Problema de Machine Learning de Regressão: Previsão de tráfego futuro

1 - Definindo o problema de negócio

Este conjunto de dados inclui informações sobre o volume de tráfego em determinadas estradas ao longo do tempo, juntamente com características como clima e feriados, e o objetivo é prever o volume de tráfego futuro.

2 - Decisões

O problema de negócio já informa que é requerido um modelo de Machine Learning. No dataset, temos a coluna “traffic_volume” que é a variável que queremos prever. Desta forma, iremos utilizar aprendizagem supervisionada.

3 - Versão python e import dos pacotes utilizados

In [1]:
```
# Versão da Linguagem Python
from platform import python_version
print('Versão da Linguagem Python Usada Neste Jupyter Notebook:', python_version())
```

```
Versão da Linguagem Python Usada Neste Jupyter Notebook: 3.9.13
```

In [2]:
```
# Para atualizar um pacote, execute o comando abaixo no terminal ou prompt de comar
# pip install -U nome_pacote

# Para instalar a versão exata de um pacote, execute o comando abaixo no terminal c
#!pip install nome_pacote==versão_desejada

# Depois de instalar ou atualizar o pacote, reinicie o jupyter notebook.

# Instala o pacote watermark.
# Esse pacote é usado para gravar as versões de outros pacotes usados neste jupyter
#!pip install -q -U watermark
```

In [3]:
```
#!pip install keras==2.13.1
#!pip install tensorflow==2.13.0
#!pip install --upgrade tensorflow
```

In [4]:
```
# Imports
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('whitegrid')
```

```
import sklearn
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, TimeDistributed, Conv1D, MaxPoolir
from sklearn.preprocessing import LabelEncoder
from pmdarima.arima import auto_arima
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import train_test_split
from sklearn.feature_selection import RFE
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.stattools import adfuller
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
from statsmodels.tsa.arima.model import ARIMA
from sklearn.neural_network import MLPRegressor
from xgboost import XGBRegressor
from lightgbm import LGBMRegressor
from sklearn.metrics import explained_variance_score, mean_absolute_error, mean_squ
%matplotlib inline
import warnings
warnings.filterwarnings("ignore", category=FutureWarning)
```

In [5]:
```
# Versões dos pacotes usados neste jupyter notebook
%reload_ext watermark
%watermark -a "Danilo Temerloglou de Abreu" --iversions
```

```
Author: Danilo Temerloglou de Abreu

pandas    : 1.3.4
seaborn   : 0.12.2
sklearn   : 1.2.1
matplotlib: 3.7.1
numpy     : 1.23.5
tensorflow: 2.16.1
```

4 - Dicionário de dados

In [6]:
```
#holiday - Feriados nacionais dos USA mais feriados regionais, Feira Estadual de Mi
#temp - Temperatura média em Kelvin
#rain_1h - Quantidade em mm de chuva que ocorreu na hora
#snow_1h - Quantidade em mm de neve que ocorreu na hora
#clouds_all - Porcentagem de cobertura de nuvens
#weather_main - Breve descrição textual do clima atual
#weather_description - Descrição textual mais longa do clima atual
#date_time - Hora dos dados coletados no horário local CST
#traffic_volume - Volume de tráfego no sentido oeste relatado por hora I-94 ATR 301
```

5 - Carregando o Conjunto de dados

In [7]:
```
# Carrega o dataset
df = pd.read_csv('Metro_Interstate_Traffic_Volume.csv')
```

6 - EDA Análise Exploratória de Dados

In [8]:
```
# Shape
df.shape
```

Out[8]:
```
(48204, 9)
```

In [9]:
```
#nomes das colunas
df.columns
```

Out[9]:
```
Index(['holiday', 'temp', 'rain_1h', 'snow_1h', 'clouds_all', 'weather_main',
       'weather_description', 'date_time', 'traffic_volume'],
      dtype='object')
```

In [10]:
```
# Info
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48204 entries, 0 to 48203
Data columns (total 9 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   holiday              48204 non-null  object 
 1   temp                 48204 non-null  float64
 2   rain_1h              48204 non-null  float64
 3   snow_1h              48204 non-null  float64
 4   clouds_all           48204 non-null  int64  
 5   weather_main         48204 non-null  object 
 6   weather_description  48204 non-null  object 
 7   date_time            48204 non-null  object 
 8   traffic_volume       48204 non-null  int64  
dtypes: float64(3), int64(2), object(4)
memory usage: 3.3+ MB
```

In [11]:
```
# Amostra
df.sample(5)
```

Out[11]:

	holiday	temp	rain_1h	snow_1h	clouds_all	weather_main	weather_description	date_tim
42418	None	268.69	0.0	0.0	1	Clear	sky is clear	2018-03 1 04:00:0
39627	None	266.50	0.0	0.0	75	Snow	light snow	2017-12 0 12:00:0
7169	None	295.20	0.0	0.0	90	Thunderstorm	proximity thunderstorm with rain	2013-06 2 05:00:0
17206	None	292.53	0.0	0.0	90	Clouds	overcast clouds	2015-08 0 08:00:0
42838	None	266.61	0.0	0.0	1	Clear	sky is clear	2018-04 0 04:00:0

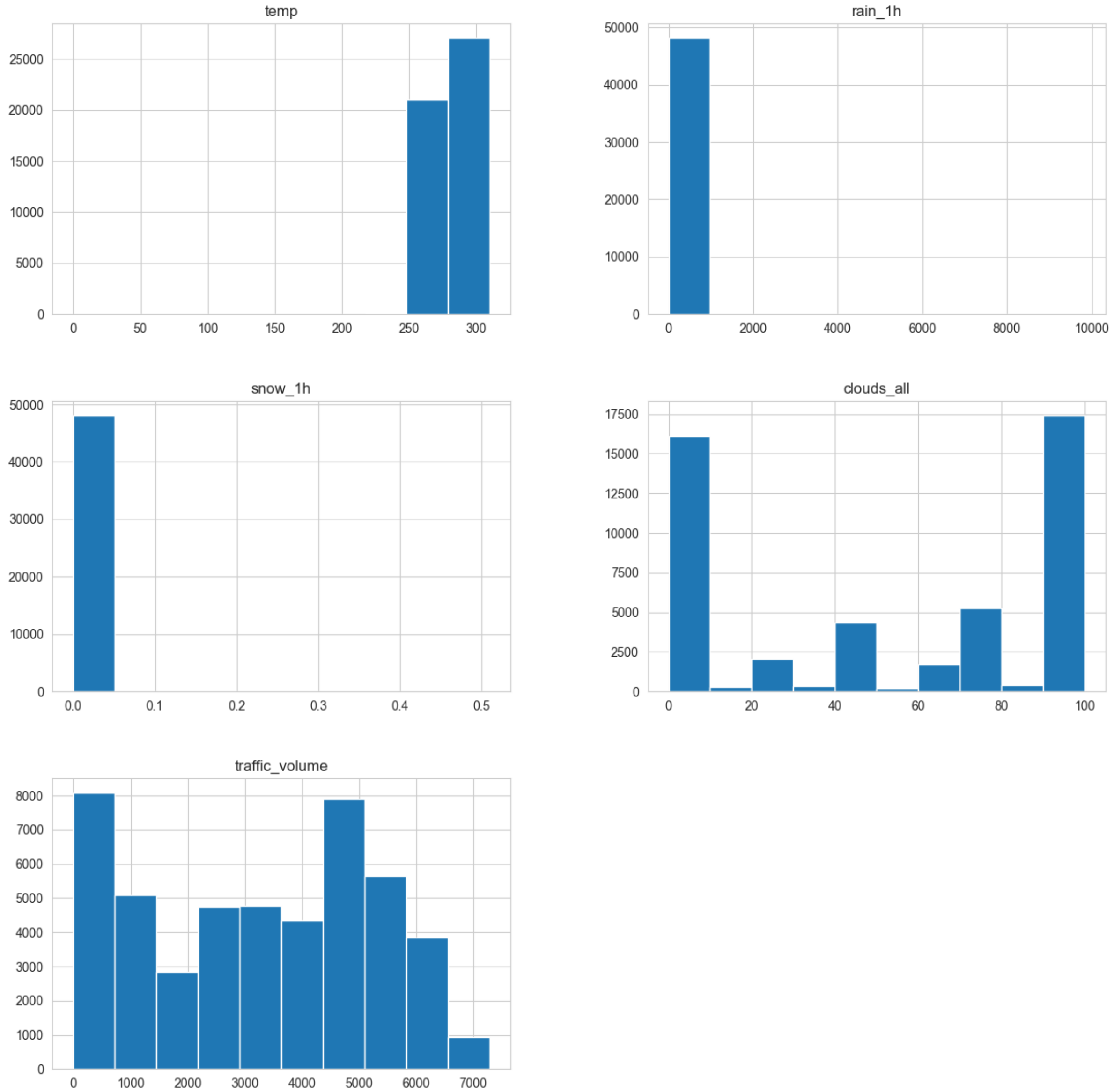
Exploração das variáveis numéricas

In [12]:
```
df.describe()
```

Out[12]:

	temp	rain_1h	snow_1h	clouds_all	traffic_volume
count	48204.000000	48204.000000	48204.000000	48204.000000	48204.000000
mean	281.205870	0.334264	0.000222	49.362231	3259.818355
std	13.338232	44.789133	0.008168	39.015750	1986.860670
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	272.160000	0.000000	0.000000	1.000000	1193.000000
50%	282.450000	0.000000	0.000000	64.000000	3380.000000
75%	291.806000	0.000000	0.000000	90.000000	4933.000000
max	310.070000	9831.300000	0.510000	100.000000	7280.000000

In [13]:
```
# Plot
df.hist(figsize = (15,15), bins = 10)
plt.show()
```



In [14]:
```
# Insighs:
# temperaturas concentram-se de 250 a 300K = -23 a 26 °C
# média baixa de chuva e de neve durante 1 hora
# maioria dos dados está com tempo aberto ou nublado
# volume de tráfego está com boa variedade de valores
```

In [15]:
```
# Correlação (tabela)
df.corr()
```

Out[15]:

	temp	rain_1h	snow_1h	clouds_all	traffic_volume
temp	1.000000	0.009069	-0.019755	-0.101976	0.130299
rain_1h	0.009069	1.000000	-0.000090	0.004818	0.004714
snow_1h	-0.019755	-0.000090	1.000000	0.027931	0.000733
clouds_all	-0.101976	0.004818	0.027931	1.000000	0.067054
traffic_volume	0.130299	0.004714	0.000733	0.067054	1.000000

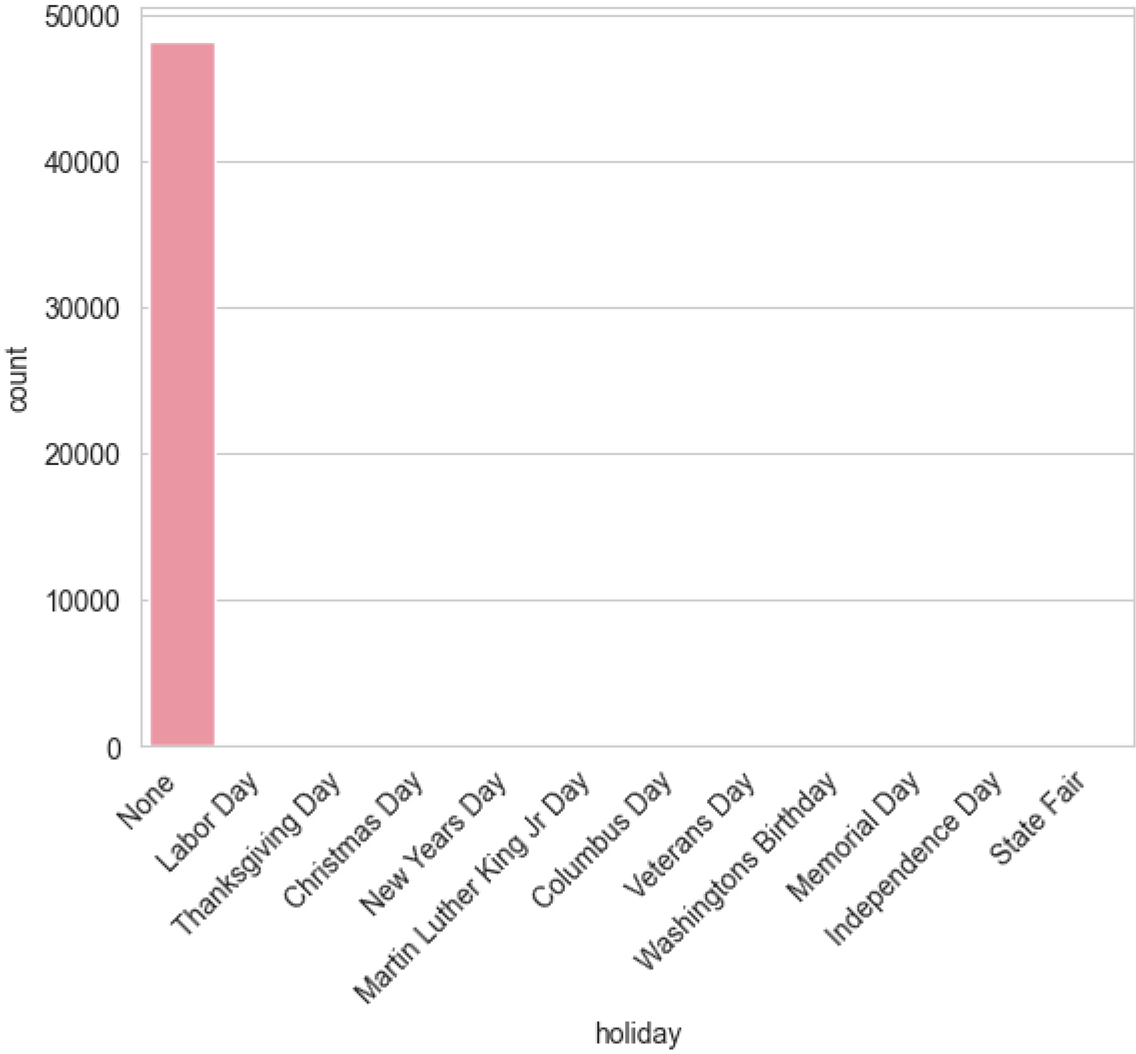
In [16]:
```
#A variável traffic_volume (que é a que queremos prever) tem baixa correlação com 
# As variáveis preditoras numéricas tem baixa correlação entre si o que é bom para
```

Exploração das variáveis categóricas

In [17]:
```
df['holiday'].value_counts()
```

Out[17]:
```
None                         48143
Labor Day                        7
Thanksgiving Day                 6
Christmas Day                    6
New Years Day                    6
Martin Luther King Jr Day        6
Columbus Day                     5
Veterans Day                     5
Washingtons Birthday             5
Memorial Day                     5
Independence Day                 5
State Fair                       5
Name: holiday, dtype: int64
```

In [18]:
```
ax = sns.countplot(data=df, x='holiday', order=df['holiday'].value_counts().index)
ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right')
plt.show()
```



In [19]:
```
quantidade_de_categorias_holiday = df['holiday'].nunique()
print("Quantidade de categorias de feriados:", quantidade_de_categorias_holiday)
```

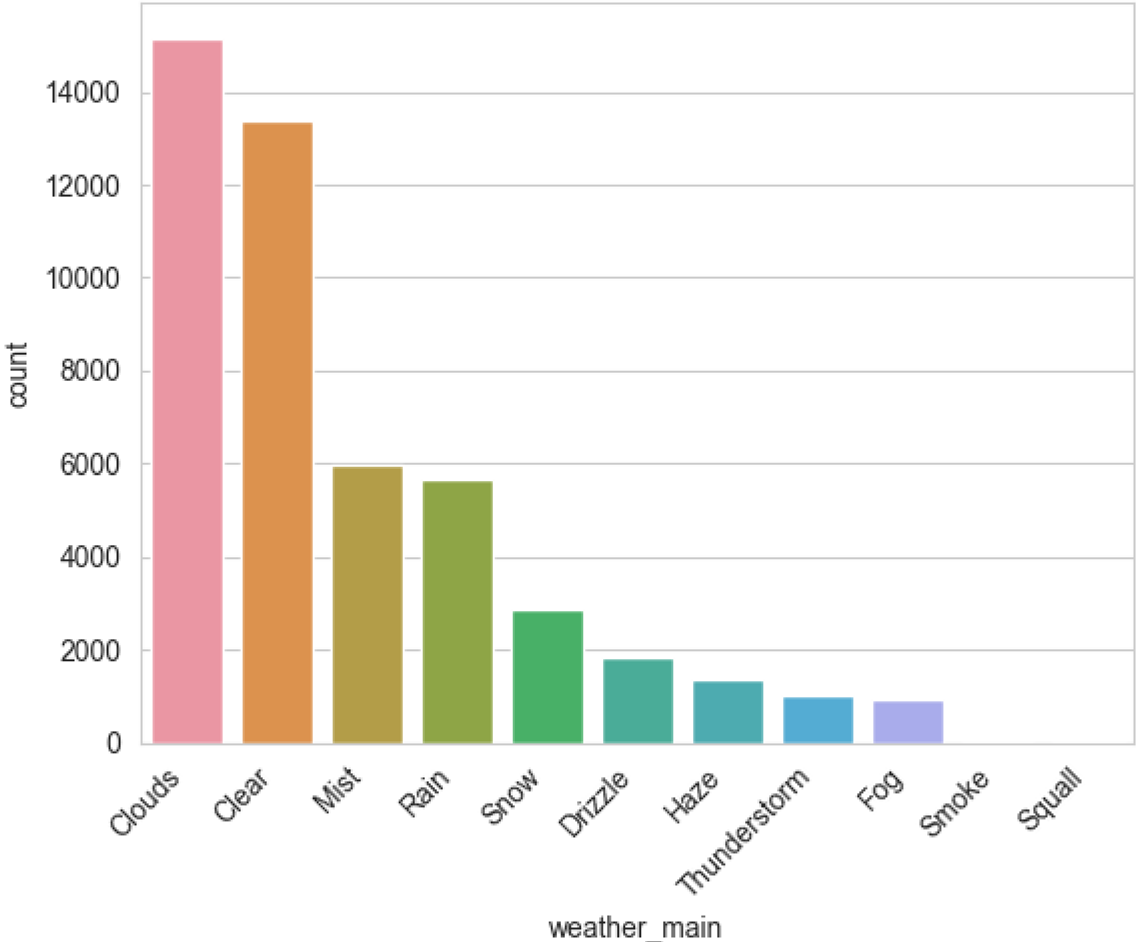
```
Quantidade de categorias de feriados: 12
```

In [20]:
```
# grande maioria de dias não é feriado
```

In [21]:
```
df['weather_main'].value_counts()
```

Out[21]:
```
Clouds          15164
Clear           13391
Mist             5950
Rain             5672
Snow             2876
Drizzle          1821
Haze             1360
Thunderstorm     1034
Fog               912
Smoke              20
Squall              4
Name: weather_main, dtype: int64
```

In [22]:
```
ax = sns.countplot(data=df, x='weather_main', order=df['weather_main'].value_counts
ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right')
plt.show()
```



