Startup

Import libs

In [ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import LabelEncoder
from xgboost import XGBRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
```

Carregar arquivo

In [ ]:
```
df = pd.read_csv('assets/precos_carros_brasil.csv')
```

```
C:\Users\Lenovo\AppData\Local\Temp\ipykernel_46448\4038775297.py:1: DtypeWarning: Co
lumns (1,2,3,4,5,6,7,8) have mixed types. Specify dtype option on import or set low_
memory=False.
  df = pd.read_csv('assets/precos_carros_brasil.csv')
```

Verfica se há valores faltantes no arquivo, se sim irá preencher com 'indefinido' e depois remover linhas que fipe_code e model são iguais a 'indefinido'

In [ ]:
```
if df.isnull().any().any():
    df.fillna('indefinido', inplace=True)
    df = df[(df['fipe_code'] != 'indefinido') & (df['model'] != 'indefinido')]
    print('Valores nulos encontrados e substituídos por "indefinido", e removidos l
else:
    print('Não há valores nulos')
```

```
Valores nulos encontrados e substituídos por "indefinido", e removidos linhas que fi
pe_code e model são "indefinido"
```

Verifica se há dados duplicados

In [ ]:
```
duplicated_rows = df.duplicated()
if duplicated_rows.any():
    print("Há dados duplicados.")
else:
    print("Não há dados duplicados.")
```

```
Há dados duplicados.
```

Converter as colunas year_of_reference, year_model e avg_price_brl para numericos

In [ ]:
```
df['year_of_reference'] = pd.to_numeric(df['year_of_reference'], errors='coerce')
df['year_model'] = pd.to_numeric(df['year_model'], errors='coerce')
df['avg_price_brl'] = pd.to_numeric(df['avg_price_brl'], errors='coerce')
```

Criar duas categorias para separação entre colunas numéricas e categóricas

In [ ]:
```
categorical_columns = df.select_dtypes(exclude='number').columns.tolist()
numeric_columns = df.select_dtypes(include='number').columns.tolist()
```

Colunas não numéricas

In [ ]:
```
categorical_columns
```

Out[ ]:
```
['month_of_reference',
 'fipe_code',
 'authentication',
 'brand',
 'model',
 'fuel',
 'gear',
 'engine_size']
```

Colunas numéricas

In [ ]:
```
numeric_columns
```

Out[ ]:
```
['year_of_reference', 'year_model', 'avg_price_brl']
```

Contagem de valores por modelo e marca do carro

In [ ]:
```
count_values = df.groupby(['model', 'fipe_code', 'brand']).size().reset_index(name=
count_values
```

Out[ ]:

	model	fipe_code	brand	count
0	350Z 3.5 V6 280cv/ 312cv 2p	023051-0	Nissan	150
1	500 ABARTH MULTIAIR 1.4 TB 16V 3p	001429-0	Fiat	50
2	500 Cabrio Dualogic Flex 1.4 8V	001420-6	Fiat	75
3	500 Cabrio Flex 1.4 8V Mec.	001421-4	Fiat	50
4	500 Cabrio/500 Coupe Gucci/Flex 1.4 Aut.	001392-7	Fiat	100
...	...	...	...	...
2107	up! move I MOTION 1.0 T. Flex 12V 3p	005372-4	VW - VolksWagen	50
2108	up! move I MOTION 1.0 T. Flex 12V 5p	005399-6	VW - VolksWagen	125
2109	up! take 1.0 T. Flex 12V 3p	005376-7	VW - VolksWagen	100
2110	up! take 1.0 Total Flex 12V 5p	005365-1	VW - VolksWagen	150
2111	up! track 1.0 Total Flex 12V 5p	005468-2	VW - VolksWagen	25

2112 rows × 4 columns

Visualização de Dados

Gráfico de distribuição quantidade de carros por marca

In [ ]:

