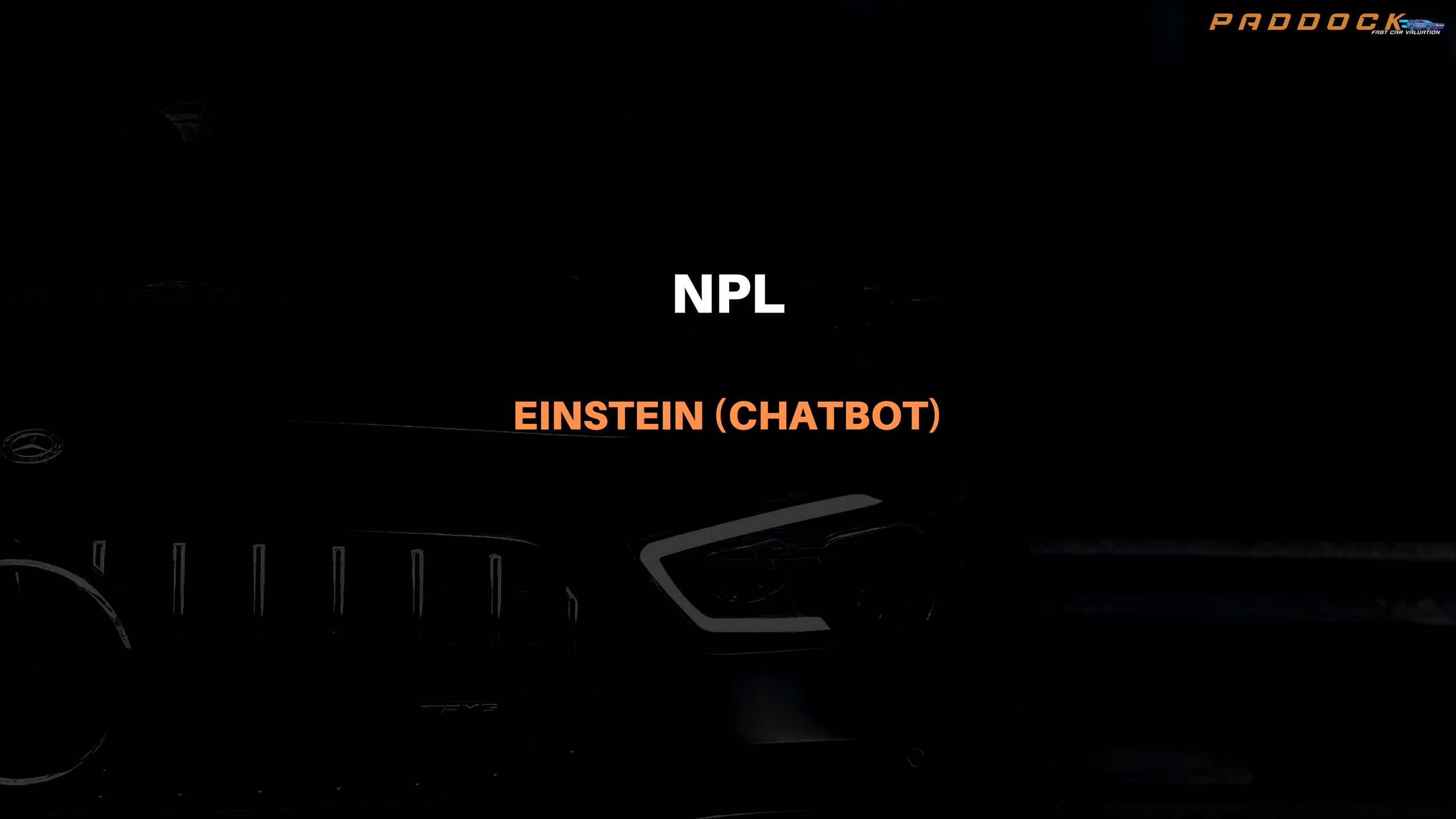
Tabla comparativa

Algoritmos de Machine Learning	MSE	R2_Score	Casos
TensorFlow - GradientBoostedTreesModel			
model_bg_complete	12093.21	0.86	179502
model_bg_limit	1861.69	0.97	176552
model_bg_less_limit	1801.79	0.97	176492
model_bg_less_columns	1827.12	0.97	176492
model_bg_less_columns_models	1756.04	0.98	176207
TensorFlow - RandomForestModel			
model_rf_complete	12003.32	0.86	179502
model_rf_limit	2823.97	0.94	176552
