# Road Traffic Prediction : EDA, Prophet, SARIMA and SARIMAX

## Context

Traffic congestion is increasing in cities worldwide, driven by growing urban populations, outdated infrastructure, poorly coordinated traffic signals, and a lack of real-time data. The consequences are substantial. According to traffic data and analytics firm INRIX, U.S. commuters lost $305 billion in 2017 due to wasted fuel, lost time, and higher costs of transporting goods through congested areas. With limited physical space and financial resources to build more roads, cities need to adopt new strategies and technologies to enhance traffic management.

## Content

This dataset contains 48.1k (48120) observations of the number of vehicles each hour in four different junctions. In this project, we'll focus solely on data from Junction 1.

```
# !pip install prophet
# !pip install holidays

# pip install pmdarima

# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that gets preserved as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved outside of the current session

import pandas as pd
import numpy as np
```

```
import matplotlib.pyplot as plt
from statsmodels.tsa.seasonal import seasonal_decompose
from pandas.api.types import CategoricalDtype
import holidays
from sklearn.linear_model import LinearRegression
from datetime import datetime
from prophet import Prophet
from sklearn.metrics import mean_squared_error, mean_absolute_error,
mean_absolute_percentage_error
import warnings
warnings.filterwarnings("ignore")
```

## Import time series data

```
df =
pd.read_csv('https://docs.google.com/spreadsheets/d/1GO0WgbDW6UmYqxj51
54QF6FvDDhLeWJ7_EgyMcDK2YM/export?
format=csv',index_col=[0],parse_dates=[0])
df.head()
```


{"summary":"{\n  \"name\": \"df\",\n  \"rows\": 48120,\n  \"fields\": [\n    {\n      \"column\": \"DateTime\",\n      \"properties\": {\n        \"dtype\": \"date\",\n        \"min\": \"2015-11-01 00:00:00\",\n        \"max\": \"2017-06-30 23:00:00\",\n        \"num_unique_values\": 14592,\n        \"samples\": [\n          \"2016-05-13 20:00:00\",\n          \"2016-11-03 20:00:00\",\n          \"2015-12-08 19:00:00\"\n        ],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n      }\n    },\n    {\n      \"column\": \"Junction\",\n      \"properties\": {\n        \"dtype\": \"number\",\n        \"std\": 0,\n        \"min\": 1,\n        \"max\": 4,\n        \"num_unique_values\": 4,\n        \"samples\": [\n          2,\n          4,\n          1\n        ],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n      }\n    },\n    {\n      \"column\": \"Vehicles\",\n      \"properties\": {\n        \"dtype\": \"number\",\n        \"std\": 20,\n        \"min\": 1,\n        \"max\": 180,\n        \"num_unique_values\": 141,\n        \"samples\": [\n          73,\n          99,\n          38\n        ],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n      }\n    },\n    {\n      \"column\": \"ID\",\n      \"properties\": {\n        \"dtype\": \"number\",\n        \"std\": 5944853,\n        \"min\": 20151101001,\n        \"max\": 20170630234,\n        \"num_unique_values\": 48120,\n        \"samples\": [\n          20161223082,\n          20160828203,\n          20170424063\n        ],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n      }\n    }\n  ]\n}","type":"dataframe","variable_name":"df"}

```
df = df.reset_index()
df['DateTime'] = pd.to_datetime(df['DateTime'])  # Ensure it's in
datetime format
df.set_index('DateTime', inplace=True)  # Set it back as the index

df
```


{"summary":"{\n  \"name\": \"df\",\n  \"rows\": 48120,\n  \"fields\":
[\n    {\n      \"column\": \"DateTime\",\n      \"properties\": {\n
\"dtype\": \"date\",\n        \"min\": \"2015-11-01 00:00:00\",\n
\"max\": \"2017-06-30 23:00:00\",\n        \"num_unique_values\":
14592,\n        \"samples\": [\n          \"2016-05-13 20:00:00\",\n
\"2016-11-03 20:00:00\",\n          \"2015-12-08 19:00:00\"\
n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"Junction\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 0,\n        \"min\": 1,\n
\"max\": 4,\n        \"num_unique_values\": 4,\n        \"samples\":
[\n          2,\n          4,\n          1\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"Vehicles\",\n      \"properties\":
{\n        \"dtype\": \"number\",\n        \"std\": 20,\n
\"min\": 1,\n        \"max\": 180,\n        \"num_unique_values\":
141,\n        \"samples\": [\n          73,\n          99,\n
38\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"ID\",\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 5944853,\n        \"min\": 20151101001,\n        \"max\":
20170630234,\n        \"num_unique_values\": 48120,\n
\"samples\": [\n          20161223082,\n          20160828203,\n
20170424063\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    }\n  ]\
n}","type":"dataframe","variable_name":"df"}


## Pre-processing

```
df = df[df['Junction'] == 1]             # Filter for Junction 1
df = df.drop(columns=['ID', 'Junction']) # Drop the 'ID' and
'Junction' columns
df.head()
```


{"summary":"{\n  \"name\": \"df\",\n  \"rows\": 14592,\n  \"fields\":
[\n    {\n      \"column\": \"DateTime\",\n      \"properties\": {\n
\"dtype\": \"date\",\n        \"min\": \"2015-11-01 00:00:00\",\n
\"max\": \"2017-06-30 23:00:00\",\n        \"num_unique_values\":
14592,\n        \"samples\": [\n          \"2016-05-13 20:00:00\",\n
\"2016-11-03 20:00:00\",\n          \"2015-12-08 19:00:00\"\
n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"Vehicles\",\n      \"properties\": {\n        \"dtype\":

```
\"number\",\n        \"std\": 23,\n        \"min\": 5,\n
\"max\": 156,\n        \"num_unique_values\": 133,\n
\"samples\": [\n          62,\n          77,\n          38\
n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    }\n  ]\
n}","type":"dataframe","variable_name":"df"}
```



```
df.shape
```

```
(14592, 1)
```

```
# check for missing values and fill them if there
if(df.isnull().sum().sum()==0):
    print('No missing values.')
else:
    df.fillna(method='ffill',inplace=True)
```

```
No missing values.
```

# Feature engineering

```
cat_type =
CategoricalDtype(categories=['Monday','Tuesday','Wednesday',

'Thursday','Friday','Saturday','Sunday'],
                            ordered=True)
us_holidays = holidays.US(years=[2015, 2016, 2017])

def create_features(df, label=None):
    """
    Creates time series features from datetime index.
    """
    df = df.copy()
    df['date'] = df.index
    df['hour'] = df['date'].dt.hour
    df['weekday'] = df['date'].dt.day_name()
    df['weekday'] = df['weekday'].astype(cat_type)
    df['month'] = df['date'].dt.month
    df['year'] = df['date'].dt.year
    df['isholiday'] = df['date'].dt.normalize().isin(us_holidays)
    df['date_offset'] = (df.date.dt.month*100 + df.date.dt.day -
320)%1300

    df['season'] = pd.cut(df['date_offset'], [0, 300, 602, 900, 1300],
                          labels=['Spring', 'Summer', 'Fall',
'Winter']
                   )
    X = df[['hour','isholiday','weekday','month','year','season']]
    if label:
        y = df[label]
```

```
        return X, y
    return X

X, y = create_features(df, label='Vehicles')
features_and_target = pd.concat([X, y], axis=1)

# Display the first few rows to verify
print(features_and_target[features_and_target['isholiday'] == True])
```

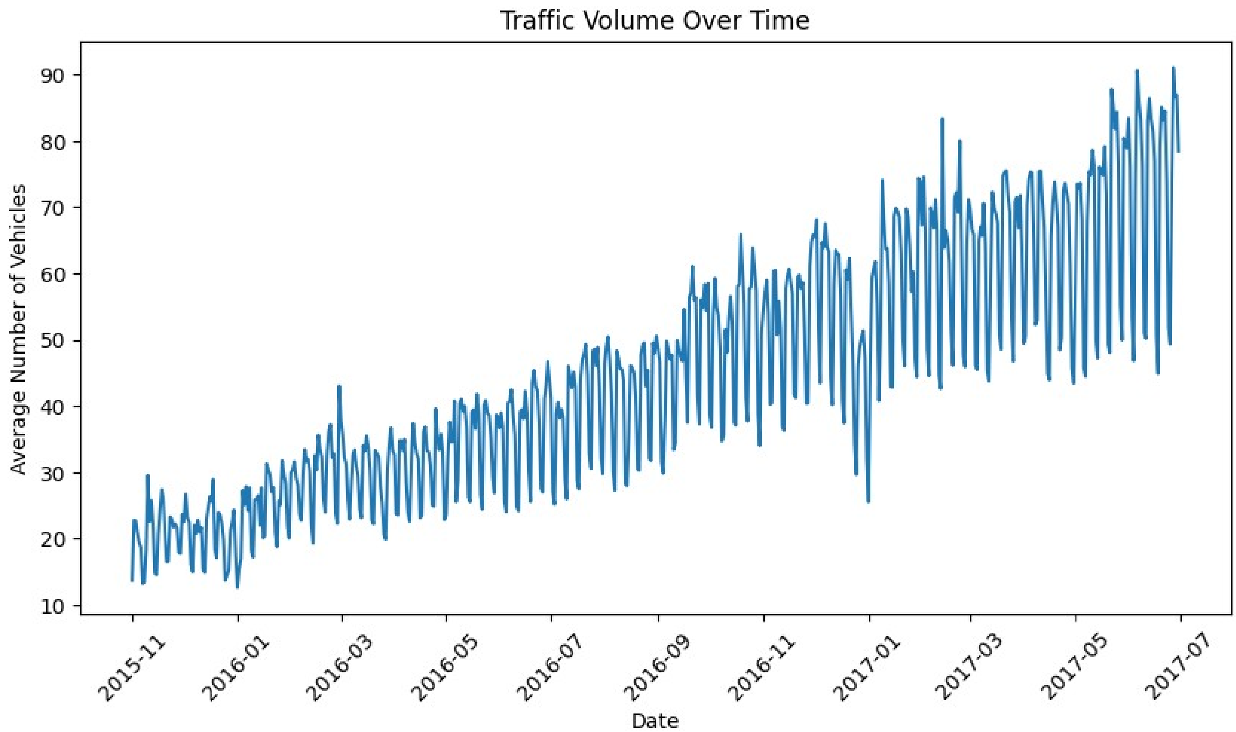
```
                     hour  isholiday    weekday  month  year  season
Vehicles
DateTime

2015-11-11 00:00:00     0       True  Wednesday     11  2015    Fall
28
2015-11-11 01:00:00     1       True  Wednesday     11  2015    Fall
25
2015-11-11 02:00:00     2       True  Wednesday     11  2015    Fall
19
2015-11-11 03:00:00     3       True  Wednesday     11  2015    Fall
21
2015-11-11 04:00:00     4       True  Wednesday     11  2015    Fall
20
...                   ...        ...        ...    ...   ...     ...
...
2017-05-29 19:00:00    19       True     Monday      5  2017  Spring
104
2017-05-29 20:00:00    20       True     Monday      5  2017  Spring
93
2017-05-29 21:00:00    21       True     Monday      5  2017  Spring
84
2017-05-29 22:00:00    22       True     Monday      5  2017  Spring
89
2017-05-29 23:00:00    23       True     Monday      5  2017  Spring
80

[456 rows x 7 columns]
```

## Data Visualization

#why hourly to monthly ->original data (df) has hourly observations, it can be noisy and difficult to interpret overall patterns

```
# For better readability, resample the data by day and take the mean
plt.figure(figsize=(10, 5))
df_daily = df.resample('D').mean()
plt.plot(df_daily.index, df_daily['Vehicles'])
plt.title('Traffic Volume Over Time')
plt.xlabel('Date')
```

```
plt.xticks(rotation=45)
plt.ylabel('Average Number of Vehicles')
plt.show()
```




#Cross-Covarience

#Problem with choosing Air Quality / Pollution Data dataset

air pollution is influenced by many factors, not just traffic, which can make the relationship noisy and hard to interpret in a clean way

1.Multiple Influencers:

```
  Industrial emissions
  Construction dust
  Weather conditions (e.g., wind, rain disperses pollutants)
  Fires, Diwali fireworks, etc.
```

2.Time Lag Effects:

```
  Pollution build-up may not show up the same day as traffic.
  Rain can clear pollution even if traffic is high that day.
```

#Holidays

```
import pandas as pd # This line imports the pandas library and assigns it the alias 'pd'
holiday =
pd.read_csv('https://docs.google.com/spreadsheets/d/1yHtF0Uirn2TMU-5qSpEE-bDaslSqrFO2YSM2G2x1Psk/export?format=csv',
index_col=[0],parse_dates=[0])
holiday.head()


holiday = holiday.drop(columns=['WeekDay', 'Month','Day','Year']) # Drop  columns
holiday.head()
```

{"summary":"{\n  \"name\": \"holiday\",\n  \"rows\": 342,\n  \"fields\": [\n    {\n      \"column\": \"Date\",\n      \"properties\": {\n        \"dtype\": \"date\",\n        \"min\": \"2004-01-01 00:00:00\",\n        \"max\": \"2021-12-31 00:00:00\",\n        \"num_unique_values\": 336,\n        \"samples\": [\n          \"2010-04-04 00:00:00\",\n          \"2013-09-02 00:00:00\",\n          \"2014-11-11 00:00:00\"\n        ],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n      }\n    },\n    {\n      \"column\": \"Holiday\",\n      \"properties\": {\n        \"dtype\": \"category\",\n        \"num_unique_values\": 18,\n        \"samples\": [\n          \"4th of July\",\n          \"Christmas Day\",\n          \"Martin Luther King, Jr. Day\"\n        ],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n      }\n    }\n  ]\n}","type":"dataframe","variable_name":"holiday"}

```
# # holiday.drop(columns=['Date'], errors='ignore', inplace=True)  # Remove existing 'Date' column if present
# # holiday = holiday.reset_index()  # Now reset index safely
# holiday['Date'] = pd.to_datetime(holiday.index)
# holiday['Date'] = pd.to_datetime(holiday['Date'])  # Convert 'Date' to DateTime
# # holiday.set_index('Date', inplace=True)  # Set 'Date' as index again


#
# Ensure 'Date' is actually a column
if 'Date' not in holiday.columns:
    holiday = holiday.reset_index()  # Convert index to column

# Convert Date to datetime
holiday['Date'] = pd.to_datetime(holiday['Date'])


import pandas as pd
import holidays
```