In [23]:
```
# maioria dos dados está com tempo aberto ou nublado
```

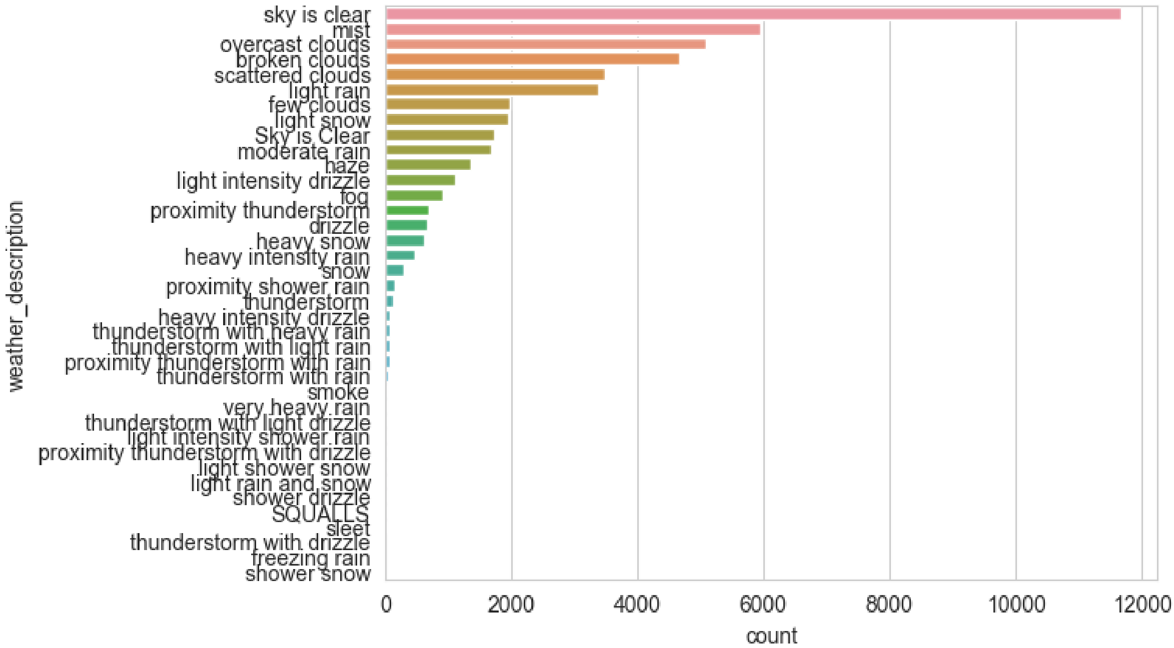
In [24]:
```
quantidade_de_categorias_weather_main = df['weather_main'].nunique()
print("Quantidade de categorias de tempo_resumo:", quantidade_de_categorias_weather
```

```
Quantidade de categorias de tempo_resumo: 11
```

In [25]:
```
df['weather_description'].value_counts()
```

Out[25]:
```
sky is clear                           11665
mist                                    5950
overcast clouds                         5081
broken clouds                           4666
scattered clouds                        3461
light rain                              3372
few clouds                              1956
light snow                              1946
Sky is Clear                            1726
moderate rain                           1664
haze                                    1360
light intensity drizzle                 1100
fog                                      912
proximity thunderstorm                   673
drizzle                                  651
heavy snow                               616
heavy intensity rain                     467
snow                                     293
proximity shower rain                    136
thunderstorm                             125
heavy intensity drizzle                   64
thunderstorm with heavy rain              63
thunderstorm with light rain              54
proximity thunderstorm with rain          52
thunderstorm with rain                    37
smoke                                     20
very heavy rain                           18
thunderstorm with light drizzle           15
light intensity shower rain               13
proximity thunderstorm with drizzle       13
light shower snow                         11
light rain and snow                        6
shower drizzle                             6
SQUALLS                                    4
sleet                                      3
thunderstorm with drizzle                  2
freezing rain                              2
shower snow                                1
Name: weather_description, dtype: int64
```

In [26]:
```
ax = sns.countplot(data=df, y='weather_description', orient='h', order=df['weather_
plt.show()
```



In [27]:
```
# maioria dos dados está com tempo aberto ou nublado
```

In [28]:
```
quantidade_de_categorias_weather_description = df['weather_description'].nunique()
print("Quantidade de categorias de tempo_resumo:", quantidade_de_categorias_weather
```

```
Quantidade de categorias de tempo_resumo: 38
```

Tratando a variável date_time

In [29]:
```
#converte variável date_time para tipo datetime
df['date_time'] = pd.to_datetime(df['date_time'], format='%Y-%m-%d %H:%M:%S')
```

In [30]:
```
#verifica tipo
df['date_time'].dtypes
```

Out[30]:
```
dtype('<M8[ns]')
```

In [31]:
```
#cria duas variáveis 'data' e 'hora'
df['data'] = df['date_time'].dt.date
df['hora_completa'] = df['date_time'].dt.time
#exclui a coluna 'date_time'
df = df.drop(columns=['date_time'])
```

In [32]:
```
df.sample(5)
```

Out[32]:

	holiday	temp	rain_1h	snow_1h	clouds_all	weather_main	weather_description	traffic_v
29636	None	266.51	0.00	0.0	1	Clear	sky is clear	
10525	None	260.50	0.25	0.0	64	Snow	light snow	
11951	None	0.00	0.00	0.0	0	Clear	sky is clear	
36382	None	288.01	0.00	0.0	1	Clear	sky is clear	
43185	None	277.15	0.00	0.0	90	Rain	light rain	

In [33]:
```
print(df.dtypes)
```

```
holiday                 object
temp                   float64
rain_1h                float64
snow_1h                float64
clouds_all               int64
weather_main            object
weather_description     object
traffic_volume           int64
data                    object
hora_completa           object
dtype: object
```

In [34]:
```
df.shape
```

Out[34]:
```
(48204, 10)
```

In [35]:
```
#converte a data e obriga o que estiver em formato errado a ficar como NaT (not a T
df['data'] = pd.to_datetime(df['data'], errors='coerce')
# Exclua as linhas com valores NaT na coluna 'data' e 'hora'
df = df.dropna(subset=['data'])
```

In [36]:
```
df.shape
```

Out[36]:
```
(48204, 10)
```

In [37]:
```
df.sample(5)
```

Out[37]:

	holiday	temp	rain_1h	snow_1h	clouds_all	weather_main	weather_description	traffic_v
1344	None	273.99	0.0	0.0	1	Mist	mist	
16968	None	292.84	0.0	0.0	1	Clear	sky is clear	
33320	None	280.65	0.0	0.0	75	Clouds	broken clouds	
33408	None	292.46	0.0	0.0	40	Clouds	scattered clouds	
6324	None	280.66	0.0	0.0	90	Mist	mist	

In [38]:
```
#problemas de formato na coluna 'hora_completa'
print(df['hora_completa'].unique())
```

```
[datetime.time(9, 0) datetime.time(10, 0) datetime.time(11, 0)
 datetime.time(12, 0) datetime.time(13, 0) datetime.time(14, 0)
 datetime.time(15, 0) datetime.time(16, 0) datetime.time(17, 0)
 datetime.time(18, 0) datetime.time(19, 0) datetime.time(20, 0)
 datetime.time(21, 0) datetime.time(22, 0) datetime.time(23, 0)
 datetime.time(0, 0) datetime.time(1, 0) datetime.time(2, 0)
 datetime.time(3, 0) datetime.time(4, 0) datetime.time(5, 0)
 datetime.time(6, 0) datetime.time(8, 0) datetime.time(7, 0)]
```

In [39]:
```
# Converte a coluna de datetime.time para uma string formatada
df['hora_completa'] = df['hora_completa'].astype(str)
# Extrai os dois primeiros dígitos de cada valor na coluna
df['apenas_hora'] = df['hora_completa'].str[:2]
```

In [40]:
```
df.shape
```

Out[40]:
```
(48204, 11)
```

In [41]:
```
df.sample(5)
```

Out[41]:

	holiday	temp	rain_1h	snow_1h	clouds_all	weather_main	weather_description	traffic_v
35202	None	298.29	0.0	0.0	75	Thunderstorm	proximity thunderstorm	
44776	None	291.15	0.0	0.0	1	Rain	moderate rain	
48014	None	296.90	0.0	0.0	40	Clouds	scattered clouds	
342	None	288.86	0.0	0.0	75	Clouds	broken clouds	
33753	None	284.79	0.0	0.0	90	Rain	heavy intensity rain	

In [42]:

```
#exclui a coluna 'hora_completa'
df = df.drop(columns=['hora_completa'])
```

In [43]:

```
df.sample(5)
```

Out[43]:

	holiday	temp	rain_1h	snow_1h	clouds_all	weather_main	weather_description	traffic_v
32973	None	287.69	0.00	0.0	1	Clear	sky is clear	
7036	None	292.85	1.52	0.0	88	Rain	moderate rain	
23430	None	280.01	0.00	0.0	1	Clear	sky is clear	
33177	None	285.48	0.00	0.0	1	Clear	sky is clear	
34947	None	295.77	0.00	0.0	90	Clouds	overcast clouds	

In [44]:

```
#alterar a coluna 'data' para formato 'dia-mês-ano'
df['data'] = df['data'].dt.strftime('%d-%m-%Y')
```

In [45]:

```
df.sample(5)
```

Out[45]:

	holiday	temp	rain_1h	snow_1h	clouds_all	weather_main	weather_description	traffic_v
23585	None	290.99	0.0	0.0	40	Thunderstorm	proximity thunderstorm	
41872	None	270.00	0.0	0.0	20	Clouds	few clouds	
45508	None	301.65	0.0	0.0	40	Clouds	scattered clouds	
5794	None	281.05	0.0	0.0	90	Clouds	overcast clouds	
19374	None	278.15	0.0	0.0	5	Clear	sky is clear	

In [46]:

```
#mudando 'data' para tipo 'datetime'
df['data'] = pd.to_datetime(df['data'])
#criando as variáveis 'dia','mes','ano'
df['dia'] = df['data'].dt.day
df['mes'] = df['data'].dt.month
df['ano'] = df['data'].dt.year
```

In [47]:

```
print(df.dtypes)
```

```
holiday                          object
temp                            float64
rain_1h                         float64
snow_1h                         float64
clouds_all                        int64
weather_main                     object
weather_description              object
traffic_volume                    int64
data                     datetime64[ns]
apenas_hora                      object
dia                               int64
mes                               int64
ano                               int64
dtype: object
```

In [48]:

```
df.sample(5)
```

Out[48]:

	holiday	temp	rain_1h	snow_1h	clouds_all	weather_main	weather_description	traffic_v
8212	None	290.16	0.00	0.0	92	Clouds	overcast clouds	
5868	None	293.30	0.00	0.0	40	Clouds	scattered clouds	
18350	None	295.86	1.52	0.0	90	Rain	moderate rain	
10320	None	274.59	0.00	0.0	64	Drizzle	drizzle	
25544	None	291.19	0.00	0.0	0	Clear	Sky is Clear	

In [49]:
```
# Ordene o DataFrame por dia, mês e ano ao mesmo tempo em ordem crescente
df = df.sort_values(by=['ano', 'mes', 'dia','apenas_hora'])

# Se desejar, você pode redefinir o índice do DataFrame após a ordenação
df = df.reset_index(drop=True)
```

In [50]:
```
df.head(5)
```

Out[50]:

	holiday	temp	rain_1h	snow_1h	clouds_all	weather_main	weather_description	traffic_volum
0	None	271.73	0.0	0.0	1	Clear	sky is clear	71
1	None	270.91	0.0	0.0	1	Clear	sky is clear	45
2	None	270.15	0.0	0.0	1	Clear	sky is clear	32
3	None	269.68	0.0	0.0	1	Clear	sky is clear	39
4	None	269.44	0.0	0.0	1	Clear	sky is clear	77

In [51]:
```
colunas_para_manter = [col for col in df.columns if col not in ['apenas_hora', 'tra
# Reorganizando a ordem das colunas
df = df[colunas_para_manter + ['apenas_hora', 'traffic_volume']]
```

In [52]:
```
#mudando a coluna 'apenas_hora' para tipo int
df['apenas_hora'] = df['apenas_hora'].astype(int)
```

In [53]:
```
df.sample(5)
```

Out[53]:

	holiday	temp	rain_1h	snow_1h	clouds_all	weather_main	weather_description	data	c
27822	None	256.65	0.00	0.0	90	Haze	haze	2016-11-01	
22424	None	295.68	0.28	0.0	92	Rain	light rain	2016-04-08	
12608	None	272.28	0.00	0.0	75	Clouds	broken clouds	2014-03-18	
7253	None	280.67	0.00	0.0	36	Clouds	scattered clouds	2013-07-10	
4478	None	267.88	0.00	0.0	40	Clouds	scattered clouds	2013-03-28	

In [54]:
```
# Ordene o DataFrame por dia, mês e ano ao mesmo tempo em ordem crescente
df = df.sort_values(by=['ano', 'mes', 'dia','apenas_hora'])

# Se desejar, você pode redefinir o índice do DataFrame após a ordenação
df = df.reset_index(drop=True)
```

In [55]:
```
df.head(10)
```

Out[55]:

	holiday	temp	rain_1h	snow_1h	clouds_all	weather_main	weather_description	data	dia	ı
0	None	271.73	0.0	0.0	1	Clear	sky is clear	2012-01-11	11	
1	None	270.91	0.0	0.0	1	Clear	sky is clear	2012-01-11	11	
2	None	270.15	0.0	0.0	1	Clear	sky is clear	2012-01-11	11	
3	None	269.68	0.0	0.0	1	Clear	sky is clear	2012-01-11	11	
4	None	269.44	0.0	0.0	1	Clear	sky is clear	2012-01-11	11	
5	None	268.96	0.0	0.0	1	Clear	sky is clear	2012-01-11	11	
6	None	268.61	0.0	0.0	1	Clear	sky is clear	2012-01-11	11	
7	None	268.74	0.0	0.0	1	Clear	sky is clear	2012-01-11	11	
8	None	268.45	0.0	0.0	20	Clouds	few clouds	2012-01-11	11	
9	None	270.90	0.0	0.0	1	Clear	sky is clear	2012-01-11	11	

In [56]:
```
#até aqui tenho o dataset df faltando tratar as variáveis categóricas holiday, weat
```

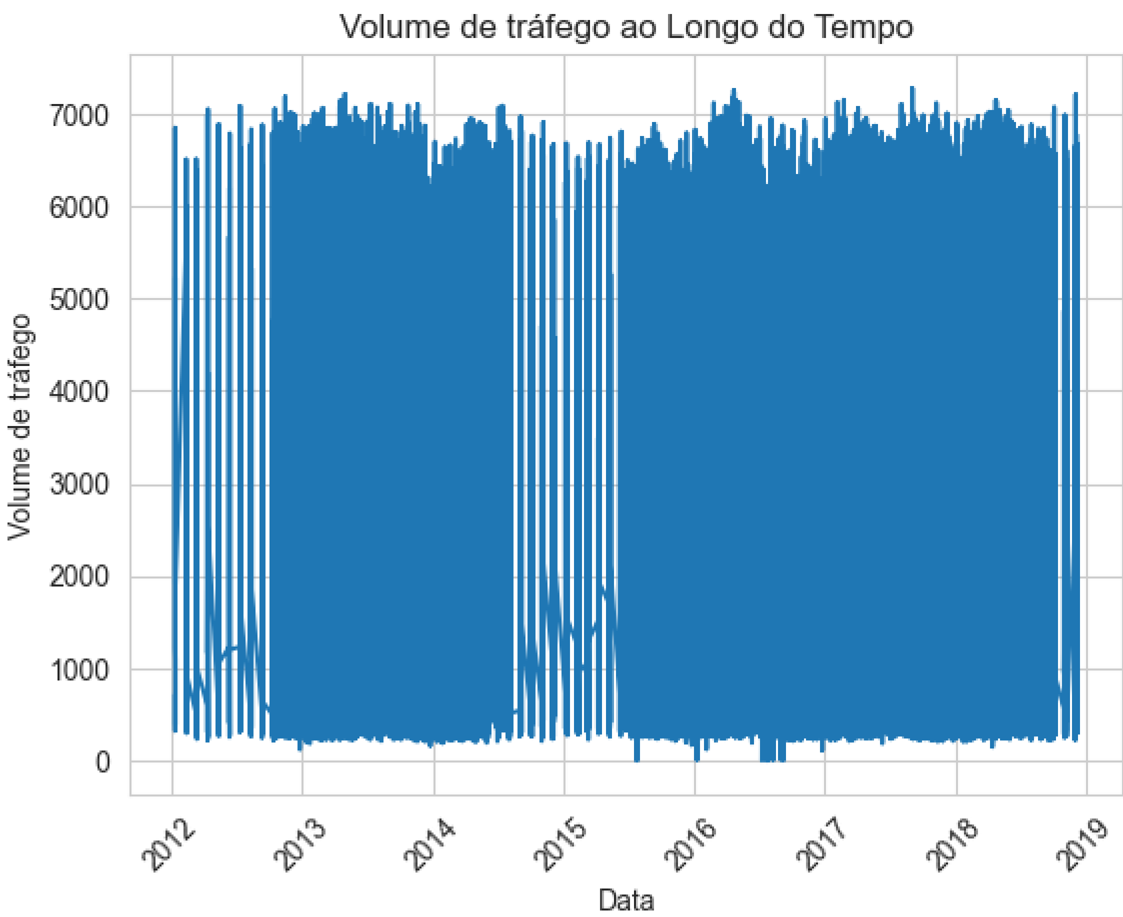
In [57]:
```
#gráfico da variável target que é o 'traffic_volume'
plt.plot(df['data'], df['traffic_volume'])
```

```python
# Rotule os eixos
plt.xlabel('Data')
plt.ylabel('Volume de tráfego')

# Adicione um título ao gráfico
plt.title('Volume de tráfego ao Longo do Tempo')

# Rotacione os rótulos do eixo x para torná-los mais legíveis, se necessário
plt.xticks(rotation=45)

# Mostre o gráfico
plt.show()
```



In [58]:

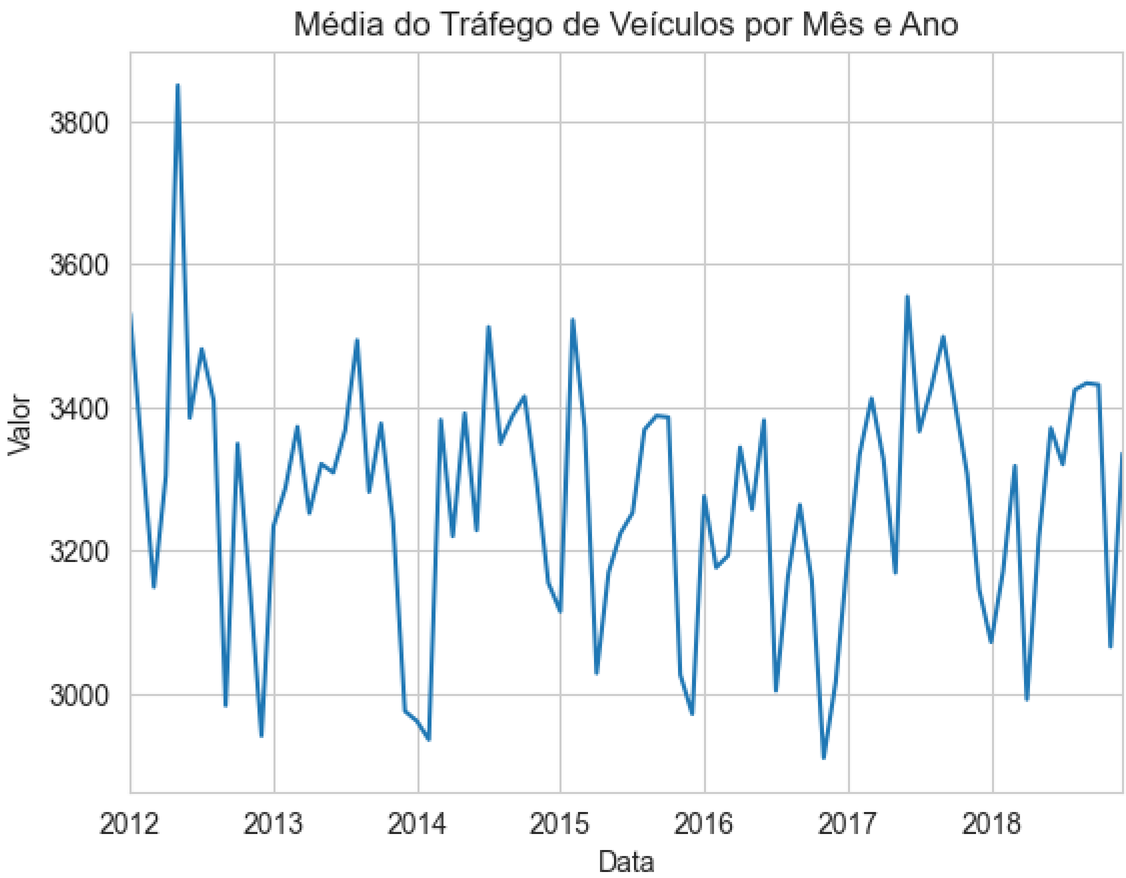
```python
#visualização ficou muito ruim
#vamos agrupar os dados por mês e ano para melhorar a visualização
```