model_rf_less_limit	2813.75	0.94	176492
model_rf_less_columns	2792.48	0.94	176492
model_rf_less_columns_models	2731.08	0.94	176207
SkLearn - RandomForestRegressor			
rf_sk_complete	11500.59	0.87	179502
rf_sk_limit	1753.63	0.98	176552
rf_sk_less_limit	1725.31	0.98	176492
rf_sk_less_columns	1831.87	0.97	176492
rf_sk_less_columns_models	1729.73	0.98	176207

PADDOCK
FAST CAR VALUATION

NPL

EINSTEIN (CHATBOT)



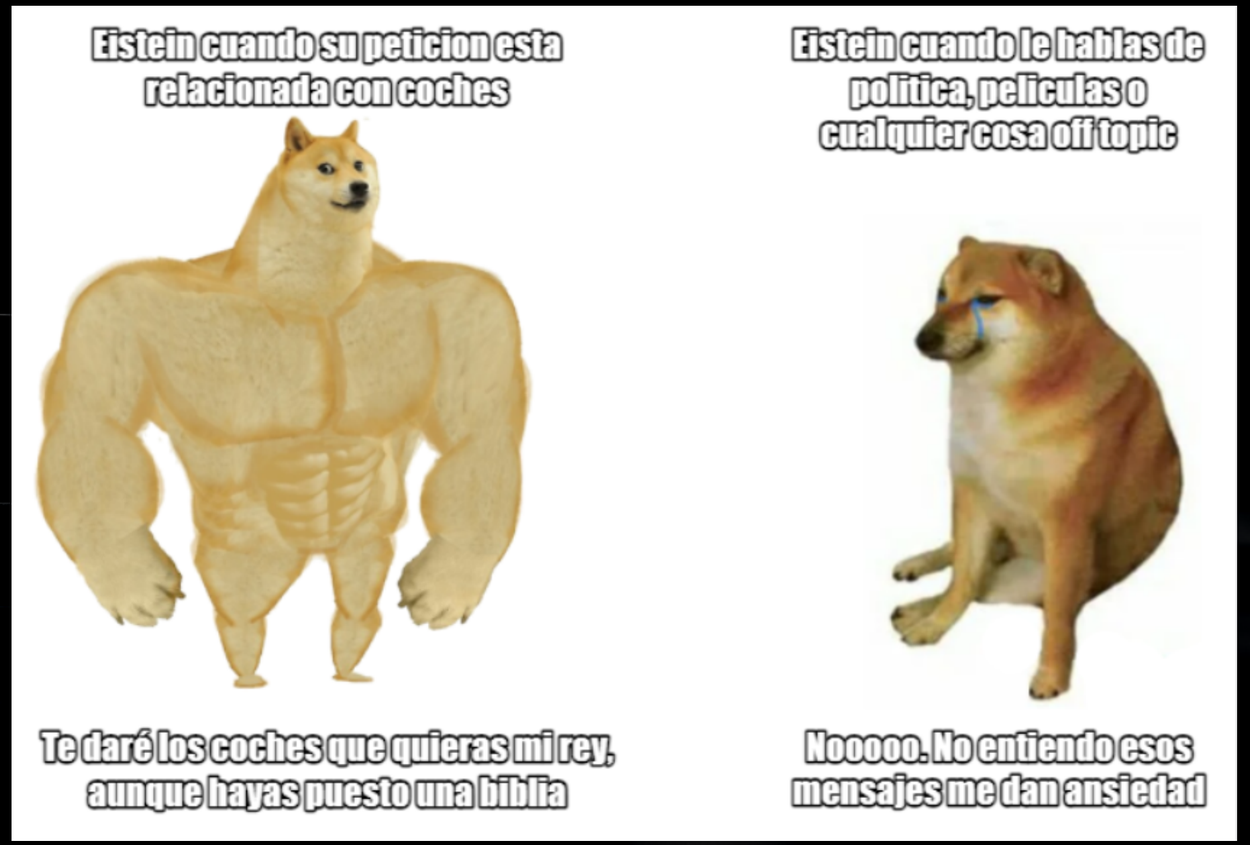
¿QUE QUEREMOS DE NUESTRO MODELO?