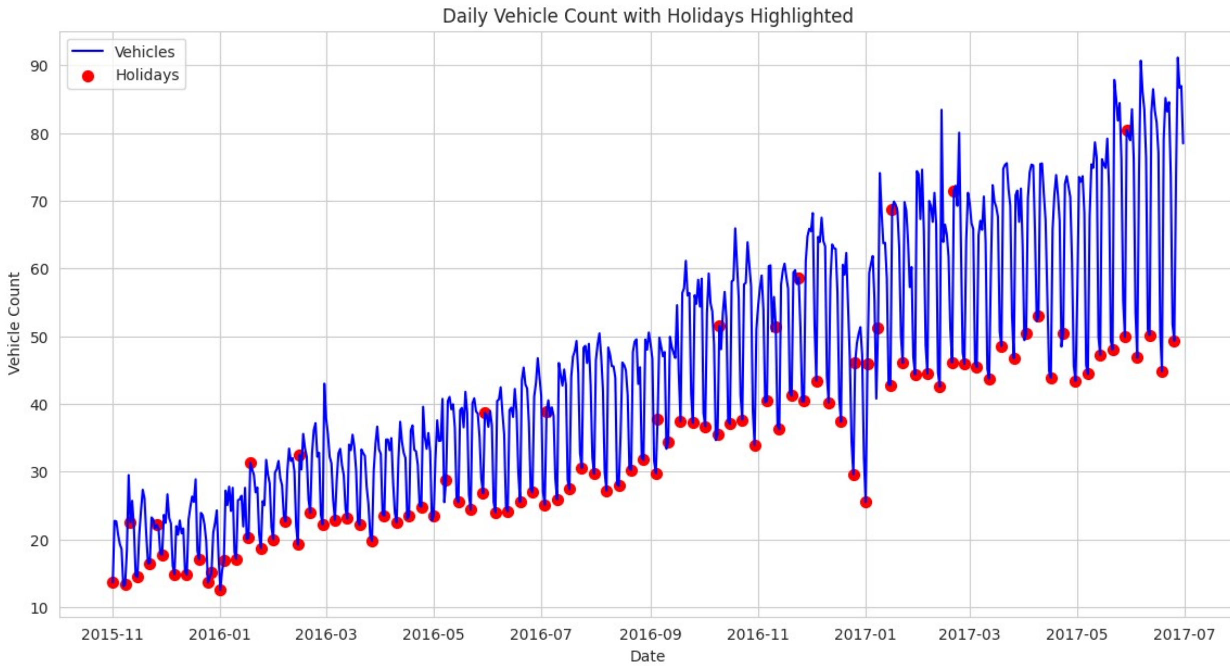
```
# Create a US holidays calendar for the years 2015-2017
us_holidays = holidays.US(years=[2015, 2016, 2017])

# Create a DataFrame from the holidays calendar
holiday = pd.DataFrame(list(us_holidays.items()), columns=['Date',
'Holiday'])

# Convert 'Date' column to datetime
holiday['Date'] = pd.to_datetime(holiday['Date'])

# Define the date range you want to include Sundays for
start_date = holiday['Date'].min()
end_date = holiday['Date'].max()

# Generate all Sundays between the date range
all_sundays = pd.date_range(start=start_date, end=end_date, freq='W-
SUN')

# Create a DataFrame for Sundays
sunday_df = pd.DataFrame({'Date': all_sundays, 'Holiday': 'Sunday'})

# Combine with the original dataset
combined_df = pd.concat([holiday, sunday_df], ignore_index=True)

# Remove duplicates if any (based on Date and Holiday)
combined_df = combined_df.drop_duplicates(subset=['Date', 'Holiday'])

# Sort by Date
combined_holidays =
combined_df.sort_values(by='Date').reset_index(drop=True)


# Merge the holiday dataset with df_daily
# df_daily['isHoliday'] =
df_daily.index.isin(holiday['Date']).astype(int)
df_daily['isHoliday'] =
df_daily.index.isin(combined_holidays['Date']).astype(int)
#

print(df_daily.head())  # Verify changes
```

```
             Vehicles  Vehicles_diff  Vehicles_log  Vehicles_sqrt  \
DateTime
2015-11-01  13.625000       0.000000      2.611906       3.691206
2015-11-02  22.750000       9.125000      3.124565       4.769696
2015-11-03  22.666667      -0.083333      3.120895       4.760952
2015-11-04  20.750000      -1.916667      3.032546       4.555217
2015-11-05  19.333333      -1.416667      2.961831       4.396969

            Vehicles_boxcox  Vehicles_boxcox_diff  Vehicles_log_var  \
DateTime
```

```
2015-11-01         4.433244                   NaN              NaN
2015-11-02         5.937561              1.504317              NaN
2015-11-03         5.925734             -0.011828              NaN
2015-11-04         5.645836             -0.279898              NaN
2015-11-05         5.428386             -0.217450              NaN

            Vehicles_sqrt_var  Vehicles_boxcox_var
Vehicles_boxcox_diff_var  \
DateTime

2015-11-01                NaN                  NaN
NaN
2015-11-02                NaN                  NaN
NaN
2015-11-03                NaN                  NaN
NaN
2015-11-04                NaN                  NaN
NaN
2015-11-05                NaN                  NaN
NaN

            isHoliday
DateTime
2015-11-01          1
2015-11-02          0
2015-11-03          0
2015-11-04          0
2015-11-05          0
```

```
import matplotlib.pyplot as plt

# Ensure the 'DateTime' index is sorted
df_daily = df_daily.sort_index()

# Plot the entire time series in blue
plt.figure(figsize=(14, 7))
plt.plot(df_daily.index, df_daily['Vehicles'], color='blue',
label='Vehicles')

# Overlay holidays with red markers
plt.scatter(
    df_daily.index[df_daily['isHoliday'] == 1],
    df_daily['Vehicles'][df_daily['isHoliday'] == 1],
    color='red', label='Holidays', marker='o', s=50
)

# Add labels and title
plt.xlabel('Date')
plt.ylabel(' Vehicle Count')
plt.title('Daily Vehicle Count with Holidays Highlighted')
```

```
plt.legend()

# Display the plot
plt.show()
```




#Observations

1.Overall upward/inceasing Trend:

```
  Population and Driving Trends: The American Driving Survey (2014-
2017) noted a general increase in the number
   of drivers and total miles driven annually, contributing to  an
overall upward trend in traffic volume
   during our dataset period.
```

2.Weekly pattern :

```
  Strong weekly pattern: The spikes follow a repetitive pattern,
likely corresponding to weekday peaks(e.g.,Mondays or
  Fridays).
```

3.On Weekend or Holiday :

```
  In above plot red dot is vehicle congestion on holidays.As we can
clearly see that on most of the holiday traffic
  is lowest  than any normal day.That means people prefer staying at
home than going outside on holidays
```

4.Christmas and New year

```
  During Christmas and new year (December end and january start),
there is significan drop in vehicles on both years. That is because of
long weekend
  holiday on these festivals
```

5.Holiday with high traffic :

```
  We can see that some dots which are some holidays have more traffic
than normal days , those are pre-festival preparation or post-festival
end.
```

```
# Calculate the average vehicle count on holidays
holiday_avg = df_daily[df_daily['isHoliday'] == 1]['Vehicles'].mean()

# Calculate the average vehicle count on non-holidays
non_holiday_avg = df_daily[df_daily['isHoliday'] == 0]
['Vehicles'].mean()

print(f"Average Vehicles on Holidays: {holiday_avg}")
print(f"Average Vehicles on Non-Holidays: {non_holiday_avg}")

# Calculate other useful statistics for comparison

# Percentage difference in average vehicles
percentage_diff = ((holiday_avg - non_holiday_avg) / non_holiday_avg)
* 100

print(f"Percentage Difference: {percentage_diff:.2f}%")

# Standard deviation of vehicle counts on holidays and non-holidays
holiday_std = df_daily[df_daily['isHoliday'] == 1]['Vehicles'].std()
non_holiday_std = df_daily[df_daily['isHoliday'] == 0]
['Vehicles'].std()

print(f"Standard Deviation on Holidays: {holiday_std}")
print(f"Standard Deviation on Non-Holidays: {non_holiday_std}")


# Calculate the median vehicle count on holidays and non-holidays
holiday_median = df_daily[df_daily['isHoliday'] == 1]
['Vehicles'].median()
non_holiday_median = df_daily[df_daily['isHoliday'] == 0]
['Vehicles'].median()

print(f"Median Vehicles on Holidays: {holiday_median}")
print(f"Median Vehicles on Non-Holidays: {non_holiday_median}")
```

```
Average Vehicles on Holidays: 33.98197115384615
Average Vehicles on Non-Holidays: 47.33738425925926
Percentage Difference: -28.21%
Standard Deviation on Holidays: 13.651774490924161
Standard Deviation on Non-Holidays: 18.468376162756513
Median Vehicles on Holidays: 32.125
Median Vehicles on Non-Holidays: 45.60416666666667
```

#Observation There is significant drop in traffic in holiday days than non-holidays day.

#Mean and Variance over the time function

```
def mean_over_time(process: np.array) -> np.array:
    mean_func = []

    for i in range(len(process)):
        mean_func.append(np.mean(process[:i]))

    return mean_func

def var_over_time(process: np.array) -> np.array:
    var_func = []

    for i in range(len(process)):
        var_func.append(np.var(process[:i]))

    return var_func

# Install required libraries if needed (uncomment if necessary)
# !pip install pandas numpy matplotlib statsmodels sklearn seaborn

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.arima_model import ARMA  # For a pure MA model, 
p=0, q>0

from sklearn.metrics import mean_squared_error, r2_score
import math

# Optional: nicer plot style
sns.set_style('whitegrid')
plt.rcParams['figure.figsize'] = (12, 6)
```

```python
def adf_test(series, title=''):
    """
    Perform ADF test and print the results.
    """
    print(f'Augmented Dickey-Fuller Test: {title}')
    result = adfuller(series.dropna(), autolag='AIC')
    labels = ['ADF Test Statistic','p-value','# Lags Used','Number of Observations Used']
    out = dict(zip(labels, result[0:4]))
    for key, val in out.items():
        print(f"   {key} : {val}")
    for key,val in result[4].items():
        print(f"   Critical Value {key} : {val}")
    print("")

# Perform ADF test on the 'Close' prices
adf_test(df_daily['Vehicles'], 'Original data')
```

```
Augmented Dickey-Fuller Test: Original data
   ADF Test Statistic : -0.3413815102045766
   p-value : 0.9194355530673934
   # Lags Used : 18
   Number of Observations Used : 589
   Critical Value 1% : -3.4415011513018263
   Critical Value 5% : -2.8664595311890215
   Critical Value 10% : -2.569389981494346
```

By above ADF result, we can see that p-value is more than 0.05, so it's not stationary.It means unit roots lies outiside unit circle.

To make it stationary, We need different transformations methods

#what is stationary ? stationary means constant over the time or it does not depent on time. For simple model analysis stationary series is required, so it our data is not , then we need to transform it using different method on it

```python

# Calculate the first difference of the 'Vehicles' column
df_daily['Vehicles_diff'] = df_daily['Vehicles'].diff()

# Print the first few rows to verify
# print(df_daily.head())
# Fill the first NaN value in 'Vehicles_diff' with 0
df_daily['Vehicles_diff'].fillna(0, inplace=True)

# Print the first few rows to verify
print(df_daily.head())
```

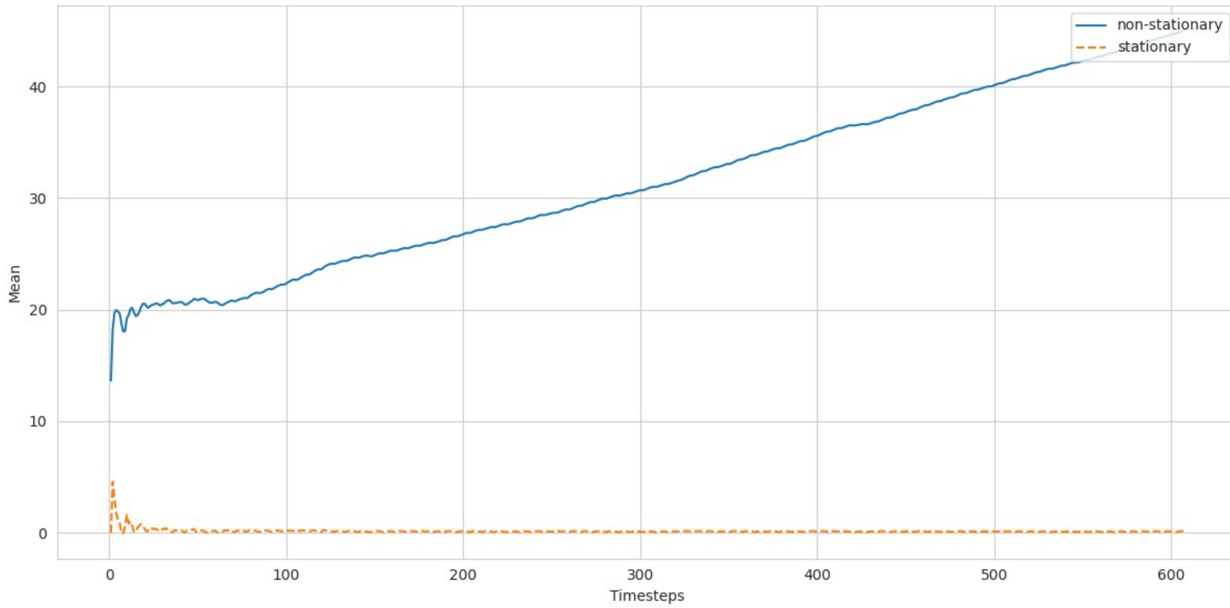
```
             Vehicles  Vehicles_diff
DateTime
2015-11-01  13.625000       0.000000
2015-11-02  22.750000       9.125000
2015-11-03  22.666667      -0.083333
2015-11-04  20.750000      -1.916667
2015-11-05  19.333333      -1.416667
```

```
adf_test(df_daily['Vehicles_diff'], 'differences data')
```

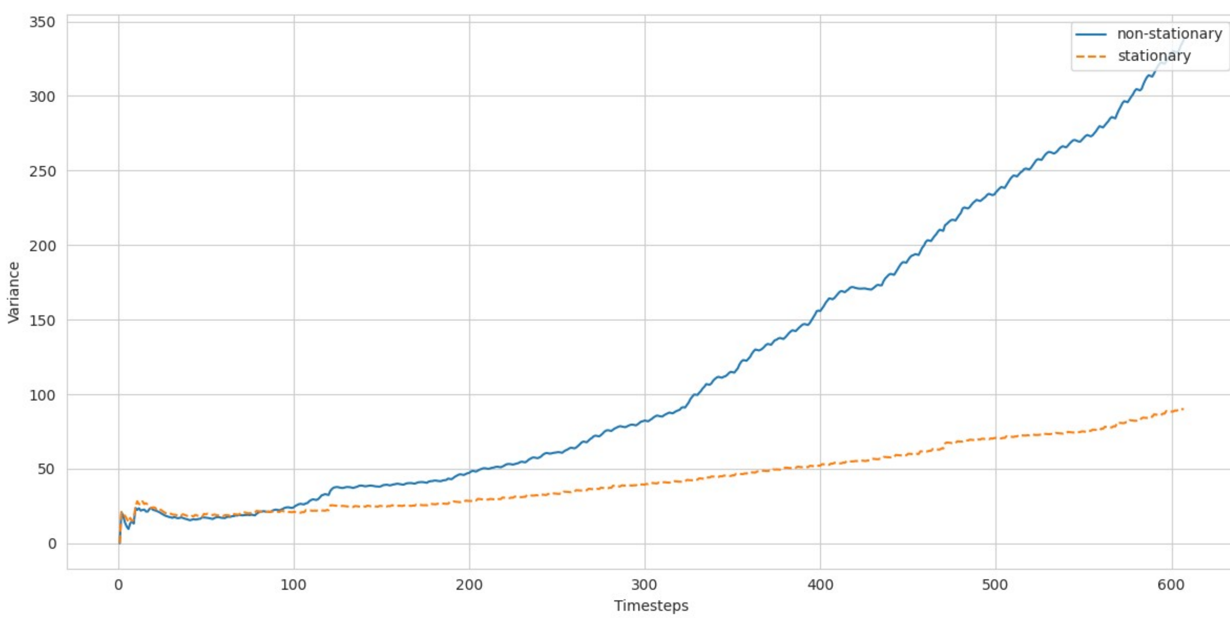
```
Augmented Dickey-Fuller Test: differences data
   ADF Test Statistic : -8.929825562401408
   p-value : 9.884150674420592e-15
   # Lags Used : 19
   Number of Observations Used : 588
   Critical Value 1% : -3.44152019959894
   Critical Value 5% : -2.8664679191981297
   Critical Value 10% : -2.569394451038919
```

After applying ADF test on difference data, our p-value is less than 0.05 so we could say that now our series is stationary.

```
non_stationary_var = var_over_time(df_daily['Vehicles'])
non_stationary_mean = mean_over_time(df_daily['Vehicles'])
stationary_var = var_over_time(df_daily['Vehicles_diff'])
stationary_mean = mean_over_time(df_daily['Vehicles_diff'])

fig, ax = plt.subplots()

ax.plot(non_stationary_mean, linestyle='-', label='non-stationary')
ax.plot(stationary_mean, linestyle='--', label='stationary')
ax.set_xlabel('Timesteps')
ax.set_ylabel('Mean')
ax.legend(loc=1)

plt.tight_layout()
```




```
fig, ax = plt.subplots()

ax.plot(non_stationary_var, linestyle='-', label='non-stationary')
ax.plot(stationary_var, linestyle='--', label='stationary')
ax.set_xlabel('Timesteps')
ax.set_ylabel('Variance')
ax.legend(loc=1)

plt.tight_layout()
```




#If your stationary time series still has fluctuating variance, you might need to stabilize the variance further

Check for Conditional Heteroskedasticity (ARCH Effects) Even if your data is stationary in mean, the variance might still be fluctuating due to conditional heteroskedasticity (ARCH/GARCH effects). You can check this using the ARCH test:

```
from statsmodels.tsa.stattools import adfuller
from statsmodels.stats.diagnostic import het_arch


# Example: Checking for ARCH effects (heteroskedasticity)
arch_test_p_value = het_arch(df_daily['Vehicles_diff'])[1]
print(f"ARCH Test p-value: {arch_test_p_value}")  # < 0.05 suggests
volatility clustering
#If the ARCH test p-value is low (< 0.05), you have time-dependent
variance (volatility clustering).
```

```
ARCH Test p-value: 2.1149139090414235e-79
```

Since our p value of ARCH test is less than 0.05 --> we have time-dependent varience

#2. Apply a Variance-Stabilizing Transformation If variance is fluctuating, try:

a) Log Transformation (For High Variance Differences) Use when variance increases with larger values.