In [59]:

```python
# Crie uma coluna de data concatenando 'ano' e 'mes'
df['mes_ano'] = pd.to_datetime(df['mes'].astype(str) + '-' + df['ano'].astype(str),

# Agrupe os dados pela nova coluna de data e aplique a função de agregação desejado
dados_agrupados = df.groupby('mes_ano')['traffic_volume'].mean()  # Por exemplo, co

# Plotar os dados agrupados
dados_agrupados.plot(kind='line', xlabel='Data', ylabel='Valor', title='Média do Tr
plt.show()
```

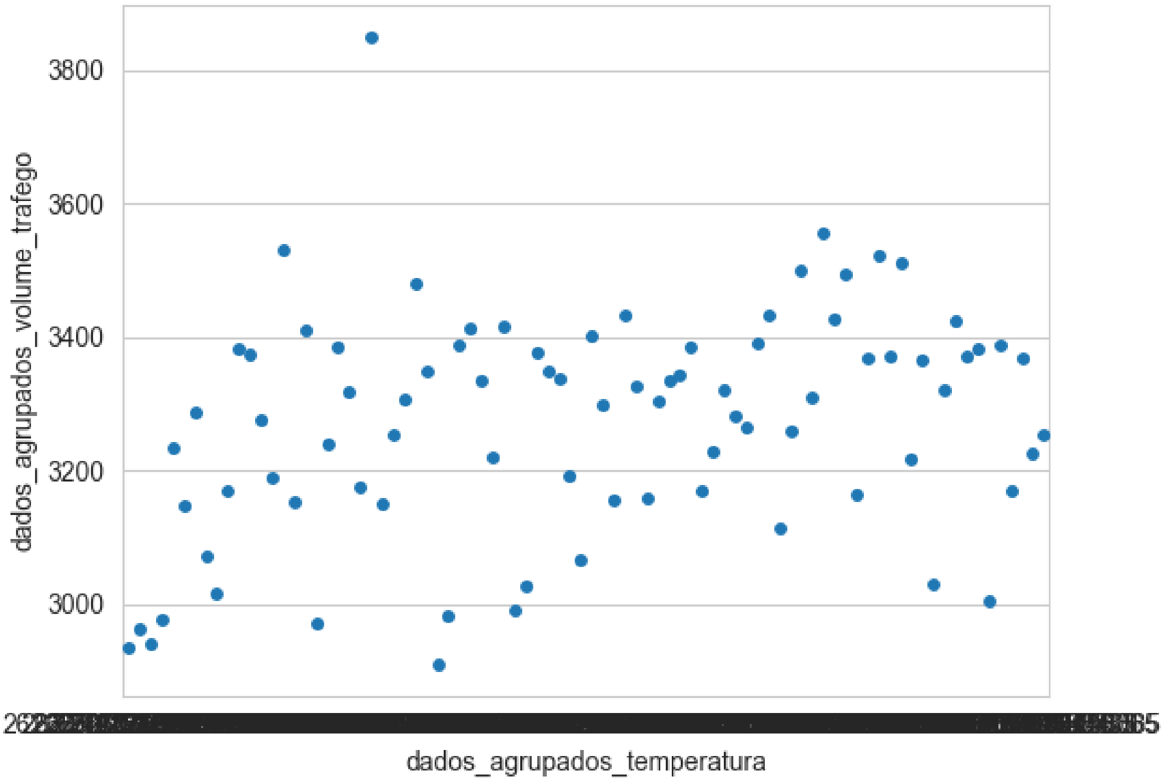


In [60]:
```
#vamos que de 2013 a 2019 ocorre uma sazonalidade sendo o meio do ano o período em
```

Verificando a relação entre atributos

In [61]:
```
# Agrupe os dados pela nova coluna de data e aplique a função de agregação desejadc
dados_agrupados_temp = df.groupby('mes_ano')['temp'].mean()
# Plotar os dados agrupados
sns.stripplot(data=df, x=dados_agrupados_temp, y=dados_agrupados, jitter=True)
plt.xlabel('dados_agrupados_temperatura')
plt.ylabel('dados_agrupados_volume_trafego')
```

Out[61]:
```
Text(0, 0.5, 'dados_agrupados_volume_trafego')
```



Observando o gráfico de dispersão verificamos que não há correlação entre a temperatura e o volume de tráfego.

7 - Pré-Processamento de Dados Para Construção de Modelos de Machine Learning

In [62]:
```
df.shape
```
Out[62]:
```
(48204, 14)
```

In [63]:
```
# Verificando valores ausentes
numero_ausentes = df.isnull().sum()
print('A quantidade de valores ausentes em cada coluna é:\n', numero_ausentes)
```
```
A quantidade de valores ausentes em cada coluna é:
 holiday                0
temp                   0
rain_1h                0
snow_1h                0
clouds_all             0
weather_main           0
weather_description    0
data                   0
dia                    0
mes                    0
ano                    0
apenas_hora            0
traffic_volume         0
mes_ano                0
dtype: int64
```

In [64]:
```
# Verifica registros duplicados (remove uma das duplicatas)
numero_duplicados = df.duplicated().sum()
print('A quantidade de valores duplicados é: ', numero_duplicados)
```

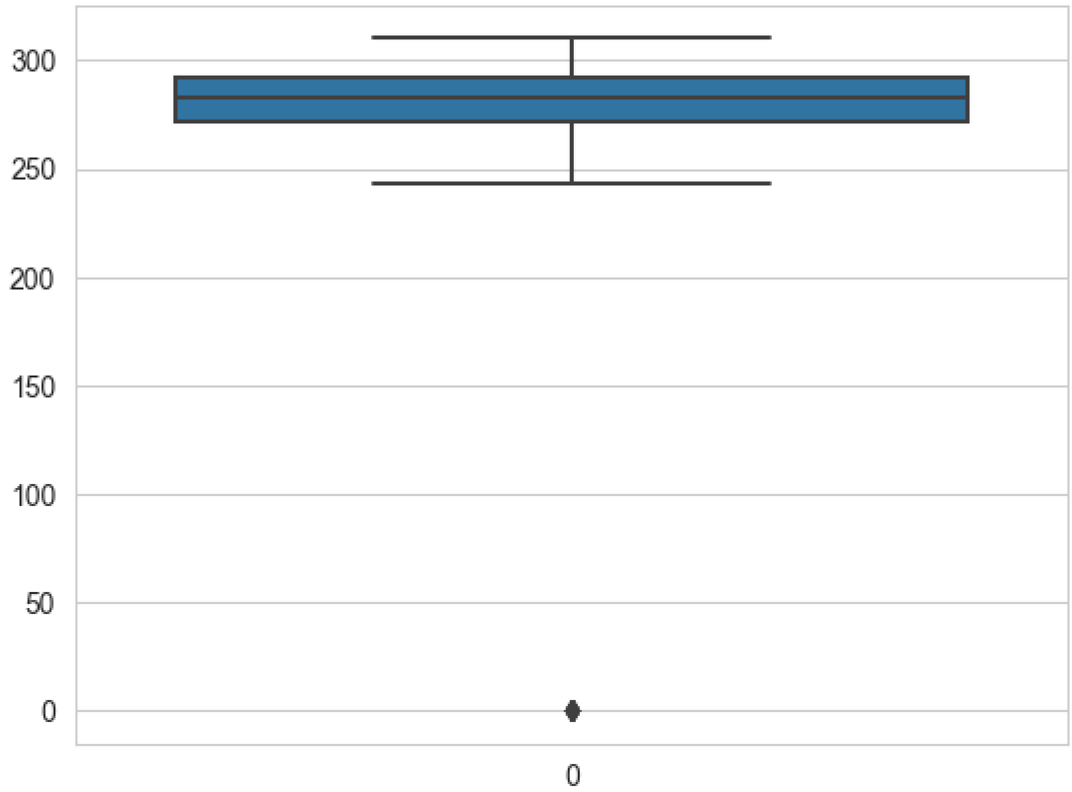
```
A quantidade de valores duplicados é:  17
```

In [65]:
```
#remove valores duplicados
df = df.drop_duplicates()
```

Tratamento de outliers

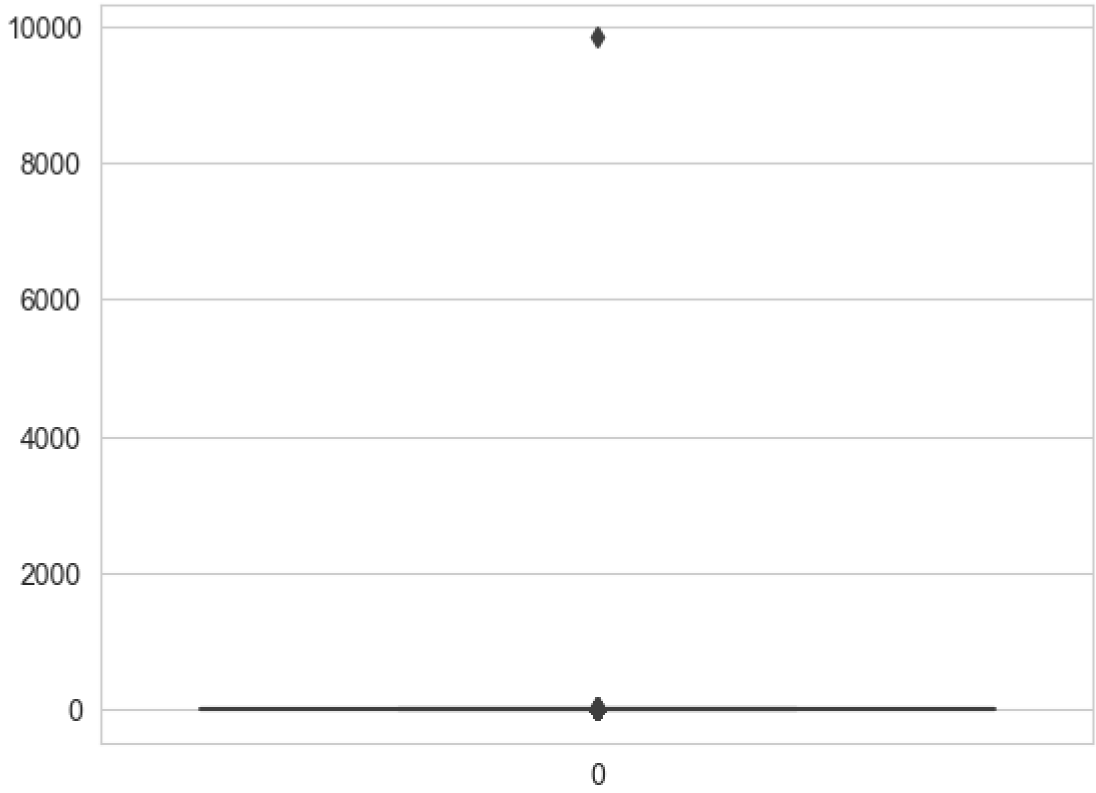
In [66]:
```
# Boxplot
sns.boxplot(df.temp)
```

Out[66]:
```
<Axes: >
```



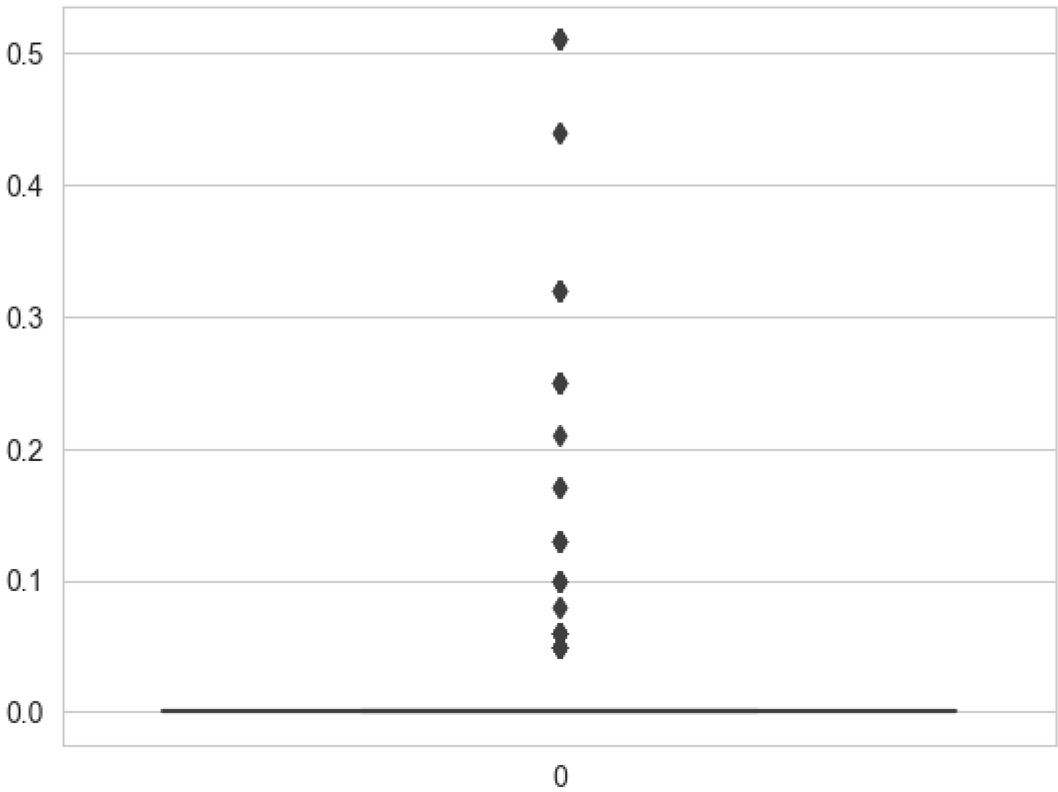
In [67]:
```
# Boxplot
sns.boxplot(df.rain_1h)
```

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



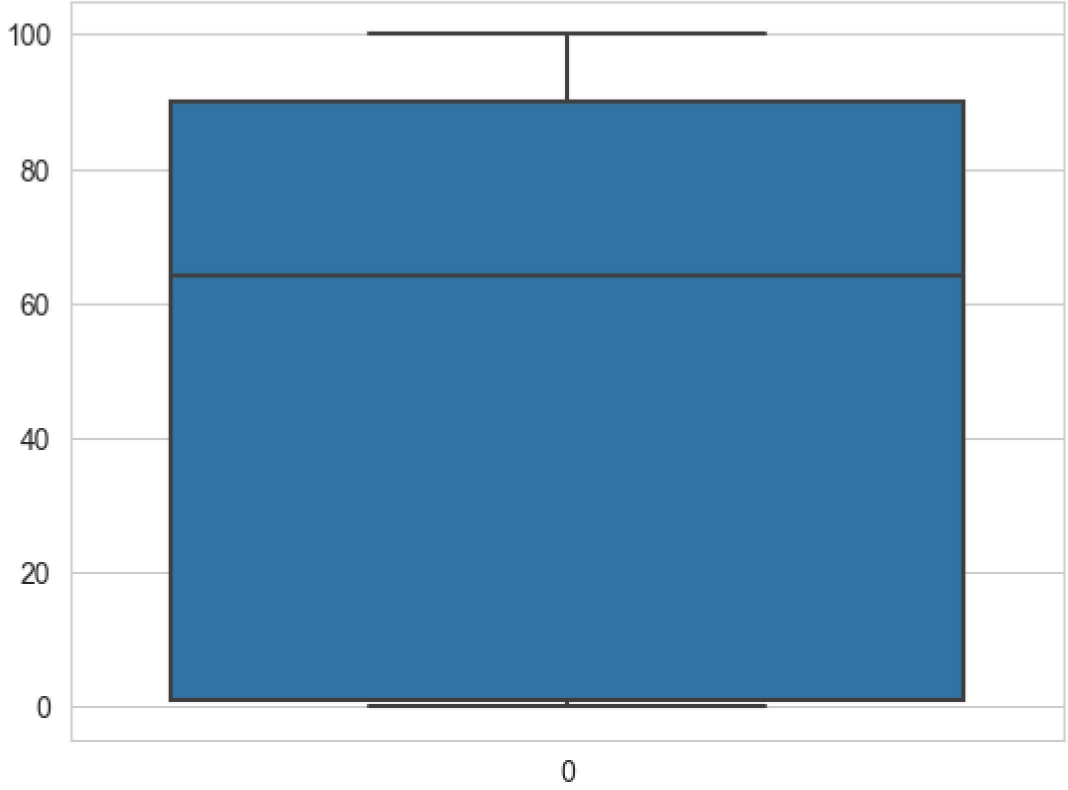
In [68]:
```
# Boxplot
sns.boxplot(df.snow_1h)
```

Out[68]: <Axes: >



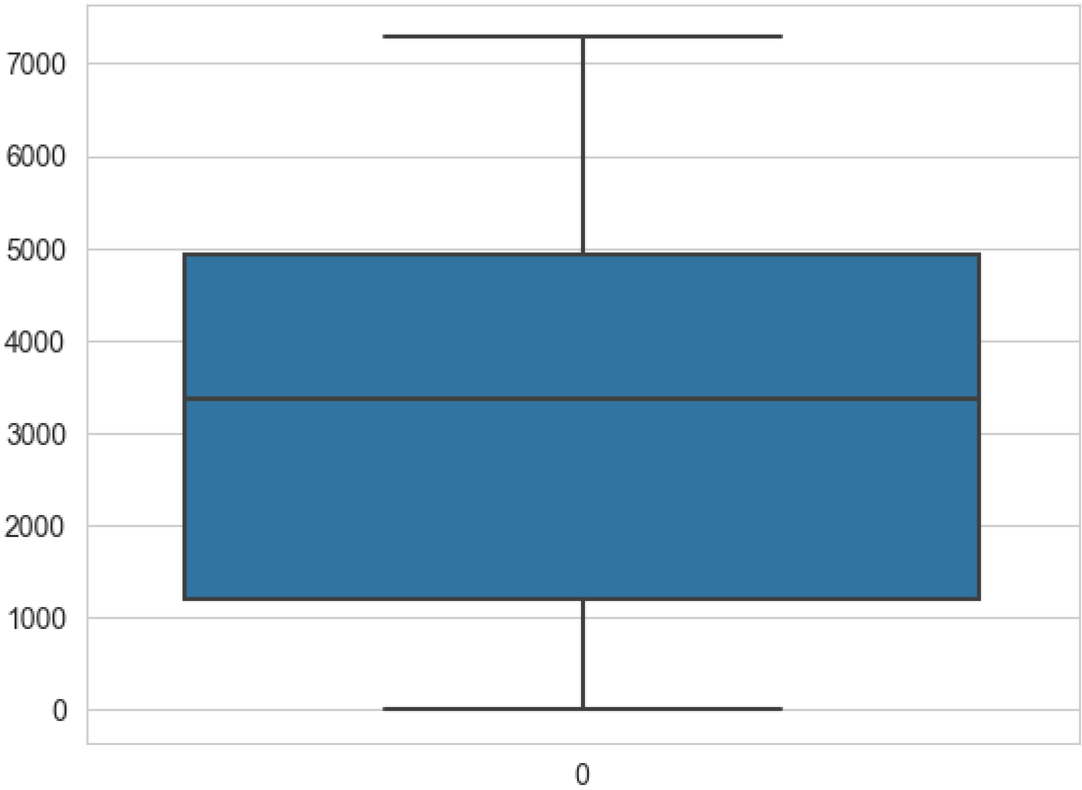
In [69]:
```
# Boxplot
sns.boxplot(df.clouds_all)
```