Sacar el contexto

¿COMO LO ENTRENAMOS?

¿MODELOS ESCOGIDOS?

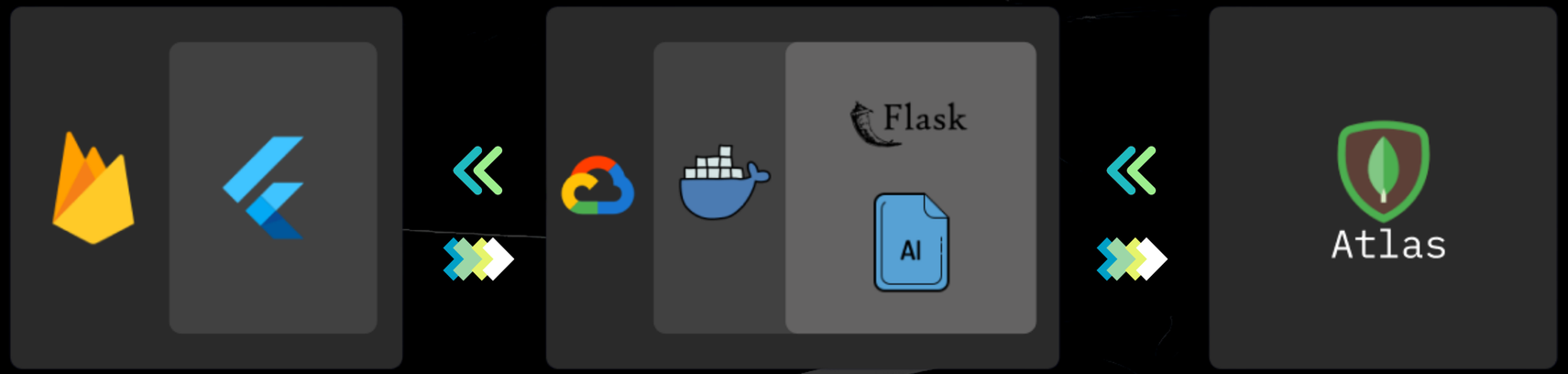
CONCLUSIONES DE NUESTRO CHATBOT



PADDOCK
FAST CAR VALUATION

DESARRALLO WEB

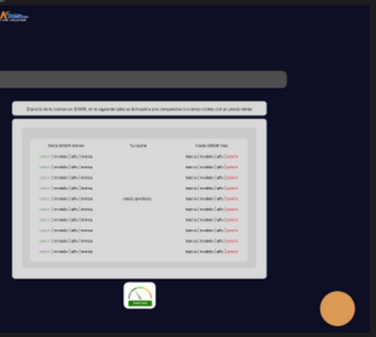
PADDOCK
FAST CAR VALUATION



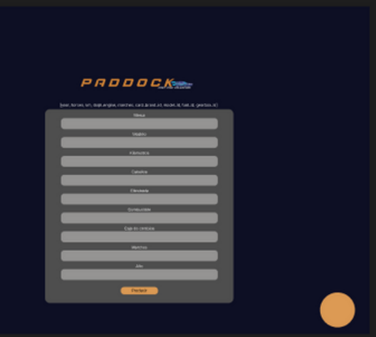
PADDOCK
FAST CAR VALUATION

Prototipo

Chatbot_predict_2

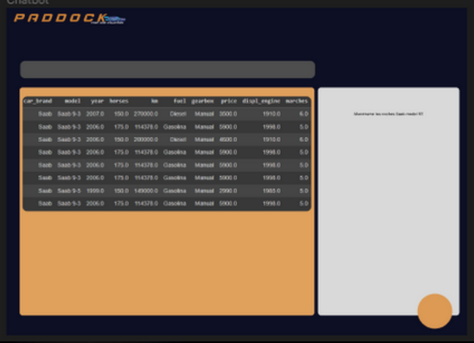


Predictor



Panel_principal

Chatbot



PADDOCK
FAST CAR VALUATION

DEMO

PADDOCK
FAST CAR VALUATION

CONCLUSIONES Y POTENCIAL DEL PROYECTO


PADDOCK
FAST CAR VALUATION
MUCHAS GRACIAS
github.com/Legodark/paddock