python Copy Edit df["new_series"] = df["original_series"].apply(lambda x: np.log(x) if x > 0 else np.nan)

b) Square Root Transformation (For Smaller Variance Differences) Works for moderate variance fluctuations.

python Copy Edit df["new_series"] = df["original_series"]**0.5

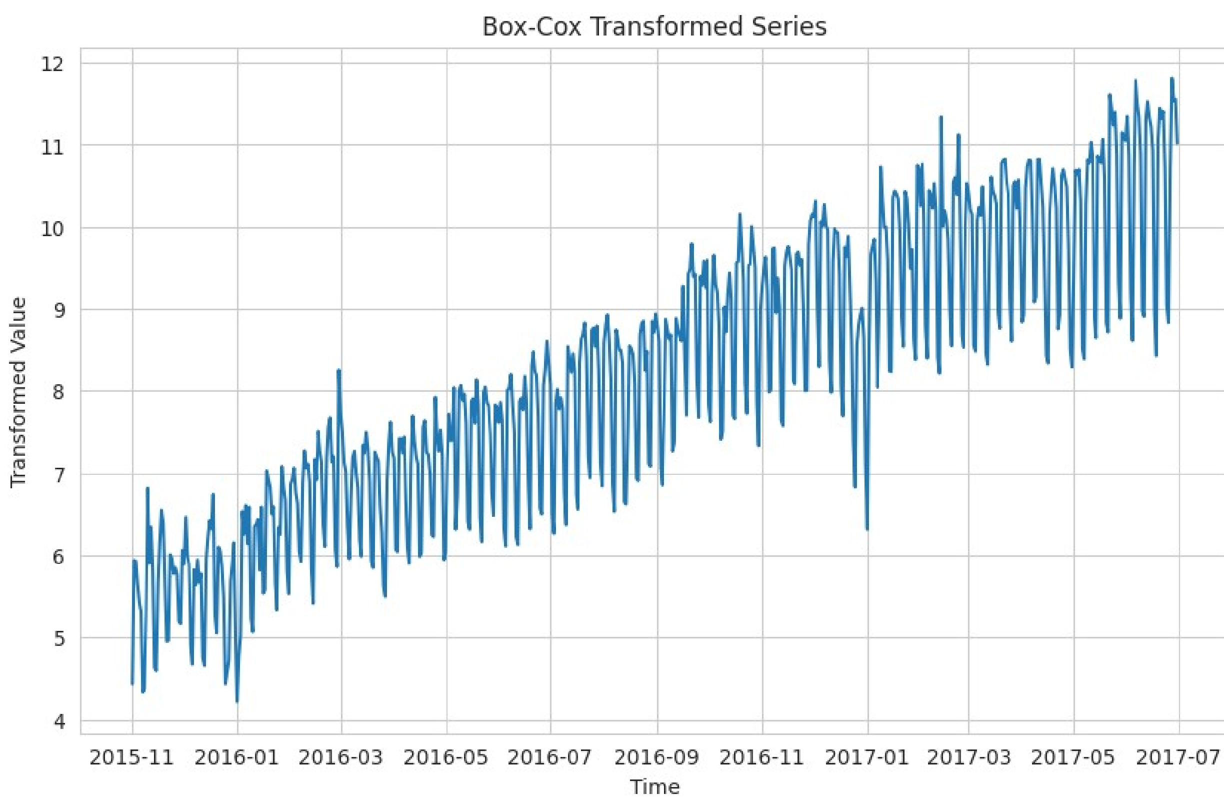
c) Box-Cox Transformation (Best for Strong Variance Fluctuations) More flexible than log or square root. Requires positive values.

python Copy Edit from scipy.stats import boxcox

df["new_series"], lambda_value = boxcox(df["original_series"])

```
# df_daily["Vehicles_diff_log"] =
df_daily["Vehicles_diff"].apply(lambda x: np.log(x) if x > 0 else
np.nan)
df_daily["Vehicles_log"] = np.log(df_daily["Vehicles"])
df_daily["Vehicles_sqrt"] = np.sqrt(df_daily["Vehicles"])

# prompt: apply box-cox transformation

from scipy.stats import boxcox

# Assuming df_daily and the necessary columns exist as in your
```

```
provided code

# Apply Box-Cox transformation to 'Vehicles_diff'
df_daily["Vehicles_boxcox"], lambda_value =
boxcox(df_daily["Vehicles"])
df_daily["Vehicles_boxcox_diff"] =
pd.Series(df_daily["Vehicles_boxcox"]).diff().dropna()

print(f"Box-Cox lambda value: {lambda_value}")

# Now you can analyze or use the 'Vehicles_diff_boxcox' column
# for further time series analysis, as it has a more stable variance.

# Example: Plot the transformed series
plt.figure(figsize=(10, 6))
plt.plot(df_daily["Vehicles_boxcox"])
plt.title('Box-Cox Transformed Series')
plt.xlabel('Time')
plt.ylabel('Transformed Value')
plt.show()

Box-Cox lambda value: 0.37477611460652605
```

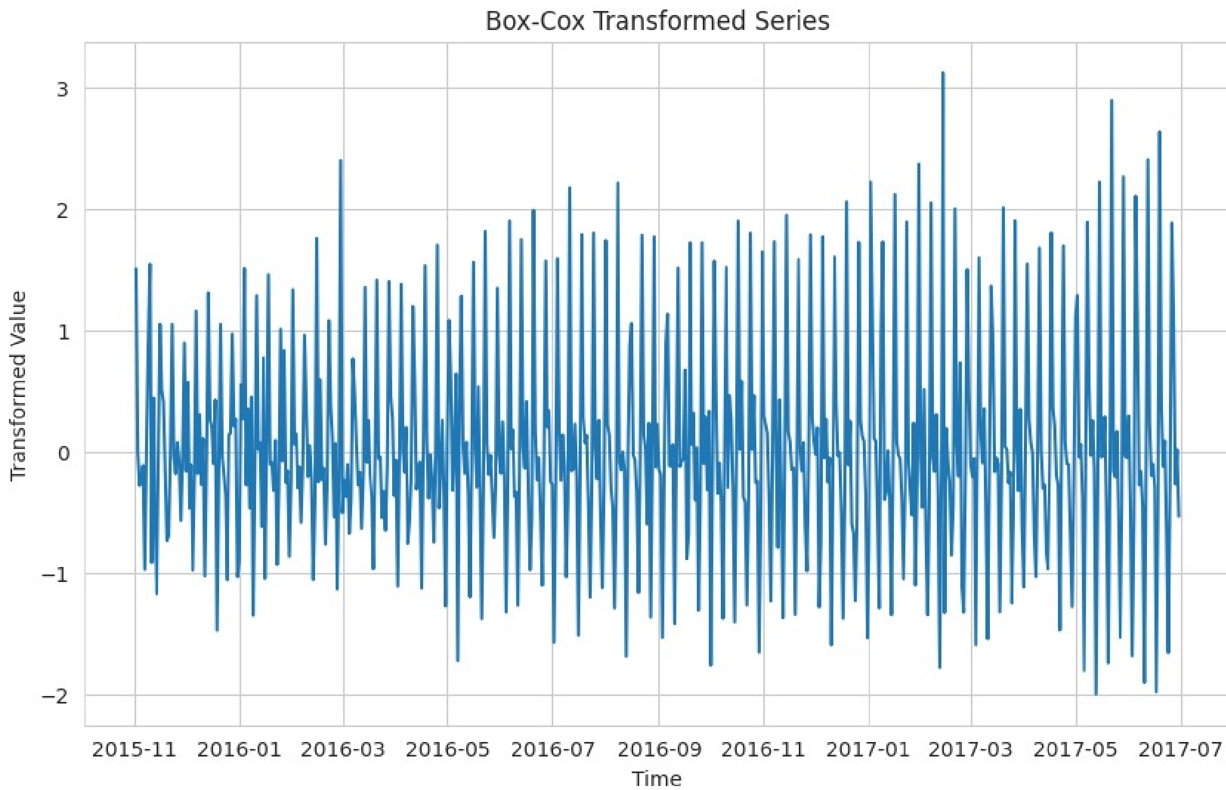



#Why do we difference after Box-Cox? Short answer: ▯ Yes, it's usually necessary to difference after Box-Cox if your data still has a trend or is not stationary in mean — because:

Box-Cox transformation helps to stabilize variance (i.e., handles heteroscedasticity).

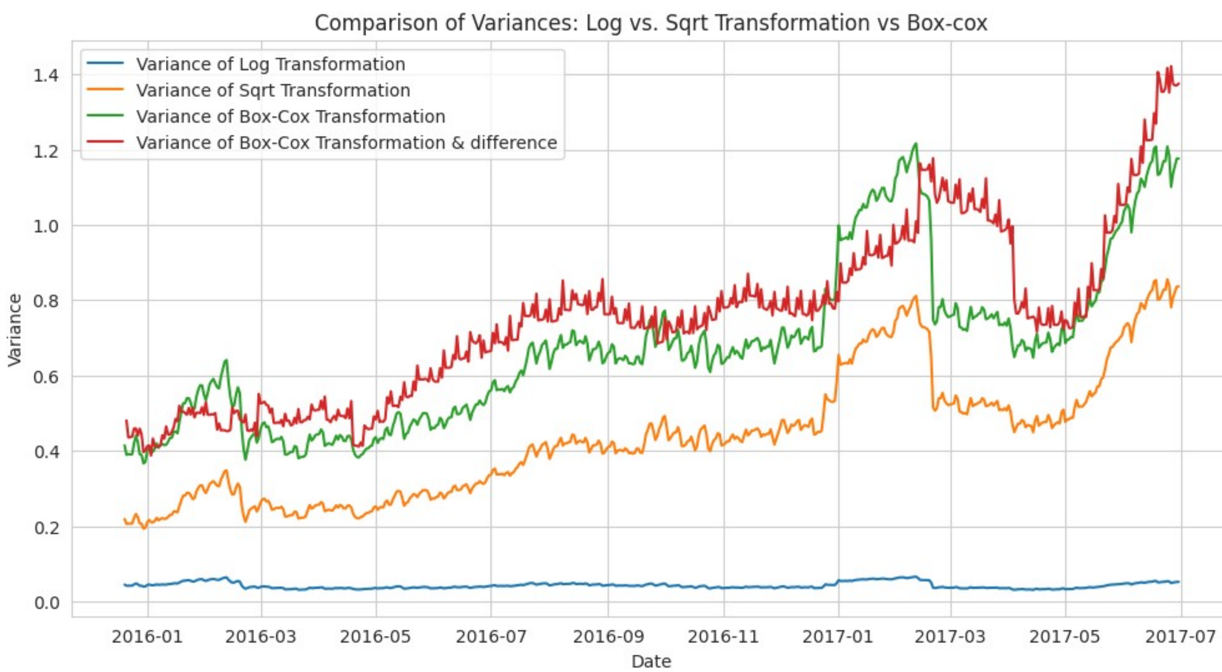
But it does not remove trends or seasonality, so your mean may still not be stationary

```
plt.figure(figsize=(10, 6))
plt.plot(df_daily["Vehicles_boxcox_diff"])
plt.title('Box-Cox Transformed Series')
plt.xlabel('Time')
plt.ylabel('Transformed Value')
plt.show()
```




```
# prompt: for df_daily plot it's varience of _log and _sqrt and
compare it with each other

# Assuming df_daily is already defined and populated as in the
provided code.

# Calculate variances of log and sqrt transformations
df_daily['Vehicles_log_var'] =
df_daily['Vehicles_log'].rolling(window=50).var()
df_daily['Vehicles_sqrt_var'] =
df_daily['Vehicles_sqrt'].rolling(window=50).var()
df_daily['Vehicles_boxcox_var'] =
df_daily['Vehicles_boxcox'].rolling(window=50).var()
df_daily['Vehicles_boxcox_diff_var'] =
```

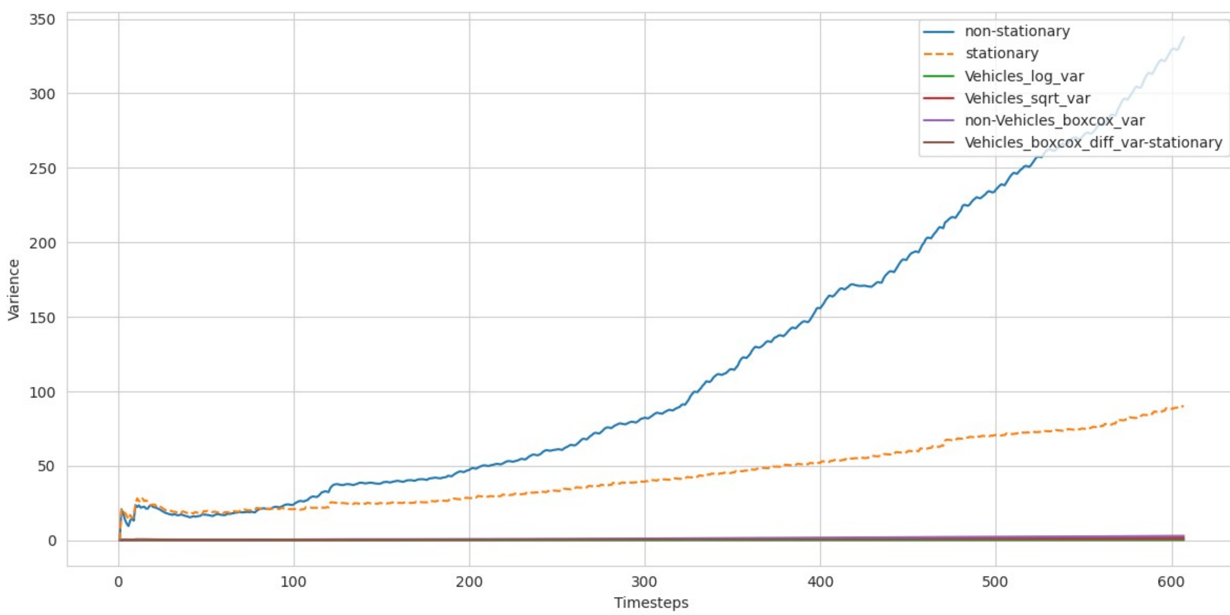
```
df_daily['Vehicles_boxcox_diff'].rolling(window=50).var()


# Plotting the variances
plt.figure(figsize=(12, 6))
plt.plot(df_daily.index, df_daily['Vehicles_log_var'], label='Variance
of Log Transformation')
plt.plot(df_daily.index, df_daily['Vehicles_sqrt_var'],
label='Variance of Sqrt Transformation')
plt.plot(df_daily.index, df_daily['Vehicles_boxcox_var'],
label='Variance of Box-Cox Transformation')
plt.plot(df_daily.index, df_daily['Vehicles_boxcox_diff_var'],
label='Variance of Box-Cox Transformation & difference')

plt.xlabel('Date')
plt.ylabel('Variance')
plt.title('Comparison of Variances: Log vs. Sqrt Transformation vs
Box-cox')
plt.legend()
plt.grid(True)
plt.show()
```




As you can see log transformation has most stable variance

```
non_stationary_var = var_over_time(df_daily['Vehicles'])
stationary_var = var_over_time(df_daily['Vehicles_diff'])
Vehicles_log_var = var_over_time(df_daily['Vehicles_log'])
Vehicles_sqrt_var = var_over_time(df_daily['Vehicles_sqrt'])
Vehicles_boxcox_var = var_over_time(df_daily['Vehicles_boxcox'])
```

```
Vehicles_boxcox_diff_var =
var_over_time(df_daily['Vehicles_boxcox_diff'])
# non_stationary_mean = mean_over_time(df_daily['Vehicles'])
# stationary_mean = mean_over_time(df_daily['Vehicles_diff'])

fig, ax = plt.subplots()

ax.plot(non_stationary_var, linestyle='-', label='non-stationary')
ax.plot(stationary_var, linestyle='--', label='stationary')
ax.plot(Vehicles_log_var, linestyle='-', label='Vehicles_log_var')
ax.plot(Vehicles_sqrt_var, linestyle='-', label='Vehicles_sqrt_var')
ax.plot(Vehicles_boxcox_var, linestyle='-', label='non-
Vehicles_boxcox_var')
ax.plot(Vehicles_boxcox_diff_var, linestyle='-',
label='Vehicles_boxcox_diff_var-stationary')
ax.set_xlabel('Timesteps')
ax.set_ylabel('Varience')
ax.legend(loc=1)

plt.tight_layout()
```




#ACF and PACF plots

as you can see in below plot is that after 7 lag pattern is reapiting, that is signify that after 7 lag there is some relation/correlations between data that means weakly