Out[69]: <Axes: >



In [70]:
```
# Boxplot
sns.boxplot(df.traffic_volume)
```

Out[70]: <Axes: >



In [71]:
```
#outliers - variável temp
# Calcular os quartis
Q1 = df['temp'].quantile(0.25)
Q3 = df['temp'].quantile(0.75)

# Calcular o intervalo interquartil (IQR)
```

```
IQR = Q3 - Q1

# Definir limites para identificar outliers
limite_inferior = Q1 - 1.5 * IQR
limite_superior = Q3 + 1.5 * IQR

# Identificar outliers
outliers_inferiores = df[df['temp'] < limite_inferior]
outliers_superiores = df[df['temp'] > limite_superior]

# Contar a quantidade de outliers inferiores e superiores
quantidade_outliers_inferiores = len(outliers_inferiores)
quantidade_outliers_superiores = len(outliers_superiores)

print("Quantidade de outliers inferiores:", quantidade_outliers_inferiores)
print("Quantidade de outliers superiores:", quantidade_outliers_superiores)
```

```
Quantidade de outliers inferiores: 10
Quantidade de outliers superiores: 0
```

In [72]:
```
# Decisão: Manter o outlier
```

In [73]:
```
#outliers - variável rain_1h
# Calcular os quartis
Q1 = df['rain_1h'].quantile(0.25)
Q3 = df['rain_1h'].quantile(0.75)

# Calcular o intervalo interquartil (IQR)
IQR = Q3 - Q1

# Definir limites para identificar outliers
limite_inferior = Q1 - 1.5 * IQR
limite_superior = Q3 + 1.5 * IQR

# Identificar outliers
outliers_inferiores = df[df['rain_1h'] < limite_inferior]
outliers_superiores = df[df['rain_1h'] > limite_superior]

# Contar a quantidade de outliers inferiores e superiores
quantidade_outliers_inferiores = len(outliers_inferiores)
quantidade_outliers_superiores = len(outliers_superiores)

print("Quantidade de outliers inferiores:", quantidade_outliers_inferiores)
print("Quantidade de outliers superiores:", quantidade_outliers_superiores)
```

```
Quantidade de outliers inferiores: 0
Quantidade de outliers superiores: 3467
```

In [74]:
```
# Decisão: Manter o outlier
```

In [75]:
```
#outliers - variável snow_1h
# Calcular os quartis
Q1 = df['snow_1h'].quantile(0.25)
Q3 = df['snow_1h'].quantile(0.75)

# Calcular o intervalo interquartil (IQR)
IQR = Q3 - Q1

# Definir limites para identificar outliers
limite_inferior = Q1 - 1.5 * IQR
limite_superior = Q3 + 1.5 * IQR

# Identificar outliers
outliers_inferiores = df[df['snow_1h'] < limite_inferior]
```

```
outliers_superiores = df[df['snow_1h'] > limite_superior]

# Contar a quantidade de outliers inferiores e superiores
quantidade_outliers_inferiores = len(outliers_inferiores)
quantidade_outliers_superiores = len(outliers_superiores)

print("Quantidade de outliers inferiores:", quantidade_outliers_inferiores)
print("Quantidade de outliers superiores:", quantidade_outliers_superiores)
```

```
Quantidade de outliers inferiores: 0
Quantidade de outliers superiores: 63
```

In [76]:
```
# Decisão: Manter o outlier
```

In [77]:
```
#outliers - variável clouds_all
# Calcular os quartis
Q1 = df['clouds_all'].quantile(0.25)
Q3 = df['clouds_all'].quantile(0.75)

# Calcular o intervalo interquartil (IQR)
IQR = Q3 - Q1

# Definir limites para identificar outliers
limite_inferior = Q1 - 1.5 * IQR
limite_superior = Q3 + 1.5 * IQR

# Identificar outliers
outliers_inferiores = df[df['clouds_all'] < limite_inferior]
outliers_superiores = df[df['clouds_all'] > limite_superior]

# Contar a quantidade de outliers inferiores e superiores
quantidade_outliers_inferiores = len(outliers_inferiores)
quantidade_outliers_superiores = len(outliers_superiores)

print("Quantidade de outliers inferiores:", quantidade_outliers_inferiores)
print("Quantidade de outliers superiores:", quantidade_outliers_superiores)
```

```
Quantidade de outliers inferiores: 0
Quantidade de outliers superiores: 0
```

In [78]:
```
 # Decisão: Manter. Não tem outliers.
```

In [79]:
```
#outliers - variável traffic_volume
# Calcular os quartis
Q1 = df['traffic_volume'].quantile(0.25)
Q3 = df['traffic_volume'].quantile(0.75)

# Calcular o intervalo interquartil (IQR)
IQR = Q3 - Q1

# Definir limites para identificar outliers
limite_inferior = Q1 - 1.5 * IQR
limite_superior = Q3 + 1.5 * IQR

# Identificar outliers
outliers_inferiores = df[df['traffic_volume'] < limite_inferior]
outliers_superiores = df[df['traffic_volume'] > limite_superior]

# Contar a quantidade de outliers inferiores e superiores
quantidade_outliers_inferiores = len(outliers_inferiores)
quantidade_outliers_superiores = len(outliers_superiores)
```

```
print("Quantidade de outliers inferiores:", quantidade_outliers_inferiores)
print("Quantidade de outliers superiores:", quantidade_outliers_superiores)
```

```
Quantidade de outliers inferiores: 0
Quantidade de outliers superiores: 0
```

In [80]:
```
# Decisão:  Manter. Não tem outliers.
```

Tratamento de variaveis categóricas

In [81]:
```
df.sample(5)
```

Out[81]:

	holiday	temp	rain_1h	snow_1h	clouds_all	weather_main	weather_description	data	c
6420	None	276.70	0.0	0.0	90	Clouds	overcast clouds	2013-06-05	
15297	None	264.63	0.0	0.0	64	Clouds	broken clouds	2014-09-01	
4556	None	277.34	0.0	0.0	90	Rain	moderate rain	2013-03-31	
42029	None	299.48	0.0	0.0	90	Clouds	overcast clouds	2018-03-08	
15421	None	293.63	0.0	0.0	90	Clouds	overcast clouds	2014-09-06	

In [82]:
```
df['holiday'].value_counts()
```

Out[82]:
```
None                          48126
Labor Day                         7
Thanksgiving Day                  6
Christmas Day                     6
New Years Day                     6
Martin Luther King Jr Day         6
Columbus Day                      5
Veterans Day                      5
Washingtons Birthday              5
Independence Day                  5
Memorial Day                      5
State Fair                        5
Name: holiday, dtype: int64
```

In [83]:
```
df['weather_main'].value_counts()
```

Out[83]:
```
Clouds          15158
Clear           13384
Mist             5949
Rain             5672
Snow             2875
Drizzle          1820
Haze             1360
Thunderstorm     1033
Fog               912
Smoke              20
Squall              4
Name: weather_main, dtype: int64
```

In [84]:
```
df['weather_description'].value_counts()
```

Out[84]:
```
sky is clear                           11659
mist                                    5949
overcast clouds                         5079
broken clouds                           4663
scattered clouds                        3460
light rain                              3372
few clouds                              1956
light snow                              1945
Sky is Clear                            1725
moderate rain                           1664
haze                                    1360
light intensity drizzle                 1099
fog                                      912
proximity thunderstorm                   673
drizzle                                  651
heavy snow                               616
heavy intensity rain                     467
snow                                     293
proximity shower rain                    136
thunderstorm                             124
heavy intensity drizzle                   64
thunderstorm with heavy rain              63
thunderstorm with light rain              54
proximity thunderstorm with rain          52
thunderstorm with rain                    37
smoke                                     20
very heavy rain                           18
thunderstorm with light drizzle           15
proximity thunderstorm with drizzle       13
light intensity shower rain               13
light shower snow                         11
light rain and snow                        6
shower drizzle                             6
SQUALLS                                    4
sleet                                      3
freezing rain                              2
thunderstorm with drizzle                  2
shower snow                                1
Name: weather_description, dtype: int64
```

In [85]:
```
#decisão - excluir a variável 'weather_description'
#exclui a coluna 'hora_completa'
df = df.drop(columns=['weather_description'])
```

In [86]:
```
df.sample(5)
```

Out[86]:

	holiday	temp	rain_1h	snow_1h	clouds_all	weather_main	data	dia	mes	ano	apen
9208	None	289.30	0.00	0.0	92	Mist	2013-10-06	6	10	2013	
44444	None	286.08	2.79	0.0	1	Rain	2018-06-09	9	6	2018	
46064	None	299.95	0.00	0.0	75	Clouds	2018-08-14	14	8	2018	
8593	None	302.57	0.00	0.0	0	Clear	2013-09-07	7	9	2013	
10536	None	301.21	0.00	0.0	8	Clear	2013-12-07	7	12	2013	

In [87]:
```
print(df.dtypes)
```

```
holiday                   object
temp                     float64
rain_1h                  float64
snow_1h                  float64
clouds_all                 int64
weather_main              object
data              datetime64[ns]
dia                        int64
mes                        int64
ano                        int64
apenas_hora                int32
traffic_volume             int64
mes_ano           datetime64[ns]
dtype: object
```

In [88]:
```
qtde_holiday = df['holiday'].nunique()
qtde_holiday
```

Out[88]:
```
12
```

In [89]:
```
# Obter categorias únicas da coluna 'holiday'
cat_holiday = df['holiday'].unique()

# Criar um dicionário para mapear categorias para valores ordinais
mapeamento = {categoria : i+1 for i, categoria in enumerate(cat_holiday)}

# Aplicar o mapeamento à coluna 'holiday'
df['holiday'] = df['holiday'].map(mapeamento)

print(df)
```

```
       holiday    temp  rain_1h  snow_1h  clouds_all weather_main       data  \
0            1  271.73      0.0      0.0           1        Clear 2012-01-11
1            1  270.91      0.0      0.0           1        Clear 2012-01-11
2            1  270.15      0.0      0.0           1        Clear 2012-01-11
3            1  269.68      0.0      0.0           1        Clear 2012-01-11
4            1  269.44      0.0      0.0           1        Clear 2012-01-11
...        ...     ...      ...      ...         ...          ...        ...
48199        1  300.14      0.0      0.0          20       Clouds 2018-12-09
48200        1  297.82      0.0      0.0           5        Clear 2018-12-09
48201        1  296.10      0.0      0.0           5        Clear 2018-12-09
48202        1  295.32      0.0      0.0           5        Clear 2018-12-09
48203        1  294.46      0.0      0.0           1        Clear 2018-12-09

       dia  mes   ano  apenas_hora  traffic_volume    mes_ano
0       11    1  2012            0             716 2012-01-01
1       11    1  2012            1             453 2012-01-01
2       11    1  2012            2             324 2012-01-01
3       11    1  2012            3             390 2012-01-01
4       11    1  2012            4             775 2012-01-01
...    ...  ...   ...          ...             ...        ...
48199    9   12  2018           19            3510 2018-12-01
48200    9   12  2018           20            3064 2018-12-01
48201    9   12  2018           21            2705 2018-12-01
48202    9   12  2018           22            1813 2018-12-01
48203    9   12  2018           23            2842 2018-12-01

[48187 rows x 13 columns]
```

In [90]:
```
qtde_weather_main = df['weather_main'].nunique()
qtde_weather_main
```

Out[90]:
```
11
```

In [91]:
```
# Obter categorias únicas da coluna 'holiday'
cat_weather_main = df['weather_main'].unique()

# Criar um dicionário para mapear categorias para valores ordinais
mapeamento = {categoria : i+1 for i, categoria in enumerate(cat_weather_main)}

# Aplicar o mapeamento à coluna 'holiday'
df['weather_main'] = df['weather_main'].map(mapeamento)

print(df)
```

```
       holiday    temp  rain_1h  snow_1h  clouds_all  weather_main       data  \
0            1  271.73      0.0      0.0           1             1 2012-01-11
1            1  270.91      0.0      0.0           1             1 2012-01-11
2            1  270.15      0.0      0.0           1             1 2012-01-11
3            1  269.68      0.0      0.0           1             1 2012-01-11
4            1  269.44      0.0      0.0           1             1 2012-01-11
...        ...     ...      ...      ...         ...           ...        ...
48199        1  300.14      0.0      0.0          20             2 2018-12-09
48200        1  297.82      0.0      0.0           5             1 2018-12-09
48201        1  296.10      0.0      0.0           5             1 2018-12-09
48202        1  295.32      0.0      0.0           5             1 2018-12-09
48203        1  294.46      0.0      0.0           1             1 2018-12-09

       dia  mes   ano  apenas_hora  traffic_volume     mes_ano
0       11    1  2012            0             716  2012-01-01
1       11    1  2012            1             453  2012-01-01
2       11    1  2012            2             324  2012-01-01
3       11    1  2012            3             390  2012-01-01
4       11    1  2012            4             775  2012-01-01
...    ...  ...   ...          ...             ...         ...
48199    9   12  2018           19            3510  2018-12-01
48200    9   12  2018           20            3064  2018-12-01
48201    9   12  2018           21            2705  2018-12-01
48202    9   12  2018           22            1813  2018-12-01
48203    9   12  2018           23            2842  2018-12-01

[48187 rows x 13 columns]
```

In [92]:
```
#cria variáveis dummy para 'holiday' e 'weather_main'
#df = pd.get_dummies(df, columns=['holiday', 'weather_main'])
```

In [93]:
```
df.head(5)
```

Out[93]:

	holiday	temp	rain_1h	snow_1h	clouds_all	weather_main	data	dia	mes	ano	apenas_hc
0	1	271.73	0.0	0.0	1	1	2012-01-11	11	1	2012	
1	1	270.91	0.0	0.0	1	1	2012-01-11	11	1	2012	
2	1	270.15	0.0	0.0	1	1	2012-01-11	11	1	2012	
3	1	269.68	0.0	0.0	1	1	2012-01-11	11	1	2012	
4	1	269.44	0.0	0.0	1	1	2012-01-11	11	1	2012	

In [94]:
```
# Armazenar a coluna que queremos mover
coluna_a_mover = df.pop('traffic_volume')

# Anexar a coluna de volta ao final do DataFrame
df['traffic_volume'] = coluna_a_mover
```

In [95]:
```
df.head(5)
```

Out[95]:

	holiday	temp	rain_1h	snow_1h	clouds_all	weather_main	data	dia	mes	ano	apenas_hc
0	1	271.73	0.0	0.0	1	1	2012-01-11	11	1	2012	
1	1	270.91	0.0	0.0	1	1	2012-01-11	11	1	2012	
2	1	270.15	0.0	0.0	1	1	2012-01-11	11	1	2012	
3	1	269.68	0.0	0.0	1	1	2012-01-11	11	1	2012	
4	1	269.44	0.0	0.0	1	1	2012-01-11	11	1	2012	

In [96]:
```
df.columns
```

Out[96]:
```
Index(['holiday', 'temp', 'rain_1h', 'snow_1h', 'clouds_all', 'weather_main',
       'data', 'dia', 'mes', 'ano', 'apenas_hora', 'mes_ano',
       'traffic_volume'],
      dtype='object')
```

In [97]:
```
df.shape
```

Out[97]:
```
(48187, 13)
```

In [98]:
```
df.dtypes
```

Out[98]:
```
holiday                    int64
temp                     float64
rain_1h                  float64
snow_1h                  float64
clouds_all                 int64
weather_main               int64
data              datetime64[ns]
dia                        int64
mes                        int64
ano                        int64
apenas_hora                int32
mes_ano           datetime64[ns]
traffic_volume             int64
dtype: object
```

In [99]:
```
df.sample(5)
```

Out[99]:

	holiday	temp	rain_1h	snow_1h	clouds_all	weather_main	data	dia	mes	ano	apen
22837	1	289.23	0.0	0.0	40	9	2016-04-24	24	4	2016	
12052	1	267.90	0.0	0.0	90	2	2014-02-17	17	2	2014	
33841	1	284.84	0.0	0.0	90	2	2017-05-18	18	5	2017	
17491	1	302.58	0.0	0.0	40	2	2015-07-26	26	7	2015	
45456	1	291.35	0.0	0.0	90	6	2018-07-20	20	7	2018	

8 - Construção, Treinamento e Avaliação do Modelo 1 com Regressão Logística (Benchmark)

In [100…

```
# Preparando os dados de treino e teste
X = df.drop(columns=['traffic_volume', 'data', 'mes_ano'])
y = df['traffic_volume']

X_treino, X_teste, y_treino, y_teste = train_test_split(X, y, test_size=0.2, random
```

In [101…

```
X_treino.dtypes
```

Out[101]:

```
holiday           int64
temp            float64
rain_1h         float64
snow_1h         float64
clouds_all        int64
weather_main      int64
dia               int64
mes               int64
ano               int64
apenas_hora       int32
dtype: object
```

Padronização

In [102…

```
scaler = StandardScaler()
```

In [103…

```
scaler.fit(X_treino)
```

Out[103]:

```
▾ StandardScaler
StandardScaler()
```

In [104…

```
X_treino = scaler.transform(X_treino)
```

In [105…

```
X_teste = scaler.transform(X_teste)
```

In [106…

```
X_treino[:5]
```

Out[106]:

```
array([[-0.03148663, -0.29427646, -0.00776763, -0.02489695, -1.26456512,
        -0.96219611, -0.30850414,  1.01831146,  0.2572608 , -0.05734534],
       [-0.03148663, -0.45209304, -0.00776763, -0.02489695,  1.04227068,
         0.73806851, -1.67928199,  1.01831146,  1.31261321,  1.67092796],
       [-0.03148663,  0.61119429, -0.00776763, -0.02489695,  1.04227068,
         0.73806851,  1.1765052 ,  0.4322164 ,  0.78493701, -1.20952754],
       [-0.03148663, -0.37735742, -0.00776763, -0.02489695,  0.17079938,
        -0.53712995,  0.49111628,  1.01831146,  0.2572608 ,  1.23885963],
       [-0.03148663,  1.23038965, -0.00776763, -0.02489695, -1.23893361,
        -0.96219611,  1.29073669,  0.13916888, -0.27041541, -0.34539089]])
```