```
plt.figure(figsize=(20, 10))
df.groupby('brand')['fipe_code'].count().plot(kind='bar')
plt.xlabel('Marcas')
plt.ylabel('Quantidade de Carros')
plt.title('Distribuição da Quantidade de Carros por Marca')

plt.show()
```

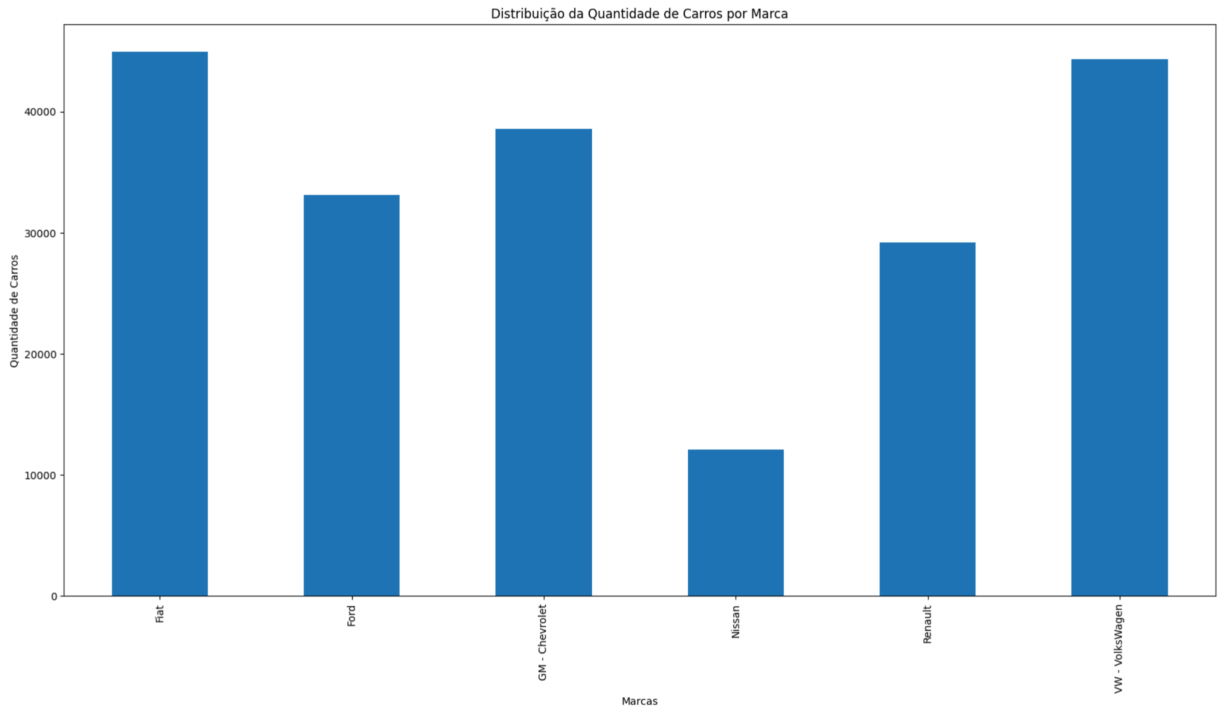


Gráfico de distribuição quantidade de carros por tipo de engrenagem

In [ ]:

```
plt.figure(figsize=(20, 10))
df.groupby('gear')['fipe_code'].count().plot(kind='bar')
plt.xlabel('Marcas')
plt.ylabel('Quantidade de Carros')
plt.title('Distribuição da Quantidade de Carros por Engrenagem')