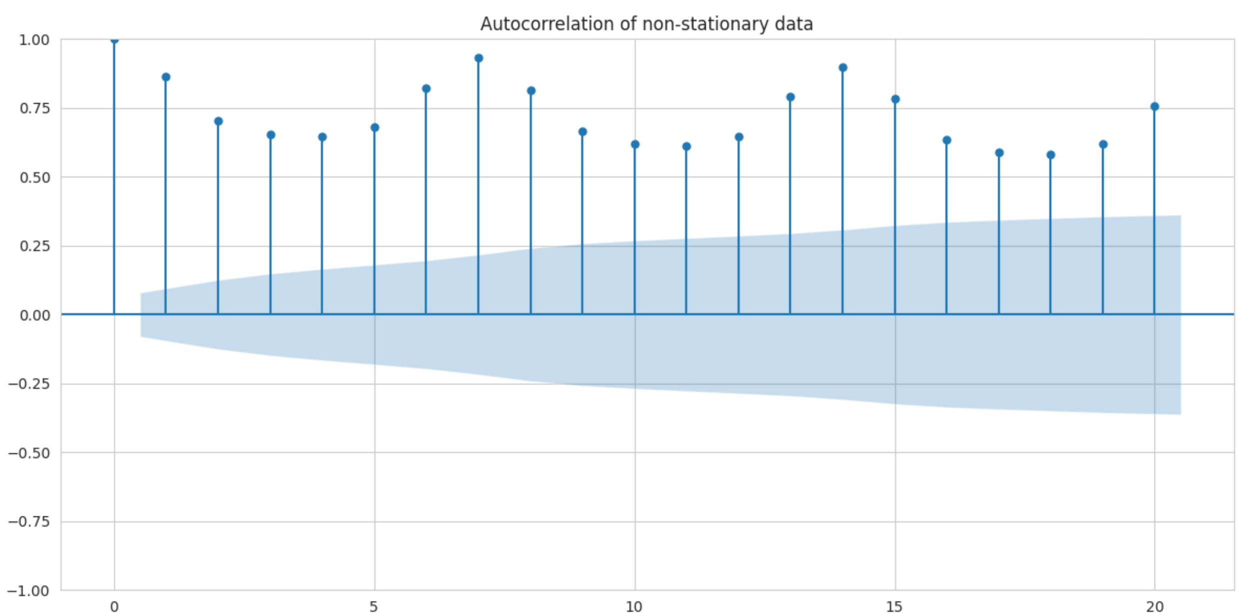
## ACF – Autocorrelation Function

- **What it measures:** The **correlation between a time series and its own lagged values** (i.e., how current values are related to past values).
- **Includes indirect effects:** It captures both **direct and indirect correlations**.
- For example, lag 2 autocorrelation reflects not just the direct effect of lag 2, but also the **effect of lag 1 influencing lag 2**.
- **Used to identify:** The MA (Moving Average) part in ARIMA models.

## PACF – Partial Autocorrelation Function

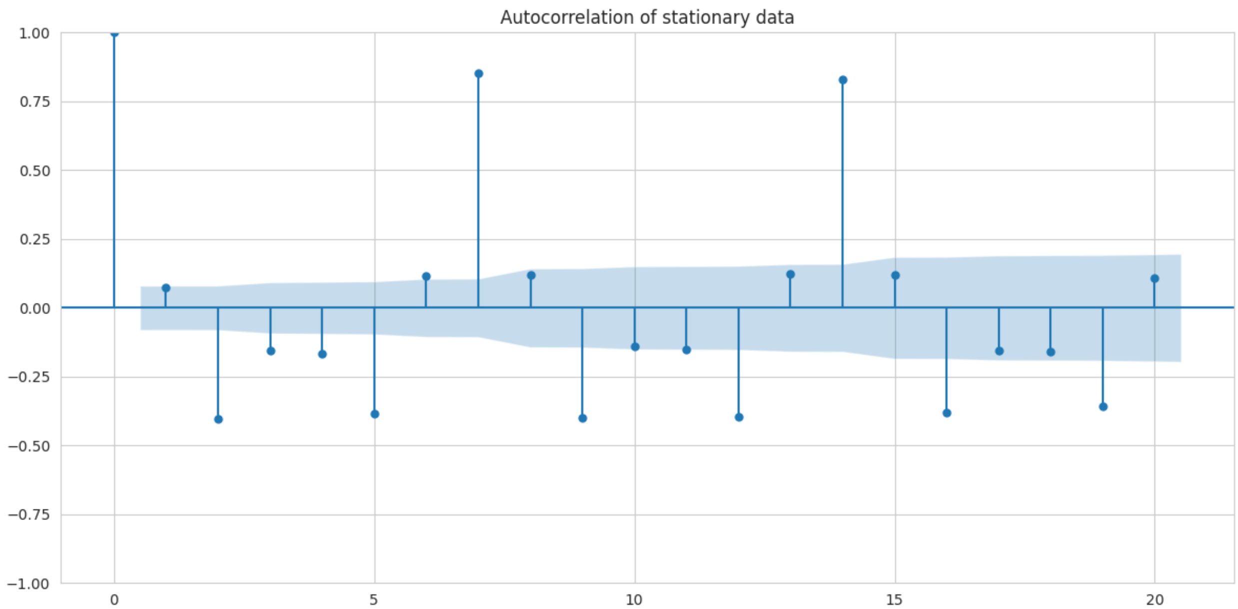
- **What it measures:** The **correlation between a time series and its lagged values, after removing the effects of all shorter lags**.
- **Only direct effects:** It answers the question: “Is there a direct relationship between lag *k* and the series, ignoring lags 1 to *k-1*?”
- **Used to identify:** The AR (Autoregressive) part in ARIMA models.

```
plot_acf(df_daily['Vehicles'], lags=20)
plt.title("Autocorrelation of non-stationary data")
plt.tight_layout()
plt.show()
```

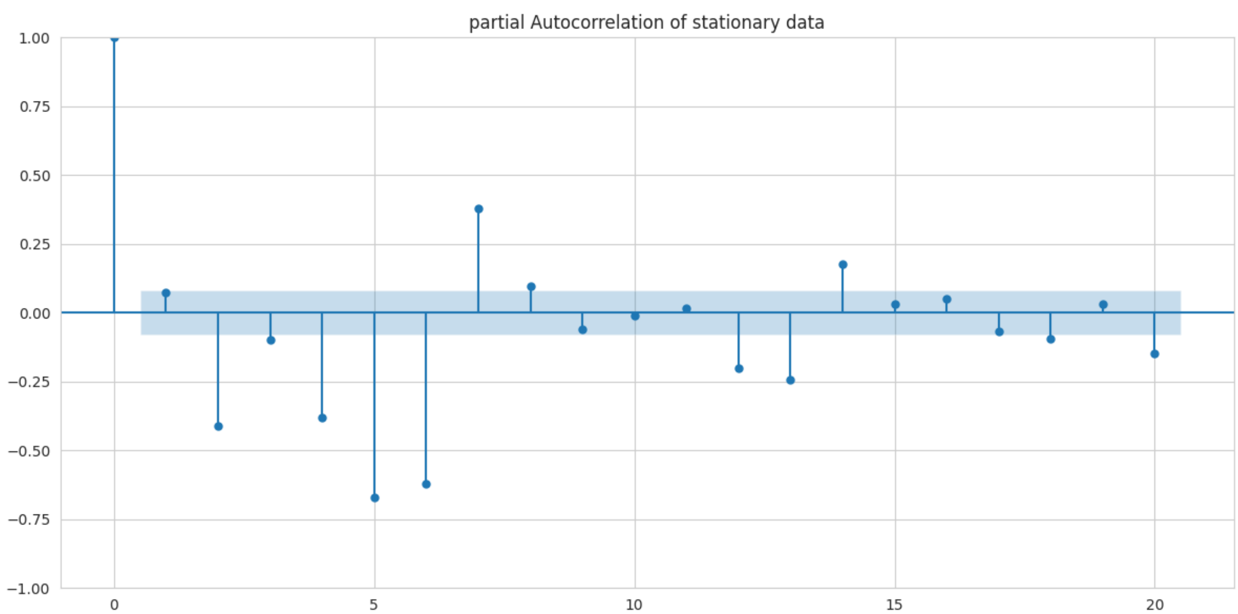



```
plot_acf(df_daily['Vehicles_diff'], lags=20);
plt.title("Autocorrelation of stationary data")
```

```
plt.tight_layout()
plt.show()
```

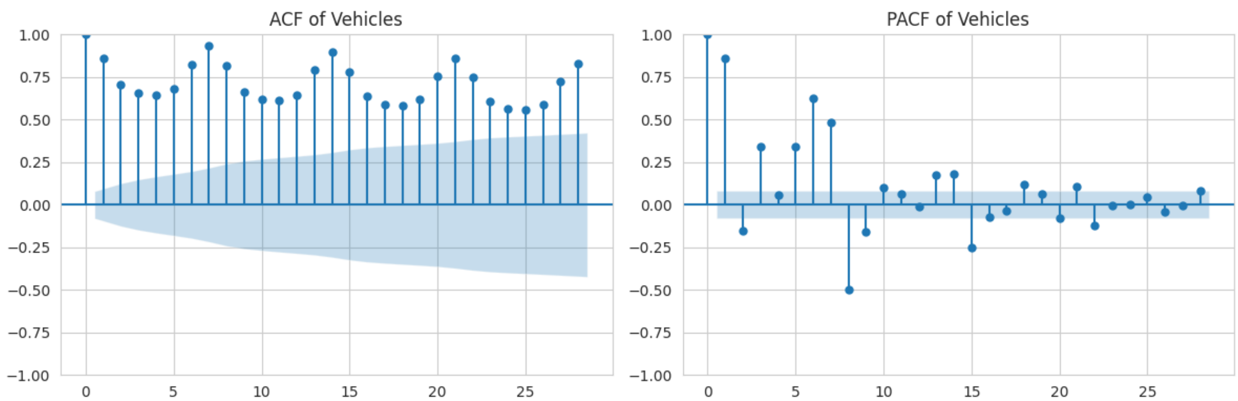



```
plot_pacf(df_daily['Vehicles_diff'], lags=20);
plt.title("partial Autocorrelation of stationary data")
plt.tight_layout()
plt.show()
```

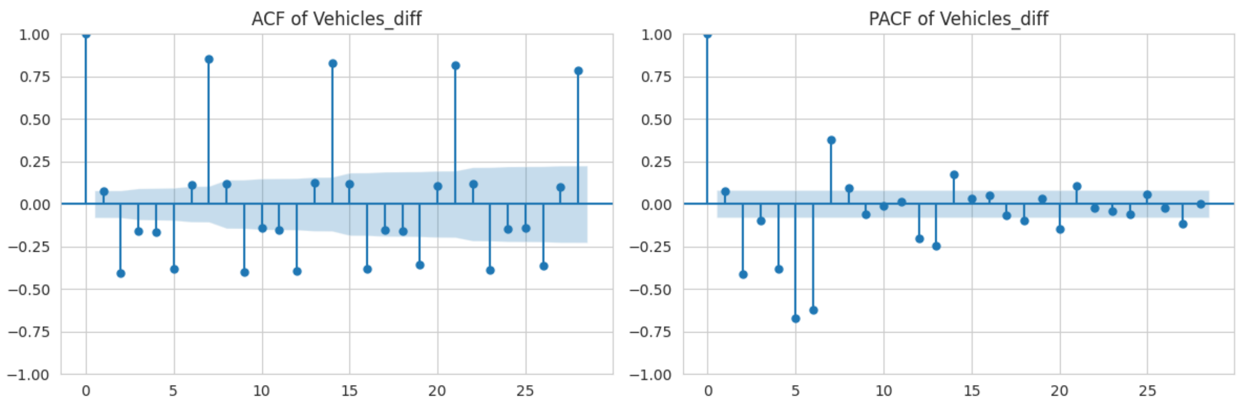



```
By above ADF result, we can see that p-value is more than 0.05, so
it's not stationary.It means unit roots lies outiside unit circle.
```

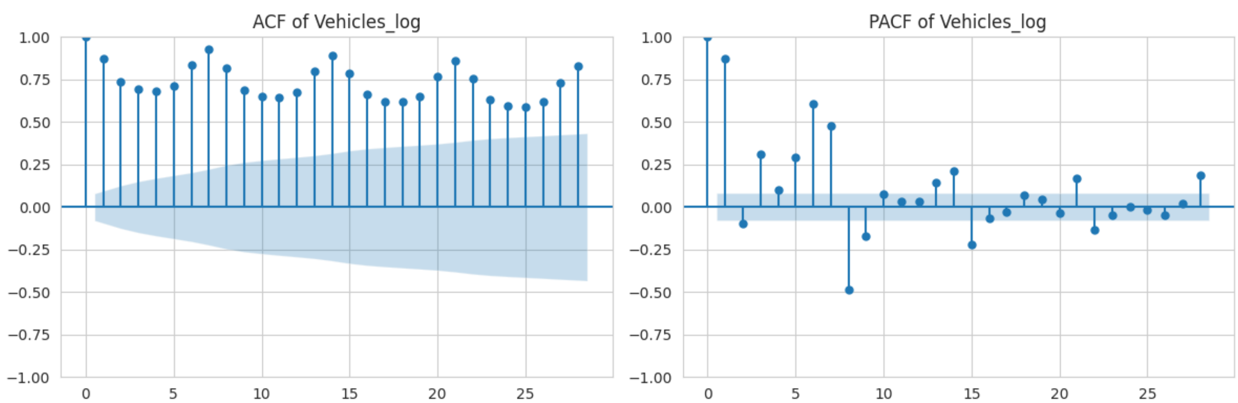
```python
import matplotlib.pyplot as plt
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

fig, axes = plt.subplots(1, 2, figsize=(12, 4))

# ACF plot
plot_acf(df_daily['Vehicles'], ax=axes[0])
axes[0].set_title('ACF of Vehicles')

# PACF plot
plot_pacf(df_daily['Vehicles'], ax=axes[1])
axes[1].set_title('PACF of Vehicles')

plt.tight_layout()
plt.show()
```




```python
import matplotlib.pyplot as plt
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

fig, axes = plt.subplots(1, 2, figsize=(12, 4))

# ACF plot
plot_acf(df_daily['Vehicles_diff'], ax=axes[0])
axes[0].set_title('ACF of Vehicles_diff')

# PACF plot
plot_pacf(df_daily['Vehicles_diff'], ax=axes[1])
axes[1].set_title('PACF of Vehicles_diff')

plt.tight_layout()
plt.show()
```

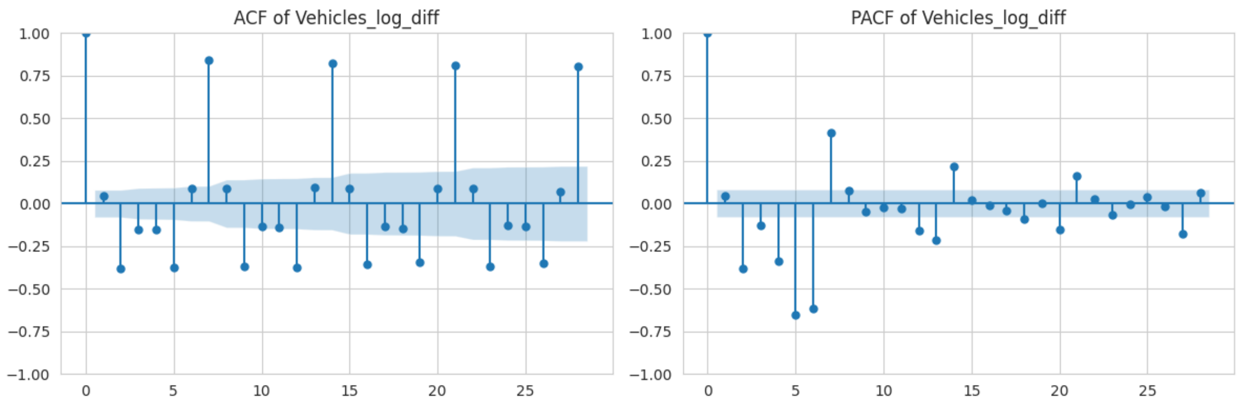



```python
import matplotlib.pyplot as plt
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

fig, axes = plt.subplots(1, 2, figsize=(12, 4))

# ACF plot
plot_acf(df_daily['Vehicles_log'], ax=axes[0])
axes[0].set_title('ACF of Vehicles_log')

# PACF plot
plot_pacf(df_daily['Vehicles_log'], ax=axes[1])
axes[1].set_title('PACF of Vehicles_log')

plt.tight_layout()
plt.show()
```