In [107…

```
X_teste[:5]
```

Out[107]:

```
array([[-0.03148663,  0.20435836, -0.00277587, -0.02489695,  1.04227068,
         0.73806851,  0.60534777,  0.72526393,  1.31261321, -0.34539089],
       [-0.03148663,  1.14917148, -0.00776763, -0.02489695,  0.78595559,
         1.16313467,  0.2626533 , -0.15387865, -0.79809161,  1.52690518],
       [-0.03148663,  1.45765148, -0.00776763, -0.02489695, -1.23893361,
        -0.96219611,  0.03419033,  0.72526393,  1.31261321,  1.23885963],
       [-0.03148663, -0.59515622, -0.00776763, -0.02489695, -1.23893361,
        -0.96219611,  0.83381074, -1.03302123, -1.32576782,  1.09483686],
       [-0.03148663, -1.08022984, -0.00776763, -0.02489695, -1.23893361,
        -0.96219611,  0.2626533 , -1.32606875,  1.31261321, -0.77745922]])
```

8.1 - Modelo de Regressão Linear Múltipla

In [108…

```
# Cria o modelo
modelo_v1 = LinearRegression()
# Treinamento
modelo_v1.fit(X_treino, y_treino)
# Avaliação do modelo
y_pred = modelo_v1.predict(X_teste)
```

In [109…

```
# Calcula as métricas de avaliação do modelo
evs_1 = explained_variance_score(y_teste, y_pred)
mae_1 = mean_absolute_error(y_teste, y_pred)
mse_1 = mean_squared_error(y_teste, y_pred)
rmse_1 = np.sqrt(mse_1)
r2_1 = r2_score(y_teste, y_pred)

print("Resultados do modelo de Regressão linear múltipla")
print("Explained Variance Score:", evs_1)
print("Mean Absolute Error:", mae_1)
print("Mean Squared Error:", mse_1)
print("Root Mean Squared Error:", rmse_1)
print("R² Score:", r2_1)
```

```
Resultados do modelo de Regressão linear múltipla
Explained Variance Score: 0.13053905958517564
Mean Absolute Error: 1637.4750590437454
Mean Squared Error: 3435784.5965426057
Root Mean Squared Error: 1853.5869541358468
R² Score: 0.13048000277479554
```

8.2 - Modelo de Random Forest

In [110…

```
# Cria o modelo
modelo_v2 = RandomForestRegressor(max_depth=3)
# Treinamento
```

```
modelo_v2.fit(X_treino, y_treino)
# Avaliação do modelo
y_pred = modelo_v2.predict(X_teste)
```

In [111…

```
# Calcula as métricas de avaliação do modelo
evs_2 = explained_variance_score(y_teste, y_pred)
mae_2 = mean_absolute_error(y_teste, y_pred)
mse_2 = mean_squared_error(y_teste, y_pred)
rmse_2 = np.sqrt(mse_2)
r2_2 = r2_score(y_teste, y_pred)

print("Resultados do modelo Random Forest")
print("Explained Variance Score:", evs_1)
print("Mean Absolute Error:", mae_1)
print("Mean Squared Error:", mse_1)
print("Root Mean Squared Error:", rmse_1)
print("R² Score:", r2_1)
```

```
Resultados do modelo Random Forest
Explained Variance Score: 0.13053905958517564
Mean Absolute Error: 1637.4750590437454
Mean Squared Error: 3435784.5965426057
Root Mean Squared Error: 1853.5869541358468
R² Score: 0.13048000277479554
```

8.3 - Modelo de Rede Neural

In [112…

```
# Criar o modelo
modelo_v3 = MLPRegressor(hidden_layer_sizes=(100, 50), max_iter=500, activation='re
# Treinamento
modelo_v3.fit(X_treino, y_treino)
# Avaliação do modelo
y_pred = modelo_v3.predict(X_teste)
```

```
C:\Users\Chilov\anaconda3\lib\site-packages\sklearn\neural_network\_multilayer_per
ceptron.py:684: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (500)
reached and the optimization hasn't converged yet.
  warnings.warn(
```

In [113…

```
# Calcula as métricas de avaliação do modelo
evs_3 = explained_variance_score(y_teste, y_pred)
mae_3 = mean_absolute_error(y_teste, y_pred)
mse_3 = mean_squared_error(y_teste, y_pred)
rmse_3 = np.sqrt(mse_3)
r2_3 = r2_score(y_teste, y_pred)

print("Resultados do modelo de Redes Neurais")
print("Explained Variance Score:", evs_3)
print("Mean Absolute Error:", mae_3)
print("Mean Squared Error:", mse_3)
print("Root Mean Squared Error:", rmse_3)
print("R² Score:", r2_3)
```

```
Resultados do modelo de Redes Neurais
Explained Variance Score: 0.7819596830526052
Mean Absolute Error: 630.9557407644278
Mean Squared Error: 861905.22660345
Root Mean Squared Error: 928.3885105942717
R² Score: 0.7818711245755108
```

8.4 - Modelo de XGBOOST

In [114…
```
# Criar o modelo
modelo_v4 = XGBRegressor(learning_rate=0.01, n_estimators=1000, max_depth=3, random
# Treinamento
modelo_v4.fit(X_treino, y_treino)
# Avaliação do modelo
y_pred = modelo_v4.predict(X_teste)
```

In [115…
```
# Calcula as métricas de avaliação do modelo
evs_4 = explained_variance_score(y_teste, y_pred)
mae_4 = mean_absolute_error(y_teste, y_pred)
mse_4 = mean_squared_error(y_teste, y_pred)
rmse_4 = np.sqrt(mse_4)
r2_4 = r2_score(y_teste, y_pred)

print("Resultados do modelo XGBOOST")
print("Explained Variance Score:", evs_4)
print("Mean Absolute Error:", mae_4)
print("Mean Squared Error:", mse_4)
print("Root Mean Squared Error:", rmse_4)
print("R² Score:", r2_4)
```

```
Resultados do modelo XGBOOST
Explained Variance Score: 0.7838492783032498
Mean Absolute Error: 633.4688980889335
Mean Squared Error: 854090.2138668308
Root Mean Squared Error: 924.1700135077045
R² Score: 0.7838489289640334
```

8.5 - Modelo de LIGHTGBM

In [116…
```
# Criar o modelo
modelo_v5 = LGBMRegressor(learning_rate=0.01, n_estimators=1000, max_depth=3, rando
# Treinamento
modelo_v5.fit(X_treino, y_treino)
# Avaliação do modelo
y_pred = modelo_v5.predict(X_teste)
```

```
C:\Users\Chilov\anaconda3\lib\site-packages\joblib\externals\loky\backend\context.
py:110: UserWarning: Could not find the number of physical cores for the following
reason:
found 0 physical cores < 1
Returning the number of logical cores instead. You can silence this warning by set
ting LOKY_MAX_CPU_COUNT to the number of cores you want to use.
  warnings.warn(
  File "C:\Users\Chilov\anaconda3\lib\site-packages\joblib\externals\loky\backend
\context.py", line 217, in _count_physical_cores
    raise ValueError(
```

```
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing
was 0.001924 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 652
[LightGBM] [Info] Number of data points in the train set: 38549, number of used fe
atures: 10
[LightGBM] [Info] Start training from score 3256.761317
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
```

```
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
```

In [117…

```python
# Calcula as métricas de avaliação do modelo
evs_5 = explained_variance_score(y_teste, y_pred)
mae_5 = mean_absolute_error(y_teste, y_pred)
mse_5 = mean_squared_error(y_teste, y_pred)
rmse_5 = np.sqrt(mse_5)
r2_5 = r2_score(y_teste, y_pred)

print("Resultados do modelo lightGBM")
print("Explained Variance Score:", evs_5)
print("Mean Absolute Error:", mae_5)
print("Mean Squared Error:", mse_5)
print("Root Mean Squared Error:", rmse_5)
print("R² Score:", r2_5)
```

```
Resultados do modelo lightGBM
Explained Variance Score: 0.7836758384799476
Mean Absolute Error: 634.1314146440678
Mean Squared Error: 854775.1417106433
Root Mean Squared Error: 924.5405030125199
R² Score: 0.7836755890935855
```

8.6 - Modelo de Séries Temporais - ARIMA

In [118…

```python
df.sample(5)
```

Out[118]:

	holiday	temp	rain_1h	snow_1h	clouds_all	weather_main	data	dia	mes	ano	apen
45639	1	290.15	0.0	0.0	90	2	2018-07-26	26	7	2018	
21481	1	272.76	0.0	0.0	1	1	2016-02-24	24	2	2016	
14188	1	300.94	0.0	0.0	75	2	2014-05-31	31	5	2014	
41876	1	271.61	0.0	0.0	90	8	2018-03-04	4	3	2018	
7687	1	283.69	0.0	0.0	0	1	2013-07-29	29	7	2013	

In [119…

```python
df.columns
```

Out[119]:

```
Index(['holiday', 'temp', 'rain_1h', 'snow_1h', 'clouds_all', 'weather_main',
       'data', 'dia', 'mes', 'ano', 'apenas_hora', 'mes_ano',
       'traffic_volume'],
      dtype='object')
```

In [120…

```python
# Preparando os dados de treino e teste
df_serie_temp = df[['data','traffic_volume']]
```

In [121…

```python
df_serie_temp
```

Out[121]:

	data	traffic_volume
0	2012-01-11	716
1	2012-01-11	453
2	2012-01-11	324
3	2012-01-11	390
4	2012-01-11	775
...	...	...
48199	2018-12-09	3510
48200	2018-12-09	3064
48201	2018-12-09	2705
48202	2018-12-09	1813
48203	2018-12-09	2842

48187 rows × 2 columns

In [122…

```
#definindo 'data' como índice
df_serie_temp.set_index('data', inplace=True)
```

In [123…

```
df_serie_temp
```

Out[123]:

data	traffic_volume
2012-01-11	716
2012-01-11	453
2012-01-11	324
2012-01-11	390
2012-01-11	775
...	...
2018-12-09	3510
2018-12-09	3064
2018-12-09	2705
2018-12-09	1813
2018-12-09	2842

48187 rows × 1 columns

In [124…

```
df_serie_temp.dtypes
```

Out[124]:

```
traffic_volume    int64
dtype: object
```

In [125…

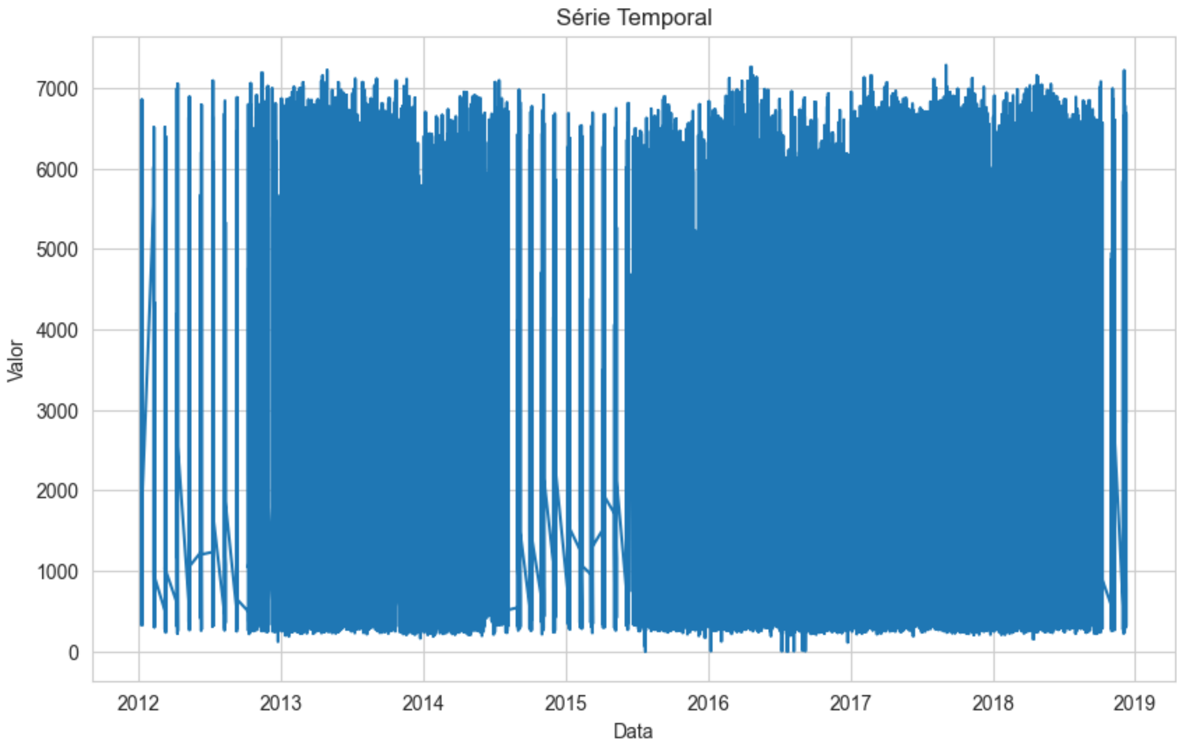
```
soma = df_serie_temp['traffic_volume'].sum()
is_numeric = np.isfinite(soma)
```

In [126…
```
is_numeric
```

Out[126]:
```
True
```

In [127…
```
#coluna traffic_volume tem valores válidos
```

In [128…
```
# Visualizando a série temporal
df_serie_temp.index = pd.to_datetime(df_serie_temp.index)

plt.figure(figsize=(10, 6))
plt.plot(df_serie_temp)
plt.title('Série Temporal')
plt.xlabel('Data')
plt.ylabel('Valor')
plt.show()
```



In [129…
```
#verificando se a série temporal é estacionária com base no Teste Dickey-Fuller Aum
resultado_adf = adfuller(df_serie_temp)

# Imprimindo os resultados
print('Estatística ADF:', resultado_adf[0])
print('Valor-p:', resultado_adf[1])
print('Valores críticos:')
for chave, valor in resultado_adf[4].items():
    print(f'   {chave}: {valor}')
```

```
Estatística ADF: -28.09090129989716
Valor-p: 0.0
Valores críticos:
   1%: -3.430485863397371
   5%: -2.8616000487800735
   10%: -2.566801961988572
```

In [130…
```
#Se a estatística ADF for menor que os valores críticos para um nível de significân
#(por exemplo, 0.01, 0.05 ou 0.10), você pode rejeitar a hipótese nula de não estac
#e concluir que a série temporal é estacionária
#Neste caso, como a estatística ADF (-28) é muito menor do que o valor crítico (-3)
#pode-se concluir com confiança que a série temporal é estacionária.
```

In [131…

```
# Dividindo os dados em conjuntos de treinamento e teste (por exemplo, 80% para tre
X_treino, X_teste, y_treino, y_teste = train_test_split(X, y, test_size=0.2, randon
#convertendo para tipo array para o treinamento
X_treino_array = X_treino.values.ravel()  # Convertendo para um array unidimensionc
y_teste_array = y_teste.values.ravel()    # Convertendo para um array unidimensionc
X_teste_array = X_teste.values.ravel()   # Convertendo para um array unidimensional
y_teste_array = y_teste.values.ravel()   # Convertendo para um array unidimensional
```

In [132…

```
# Criar o modelo
modelo_v6 = ARIMA(X_treino_array, order=(5,1,0))
```

In [133…

```
modelo_v6
```

Out[133]:

```
<statsmodels.tsa.arima.model.ARIMA at 0x211ace00d30>
```

In [134…

```
# Ajustar o modelo ARIMA aos dados de treinamento
#modelo_arima = ARIMA(X_treino, order=(5,1,0))
modelo_arima_ajustado_v6 = modelo_v6.fit()

# Fazer previsões nos dados de teste
y_pred = modelo_arima_ajustado_v6.forecast(steps=len(X_teste))

# Calculando o RMSE
rmse_6 = np.sqrt(mean_squared_error(y_teste, y_pred))
print("RMSE:", rmse_6)
```

```
RMSE: 3358.144056774965
```

8.7 - Modelo de Séries Temporais - LSTM

In [135…

```
# Função para preparar os dados para a LSTM
def preparar_dados_para_lstm(serie_temporal, passos_de_tempo):
    X, y = [], []
    for i in range(len(serie_temporal) - passos_de_tempo):
        X.append(serie_temporal[i:(i + passos_de_tempo)])
        y.append(serie_temporal[i + passos_de_tempo])
    return np.array(X), np.array(y)
```

In [136…

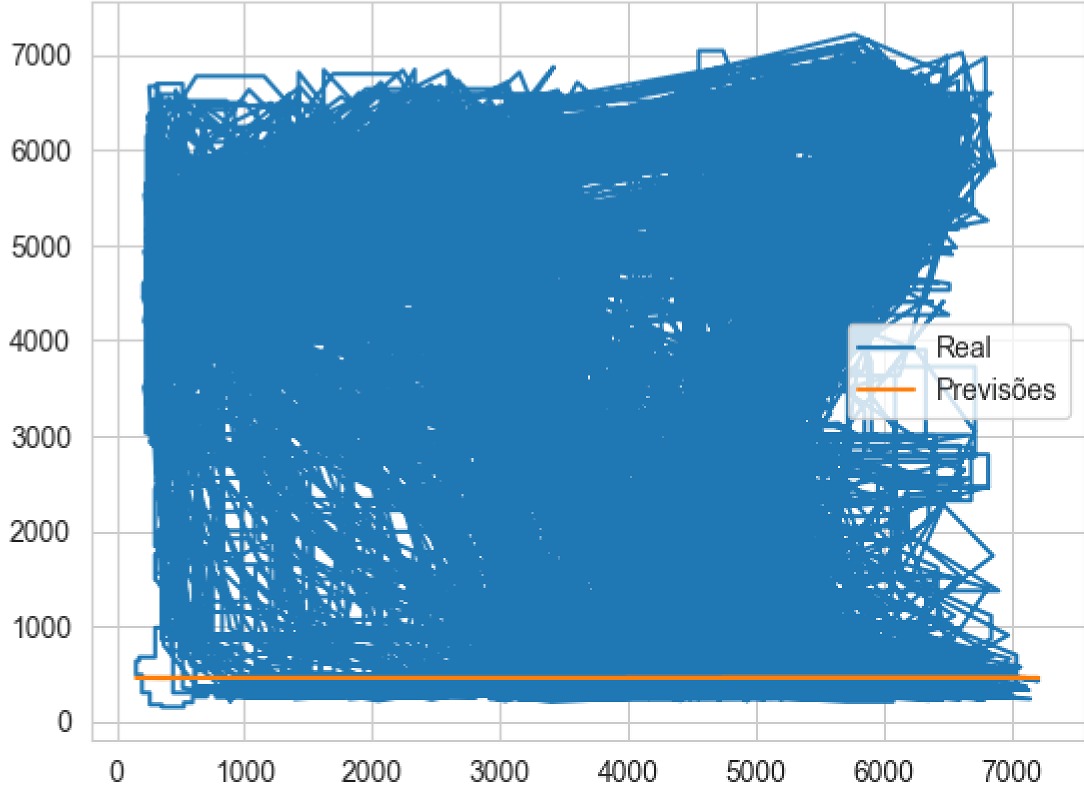
```
# Definir o número de passos de tempo
passos_de_tempo = 10
# Preparar os dados para a LSTM
X, y = preparar_dados_para_lstm(df_serie_temp['traffic_volume'], passos_de_tempo)

# Redimensionar os dados para o formato [amostras, passos de tempo, características
X = np.reshape(X, (X.shape[0], X.shape[1], 1))

# Dividir os dados em conjuntos de treinamento e teste
X_treino, X_teste, y_treino, y_teste = train_test_split(X, y, test_size=0.2, shuffl

# Criar o modelo LSTM
modelo_v7 = Sequential()
modelo_v7.add(LSTM(50, input_shape=(passos_de_tempo, 1)))
modelo_v7.add(Dense(1))
modelo_v7.compile(optimizer='adam', loss='mean_squared_error')

# Treinar o modelo
modelo_v7.fit(X_treino, y_treino, epochs=10, batch_size=32)

# Fazer previsões
y_pred = modelo_v7.predict(X_teste)
```

```
# Imprimir algumas previsões
print(y_pred[:10])
```

```
C:\Users\Chilov\anaconda3\lib\site-packages\keras\src\layers\rnn\rnn.py:204: UserW
arning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using S
equential models, prefer using an `Input(shape)` object as the first layer in the
model instead.
  super().__init__(**kwargs)
Epoch 1/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 8s 5ms/step - loss: 14515213.0000
Epoch 2/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 6s 5ms/step - loss: 14101632.0000
Epoch 3/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 7s 5ms/step - loss: 13890107.0000
Epoch 4/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 6s 5ms/step - loss: 13694529.0000
Epoch 5/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 6s 5ms/step - loss: 13365287.0000
Epoch 6/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 6s 5ms/step - loss: 13199586.0000
Epoch 7/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 6s 5ms/step - loss: 12827582.0000
Epoch 8/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 6s 5ms/step - loss: 12635863.0000
Epoch 9/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 7s 6ms/step - loss: 12286808.0000
Epoch 10/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 7s 6ms/step - loss: 12160044.0000
302/302 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step
[[456.5219 ]
 [456.5219 ]
 [456.5219 ]
 [456.5219 ]
 [456.5219 ]
 [456.5219 ]
 [456.51172]
 [456.43472]
 [456.52167]
 [456.5219 ]]
```