plt.show()
```

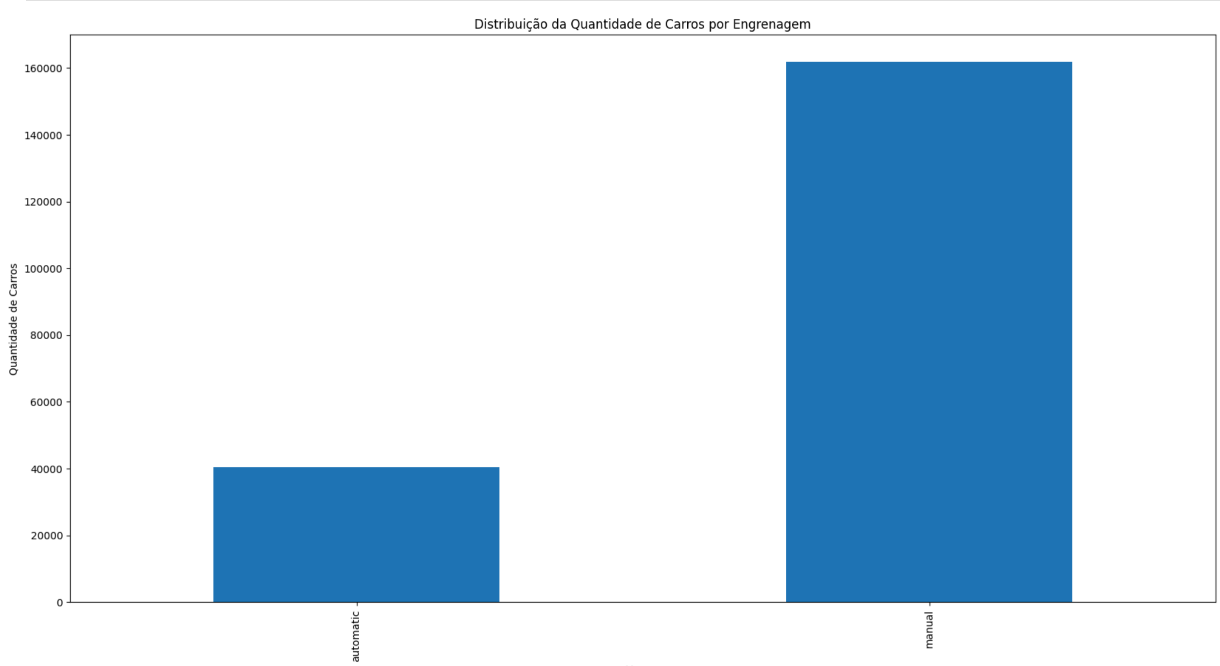
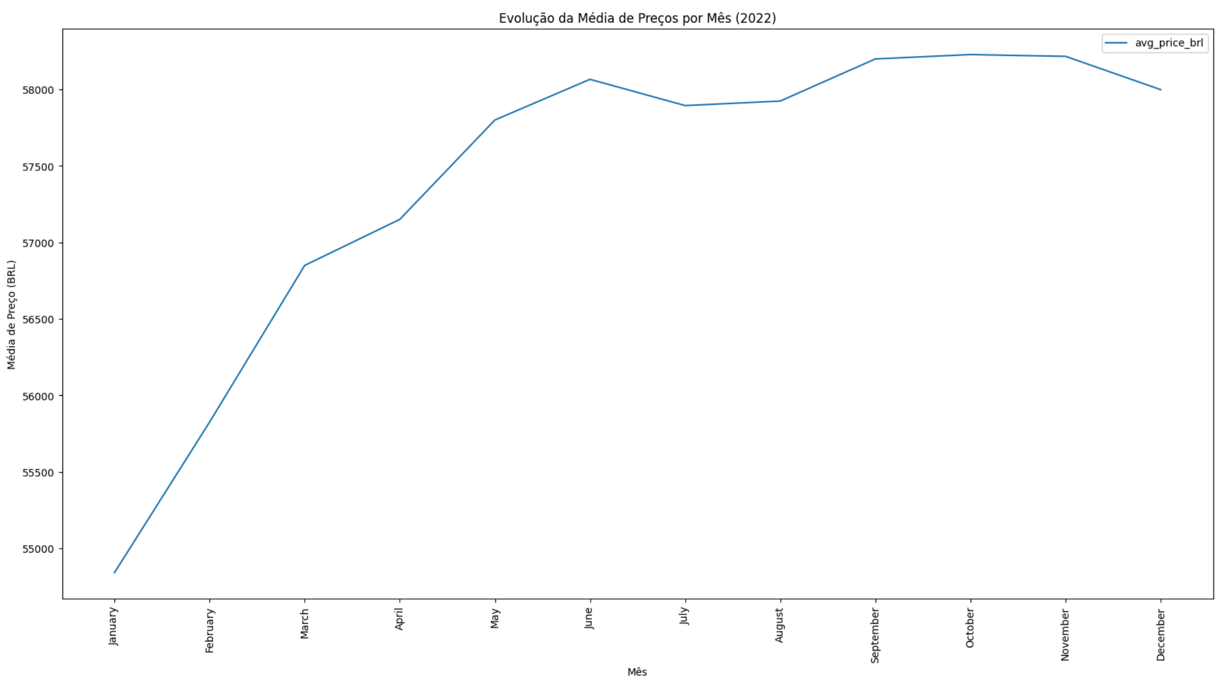


Gráfico evolução média de preço dos carros ao longo de 2022

In [ ]:

```
# filtra o ano de 2022 and agrupa por média mensal dos valores dos carros
df_from_year = df[df['year_of_reference'] == 2022]
df_avg_price_by_month = df_from_year.groupby('month_of_reference')['avg_price_brl']

# ordenar os meses cronologicamente
df_avg_price_by_month = df_avg_price_by_month.sort_values('month_of_reference', key

df_avg_price_by_month.plot(x='month_of_reference', y='avg_price_brl', kind='line',
plt.xlabel('Mês')
plt.ylabel('Média de Preço (BRL)')
plt.title('Evolução da Média de Preços por Mês (2022)')

# imprimir todos os meses no gráfico (eixo x)
df_months = df_avg_price_by_month['month_of_reference']
plt.xticks(range(0,len(df_months.index)), df_months, rotation = 'vertical')

plt.show()

df_avg_price_by_month
```



Out[ ]:

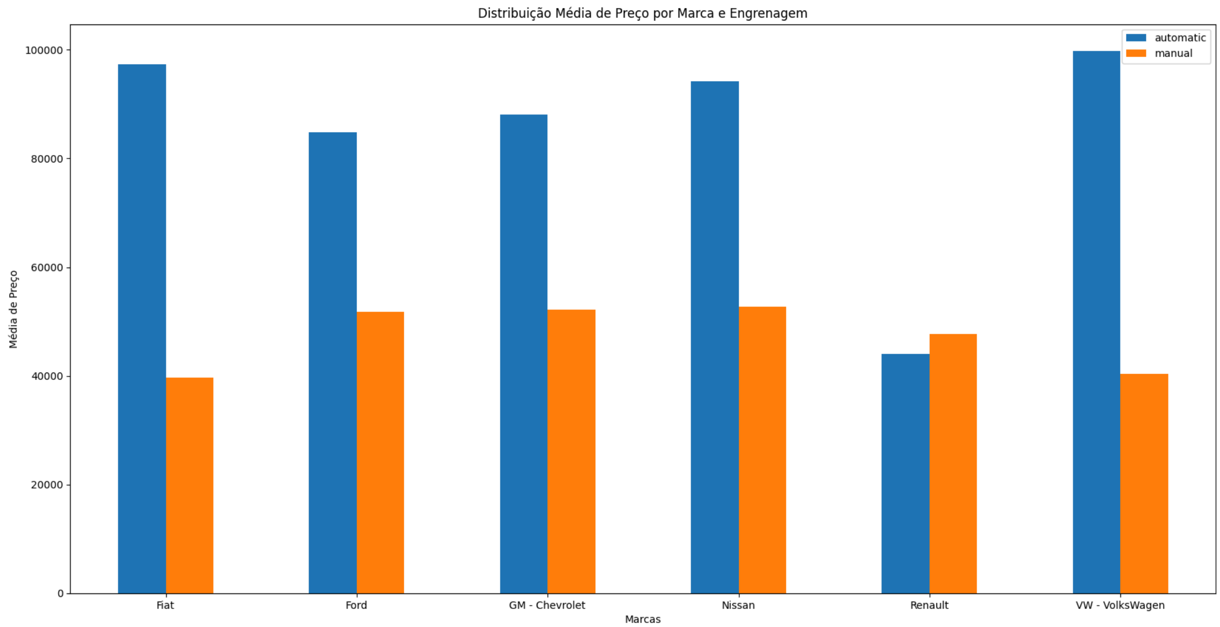
	month_of_reference	avg_price_brl
4	January	54840.270037
3	February	55824.519882
7	March	56848.951914
0	April	57150.037325
8	May	57799.763776
6	June	58065.611398
5	July	57893.997056
1	August	57923.544105
11	September	58198.936989
10	October	58227.410144
9	November	58215.626236
2	December	57998.054038

Gráfico da distribuição da média de preço dos carros por marca e tipo de engrenagem

In [ ]:

```
df_pivoted_by_gear = df.groupby(['brand','gear'])['avg_price_brl'].mean().reset_ind

df_pivoted_by_gear = df_pivoted_by_gear.pivot_table(index='brand', columns='gear',

plt.figure(figsize=(20, 10))
df_pivoted_by_gear.plot(x='brand', y=df_pivoted_by_gear.columns[1:], kind='bar', ro
plt.xlabel('Marcas')
plt.ylabel('Média de Preço')
plt.title('Distribuição Média de Preço por Marca e Engrenagem')
plt.legend()
plt.show()

df_pivoted_by_gear
```

```
<Figure size 2000x1000 with 0 Axes>
```



Out[ ]:

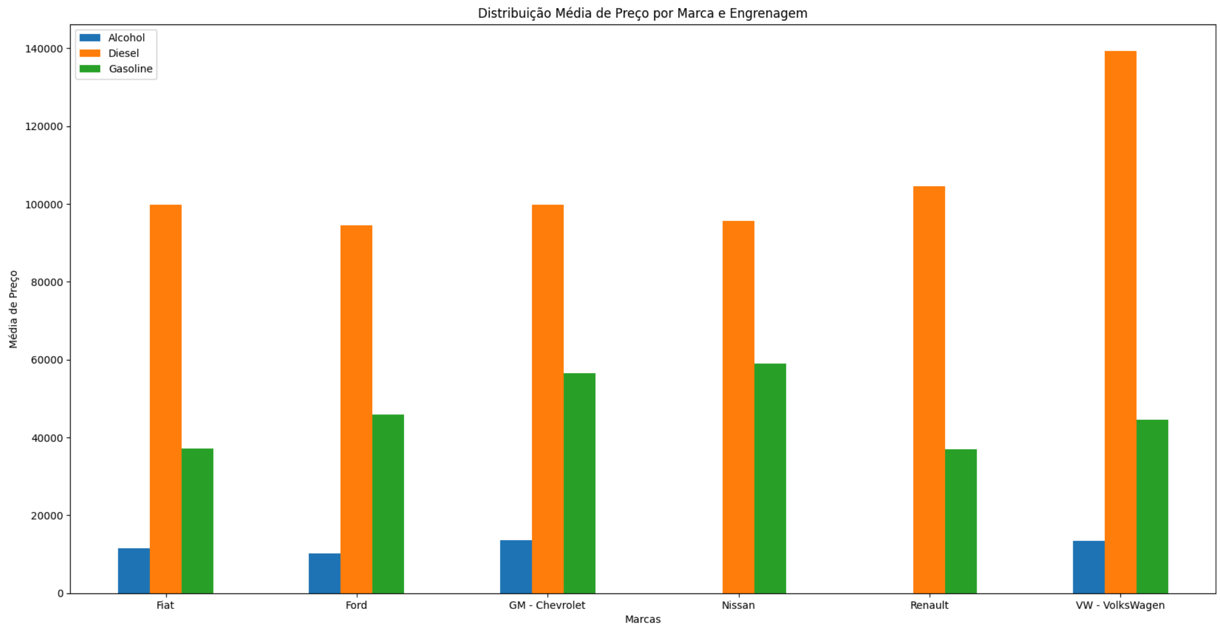
gear	brand	automatic	manual
0	Fiat	97396.801936	39694.442749
1	Ford	84769.106720	51784.851550
2	GM - Chevrolet	88156.919439	52119.422129
3	Nissan	94230.600604	52680.623596
4	Renault	44028.007521	47649.837635
5	VW - VolksWagen	99734.979181	40390.327451

Gráfico da distribuição da média de preço dos carros por marca e tipo de combustível

In [ ]:

```
df_by_brand_and_fuel = df.groupby(['brand','fuel'])['avg_price_brl'].mean().reset_i

df_pivoted_by_fuel = df_by_brand_and_fuel.pivot_table(index='brand', columns='fuel'

plt.figure(figsize=(20, 10))
df_pivoted_by_fuel.plot(x='brand', y=df_pivoted_by_fuel.columns[1:], kind='bar', ro
plt.xlabel('Marcas')
plt.ylabel('Média de Preço')
plt.title('Distribuição Média de Preço por Marca e Engrenagem')
plt.legend()
plt.show()

df_pivoted_by_fuel
```

```
<Figure size 2000x1000 with 0 Axes>
```



Out[ ]:

fuel	brand	Alcohol	Diesel	Gasoline
0	Fiat	11509.514419	99814.451429	37197.294483
1	Ford	10148.906667	94522.454826	45844.524969
2	GM - Chevrolet	13697.717687	99817.318601	56497.127255
3	Nissan	NaN	95534.071529	59043.288090
4	Renault	NaN	104529.925499	37059.317766
5	VW - VolksWagen	13392.684507	139216.276328	44653.797430

Machine Learning

Preparação Dados

Transformar month_of_reference em numérico, conforme número do mês

In [ ]:

```
month_mapping = {'January': 1, 'February': 2, 'March': 3, 'April': 4, 'May': 5, 'Ju

df['month_of_reference_number'] = df['month_of_reference'].map(month_mapping)

df.head()
```

Out[ ]:

	year_of_reference	month_of_reference	fipe_code	authentication	brand	model	
0	2021.0	January	004001-0	cfzlctzfwrcp	GM - Chevrolet	Corsa Wind 1.0 MPFI / EFI 2p	Gas
1	2021.0	January	004001-0	cdqwxwpw3y2p	GM - Chevrolet	Corsa Wind 1.0 MPFI / EFI 2p	Gas
2	2021.0	January	004001-0	cb1t3xwwj1xp	GM - Chevrolet	Corsa Wind 1.0 MPFI / EFI 2p	Gas
3	2021.0	January	004001-0	cb9gct6j65r0	GM - Chevrolet	Corsa Wind 1.0 MPFI / EFI 2p	Al
4	2021.0	January	004003-7	g15wg0gbz1fx	GM - Chevrolet	Corsa Pick-Up GL/ Champ 1.6 MPFI / EFI	Gas

Transformar brand, model, gear e fuel em numérico usando LabelEnconder

In [ ]:

```
le = LabelEncoder()
df['brand_number'] = le.fit_transform(df['brand'])
df['model_number'] = le.fit_transform(df['model'])
df['gear_number'] = le.fit_transform(df['gear'])
df['fuel_number'] = le.fit_transform(df['fuel'])

df.head()
```

Out[ ]:

	year_of_reference	month_of_reference	fipe_code	authentication	brand	model	
0	2021.0	January	004001-0	cfzlctzfwrcp	GM - Chevrolet	Corsa Wind 1.0 MPFI / EFI 2p	Gas
1	2021.0	January	004001-0	cdqwxwpw3y2p	GM - Chevrolet	Corsa Wind 1.0 MPFI / EFI 2p	Gas
2	2021.0	January	004001-0	cb1t3xwwj1xp	GM - Chevrolet	Corsa Wind 1.0 MPFI / EFI 2p	Gas
3	2021.0	January	004001-0	cb9gct6j65r0	GM - Chevrolet	Corsa Wind 1.0 MPFI / EFI 2p	Al
4	2021.0	January	004003-7	g15wg0gbz1fx	GM - Chevrolet	Corsa Pick-Up GL/ Champ 1.6 MPFI / EFI	Gas

Transformar fipe_code em numérico, removendo caracters não numéricos, assim preservando o codigo fipe

In [ ]:

```
df['fipe_code_numeric'] = df['fipe_code'].str.replace(r'\D', '', regex=True)
df['fipe_code_numeric'] = pd.to_numeric(df['fipe_code_numeric'], errors='coerce')

df.head()
```

Out[ ]:

	year_of_reference	month_of_reference	fipe_code	authentication	brand	model	
0	2021.0	January	004001-0	cfzlctzfwrcp	GM - Chevrolet	Corsa Wind 1.0 MPFI / EFI 2p	Gas
1	2021.0	January	004001-0	cdqwxwpw3y2p	GM - Chevrolet	Corsa Wind 1.0 MPFI / EFI 2p	Gas
2	2021.0	January	004001-0	cb1t3xwwj1xp	GM - Chevrolet	Corsa Wind 1.0 MPFI / EFI 2p	Gas
3	2021.0	January	004001-0	cb9gct6j65r0	GM - Chevrolet	Corsa Wind 1.0 MPFI / EFI 2p	Al
4	2021.0	January	004003-7	g15wg0gbz1fx	GM - Chevrolet	Corsa Pick-Up GL/ Champ 1.6 MPFI / EFI	Gas

Colunas de interesse para o modelo

In [ ]:

```
df_full_to_model = df.drop(df.select_dtypes(exclude='number').columns.tolist(),axis
df_full_to_model.head()
```

Out[ ]:

	year_of_reference	year_model	avg_price_brl	month_of_reference_number	brand_number
0	2021.0	2002.0	9162.0	1	2
1	2021.0	2001.0	8832.0	1	2
2	2021.0	2000.0	8388.0	1	2
3	2021.0	2000.0	8453.0	1	2
4	2021.0	2001.0	12525.0	1	2

Separar coluna target (avg_price_brl)

In [ ]:
```
df_to_model = df_full_to_model.drop(['avg_price_brl'],axis = 1)
df_target = df_full_to_model['avg_price_brl']
```

Particionar 75% / 25%

In [ ]:
```
X_train, X_test, Y_train, Y_test = train_test_split(df_to_model, df_target, test_si
```

RandomForest

Treinamento

In [ ]:
```
model_rf = RandomForestRegressor()
model_rf.fit(X_train, Y_train)
predict_values_rf = model_rf.predict(X_test)
predict_values_rf
```

Out[ ]:
```
array([ 40790.08,  11123.91,  28579.15, ...,  12640.45,  27036.94,
       177101.41])
```

Importância Variáveis

In [ ]:
```
feature_importances = pd.DataFrame(model_rf.feature_importances_, index = X_train.c
feature_importances
```

Out[ ]:

	importance
year_model	0.349768
model_number	0.297954
fuel_number	0.176292
fipe_code_numeric	0.119007
gear_number	0.021689
brand_number	0.017015
year_of_reference	0.012716
month_of_reference_number	0.005558

MSE

In [ ]:
```
mse = mean_squared_error(Y_test, predict_values_rf)
mse
```

Out[ ]: 5691205.045478143

MAE

In [ ]:
```
mae = mean_absolute_error(Y_test, predict_values_rf)
mae
```

Out[ ]: 1060.9744990509143

R^2

In [ ]:
```
r2_score(Y_test, predict_values_rf)
```

Out[ ]: 0.9978547458538981

XGBoost

Treinamento

In [ ]:
```
model_xgboost = XGBRegressor()
model_xgboost.fit(X_train, Y_train)
predict_values_xgboost = model_xgboost.predict(X_test)
predict_values_xgboost
```

Out[ ]:
```
array([ 39516.832,  11798.201,  27723.314, ...,  10567.259,  25196.072,
       178493.36 ], dtype=float32)
```

Importância Variáveis

In [ ]:
```
feature_importances_xgboost = pd.DataFrame(model_xgboost.feature_importances_, inde
feature_importances_xgboost
```

Out[ ]:

	importance
fuel_number	0.486602
year_model	0.170977
brand_number	0.138039
model_number	0.092122
gear_number	0.065926
fipe_code_numeric	0.027947
year_of_reference	0.013349
month_of_reference_number	0.005039

MSE

In [ ]:
```
mse_xgboost = mean_squared_error(Y_test, predict_values_xgboost)
mse_xgboost
```

Out[ ]:
```
34854617.46312717
```

MAE

In [ ]:
```
mae_xgboost = mean_absolute_error(Y_test, predict_values_xgboost)
mae_xgboost
```

Out[ ]:
```
3420.0102856553926
```

R^2

In [ ]:
```
r2_score(Y_test, predict_values_xgboost)
```

Out[ ]:
```
0.9868618311893406
```