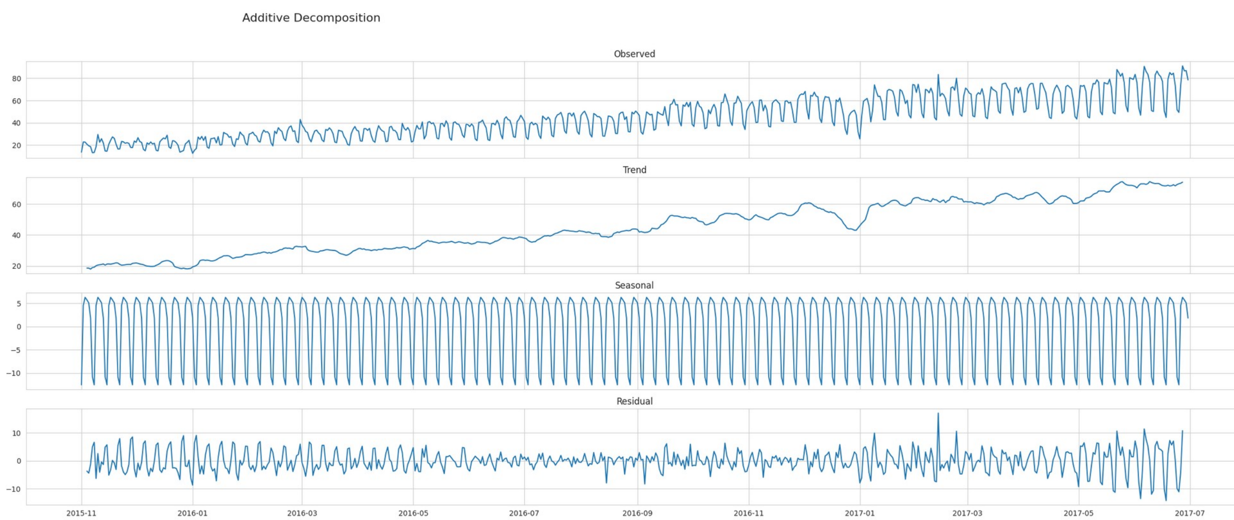

```python
df_daily['Vehicles_log_diff']= df_daily['Vehicles_log'].diff()
df_daily['Vehicles_log_diff'].fillna(0, inplace=True)

import matplotlib.pyplot as plt
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
fig, axes = plt.subplots(1, 2, figsize=(12, 4))
```

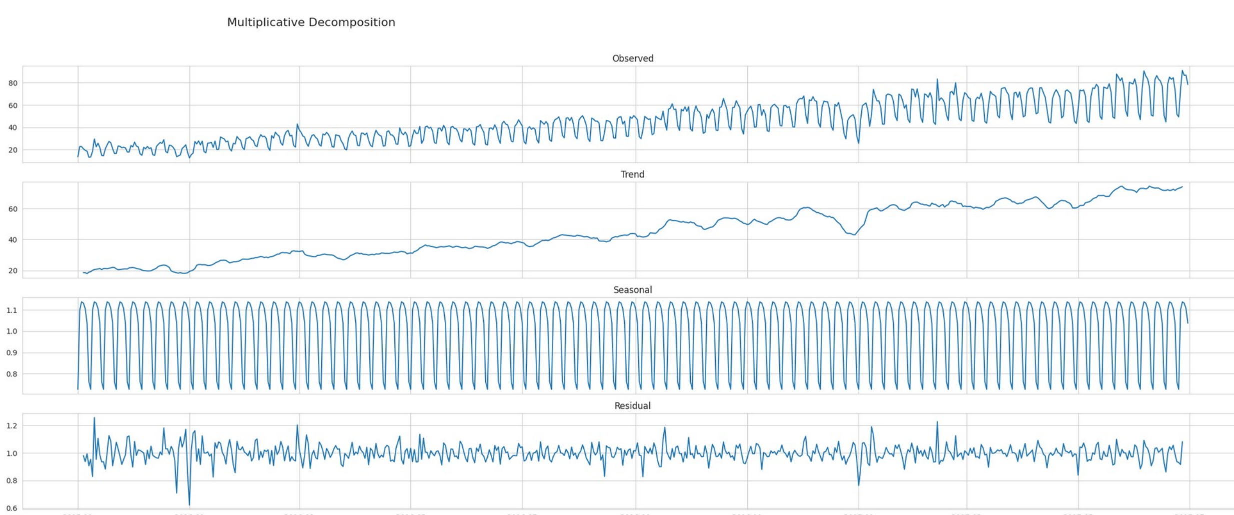
```
# ACF plot
plot_acf(df_daily['Vehicles_log_diff'], ax=axes[0])
axes[0].set_title('ACF of Vehicles_log_diff')

# PACF plot
plot_pacf(df_daily['Vehicles_log_diff'], ax=axes[1])
axes[1].set_title('PACF of Vehicles_log_diff')

plt.tight_layout()
plt.show()
```




```
# Improved Additive Decomposition Plot
result_add = seasonal_decompose(df_daily['Vehicles'],
model='additive', period=7)
fig, axes = plt.subplots(4, 1, figsize=(12, 10), sharex=True)

axes[0].plot(result_add.observed)
axes[0].set_title('Observed')

axes[1].plot(result_add.trend)
axes[1].set_title('Trend')

axes[2].plot(result_add.seasonal)
axes[2].set_title('Seasonal')

axes[3].plot(result_add.resid)
axes[3].set_title('Residual')

fig.suptitle('Additive Decomposition', fontsize=16)
plt.tight_layout(rect=[0, 0, 2, 0.96])
plt.show()


# Improved Multiplicative Decomposition Plot
result_mult = seasonal_decompose(df_daily['Vehicles'],
model='multiplicative', period=7)
```

```python
fig, axes = plt.subplots(4, 1, figsize=(12, 10), sharex=True)

axes[0].plot(result_mult.observed)
axes[0].set_title('Observed')

axes[1].plot(result_mult.trend)
axes[1].set_title('Trend')

axes[2].plot(result_mult.seasonal)
axes[2].set_title('Seasonal')

axes[3].plot(result_mult.resid)
axes[3].set_title('Residual')

fig.suptitle('Multiplicative Decomposition', fontsize=16)
plt.tight_layout(rect=[0, 0, 2, 0.96])
plt.show()
```



We decomposed data into sub-parts like deterministic part(trend and seasonality) and non-determinstic part(residual).

```
train_data = df_daily[:-int(len(df_daily) * 0.05)]
test_data = df_daily[-int(len(df_daily) * 0.05):]
# print(df_daily.shape)
# print(test_data.shape)
train_series = train_data['Vehicles']
test_series = test_data['Vehicles']
```

## BEST ARIMA MODEL

ARIMA (AutoRegressive Integrated Moving Average) is a popular model for forecasting univariate time series that captures both autoregressive (AR) and moving average (MA) patterns, while differencing (I) helps make the data stationary. It works well for non-seasonal, trend-based data.

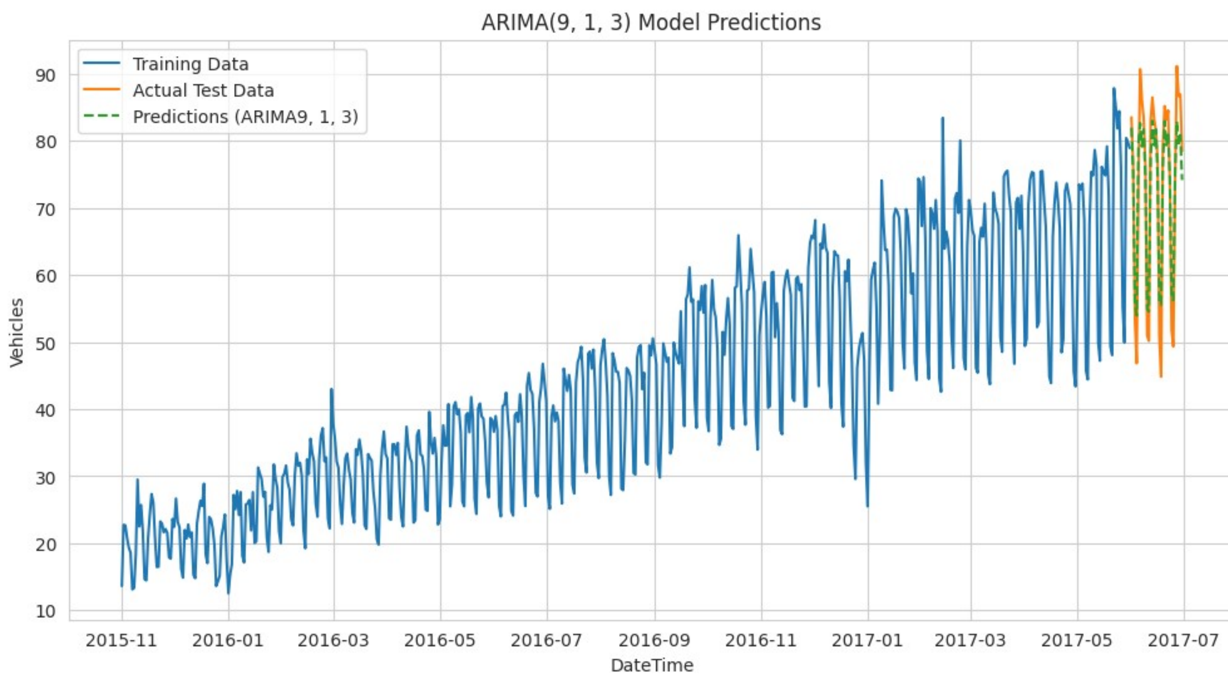
```
# # import itertools
# # import numpy as np
# # import pandas as pd
# # import matplotlib.pyplot as plt
# # import math
# # from statsmodels.tsa.arima.model import ARIMA
# # from sklearn.metrics import mean_squared_error

# # # Define possible values of p and q
# # p_values = range(0,15)  # Try AR terms from 0 to 5
# # q_values = range(0,15)  # Try MA terms from 0 to 5


# # best_aic = np.inf  # Start with a very high AIC
# # best_pq = None
# # best_model = None

# # # Iterate over all combinations of (p, q)
# # for p, q in itertools.product(p_values, q_values):
# #     try:
# #         # Fit ARMA model (ARIMA with d=0)
# #         model = ARIMA(train_data['Vehicles'], order=(p, 1, q))
# #         results = model.fit()

# #         # Check the AIC value
# #         if results.aic < best_aic:
# #             best_aic = results.aic
# #             best_pq = (p, q)
# #             best_model = results

# #         print(f"ARMA({p}, {q}) - AIC: {results.aic}")
```

```
# #     except Exception as e:
# #         print(f"ARMA({p}, {q}) failed: {e}")

# # # Print best (p, q) combination
# # print(f"\nBest Model: ARMA{best_pq} - AIC: {best_aic}")

# # # Make predictions with the best model
# # predictions = best_model.predict(start=len(train_data),
end=len(df_daily) - 1)

# # # Calculate RMSE
# # rmse = math.sqrt(mean_squared_error(test_data['Vehicles'],
predictions))
# # print(f"RMSE: {rmse}")

# # # Plot predictions
# # plt.figure(figsize=(12, 6))
# # plt.plot(train_data.index, train_data['Vehicles'], label='Training
Data')
# # plt.plot(test_data.index, test_data['Vehicles'], label='Actual
Test Data')
# # plt.plot(test_data.index, predictions, label=f'Predictions
(ARMA{best_pq})', linestyle='dashed')
# # plt.xlabel('DateTime')
# # plt.ylabel('Vehicles')
# # plt.title(f'Best ARMA{best_pq} Model Predictions')
# # plt.legend()
# # plt.show()

# import numpy as np
# import pandas as pd
# import matplotlib.pyplot as plt
# import math
# from statsmodels.tsa.arima.model import ARIMA
# from sklearn.metrics import mean_squared_error

# # Set the best (p, q) combination directly
# p, q = 7, 10  # Best model: ARMA(7, 10)

# # Fit ARIMA model (ARMA with d=0) with the best p, q values
# model = ARIMA(train_data['Vehicles'], order=(p, 1, q))
# results = model.fit()

# # Print the AIC value
# print(f"Best Model: ARMA({p}, {q}) - AIC: {results.aic}")

# # Make predictions with the best model
# predictions = results.predict(start=len(train_data),
end=len(df_daily) - 1)
```

```python
# # Calculate RMSE
# rmse = math.sqrt(mean_squared_error(test_data['Vehicles'],
predictions))
# print(f"RMSE: {rmse}")

# # Plot predictions
# plt.figure(figsize=(12, 6))
# plt.plot(train_data.index, train_data['Vehicles'], label='Training
Data')
# plt.plot(test_data.index, test_data['Vehicles'], label='Actual Test
Data')
# plt.plot(test_data.index, predictions, label=f'Predictions (ARMA{p},
{q})', linestyle='dashed')
# plt.xlabel('DateTime')
# plt.ylabel('Vehicles')
# plt.title(f'ARMA({p}, {q}) Model Predictions')
# plt.legend()
# plt.show()







import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import math
from statsmodels.tsa.arima.model import ARIMA
from sklearn.metrics import mean_squared_error, mean_absolute_error,
r2_score

# Set the best (p, d, q) combination directly
p, d, q = 9, 1, 3

# Fit ARIMA model with the best (p, d, q) values
model = ARIMA(train_data['Vehicles'], order=(p, d, q))
results = model.fit()

# Print the AIC value
print(f"Best Model: ARIMA({p}, {d}, {q}) - AIC: {results.aic}")

# Make predictions
predictions = results.predict(start=len(train_data), end=len(df_daily)
- 1)
actuals = test_data['Vehicles'].values
preds = predictions.values

# Metrics
```

```python
rmse = math.sqrt(mean_squared_error(actuals, preds))
mae = mean_absolute_error(actuals, preds)
sse = np.sum(np.square(actuals - preds))
nmse = mean_squared_error(actuals, preds) / np.var(actuals)
mape = np.mean(np.abs((actuals - preds) / actuals)) * 100
acc = 100 - mape
r2 = r2_score(actuals, preds)

# Print all metrics
print(f"RMSE: {rmse}")
print(f"MAE: {mae}")
print(f"SSE: {sse}")
print(f"NMSE: {nmse}")
print(f"MAPE: {mape}%")
print(f"Accuracy (100 - MAPE): {acc}%")
print(f"R² Score: {r2}")

# Plot predictions
plt.figure(figsize=(12, 6))
plt.plot(train_data.index, train_data['Vehicles'], label='Training
Data')
plt.plot(test_data.index, actuals, label='Actual Test Data')
plt.plot(test_data.index, preds, label=f'Predictions (ARIMA{p}, {d},
{q})', linestyle='dashed')
plt.xlabel('DateTime')
plt.ylabel('Vehicles')
plt.title(f'ARIMA({p}, {d}, {q}) Model Predictions')
plt.legend()
plt.show()
```

```
Best Model: ARIMA(9, 1, 3) - AIC: 3235.408813078857
RMSE: 4.949242782772598
MAE: 4.251567208993219
SSE: 734.8501236847994
NMSE: 0.10902985493588037
MAPE: 6.377038716390701%
Accuracy (100 - MAPE): 93.6229612836093%
R² Score: 0.8909701450641196
```




## BEST SARIMA MODEL

SARIMA (Seasonal ARIMA) extends ARIMA by incorporating seasonal components, allowing it to model data with repeating seasonal patterns (like monthly or weekly cycles). It includes additional seasonal AR, I, and MA terms.

#why need? Let's say we are analysing ice-cream data for any shop. As owner of shop we have question that how much stock of icecream will be enough for next april-may month.

As normal thought ,we would thought it will be almost same as last feb-march months. But NO IT'S NOT.

Since it's summer month, we need data of previos summer month(seasonality), we can't predict on basis of last months data. THAT IS WHY we need model which signify seasonality also.