In [137…

```
# Visualizar os resultados
plt.plot(X_teste[:,0], y_teste, label='Real')
plt.plot(X_teste[:,0], y_pred, label='Previsões')
plt.legend()
plt.show()
```



In [138…

```
#o algoritmo LSTM não capturou padrão nos dados
```

In [139…

```
# Supondo que `y_true` são os valores reais e `y_pred` são as previsões do modelo
mae_7 = mean_absolute_error(y_teste, y_pred)
print("MAE:", mae_7)
# Calcular o RMSE
rmse_7 = np.sqrt(mean_squared_error(y_teste, y_pred))
print("RMSE:", rmse_7)
```

```
MAE: 2822.707280993115
RMSE: 3422.1508876148723
```

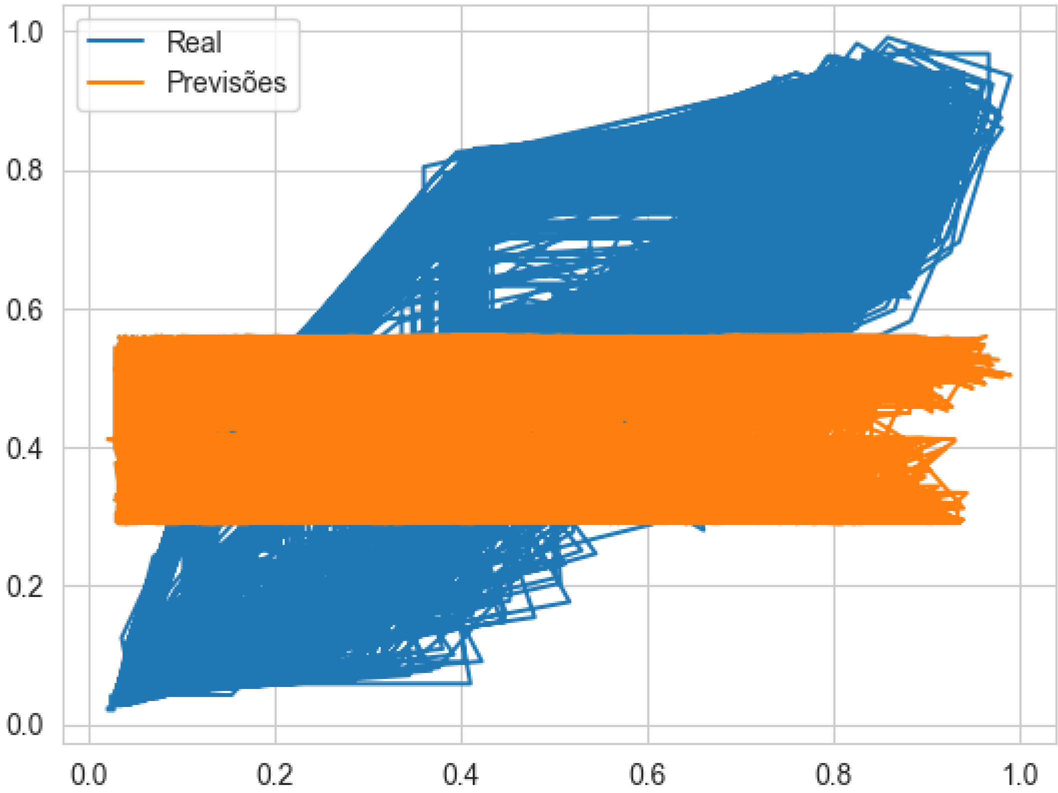
8.8 - Modelo de Séries Temporais - FNN

In [140…

```
# Normalização dos dados
scaler = MinMaxScaler()
scaled_data = scaler.fit_transform(df['traffic_volume'].values.reshape(-1, 1))

# Divisão em sequências
def create_sequences(data, seq_length):
    X, y = [], []
    for i in range(len(data) - seq_length):
        X.append(data[i:i+seq_length])
        y.append(data[i+seq_length])
    return np.array(X), np.array(y)

seq_length = 10  # ajuste conforme necessário
X, y = create_sequences(scaled_data, seq_length)

# Divisão em conjuntos de treinamento e teste
X_treino, X_teste, y_treino, y_teste = train_test_split(X, y, test_size=0.2, shuffl

# Reformatação dos dados (se necessário)
X_treino = X_treino.reshape(-1, seq_length, 1)
X_teste = X_teste.reshape(-1, seq_length, 1)
# Construir o modelo FNN
```

```
#observar que o primeiro número do input_shape deve ser o mesmo do seq_length
modelo_v8 = Sequential([
    Dense(64, activation='relu', input_shape=(10,1)),
    Dense(64, activation='relu'),
    Dense(1)
])

# Compilar o modelo
modelo_v8.compile(optimizer='adam', loss='mean_squared_error')

# Treinar o modelo
modelo_v8.fit(X_treino, y_treino, epochs=10, batch_size=32, verbose=1)

# Avaliar o modelo
loss = modelo_v8.evaluate(X_teste, y_teste)
print("Loss:", loss)

# Fazer previsões
y_pred = modelo_v8.predict(X_teste)

# Visualizar os resultados
# Selecionar o último ponto de cada sequência para plotar no eixo x
x_plot = X_teste[:, -1, 0]

# Selecionar apenas os primeiros valores de y_teste e y_pred para plotar
y_plot = y_teste[:, 0]
y_pred_plot = y_pred[:, 0]

# Plotar os valores reais
plt.plot(x_plot, y_plot, label='Real')
# Plotar as previsões
plt.plot(x_plot, y_pred_plot, label='Previsões')
plt.legend()
plt.show()
```

```
Epoch 1/10
C:\Users\Chilov\anaconda3\lib\site-packages\keras\src\layers\core\dense.py:87: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 5s 3ms/step - loss: 0.0779
Epoch 2/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.0691
Epoch 3/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.0690
Epoch 4/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.0683
Epoch 5/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.0682
Epoch 6/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - loss: 0.0680
Epoch 7/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - loss: 0.0671
Epoch 8/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.0675
Epoch 9/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.0671
Epoch 10/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.0676
302/302 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 0.0631
Loss: 0.0638209655880928
302/302 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
```



In [141…

```
#redimensionando y
y_reformulado = y[:len(y_pred)]
# Redimensionar y_pred para ter a mesma forma que y_reformulado
y_pred_reformulado = y_pred[:, -1, :]  # Selecionar apenas a última previsão de cad


# Supondo que `y` são os valores reais e `y_pred` são as previsões do modelo
mae_8 = mean_absolute_error(y_reformulado, y_pred_reformulado)
print("MAE:", mae_8)
# Calcular o RMSE
rmse_8 = np.sqrt(mean_squared_error(y_reformulado, y_pred_reformulado))
print("RMSE:", rmse_8)
```

```
MAE: 0.2529087409714181
RMSE: 0.29226953115230214
```

In [142…

```
#o algoritmo FNN não capturou padrão nos dados
```

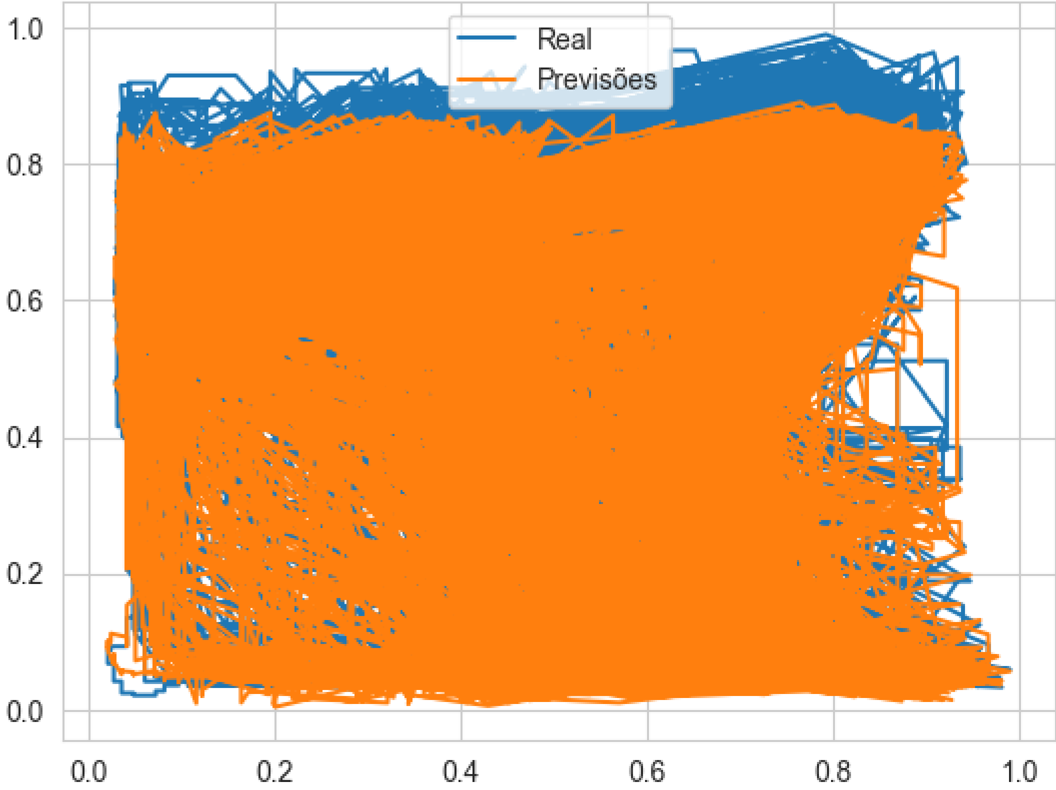
8.9 - Modelo de Séries Temporais - 1D CNN

In [143…

```
# Normalização dos dados
scaler = MinMaxScaler()
df['traffic_volume_normalized'] = scaler.fit_transform(df[['traffic_volume']])

# Divisão dos dados em sequências
def create_sequences(data, seq_length):
    X, y = [], []
    for i in range(len(data) - seq_length):
        X.append(data[i:i+seq_length])
        y.append(data[i+seq_length])
    return np.array(X), np.array(y)

seq_length = 10  # ajuste conforme necessário
X, y = create_sequences(df['traffic_volume_normalized'].values, seq_length)

# Divisão dos dados em conjuntos de treinamento e teste
```

```
X_treino, X_teste, y_treino, y_teste = train_test_split(X, y, test_size=0.2, shuffl

# Redimensionamento dos dados para 3D
X_treino = np.reshape(X_treino, (X_treino.shape[0], X_treino.shape[1], 1))
X_teste = np.reshape(X_teste, (X_teste.shape[0], X_teste.shape[1], 1))


# Construir o modelo 1D CNN
modelo_v9 = Sequential([
    Conv1D(filters=64, kernel_size=3, activation='relu', input_shape=(seq_length, 1
    MaxPooling1D(pool_size=2),
    Flatten(),
    Dense(64, activation='relu'),
    Dense(1)
])

# Compilar o modelo
modelo_v9.compile(optimizer='adam', loss='mean_squared_error')

# Treinar o modelo
modelo_v9.fit(X_treino, y_treino, epochs=10, batch_size=32, verbose=1)

# Avaliar o modelo
loss = modelo_v9.evaluate(X_teste, y_teste)
print("Loss:", loss)

# Fazer previsões
y_pred = modelo_v9.predict(X_teste)

# Visualizar os resultados
plt.plot(X_teste[:,0], y_teste, label='Real')
plt.plot(X_teste[:,0], y_pred, label='Previsões')
plt.legend()
plt.show()
```

```
Epoch 1/10
C:\Users\Chilov\anaconda3\lib\site-packages\keras\src\layers\convolutional\base_co
nv.py:107: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a lay
er. When using Sequential models, prefer using an `Input(shape)` object as the fir
st layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 5s 3ms/step - loss: 0.0263
Epoch 2/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.0073
Epoch 3/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.0066
Epoch 4/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.0063
Epoch 5/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.0060
Epoch 6/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - loss: 0.0063
Epoch 7/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - loss: 0.0061
Epoch 8/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.0059
Epoch 9/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - loss: 0.0059
Epoch 10/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - loss: 0.0057
302/302 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0034
Loss: 0.003359844908118248
302/302 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step
```



In [144…

```
#redimensionando y
y_reformulado = y[:len(y_pred)]
# Redimensionar y_pred para ter a mesma forma que y_true_reformulado
y_pred_reformulado = y_pred.squeeze()  # Remove a dimensão extra de y_pred


# Supondo que `y_true` são os valores reais e `y_pred` são as previsões do modelo
mae_9 = mean_absolute_error(y_reformulado, y_pred_reformulado)
print("MAE:", mae_9)
# Calcular o RMSE
rmse_9 = np.sqrt(mean_squared_error(y_reformulado, y_pred_reformulado))
print("RMSE:", rmse_9)
```

```
MAE: 0.3154027552191197
RMSE: 0.3853059938242588
```

In [145…

```
# bom modelo
```

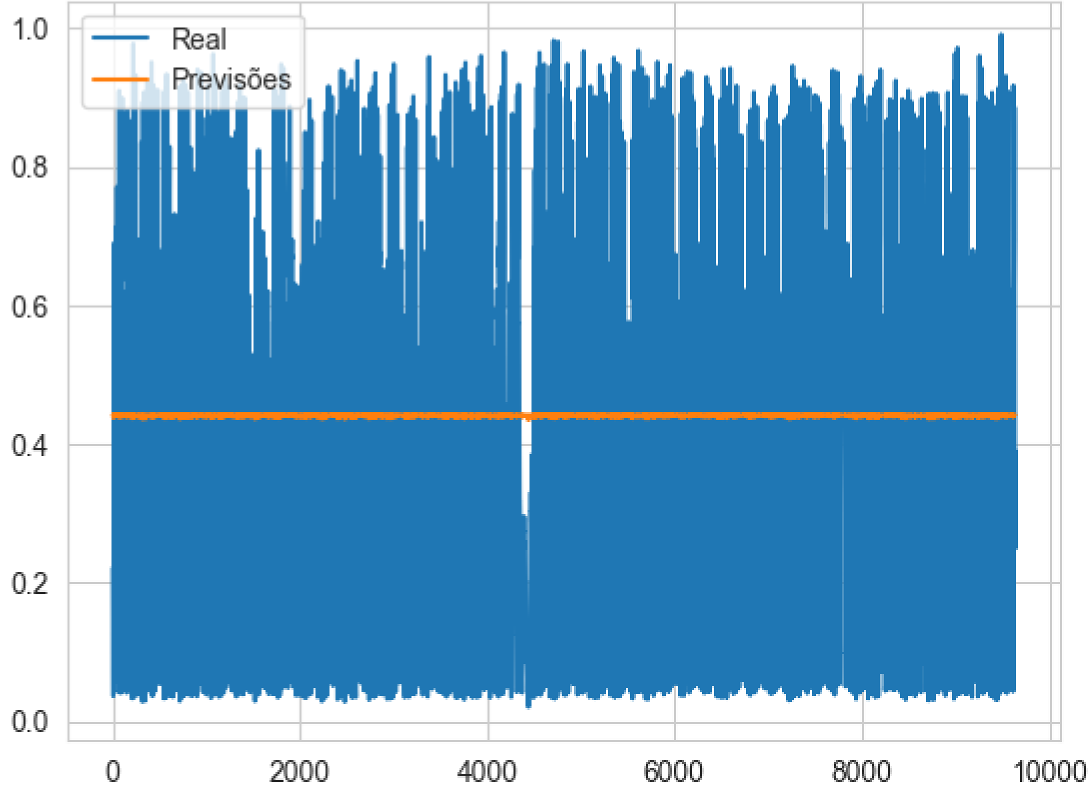
8.10 - Modelo de Séries Temporais - TANN

In [146…

```
# Supondo que 'df' é o seu DataFrame com a série temporal, onde 'traffic_volume' é
# Normalização dos dados
scaler = MinMaxScaler()
df['traffic_volume_normalized'] = scaler.fit_transform(df[['traffic_volume']])

# Divisão dos dados em sequências
def create_sequences(data, seq_length):
    X, y = [], []
    for i in range(len(data) - seq_length):
        X.append(data[i:i+seq_length])
        y.append(data[i+seq_length])
    return np.array(X), np.array(y)

seq_length = 10  # ajuste conforme necessário
X, y = create_sequences(df['traffic_volume_normalized'].values, seq_length)
```

```
# Divisão dos dados em conjuntos de treinamento e teste
X_treino, X_teste, y_treino, y_teste = train_test_split(X, y, test_size=0.2, shuffl

# Redimensionamento dos dados para 3D
X_treino = np.reshape(X_treino, (X_treino.shape[0], X_treino.shape[1], 1))
X_teste = np.reshape(X_teste, (X_teste.shape[0], X_teste.shape[1], 1))

# Construir o modelo TANN
modelo_v10 = Sequential([
    TimeDistributed(Dense(64, activation='relu'), input_shape=(seq_length, 1)),
    Dense(1)  # Camada de saída única para prever a média
])

# Compilar o modelo
modelo_v10.compile(optimizer='adam', loss='mean_squared_error')

# Treinar o modelo
modelo_v10.fit(X_treino, y_treino, epochs=10, batch_size=32, verbose=1)

# Avaliar o modelo
loss = modelo_v10.evaluate(X_teste, y_teste)
print("Loss:", loss)

# Fazer previsões
y_pred = modelo_v10.predict(X_teste)

# Visualizar os resultados
import matplotlib.pyplot as plt
# Selecionar a última previsão de cada instância de teste
y_pred_plot = y_pred[:, -1, 0]  # Selecionar apenas a última previsão de cada instá
plt.plot(y_teste, label='Real')
# Plotar as previsões
plt.plot(y_pred_plot, label='Previsões')
plt.legend()
plt.show()
```

```
Epoch 1/10
C:\Users\Chilov\anaconda3\lib\site-packages\keras\src\layers\core\wrapper.py:27: U
serWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When usi
ng Sequential models, prefer using an `Input(shape)` object as the first layer in
the model instead.
  super().__init__(**kwargs)
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 5s 3ms/step - loss: 0.0908
Epoch 2/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.0753
Epoch 3/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.0746
Epoch 4/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.0754
Epoch 5/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.0750
Epoch 6/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.0750
Epoch 7/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.0750
Epoch 8/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.0747
Epoch 9/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.0748
Epoch 10/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.0750
302/302 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0727
Loss: 0.07327903062105179
302/302 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step
```



In [147…

```
#redimensionando y
y_reformulado = y[:len(y_pred)]
# Selecionar a última previsão de cada instância de teste
y_pred_reformulado = y_pred[:, -1, 0]  # Selecionar apenas a última previsão de cad


# Supondo que `y_true` são os valores reais e `y_pred` são as previsões do modelo
mae_10 = mean_absolute_error(y_reformulado, y_pred_reformulado)
print("MAE:", mae_10)
# Calcular o RMSE
rmse_10 = np.sqrt(mean_squared_error(y_reformulado, y_pred_reformulado))
print("RMSE:", rmse_10)
```

```
MAE: 0.24454050666677205
RMSE: 0.2781357115256738
```

In [148…

```
#o algoritmo TANN não capturou padrão nos dados
```

8.11 - Avaliação do melhor algoritmo

In [149…

```
# Defina os valores para cada modelo
modelos = ['Regressão Linear Múltipla', 'Random Forest', 'Rede Neural', 'XGBoost',
evs = [evs_1, evs_2, evs_3, evs_4, evs_5, 0, 0, 0, 0, 0]
mae = [mae_1, mae_2, mae_3, mae_4, mae_5, 0, mae_7, mae_8, mae_9, mae_10]
mse = [mse_1, mse_2, mse_3, mse_4, mse_5, 0, 0, 0, 0, 0]
rmse = [rmse_1, rmse_2, rmse_3, rmse_4, rmse_5, rmse_6, rmse_7, rmse_8, rmse_9, rms
r2 = [r2_1, r2_2, r2_3, r2_4, r2_5, 0, 0, 0, 0, 0]


# Crie um DataFrame usando Pandas
df_resumo_modelos = pd.DataFrame({
    'Modelo': modelos,
    'EVS': evs,
    'MAE': mae,
    'MSE': mse,
    'RMSE': rmse,
```

```
    'R2': r2,
    })

# Exiba o DataFrame
df_resumo_modelos.index += 1
df_resumo_modelos_R2 = df_resumo_modelos.sort_values(by='R2', ascending=False)
print("                                Avaliação do modelos com base no R2\n")
print(df_resumo_modelos_R2.to_string(index=True))
#print(df_resumo_modelos.to_string(index=False))
```

```
                                Avaliação do modelos com base no R2

                         Modelo       EVS          MAE           MSE          RMSE
R2
4                       XGBoost  0.783849   633.468898  8.540902e+05    924.170014
0.783849
5                      LightGBM  0.783676   634.131415  8.547751e+05    924.540503
0.783676
3                   Rede Neural  0.781960   630.955741  8.619052e+05    928.388511
0.781871
2                 Random Forest  0.747743   704.333199  9.967572e+05    998.377261
0.747743
1    Regressão Linear Múltipla  0.130539  1637.475059  3.435785e+06   1853.586954
0.130480
6                        ARIMA  0.000000     0.000000  0.000000e+00   3358.144057
0.000000
7                         LSTM  0.000000  2822.707281  0.000000e+00   3422.150888
0.000000
8                           FNN  0.000000     0.252909  0.000000e+00      0.292270
0.000000
9                           CNN  0.000000     0.315403  0.000000e+00      0.385306
0.000000
10                         TANN  0.000000     0.244541  0.000000e+00      0.278136
0.000000
```

In [150…

```
df_resumo_modelos_evs = df_resumo_modelos.sort_values(by='EVS', ascending=False)
print("                               Avaliação do modelos com base no EVS\n")
print(df_resumo_modelos_evs.to_string(index=True))
```



```
                               Avaliação do modelos com base no EVS

                         Modelo       EVS          MAE           MSE          RMSE
R2
4                       XGBoost  0.783849   633.468898  8.540902e+05    924.170014
0.783849
5                      LightGBM  0.783676   634.131415  8.547751e+05    924.540503
0.783676
3                   Rede Neural  0.781960   630.955741  8.619052e+05    928.388511
0.781871
2                 Random Forest  0.747743   704.333199  9.967572e+05    998.377261
0.747743
1    Regressão Linear Múltipla  0.130539  1637.475059  3.435785e+06   1853.586954
0.130480
6                        ARIMA  0.000000     0.000000  0.000000e+00   3358.144057
0.000000
7                         LSTM  0.000000  2822.707281  0.000000e+00   3422.150888
0.000000
8                           FNN  0.000000     0.252909  0.000000e+00      0.292270
0.000000
9                           CNN  0.000000     0.315403  0.000000e+00      0.385306
0.000000
10                         TANN  0.000000     0.244541  0.000000e+00      0.278136
0.000000
```

In [151…
```
df_resumo_modelos_rmse = df_resumo_modelos.sort_values(by='RMSE', ascending=True)
print("                              Avaliação do modelos com base no RMSE\n")
print(df_resumo_modelos_rmse.to_string(index=True))
```

```
                              Avaliação do modelos com base no RMSE

                       Modelo       EVS          MAE           MSE         RMSE  
R2
10                       TANN  0.000000     0.244541  0.000000e+00     0.278136  
0.000000
8                         FNN  0.000000     0.252909  0.000000e+00     0.292270  
0.000000
9                         CNN  0.000000     0.315403  0.000000e+00     0.385306  
0.000000
4                     XGBoost  0.783849   633.468898  8.540902e+05   924.170014  
0.783849
5                    LightGBM  0.783676   634.131415  8.547751e+05   924.540503  
0.783676
3                 Rede Neural  0.781960   630.955741  8.619052e+05   928.388511  
0.781871
2               Random Forest  0.747743   704.333199  9.967572e+05   998.377261  
0.747743
1   Regressão Linear Múltipla  0.130539  1637.475059  3.435785e+06  1853.586954  
0.130480
6                       ARIMA  0.000000     0.000000  0.000000e+00  3358.144057  
0.000000
7                        LSTM  0.000000  2822.707281  0.000000e+00  3422.150888  
0.000000
```

Seleção do Modelo

O melhor modelo é o v_9. Então seguiremos com o modelo_v9 1D CNN

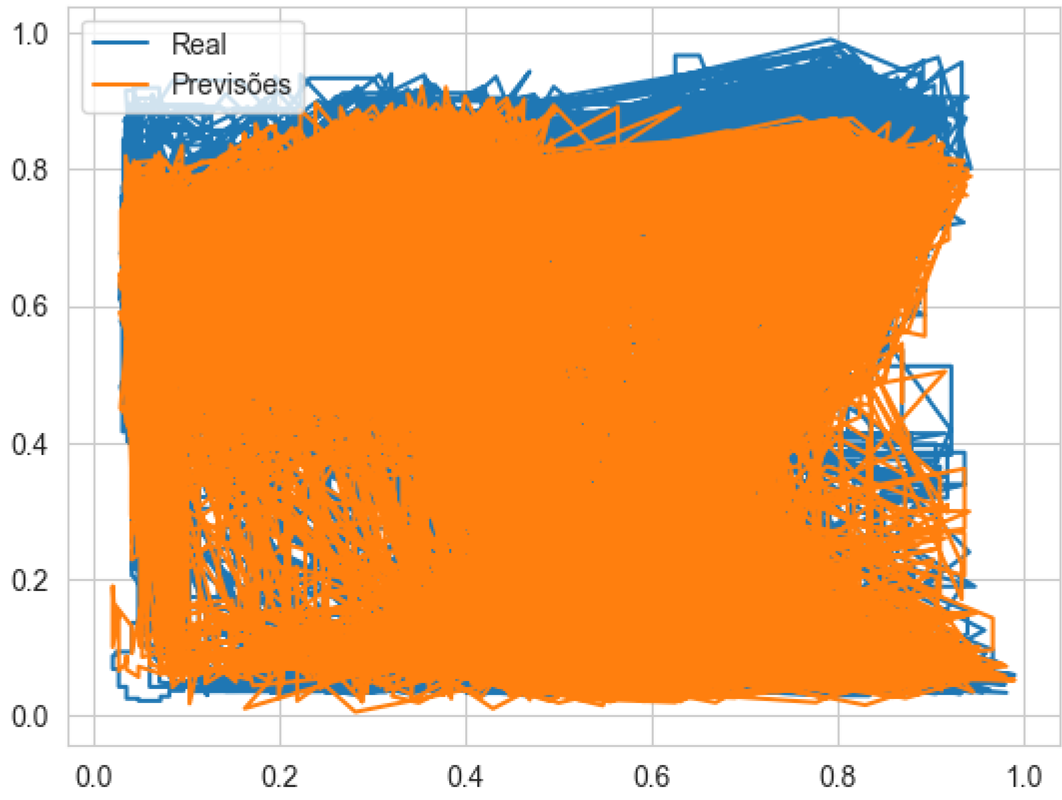
8.12 - Otimização do modelo

8.12.1 - Otimização somente com mudança de hiperparâmetro - alterando kernel_size

In [152…
```
# Normalização dos dados
scaler = MinMaxScaler()
df['traffic_volume_normalized'] = scaler.fit_transform(df[['traffic_volume']])

# Divisão dos dados em sequências
def create_sequences(data, seq_length):
    X, y = [], []
    for i in range(len(data) - seq_length):
        X.append(data[i:i+seq_length])
        y.append(data[i+seq_length])
    return np.array(X), np.array(y)

seq_length = 10  # ajuste conforme necessário
X, y = create_sequences(df['traffic_volume_normalized'].values, seq_length)

# Divisão dos dados em conjuntos de treinamento e teste
X_treino, X_teste, y_treino, y_teste = train_test_split(X, y, test_size=0.2, shuffl

# Redimensionamento dos dados para 3D
X_treino = np.reshape(X_treino, (X_treino.shape[0], X_treino.shape[1], 1))
```

```
X_teste = np.reshape(X_teste, (X_teste.shape[0], X_teste.shape[1], 1))


# Construir o modelo 1D CNN
modelo_v11 = Sequential([
    Conv1D(filters=64, kernel_size=4, activation='relu', input_shape=(seq_length, 1
    MaxPooling1D(pool_size=2),
    Flatten(),
    Dense(64, activation='relu'),
    Dense(1)
])

# Compilar o modelo
modelo_v11.compile(optimizer='adam', loss='mean_squared_error')

# Treinar o modelo
modelo_v11.fit(X_treino, y_treino, epochs=10, batch_size=32, verbose=1)

# Avaliar o modelo
loss = modelo_v11.evaluate(X_teste, y_teste)
print("Loss:", loss)

# Fazer previsões
y_pred = modelo_v11.predict(X_teste)

# Visualizar os resultados
plt.plot(X_teste[:,0], y_teste, label='Real')
plt.plot(X_teste[:,0], y_pred, label='Previsões')
plt.legend()
plt.show()
```

```
Epoch 1/10
C:\Users\Chilov\anaconda3\lib\site-packages\keras\src\layers\convolutional\base_co
nv.py:107: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a lay
er. When using Sequential models, prefer using an `Input(shape)` object as the fir
st layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 5s 3ms/step - loss: 0.0371
Epoch 2/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - loss: 0.0159
Epoch 3/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.0139
Epoch 4/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.0129
Epoch 5/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.0123
Epoch 6/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.0123
Epoch 7/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.0118
Epoch 8/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.0119
Epoch 9/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.0114
Epoch 10/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - loss: 0.0113
302/302 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0079
Loss: 0.00763642368838191
302/302 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
```



In [153…

```
#redimensionando y
y_reformulado = y[:len(y_pred)]
# Redimensionar y_pred para ter a mesma forma que y_true_reformulado
y_pred_reformulado = y_pred.squeeze()  # Remove a dimensão extra de y_pred


# Supondo que `y_true` são os valores reais e `y_pred` são as previsões do modelo
mae_11 = mean_absolute_error(y_reformulado, y_pred_reformulado)
print("MAE:", mae_11)
# Calcular o RMSE
rmse_11 = np.sqrt(mean_squared_error(y_reformulado, y_pred_reformulado))
print("RMSE:", rmse_11)
```

```
MAE: 0.30732144461489064
RMSE: 0.37487337676039667
```

In [154…

```
# após testes, verificou-se que o melhor kernel_size é 4.
```

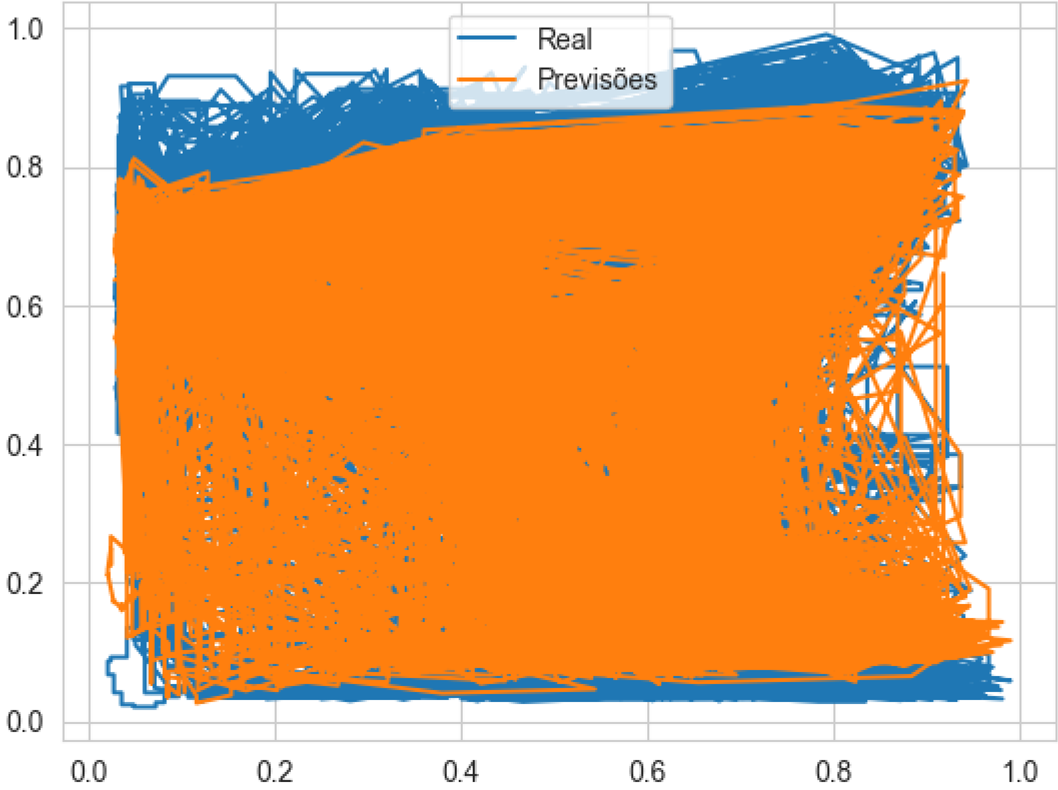
8.12.2 - Otimização alterando o pool_size

In [155…

```
# Normalização dos dados
scaler = MinMaxScaler()
df['traffic_volume_normalized'] = scaler.fit_transform(df[['traffic_volume']])

# Divisão dos dados em sequências
def create_sequences(data, seq_length):
    X, y = [], []
    for i in range(len(data) - seq_length):
        X.append(data[i:i+seq_length])
        y.append(data[i+seq_length])
    return np.array(X), np.array(y)

seq_length = 10  # ajuste conforme necessário
X, y = create_sequences(df['traffic_volume_normalized'].values, seq_length)

# Divisão dos dados em conjuntos de treinamento e teste
```

```
X_treino, X_teste, y_treino, y_teste = train_test_split(X, y, test_size=0.2, shuffl

# Redimensionamento dos dados para 3D
X_treino = np.reshape(X_treino, (X_treino.shape[0], X_treino.shape[1], 1))
X_teste = np.reshape(X_teste, (X_teste.shape[0], X_teste.shape[1], 1))


# Construir o modelo 1D CNN
modelo_v12 = Sequential([
    Conv1D(filters=64, kernel_size=4, activation='relu', input_shape=(seq_length, 1
    MaxPooling1D(pool_size=4),
    Flatten(),
    Dense(64, activation='relu'),
    Dense(1)
])

# Compilar o modelo
modelo_v12.compile(optimizer='adam', loss='mean_squared_error')

# Treinar o modelo
modelo_v12.fit(X_treino, y_treino, epochs=10, batch_size=32, verbose=1)

# Avaliar o modelo
loss = modelo_v12.evaluate(X_teste, y_teste)
print("Loss:", loss)

# Fazer previsões
y_pred = modelo_v12.predict(X_teste)

# Visualizar os resultados
plt.plot(X_teste[:,0], y_teste, label='Real')
plt.plot(X_teste[:,0], y_pred, label='Previsões')
plt.legend()
plt.show()
```

```
Epoch 1/10
C:\Users\Chilov\anaconda3\lib\site-packages\keras\src\layers\convolutional\base_co
nv.py:107: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a lay
er. When using Sequential models, prefer using an `Input(shape)` object as the fir
st layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 5s 3ms/step - loss: 0.0616
Epoch 2/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - loss: 0.0324
Epoch 3/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - loss: 0.0272
Epoch 4/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - loss: 0.0258
Epoch 5/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - loss: 0.0253
Epoch 6/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - loss: 0.0251
Epoch 7/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - loss: 0.0249
Epoch 8/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - loss: 0.0238
Epoch 9/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.0235
Epoch 10/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.0234
302/302 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0162
Loss: 0.015724292024970055
302/302 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
```



In [156…

```
#redimensionando y
y_reformulado = y[:len(y_pred)]
# Redimensionar y_pred para ter a mesma forma que y_true_reformulado
y_pred_reformulado = y_pred.squeeze()  # Remove a dimensão extra de y_pred


# Supondo que `y_true` são os valores reais e `y_pred` são as previsões do modelo
mae_12 = mean_absolute_error(y_reformulado, y_pred_reformulado)
print("MAE:", mae_12)
# Calcular o RMSE
rmse_12 = np.sqrt(mean_squared_error(y_reformulado, y_pred_reformulado))
print("RMSE:", rmse_12)
```

```
MAE: 0.29687754086710577
RMSE: 0.35995624219990624
```