Model: SARIMA(0, 1, 6)x(4, 1, 14, 7) AIC: 2507.60

```
# import itertools
# import random
# import math
# from statsmodels.tsa.statespace.sarimax import SARIMAX
# from sklearn.metrics import mean_squared_error
# import matplotlib.pyplot as plt

# # === Conflict check helper ===
```

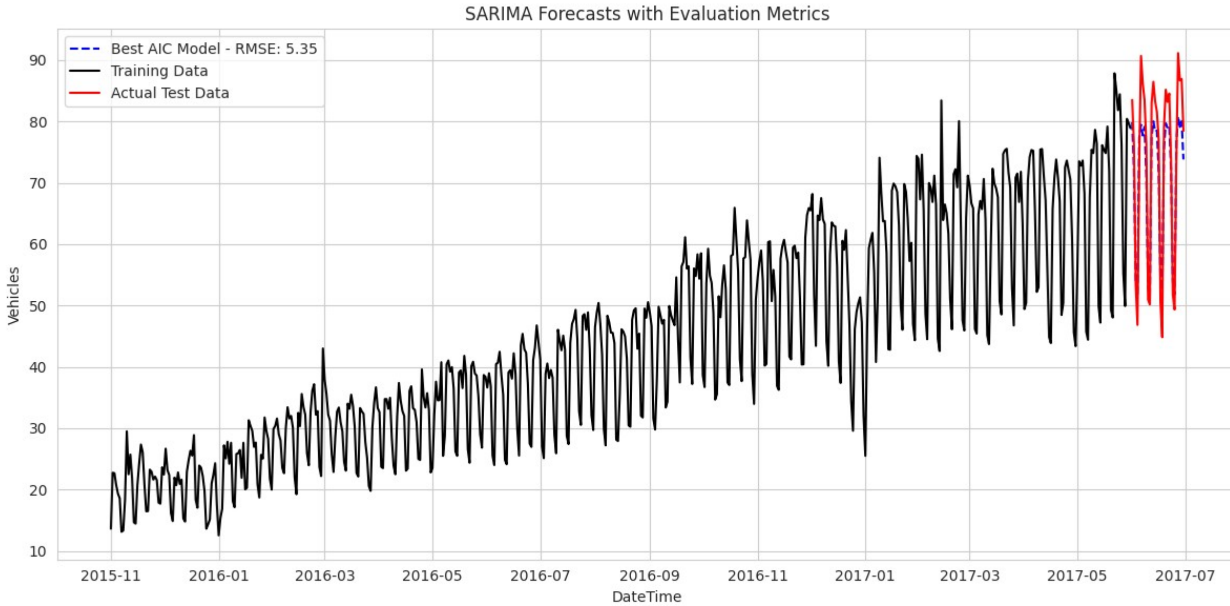
```
# def has_conflict(order, seasonal_order, s):
#     p, d, q = order
#     P, D, Q, _ = seasonal_order
#     ar_lags = set(range(1, p + 1))
#     seasonal_ar_lags = set(P * s for P in range(1, P + 1))
#     ma_lags = set(range(1, q + 1))
#     seasonal_ma_lags = set(Q * s for Q in range(1, Q + 1))
#     return bool(ar_lags & seasonal_ar_lags or ma_lags &
seasonal_ma_lags)

# # === Define parameter ranges ===
# p = q = range(0, 15)
# d = [1]
# s = 7  # weekly seasonality

# pdq = list(itertools.product(p, d, q))
# seasonal_pdq = [(x[0], x[1], x[2], s) for x in pdq]

# # === Filter valid combinations (no conflicts) ===
# valid_combinations = [
#     (order, seasonal_order)
#     for order, seasonal_order in itertools.product(pdq,
seasonal_pdq)
#     if not has_conflict(order, seasonal_order, s)
# ]

# # === Randomly select 200 valid combinations ===
# random.seed(42)
# sampled_combinations = random.sample(valid_combinations, 20)

# # === Track best models
# best_aic = float('inf')
# best_aic_model = None
# best_aic_order = None
# best_aic_seasonal = None

# best_rmse = float('inf')
# best_rmse_model = None
# best_rmse_order = None
# best_rmse_seasonal = None

# # === Grid search with sampled combinations
# for order, seasonal_order in sampled_combinations:
#     try:
#         model = SARIMAX(train_data['Vehicles'],
#                         order=order,
#                         seasonal_order=seasonal_order,
#                         enforce_stationarity=False,
#                         enforce_invertibility=False)
#         results = model.fit(disp=False)
```

```
#         pred = results.predict(start=test_data.index[0],
#                                end=test_data.index[-1])

#         rmse = math.sqrt(mean_squared_error(test_data['Vehicles'],
pred))

#         print(f"Trying SARIMA{order}x{seasonal_order} - AIC:
{results.aic:.2f}, RMSE: {rmse:.2f}")

#         if results.aic < best_aic:
#             best_aic = results.aic
#             best_aic_model = results
#             best_aic_order = order
#             best_aic_seasonal = seasonal_order

#         if rmse < best_rmse:
#             best_rmse = rmse
#             best_rmse_model = results
#             best_rmse_order = order
#             best_rmse_seasonal = seasonal_order

#     except Exception as e:
#         print(f"Error for SARIMA{order}x{seasonal_order}: {e}")
#         continue

# # === Summary ===
# print("\n====================")
# print(f"Best AIC Model:
SARIMA{best_aic_order}x{best_aic_seasonal} - AIC: {best_aic:.2f}")
# print(f"Best RMSE Model:
SARIMA{best_rmse_order}x{best_rmse_seasonal} - RMSE: {best_rmse:.2f}")
# print("====================\n")

# # === Forecast using Best RMSE Model ===
# pred = best_rmse_model.predict(start=test_data.index[0],
#                                end=test_data.index[-1])

# # === Plot results
# plt.figure(figsize=(12, 6))
# plt.plot(train_data.index, train_data['Vehicles'], label='Training
Data')
# plt.plot(test_data.index, test_data['Vehicles'], label='Actual Test
Data', color='orange')
# plt.plot(test_data.index, pred, label='Best RMSE Forecast',
linestyle='--', color='green')
# plt.xlabel('DateTime')
# plt.ylabel('Vehicles')
# plt.title('SARIMA Forecast (Best RMSE Model)')
# plt.legend()
```

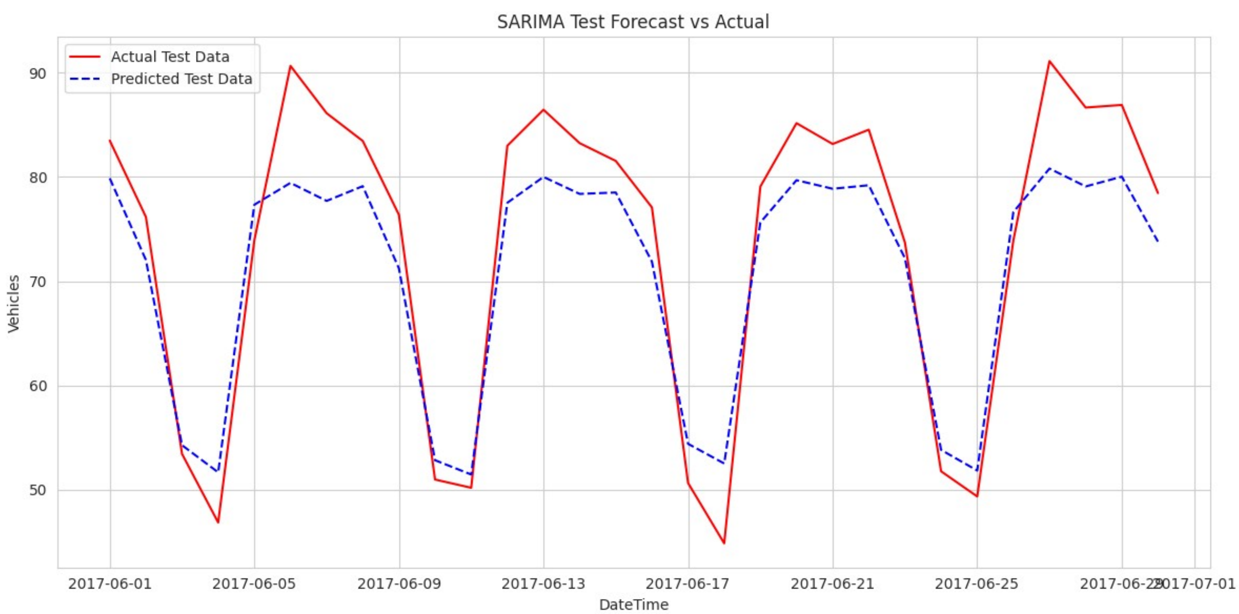
```python
# plt.tight_layout()
# plt.show()


import math
import numpy as np
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.metrics import mean_squared_error, mean_absolute_error,
r2_score
import matplotlib.pyplot as plt

# Define the specific SARIMA models to evaluate
models = [
    {"order": (0, 1, 6), "seasonal_order": (4, 1, 14, 7), "label":
"Best AIC Model", "color": "blue"},
]

# === Plot setup ===
plt.figure(figsize=(12, 6))

for model_info in models:
    order = model_info["order"]
    seasonal_order = model_info["seasonal_order"]

    try:
        # Fit the SARIMAX model
        model = SARIMAX(train_data['Vehicles'],
                        order=order,
                        seasonal_order=seasonal_order,
                        enforce_stationarity=False,
                        enforce_invertibility=False)
        results = model.fit(disp=False)

        # Forecast
        pred = results.predict(start=test_data.index[0],
end=test_data.index[-1])
        actual = test_data['Vehicles'].values
        pred_vals = pred.values

        # === Metrics Calculation ===
        rmse = math.sqrt(mean_squared_error(actual, pred_vals))
        mae = mean_absolute_error(actual, pred_vals)
        sse = np.sum(np.square(actual - pred_vals))
        nmse = mean_squared_error(actual, pred_vals) / np.var(actual)
        mape = np.mean(np.abs((actual - pred_vals) / actual)) * 100
        acc = 100 - mape
        r2 = r2_score(actual, pred_vals)

        # Print metrics
        print(f"\nModel: SARIMA{order}x{seasonal_order}")
```

```python
        print(f"AIC: {results.aic:.2f}")
        print(f"RMSE: {rmse:.2f}")
        print(f"MAE: {mae:.2f}")
        print(f"SSE: {sse:.2f}")
        print(f"NMSE: {nmse:.4f}")
        print(f"MAPE: {mape:.2f}%")
        print(f"Accuracy (100 - MAPE): {acc:.2f}%")
        print(f"R² Score: {r2:.4f}")

        # Plot predictions
        plt.plot(test_data.index, pred, label=f"{model_info['label']}
- RMSE: {rmse:.2f}", linestyle='--', color=model_info["color"])

    except Exception as e:
        print(f"Error for SARIMA{order}x{seasonal_order}: {e}")
        continue


# Plot actual data
plt.plot(train_data.index, train_data['Vehicles'], label='Training
Data', color='black')
plt.plot(test_data.index, test_data['Vehicles'], label='Actual Test
Data', color='red')

# Plot styling
plt.xlabel('DateTime')
plt.ylabel('Vehicles')
plt.title('SARIMA Forecasts with Evaluation Metrics')
plt.legend()
plt.tight_layout()
plt.show()
```

```
Model: SARIMA(0, 1, 6)x(4, 1, 14, 7)
AIC: 2507.64
RMSE: 5.35
MAE: 4.74
SSE: 859.43
NMSE: 0.1275
MAPE: 6.41%
Accuracy (100 - MAPE): 93.59%
R² Score: 0.8725
```




```python
# Plot actual and predicted test data only
plt.figure(figsize=(12, 6))
plt.plot(test_data.index, test_data['Vehicles'], label='Actual Test
Data', color='red')
plt.plot(test_data.index, pred, label='Predicted Test Data',
color='blue', linestyle='--')
plt.xlabel('DateTime')
plt.ylabel('Vehicles')
plt.title('SARIMA Test Forecast vs Actual')
plt.legend()
plt.tight_layout()
plt.show()
```



## BEST SARIMAX model

SARIMAX (Seasonal ARIMA with eXogenous variables) builds on SARIMA by including external variables (exogenous regressors) that may affect the target variable, such as temperature, holidays, or promotions. This makes it suitable for more complex forecasting tasks where outside factors influence the series. All three models assume linear relationships and normally distributed residuals, and require the time series to be made stationary through differencing. They are widely used in fields like economics, traffic forecasting, and demand prediction.

As ecogenous variable-- here we have chosen --> HOLIDAY

Best AIC Model: SARIMAX(0, 1, 6)x(4, 1, 14, 7) AIC: 2098.35

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.metrics import mean_squared_error
import itertools
import math
import holidays

# STEP 1: Load your data (assumes datetime index and 'Vehicles'
column)
# df_daily = pd.read_csv('your_file.csv', parse_dates=['Date'],
index_col='Date')
# or if already loaded:
# df_daily.index = pd.to_datetime(df_daily.index)

# STEP 2: Add Holiday & WorkingDay Features (for USA)
usa_holidays = holidays.UnitedStates()
df_daily['Holiday'] = df_daily.index.to_series().apply(lambda x: 1 if
x in usa_holidays else 0)
df_daily['WorkingDay'] = ((df_daily.index.dayofweek < 5) &
(df_daily['Holiday'] == 0)).astype(int)

# Optional: Lag features (improves model)
df_daily['Lag1'] = df_daily['Vehicles'].shift(1)
df_daily['Lag7'] = df_daily['Vehicles'].shift(7)

# Drop rows with NaN (from lags)
df_daily.dropna(inplace=True)

# STEP 3: Train-test split (last 10% as test)
train_size = int(len(df_daily) * 0.9)
train_data = df_daily.iloc[:train_size]
test_data = df_daily.iloc[train_size:]

exog_cols = ['Holiday', 'WorkingDay', 'Lag1', 'Lag7']
```

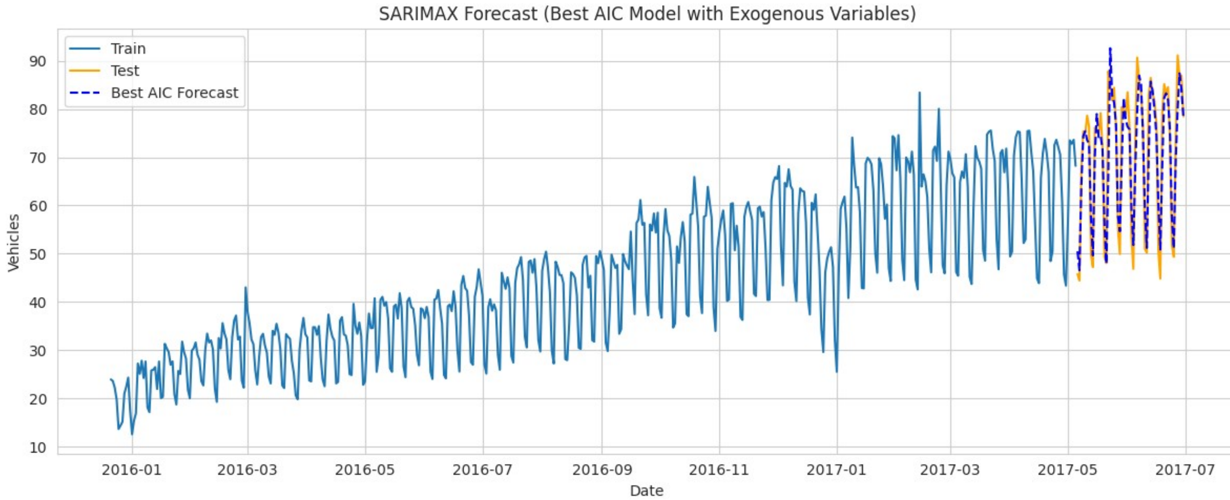
```
exog_train = train_data[exog_cols]
exog_test = test_data[exog_cols]

# import itertools
# import random
# import math
# from statsmodels.tsa.statespace.sarimax import SARIMAX
# from sklearn.metrics import mean_squared_error
# import matplotlib.pyplot as plt

# # ==== Function to avoid lag conflicts ====
# def has_conflicting_lags(order, seasonal_order, seasonal_period):
#     p, d, q = order
#     P, D, Q, s = seasonal_order

#     # AR lags
#     ar_lags = set(range(1, p + 1))
#     seasonal_ar_lags = set(P * s for P in range(1, P + 1))

#     # MA lags
#     ma_lags = set(range(1, q + 1))
#     seasonal_ma_lags = set(Q * s for Q in range(1, Q + 1))

#     # Check for conflicts
#     ar_conflict = ar_lags & seasonal_ar_lags
#     ma_conflict = ma_lags & seasonal_ma_lags

#     return bool(ar_conflict or ma_conflict)

# # ==== Parameter space ====
# p = q = range(0, 15)
# d = [1]
# s = 7  # seasonal cycle

# pdq = list(itertools.product(p, d, q))
# seasonal_pdq = [(x[0], x[1], x[2], s) for x in pdq]

# # ==== Filter valid combinations to avoid lag conflicts ====
# valid_combinations = [
#     (order, seasonal_order)
#     for order, seasonal_order in itertools.product(pdq,
seasonal_pdq)
#     if not has_conflicting_lags(order, seasonal_order, s)
# ]

# # ==== Random sample of 200 from valid combinations ====
# random.seed(42)
# sampled_combinations = random.sample(valid_combinations, 20)

# # ==== Track best AIC and RMSE models ====
```

```
# best_aic = float('inf')
# best_aic_model = None
# best_aic_order = None
# best_aic_seasonal_order = None