In [157…

```
# após testes, verificou-se que o melhor pool_size é 4.
```

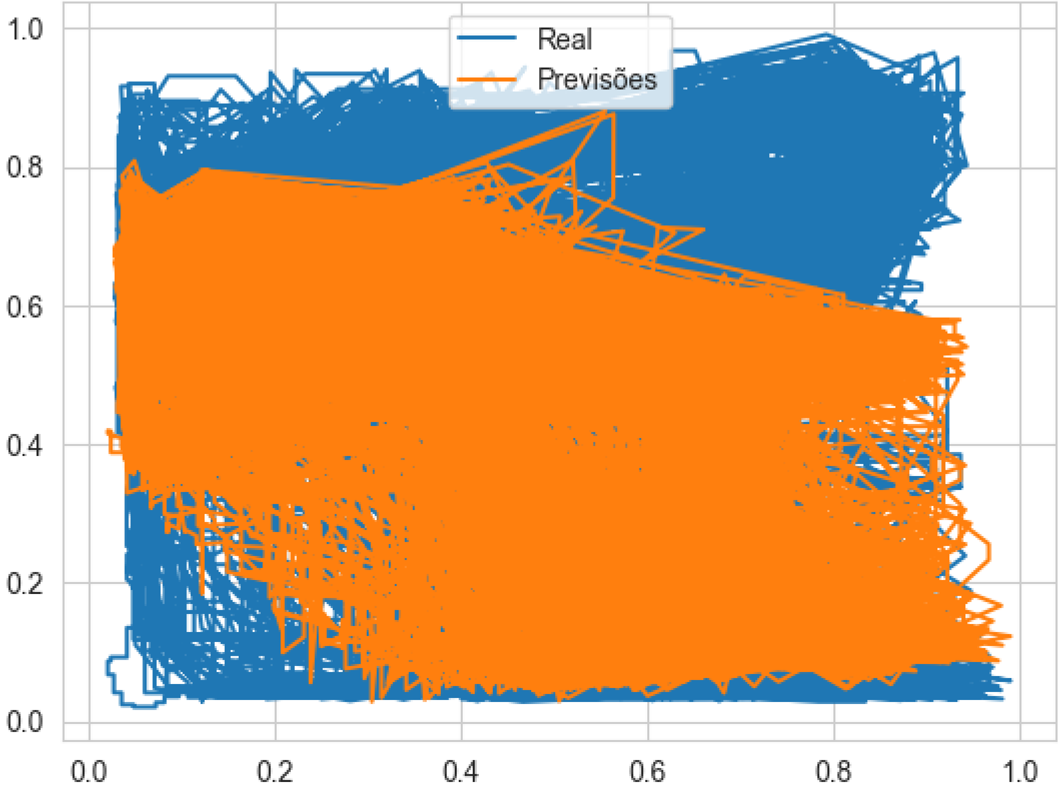
8.12.3 - Otimização alterando o batch_size

In [158…

```
# Normalização dos dados
scaler = MinMaxScaler()
df['traffic_volume_normalized'] = scaler.fit_transform(df[['traffic_volume']])

# Divisão dos dados em sequências
def create_sequences(data, seq_length):
    X, y = [], []
    for i in range(len(data) - seq_length):
        X.append(data[i:i+seq_length])
        y.append(data[i+seq_length])
    return np.array(X), np.array(y)

seq_length = 10  # ajuste conforme necessário
X, y = create_sequences(df['traffic_volume_normalized'].values, seq_length)

# Divisão dos dados em conjuntos de treinamento e teste
```

```
X_treino, X_teste, y_treino, y_teste = train_test_split(X, y, test_size=0.2, shuffl

# Redimensionamento dos dados para 3D
X_treino = np.reshape(X_treino, (X_treino.shape[0], X_treino.shape[1], 1))
X_teste = np.reshape(X_teste, (X_teste.shape[0], X_teste.shape[1], 1))


# Construir o modelo 1D CNN
modelo_v13 = Sequential([
    Conv1D(filters=64, kernel_size=4, activation='relu', input_shape=(seq_length, 1
    MaxPooling1D(pool_size=4),
    Flatten(),
    Dense(64, activation='relu'),
    Dense(1)
])

# Compilar o modelo
modelo_v13.compile(optimizer='adam', loss='mean_squared_error')

# Treinar o modelo
modelo_v13.fit(X_treino, y_treino, epochs=10, batch_size=1024, verbose=1)

# Avaliar o modelo
loss = modelo_v13.evaluate(X_teste, y_teste)
print("Loss:", loss)

# Fazer previsões
y_pred = modelo_v13.predict(X_teste)

# Visualizar os resultados
plt.plot(X_teste[:,0], y_teste, label='Real')
plt.plot(X_teste[:,0], y_pred, label='Previsões')
plt.legend()
plt.show()
```

```
Epoch 1/10
C:\Users\Chilov\anaconda3\lib\site-packages\keras\src\layers\convolutional\base_co
nv.py:107: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a lay
er. When using Sequential models, prefer using an `Input(shape)` object as the fir
st layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
38/38 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 0.1420
Epoch 2/10
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 0.0637
Epoch 3/10
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 0.0553
Epoch 4/10
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 0.0515
Epoch 5/10
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 0.0478
Epoch 6/10
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0432
Epoch 7/10
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 0.0395
Epoch 8/10
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 0.0369
Epoch 9/10
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - loss: 0.0355
Epoch 10/10
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0345
302/302 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0272
Loss: 0.027661213651299477
302/302 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
```



In [159…

```
#redimensionando y
y_reformulado = y[:len(y_pred)]
# Redimensionar y_pred para ter a mesma forma que y_true_reformulado
y_pred_reformulado = y_pred.squeeze()  # Remove a dimensão extra de y_pred


# Supondo que `y_true` são os valores reais e `y_pred` são as previsões do modelo
mae_13 = mean_absolute_error(y_reformulado, y_pred_reformulado)
print("MAE:", mae_13)
# Calcular o RMSE
rmse_13 = np.sqrt(mean_squared_error(y_reformulado, y_pred_reformulado))
print("RMSE:", rmse_13)
```

```
MAE: 0.2820397868846037
RMSE: 0.33939741550522284
```

In [160…

```
# após testes, verificou-se que o melhor batch_size é 32. Valores maiores diminuem
```

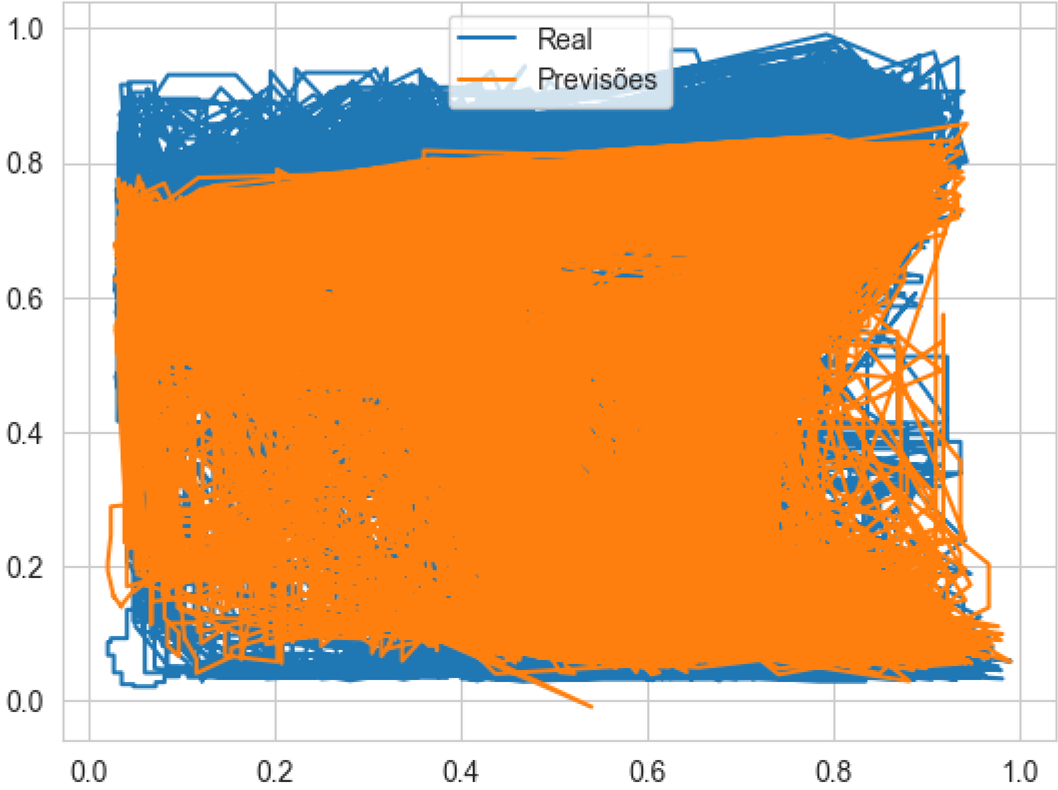
8.12.4 - Otimização alterando o epochs

In [161…

```
# Normalização dos dados
scaler = MinMaxScaler()
df['traffic_volume_normalized'] = scaler.fit_transform(df[['traffic_volume']])

# Divisão dos dados em sequências
def create_sequences(data, seq_length):
    X, y = [], []
    for i in range(len(data) - seq_length):
        X.append(data[i:i+seq_length])
        y.append(data[i+seq_length])
    return np.array(X), np.array(y)

seq_length = 10  # ajuste conforme necessário
X, y = create_sequences(df['traffic_volume_normalized'].values, seq_length)

# Divisão dos dados em conjuntos de treinamento e teste
```

```
X_treino, X_teste, y_treino, y_teste = train_test_split(X, y, test_size=0.2, shuffl

# Redimensionamento dos dados para 3D
X_treino = np.reshape(X_treino, (X_treino.shape[0], X_treino.shape[1], 1))
X_teste = np.reshape(X_teste, (X_teste.shape[0], X_teste.shape[1], 1))


# Construir o modelo 1D CNN
modelo_v14 = Sequential([
    Conv1D(filters=64, kernel_size=4, activation='relu', input_shape=(seq_length, 1
    MaxPooling1D(pool_size=4),
    Flatten(),
    Dense(64, activation='relu'),
    Dense(1)
])

# Compilar o modelo
modelo_v14.compile(optimizer='adam', loss='mean_squared_error')

# Treinar o modelo
modelo_v14.fit(X_treino, y_treino, epochs=10, batch_size=32, verbose=1)

# Avaliar o modelo
loss = modelo_v14.evaluate(X_teste, y_teste)
print("Loss:", loss)

# Fazer previsões
y_pred = modelo_v14.predict(X_teste)

# Visualizar os resultados
plt.plot(X_teste[:,0], y_teste, label='Real')
plt.plot(X_teste[:,0], y_pred, label='Previsões')
plt.legend()
plt.show()
```

```
Epoch 1/10
C:\Users\Chilov\anaconda3\lib\site-packages\keras\src\layers\convolutional\base_co
nv.py:107: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a lay
er. When using Sequential models, prefer using an `Input(shape)` object as the fir
st layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 6s 4ms/step - loss: 0.0665
Epoch 2/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - loss: 0.0319
Epoch 3/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.0276
Epoch 4/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.0267
Epoch 5/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - loss: 0.0254
Epoch 6/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.0254
Epoch 7/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.0247
Epoch 8/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - loss: 0.0242
Epoch 9/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 0.0237
Epoch 10/10
1205/1205 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - loss: 0.0236
302/302 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0166
Loss: 0.016079220920801163
302/302 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
```



In [162…

```
#redimensionando y
y_reformulado = y[:len(y_pred)]
# Redimensionar y_pred para ter a mesma forma que y_true_reformulado
y_pred_reformulado = y_pred.squeeze()  # Remove a dimensão extra de y_pred


# Supondo que `y_true` são os valores reais e `y_pred` são as previsões do modelo
mae_14 = mean_absolute_error(y_reformulado, y_pred_reformulado)
print("MAE:", mae_14)
# Calcular o RMSE
rmse_14 = np.sqrt(mean_squared_error(y_reformulado, y_pred_reformulado))
print("RMSE:", rmse_14)
```

```
MAE: 0.29537572847584115
RMSE: 0.3581548739002708
```

In [163…

```
# após testes, verificou-se que o melhor epochs é 10.
```

In [164…

```
# assim, utilizamos o modelo v_14 como final.
```

8.13 - Utilizando o modelo escolhido para previsões futuras

In [165…

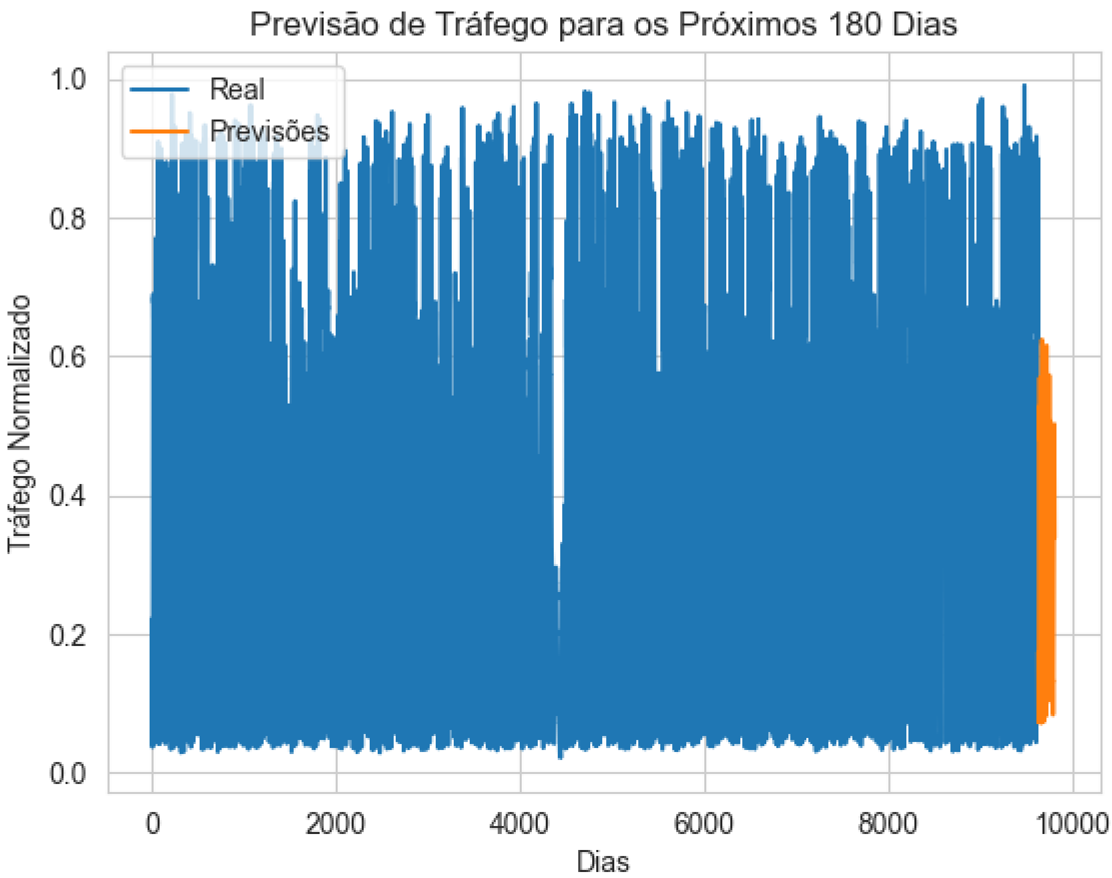
```
# para finalizar vamos fazer a previsão do volume de tráfego para os próximos 6 mes
# Definir o número de dias para prever
dias_para_prever = 180

# Copiar o último conjunto de dados de teste para iniciar a previsão
ultimo_x = X_teste[-1]

# Lista para armazenar as previsões
previsoes = []

# Fazer as previsões para os próximos dias
for _ in range(dias_para_prever):
```

```
    # Prever o próximo ponto no tempo
    proxima_predicao = modelo_v14.predict(ultimo_x.reshape(1, seq_length, 1))
    # Adicionar a previsão à lista de previsões
    previsoes.append(proxima_predicao[0, 0])
    # Atualizar os dados de entrada para a próxima iteração, descartando o primeiro
    ultimo_x = np.append(ultimo_x[1:, :], proxima_predicao, axis=0)

# Visualizar as previsões
plt.plot(y_teste, label='Real')  # Plotar os últimos dados reais
plt.plot(range(len(y_teste), len(y_teste) + dias_para_prever), previsoes, label='Pr
plt.legend()
plt.title('Previsão de Tráfego para os Próximos 180 Dias')
plt.xlabel('Dias')
plt.ylabel('Tráfego Normalizado')
plt.show()
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 37ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 40ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 50ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 43ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 37ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
```

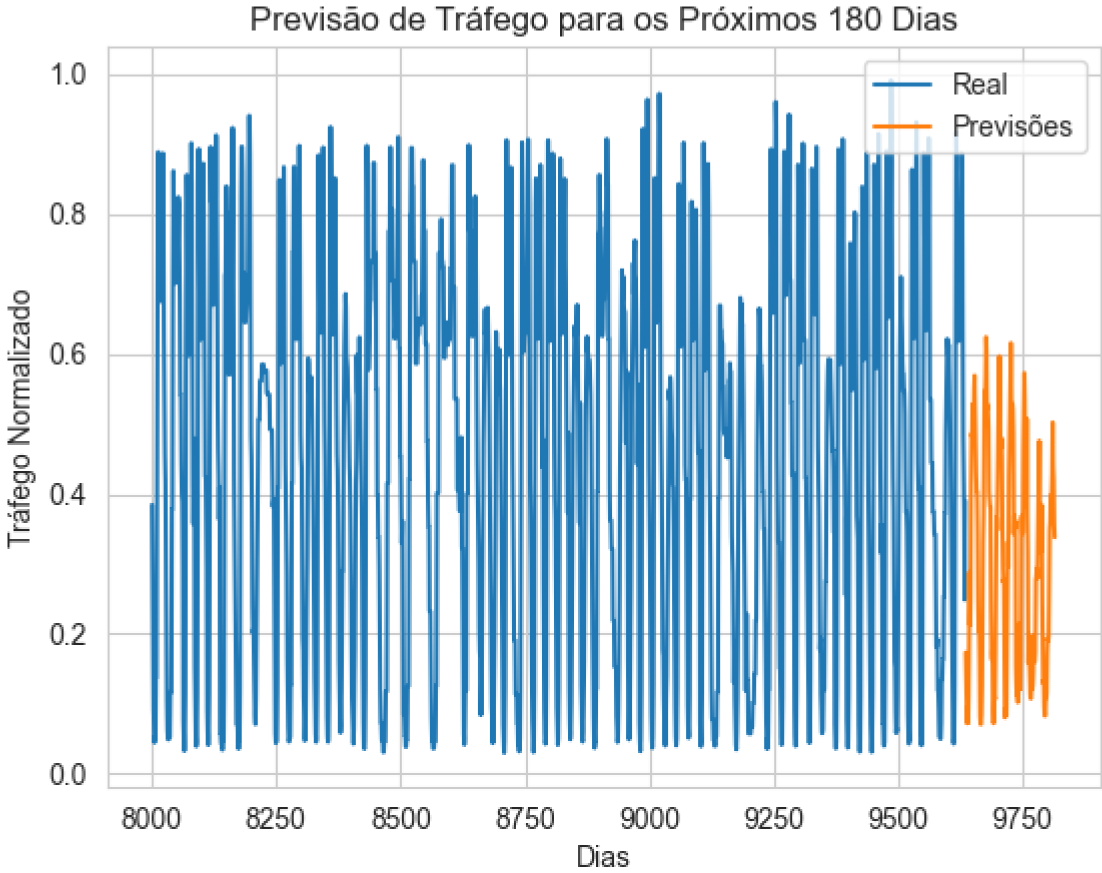


In [166…

```
#como a visualização está ruim, vamos observarapenas os últimos 2000 dias e os 60 r
```

In [167…

```
# Ajustar os índices para plotar apenas a partir de 8000
inicio = 8000
fim = inicio + dias_para_prever

# Visualizar as previsões
plt.plot(range(inicio, len(y_teste)), y_teste[inicio:], label='Real')  # Plotar os 
plt.plot(range(len(y_teste), len(y_teste) + dias_para_prever), previsoes, label='Pr
plt.legend()
plt.title('Previsão de Tráfego para os Próximos 180 Dias')
plt.xlabel('Dias')
plt.ylabel('Tráfego Normalizado')
plt.show()
```



Conclusão

O melhor modelo foi o v14 com RMSE de apenas 0.359.

Fim