# best_rmse = float('inf')
# best_rmse_model = None
# best_rmse_order = None
# best_rmse_seasonal_order = None

# # ==== Run SARIMAX on 200 random combinations ====
# for order, seasonal_order in sampled_combinations:
#     try:
#         model = SARIMAX(train_data['Vehicles'],
#                         exog=exog_train,
#                         order=order,
#                         seasonal_order=seasonal_order,
#                         enforce_stationarity=False,
#                         enforce_invertibility=False)
#         results = model.fit(disp=False)
#         pred = results.predict(start=test_data.index[0],
end=test_data.index[-1], exog=exog_test)
#         rmse = math.sqrt(mean_squared_error(test_data['Vehicles'],
pred))

#         print(f"Trying SARIMAX{order}x{seasonal_order} - AIC:
{results.aic:.2f}, RMSE: {rmse:.2f}")

#         # Track best AIC
#         if results.aic < best_aic:
#             best_aic = results.aic
#             best_aic_model = results
#             best_aic_order = order
#             best_aic_seasonal_order = seasonal_order

#         # Track best RMSE
#         if rmse < best_rmse:
#             best_rmse = rmse
#             best_rmse_model = results
#             best_rmse_order = order
#             best_rmse_seasonal_order = seasonal_order

#     except Exception as e:
#         print(f"Error for SARIMAX{order}x{seasonal_order}: {e}")
#         continue

# # ==== Output best models ====
# print("\n======================")
# print(f"Best AIC Model:
SARIMAX{best_aic_order}x{best_aic_seasonal_order} - AIC:
```

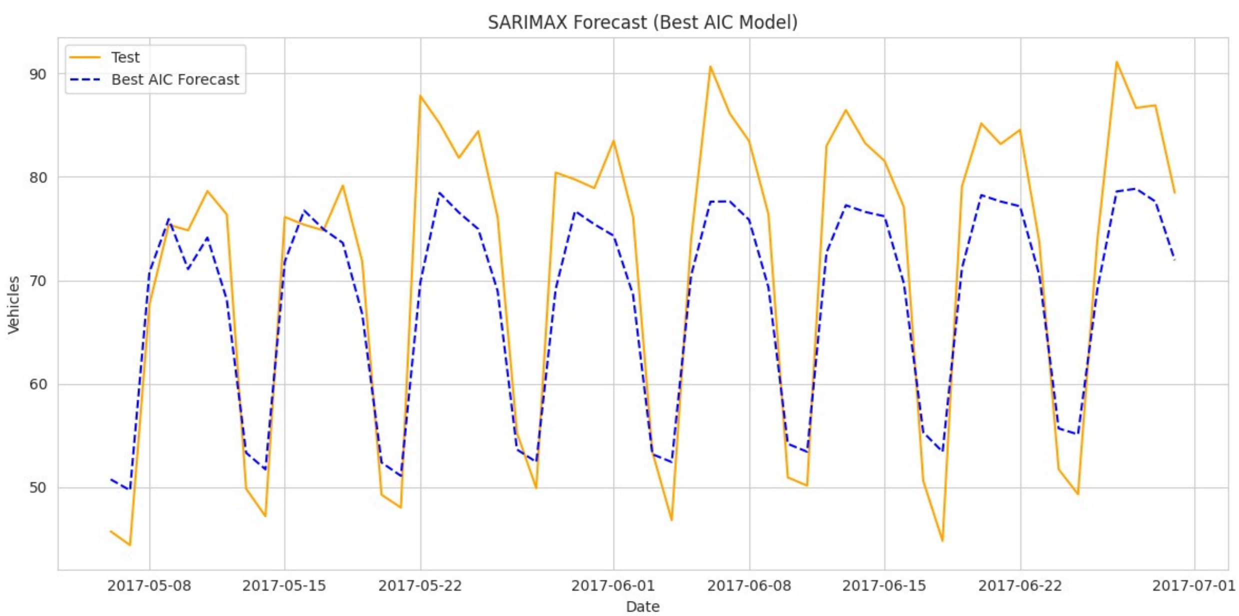
```
{best_aic:.2f}")
# print(f"Best RMSE Model:
SARIMAX{best_rmse_order}x{best_rmse_seasonal_order} - RMSE:
{best_rmse:.2f}")
# print("=====================\n")

# # ==== Plot best RMSE forecast ====
# pred = best_rmse_model.predict(start=test_data.index[0],
end=test_data.index[-1], exog=exog_test)

# plt.figure(figsize=(12, 6))
# plt.plot(train_data.index, train_data['Vehicles'], label='Train')
# plt.plot(test_data.index, test_data['Vehicles'], label='Test',
color='orange')
# plt.plot(test_data.index, pred, label='Best RMSE Forecast',
linestyle='--', color='green')
# plt.title('SARIMAX Forecast (Best RMSE Model)')
# plt.xlabel('Date')
# plt.ylabel('Vehicles')
# plt.legend()
# plt.tight_layout()
# plt.show()

import math
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.metrics import mean_squared_error, mean_absolute_error,
r2_score

# ==== Define the Best AIC Model Parameters ====
best_aic_order = (0, 1, 6)
best_aic_seasonal_order = (4, 1, 14, 7)

# ==== Fit Best AIC Model with Exogenous Variables ====
model_aic = SARIMAX(train_data['Vehicles'],
                    exog=exog_train,
                    order=best_aic_order,
                    seasonal_order=best_aic_seasonal_order,
                    enforce_stationarity=False,
                    enforce_invertibility=False)

results_aic = model_aic.fit(disp=False)

# ==== Predict ====
pred_aic = results_aic.predict(start=test_data.index[0],
                                end=test_data.index[-1],
                                exog=exog_test)

# ==== Evaluation Metrics ====
```

```python
actual = test_data['Vehicles'].values
predicted = pred_aic.values

rmse = math.sqrt(mean_squared_error(actual, predicted))
mae = mean_absolute_error(actual, predicted)
sse = np.sum(np.square(actual - predicted))
nmse = mean_squared_error(actual, predicted) / np.var(actual)
mape = np.mean(np.abs((actual - predicted) / actual)) * 100
acc = 100 - mape
r2 = r2_score(actual, predicted)

# ==== Print Model Info and Metrics ====
print(f"Best AIC Model: 
SARIMAX{best_aic_order}x{best_aic_seasonal_order}")
print(f"AIC: {results_aic.aic:.2f}")
print(f"RMSE: {rmse:.2f}")
print(f"MAE: {mae:.2f}")
print(f"SSE: {sse:.2f}")
print(f"NMSE: {nmse:.4f}")
print(f"MAPE: {mape:.2f}%")
print(f"Accuracy (100 - MAPE): {acc:.2f}%")
print(f"R² Score: {r2:.4f}")

# ==== Plot ====
plt.figure(figsize=(12, 5))
plt.plot(train_data.index, train_data['Vehicles'], label='Train')
plt.plot(test_data.index, test_data['Vehicles'], label='Test', 
color='orange')
plt.plot(test_data.index, pred_aic, label='Best AIC Forecast', 
linestyle='--', color='blue')
plt.title('SARIMAX Forecast (Best AIC Model with Exogenous 
Variables)')
plt.xlabel('Date')
plt.ylabel('Vehicles')
plt.legend()
plt.tight_layout()
plt.show()
```

```
Best AIC Model: SARIMAX(0, 1, 6)x(4, 1, 14, 7)
AIC: 2098.34
RMSE: 5.80
MAE: 4.20
SSE: 1880.73
NMSE: 0.1535
MAPE: 6.19%
Accuracy (100 - MAPE): 93.81%
R² Score: 0.8465
```




```python
# Plot actual and predicted test data only
plt.figure(figsize=(12, 6))
plt.plot(test_data.index, test_data['Vehicles'], label='Test',
color='orange')
plt.plot(test_data.index, pred_aic, label='Best AIC Forecast',
linestyle='--', color='blue')
plt.title('SARIMAX Forecast (Best AIC Model)')
plt.xlabel('Date')
plt.ylabel('Vehicles')
plt.legend()
plt.tight_layout()
plt.show()
```



#Deep Learning Models

#Need for Deep Learning in Time Series Forecasting --> PAGE 395 Traditional models like ARIMA and SARIMA work well for linear, short-term, and stationary time series. However, real-world data often includes non-linear patterns, long-term dependencies, and multiple influencing factors, which these classical models struggle to capture.

Deep learning models like RNNs, LSTMs, and GRUs are designed to learn complex, non-linear relationships and can automatically extract features from raw sequences. They excel in handling large volumes of data, long-range temporal dependencies, and multivariate inputs.

Additionally, models like LSTM can remember past information for long periods, making them ideal for sequences with trends, seasonality, and lagged effects. Deep learning also allows integration with external data sources (exogenous features), supports multistep forecasting, and adapts better to changing data patterns.

Thus, deep learning models are crucial when traditional methods fall short in performance, flexibility, and scalability for modern forecasting tasks.

## RNN, LSTM , GRU

```
# prompt: do minmaxscaller on vehicles column

from sklearn.preprocessing import MinMaxScaler

# Assuming 'Vehicles' column is already part of your dataframe
(df_daily)

# Create a MinMaxScaler object
scaler = MinMaxScaler()

# Fit the scaler to your training data
scaler.fit(train_data[['Vehicles']])

# Transform the 'Vehicles' column in both training and testing
datasets
train_data['Vehicles'] = scaler.transform(train_data[['Vehicles']])
test_data['Vehicles'] = scaler.transform(test_data[['Vehicles']])

# Now 'Vehicles' contains the scaled 'Vehicles' values
# print(train_data.head())
# print(test_data.head())
```

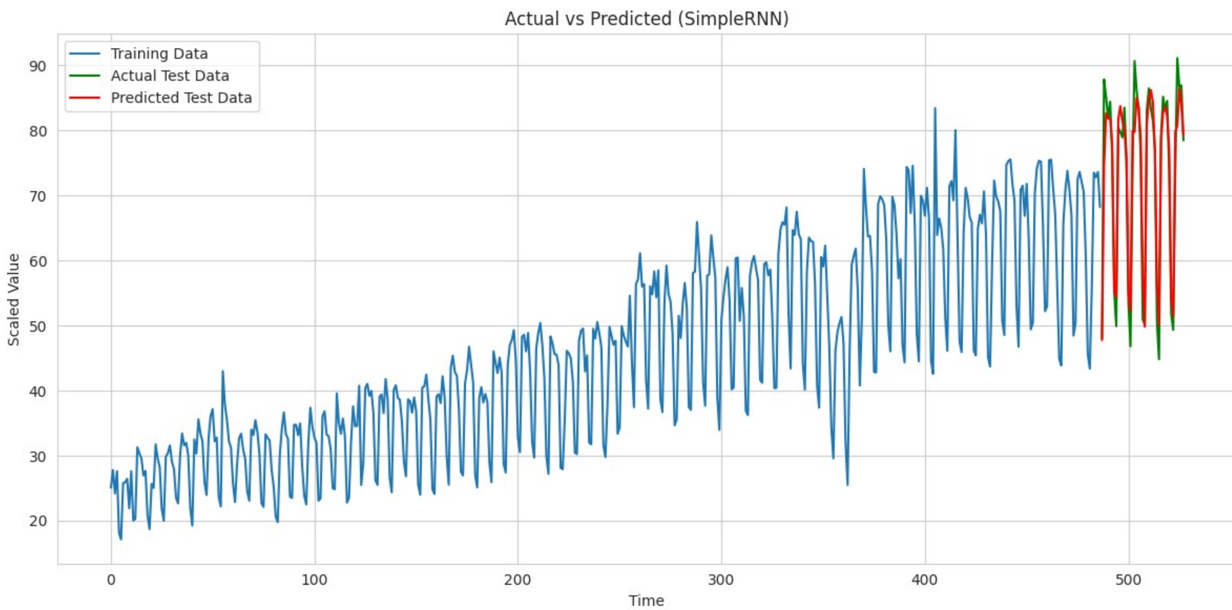
# RNN --> Page =477

Recurrent Neural Networks (RNNs) are deep learning models designed for sequential data like time series. They maintain a hidden state that captures information from previous time steps, making them suitable for modeling temporal patterns. However, RNNs suffer from vanishing gradient problems, which limits their ability to learn long-term dependencies.

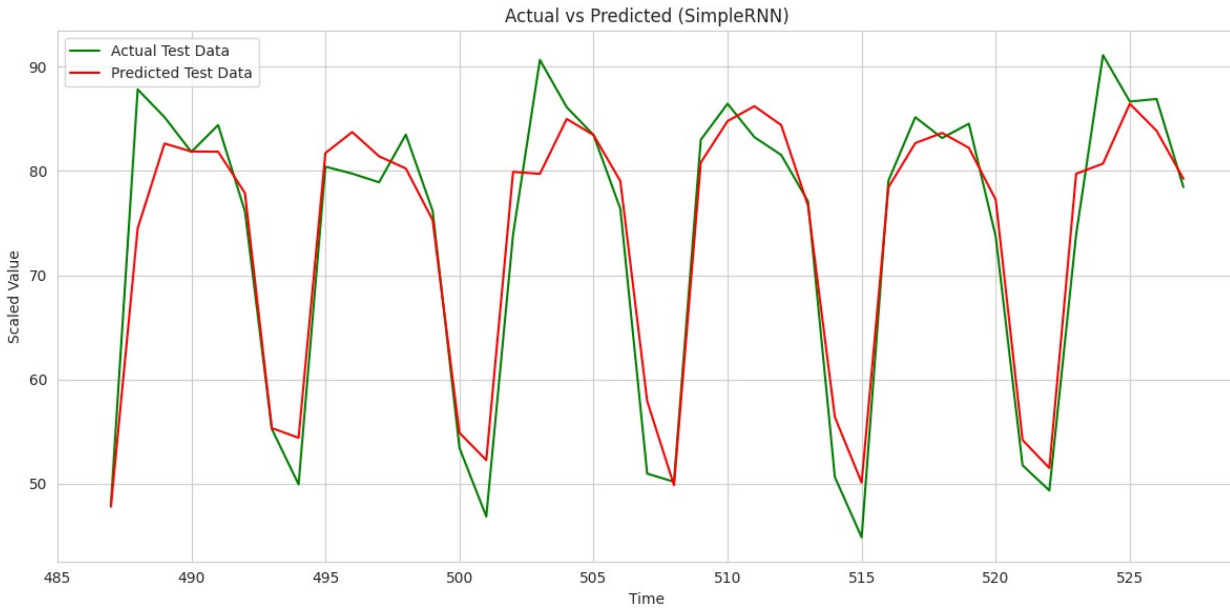
```python
import math
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from keras.models import Sequential
from keras.layers import SimpleRNN, Dense
from sklearn.metrics import mean_squared_error, mean_absolute_error,
r2_score

# --- Parameters ---
timesteps = 15

# === Sequence Creation ===
def create_sequences(data, timesteps):
    X, y = [], []
    for i in range(len(data) - timesteps):
        X.append(data[i:i+timesteps])
        y.append(data[i+timesteps])
    return np.array(X), np.array(y)

# Apply to scaled data
trainX, trainy = create_sequences(train_data['Vehicles'].values,
timesteps)
testX, testy = create_sequences(test_data['Vehicles'].values,
timesteps)

# Reshape for RNN
trainX = trainX.reshape(trainX.shape[0], timesteps, 1)
testX = testX.reshape(testX.shape[0], timesteps, 1)

# === SimpleRNN Model ===
model = Sequential()
model.add(SimpleRNN(50, activation='relu', input_shape=(timesteps,
1)))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse')

# Train the model
model.fit(trainX, trainy, epochs=50, batch_size=32, verbose=0)

# Predict
predictions = model.predict(testX).flatten()
actual = testy.flatten()

# === Metrics Calculation ===
rmse = math.sqrt(mean_squared_error(actual, predictions))
mae = mean_absolute_error(actual, predictions)
sse = np.sum(np.square(actual - predictions))
nmse = mean_squared_error(actual, predictions) / np.var(actual)
mape = np.mean(np.abs((actual - predictions) / actual)) * 100
```

```python
accuracy = 100 - mape
r2 = r2_score(actual, predictions)

# === AIC Approximation for RNN ===
# AIC = n * ln(RSS/n) + 2k
# where k = number of parameters, n = number of observations
n = len(actual)
k = model.count_params()
rss = sse

# === Print All Metrics ===
print(f"\n□ Evaluation Metrics (SimpleRNN):")
print(f"Root Mean Squared Error (RMSE): {rmse:.4f}")
print(f"Mean Absolute Error (MAE): {mae:.4f}")
print(f"Sum of Squared Errors (SSE): {sse:.2f}")
print(f"Normalized Mean Squared Error (NMSE): {nmse:.4f}")
print(f"Mean Absolute Percentage Error (MAPE): {mape:.2f}%")
print(f"Accuracy (100 − MAPE): {accuracy:.2f}%")
print(f"R² Score: {r2:.4f}")

# === Plot Results ===
plt.figure(figsize=(12, 6))
plt.plot(range(len(trainy)), trainy, label='Training Data')
plt.plot(range(len(trainy), len(trainy) + len(actual)), actual,
label='Actual Test Data', color='green')
plt.plot(range(len(trainy), len(trainy) + len(predictions)),
predictions, label='Predicted Test Data', color='red')
plt.title('Actual vs Predicted (SimpleRNN)')
plt.xlabel('Time')
plt.ylabel('Scaled Value')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 151ms/step

□ Evaluation Metrics (SimpleRNN):
Root Mean Squared Error (RMSE): 4.3238
Mean Absolute Error (MAE): 3.1060
Sum of Squared Errors (SSE): 766.52
Normalized Mean Squared Error (NMSE): 0.0858
Mean Absolute Percentage Error (MAPE): 4.44%
Accuracy (100 − MAPE): 95.56%
R² Score: 0.9142
```




```python
# Plot training data
plt.figure(figsize=(12, 6))

# Plot actual and predicted test data
plt.plot(range(len(trainy), len(trainy) + len(testy)), testy,
label='Actual Test Data', color='green')
plt.plot(range(len(trainy), len(trainy) + len(predictions)),
predictions, label='Predicted Test Data', color='red')

plt.title('Actual vs Predicted (SimpleRNN)')
plt.xlabel('Time')
plt.ylabel('Scaled Value')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```




# LSTM --> Page =480

LSTM (Long Short-Term Memory) networks are a special type of RNN that use memory cells and gating mechanisms (input, forget, and output gates) to retain information over long sequences. LSTMs are highly effective at learning complex temporal dependencies, trends, and seasonality in time series.

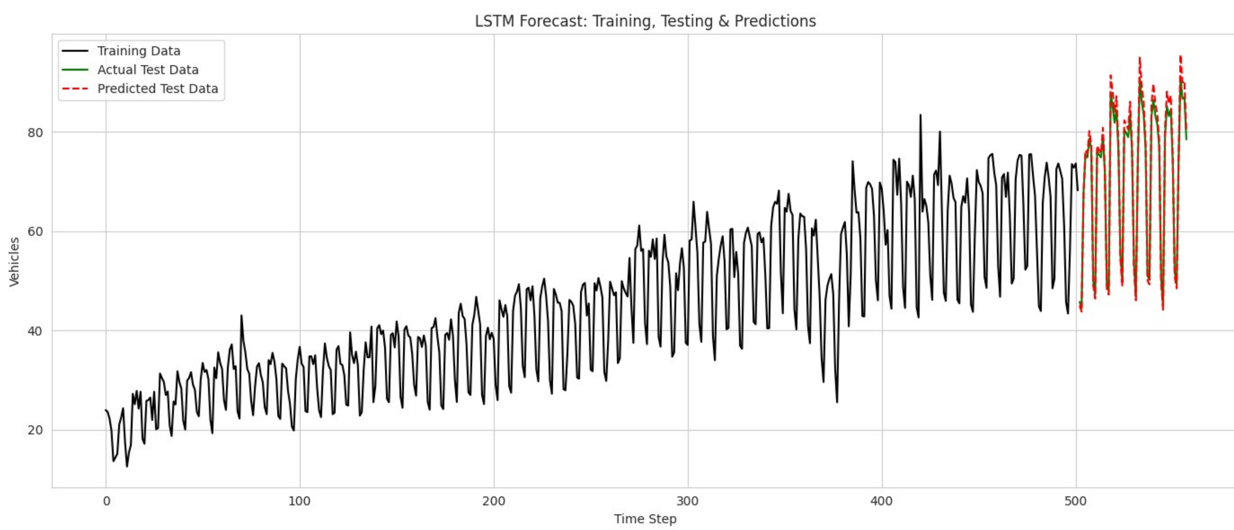
```
import numpy as np
import matplotlib.pyplot as plt
from keras.models import Sequential
from keras.layers import LSTM, Dense
from sklearn.metrics import mean_squared_error, mean_absolute_error,
r2_score

# === Parameters ===
timesteps = 1  # You can adjust based on sequence design

# === Prepare Data ===
trainX = np.array(train_data['Vehicles']).reshape(len(train_data),
timesteps, 1)
testX = np.array(test_data['Vehicles']).reshape(len(test_data),
timesteps, 1)
trainy = np.array(train_data['Vehicles'])
testy = np.array(test_data['Vehicles'])

# === Define LSTM Model ===
model = Sequential()
model.add(LSTM(50, activation='relu', input_shape=(timesteps, 1)))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse')
```

```python
# === Train the Model ===
model.fit(trainX, trainy, epochs=50, batch_size=32, verbose=0)

# === Predict ===
predictions = model.predict(testX)

# === Inverse Transform (if using scaler) ===
# Assumes 'scaler' was used during preprocessing
predictions_inv = scaler.inverse_transform(predictions)
testy_inv = scaler.inverse_transform(testy.reshape(-1, 1))

# === Metrics Calculation ===
rmse = np.sqrt(mean_squared_error(testy_inv, predictions_inv))
mae = mean_absolute_error(testy_inv, predictions_inv)
sse = np.sum(np.square(testy_inv - predictions_inv))
nmse = mean_squared_error(testy_inv, predictions_inv) /
np.var(testy_inv)
mape = np.mean(np.abs((testy_inv - predictions_inv) / testy_inv)) *
100
accuracy = 100 - mape
r2 = r2_score(testy_inv, predictions_inv)

# === Print Metrics ===
print(f"\n□ Evaluation Metrics (LSTM):")
print(f"Root Mean Squared Error (RMSE): {rmse:.4f}")
print(f"Mean Absolute Error (MAE): {mae:.4f}")
print(f"Sum of Squared Errors (SSE): {sse:.2f}")
print(f"Normalized Mean Squared Error (NMSE): {nmse:.4f}")
print(f"Mean Absolute Percentage Error (MAPE): {mape:.2f}%")
print(f"Accuracy (100 − MAPE): {accuracy:.2f}%")
print(f"R² Score: {r2:.4f}")
```

```
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 209ms/step

□ Evaluation Metrics (LSTM):
Root Mean Squared Error (RMSE): 1.9365
Mean Absolute Error (MAE): 1.6386
Sum of Squared Errors (SSE): 210.00
Normalized Mean Squared Error (NMSE): 0.0171
Mean Absolute Percentage Error (MAPE): 2.18%
Accuracy (100 − MAPE): 97.82%
R² Score: 0.9829
```

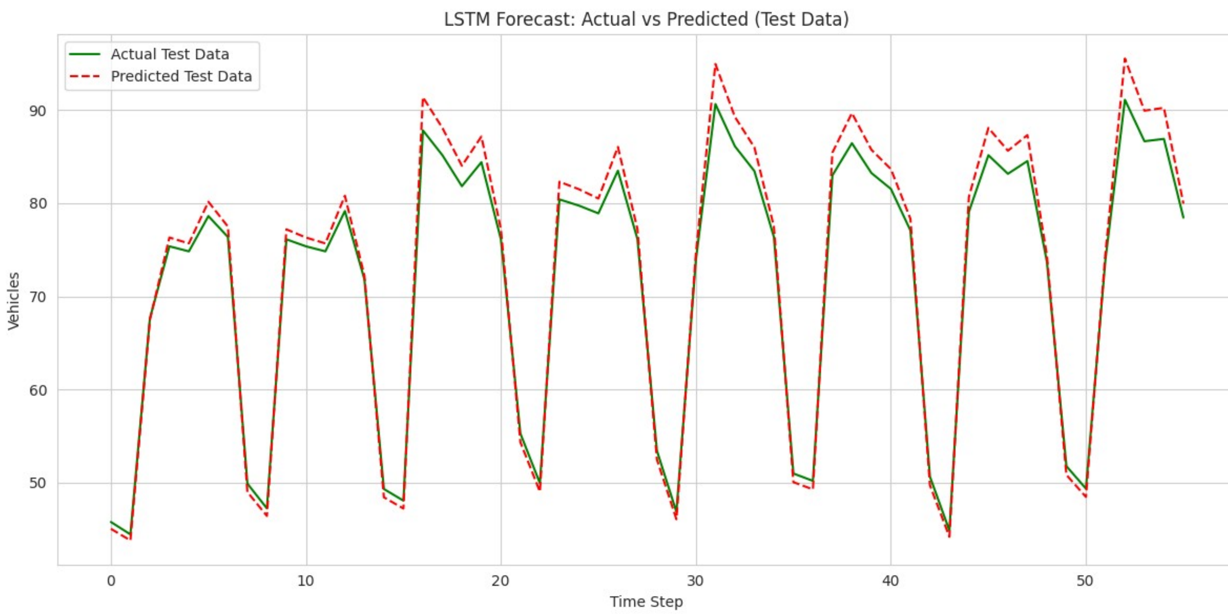
```python
import matplotlib.pyplot as plt
import numpy as np

# Combine all for smooth indexing
# Inverse-transform full train data (if needed)
trainy_inv =
scaler.inverse_transform(train_data['Vehicles'].values.reshape(-1, 1))
```

```
# === Build x-axis indexes ===
train_len = len(trainy_inv)
test_len = len(testy_inv)

# === Plot ===
plt.figure(figsize=(14, 6))
# Plot training data
plt.plot(range(train_len), trainy_inv, label='Training Data',
color='black')
# Plot actual test data
plt.plot(range(train_len, train_len + test_len), testy_inv,
label='Actual Test Data', color='green')
# Plot predicted test data
plt.plot(range(train_len, train_len + test_len), predictions_inv,
label='Predicted Test Data', color='red', linestyle='--')
# === Styling ===
plt.title('LSTM Forecast: Training, Testing & Predictions')
plt.xlabel('Time Step')
plt.ylabel('Vehicles')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```




```
import matplotlib.pyplot as plt

# === Plot ===
plt.figure(figsize=(12, 6))

# Plot actual test data
plt.plot(testy_inv, label='Actual Test Data', color='green')

# Plot predicted test data
```

```
plt.plot(predictions_inv, label='Predicted Test Data', color='red',
linestyle='--')

# === Styling ===
plt.title('LSTM Forecast: Actual vs Predicted (Test Data)')
plt.xlabel('Time Step')
plt.ylabel('Vehicles')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

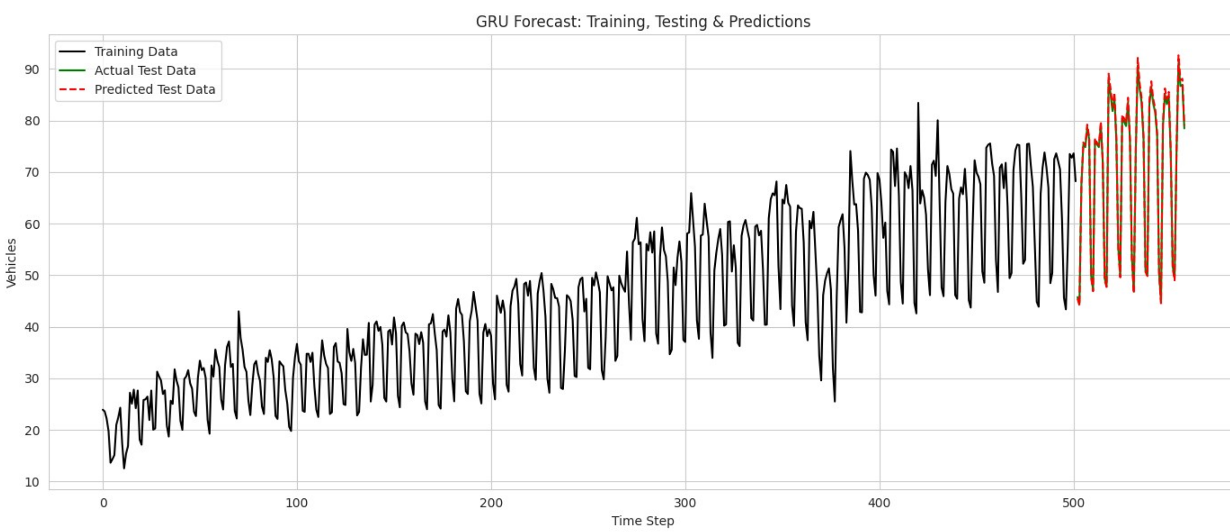



#GRU --> site = https://d2l.ai/ GRU (Gated Recurrent Unit) is a simplified version of LSTM that uses fewer gates (reset and update), making it computationally faster while still handling long-term dependencies well. GRUs often perform comparably to LSTMs with fewer parameters.v

```
import numpy as np
import matplotlib.pyplot as plt
from keras.models import Sequential
from keras.layers import GRU, Dense
from sklearn.metrics import mean_squared_error, mean_absolute_error,
r2_score

# === Parameters ===
timesteps = 1  # You can increase if you're using sequences

# === Prepare Data ===
trainX = np.array(train_data['Vehicles']).reshape(len(train_data),
timesteps, 1)
testX = np.array(test_data['Vehicles']).reshape(len(test_data),
```

```python
timesteps, 1)
trainy = np.array(train_data['Vehicles'])
testy = np.array(test_data['Vehicles'])

# === Build GRU Model ===
model = Sequential()
model.add(GRU(50, activation='relu', input_shape=(timesteps, 1)))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse')

# === Train the Model ===
model.fit(trainX, trainy, epochs=50, batch_size=32, verbose=0)

# === Predict ===
predictions = model.predict(testX)

# === Inverse Transform ===
predictions_inv = scaler.inverse_transform(predictions)
testy_inv = scaler.inverse_transform(testy.reshape(-1, 1))
trainy_inv = scaler.inverse_transform(trainy.reshape(-1, 1))

# === Metrics Calculation ===
rmse = np.sqrt(mean_squared_error(testy_inv, predictions_inv))
mae = mean_absolute_error(testy_inv, predictions_inv)
sse = np.sum(np.square(testy_inv - predictions_inv))
nmse = mean_squared_error(testy_inv, predictions_inv) /
np.var(testy_inv)
mape = np.mean(np.abs((testy_inv - predictions_inv) / testy_inv)) *
100
accuracy = 100 - mape
r2 = r2_score(testy_inv, predictions_inv)

# === Print Metrics ===
print(f"\n Evaluation Metrics (GRU):")
print(f"Root Mean Squared Error (RMSE): {rmse:.4f}")
print(f"Mean Absolute Error (MAE): {mae:.4f}")
print(f"Sum of Squared Errors (SSE): {sse:.2f}")
print(f"Normalized Mean Squared Error (NMSE): {nmse:.4f}")
print(f"Mean Absolute Percentage Error (MAPE): {mape:.2f}%")
print(f"Accuracy (100 − MAPE): {accuracy:.2f}%")
print(f"R² Score: {r2:.4f}")

# === Plot Full Data ===
plt.figure(figsize=(14, 6))

# Plot training data
plt.plot(range(len(trainy_inv)), trainy_inv, label='Training Data',
color='black')

# Plot actual test data
```

```
plt.plot(range(len(trainy_inv), len(trainy_inv) + len(testy_inv)),
testy_inv, label='Actual Test Data', color='green')

# Plot predicted test data
plt.plot(range(len(trainy_inv), len(trainy_inv) +
len(predictions_inv)), predictions_inv, label='Predicted Test Data',
color='red', linestyle='--')

# === Plot Styling ===
plt.title('GRU Forecast: Training, Testing & Predictions')
plt.xlabel('Time Step')
plt.ylabel('Vehicles')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()

2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 230ms/step

 Evaluation Metrics (GRU):
Root Mean Squared Error (RMSE): 0.6956
Mean Absolute Error (MAE): 0.6004
Sum of Squared Errors (SSE): 27.10
Normalized Mean Squared Error (NMSE): 0.0022
Mean Absolute Percentage Error (MAPE): 0.80%
Accuracy (100 − MAPE): 99.20%
R² Score: 0.9978
```




```
import matplotlib.pyplot as plt

# === Plot Test and Prediction Only ===
plt.figure(figsize=(12, 6))
```

```python
# Plot actual test data
plt.plot(testy_inv, label='Actual Test Data', color='green')

# Plot predicted test data
plt.plot(predictions_inv, label='Predicted Test Data', color='red',
linestyle='--')

# === Styling ===
plt.title('GRU Forecast: Actual vs Predicted (Test Data Only)')
plt.xlabel('Time Step')
plt.ylabel('Vehicles')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```