

```
In [829]: #All dependencies in the dependencies.txt file. This should work too
#!pip install numpy pandas IPython seaborn matplotlib folium statsmodels tensorflow scik
```

```
In [31]: # DATA
import numpy as np
import pandas as pd

# DASHBOARDS
from IPython.display import HTML

# PLOTTERS
import seaborn as sns
import matplotlib.pyplot as plt

# MAP VISUALIZER
import folium
from folium.plugins import MarkerCluster

# STATISTICS
from statsmodels.tsa.stattools import acf, pacf
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

# LSTM
import tensorflow as tf
import tensorflow.keras as keras
from tensorflow.keras.layers import Input, Bidirectional, LSTM, Dense
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
```

BASIC Exploratory Data Analysis (EDA)

First Look at The Data

```
In [32]: data = pd.read_csv("orders_autumn_2020.csv")
print(data.dtypes)
data.describe()
```

```
TIMESTAMP                                     object
ACTUAL_DELIVERY_MINUTES - ESTIMATED_DELIVERY_MINUTES    int64
ITEM_COUNT                                              int64
USER_LAT                                                float64
USER_LONG                                               float64
VENUE_LAT                                               float64
VENUE_LONG                                              float64
ESTIMATED_DELIVERY_MINUTES                            int64
ACTUAL_DELIVERY_MINUTES                                int64
CLOUD_COVERAGE                                         float64
TEMPERATURE                                             float64
WIND_SPEED                                              float64
PRECIPITATION                                           float64
dtype: object
```

Out[32]:

	ACTUAL_DELIVERY_MINUTES - ESTIMATED_DELIVERY_MINUTES	ITEM_COUNT	USER_LAT	USER_LONG	VENUE_LAT	VENUE_LONG	ES
count	18706.000000	18706.000000	18706.000000	18706.000000	18706.000000	18706.000000	
mean	-1.201058	2.688228	60.175234	24.941244	60.175643	24.941214	

std	8.979834	1.886455	0.012674	0.016540	0.011509	0.014482
min	-41.000000	1.000000	60.153000	24.909000	60.149000	24.878000
25%	-7.000000	1.000000	60.163000	24.926000	60.167000	24.930000
50%	-2.000000	2.000000	60.175000	24.943000	60.170000	24.941000
75%	5.000000	4.000000	60.186000	24.954000	60.186000	24.950000
max	34.000000	11.000000	60.201000	24.980000	60.219000	25.042000

Spatial View

1. We have **coordinates**. We can **visualize the area** where the users and venues are located
2. Plotting users and venues locations we find the dataset concerns the city of **Helsinki**
3. It's hard to tell whether some areas are more populated than others in terms of users and venues. A heatmap could clarify better (below in the Advanced EDA).

In [60]: *# Create float columns for convenience, without losing the original ones*

```
data['user_lat'] = pd.to_numeric(data['USER_LAT'])
data['user_lon'] = pd.to_numeric(data['USER_LONG'])
data['venue_lat'] = pd.to_numeric(data['VENUE_LAT'])
data['venue_lon'] = pd.to_numeric(data['VENUE_LONG'])
```

Venues

In [59]: *#import folium*
#from folium.plugins import MarkerCluster

Create a map centered at Helsinki (blue placeholder)
m = folium.Map(location=[60.1756, 24.9342], zoom_start=13)

Define Venue Coordinates
coords = zip(data["venue_lat"], data["venue_lon"])

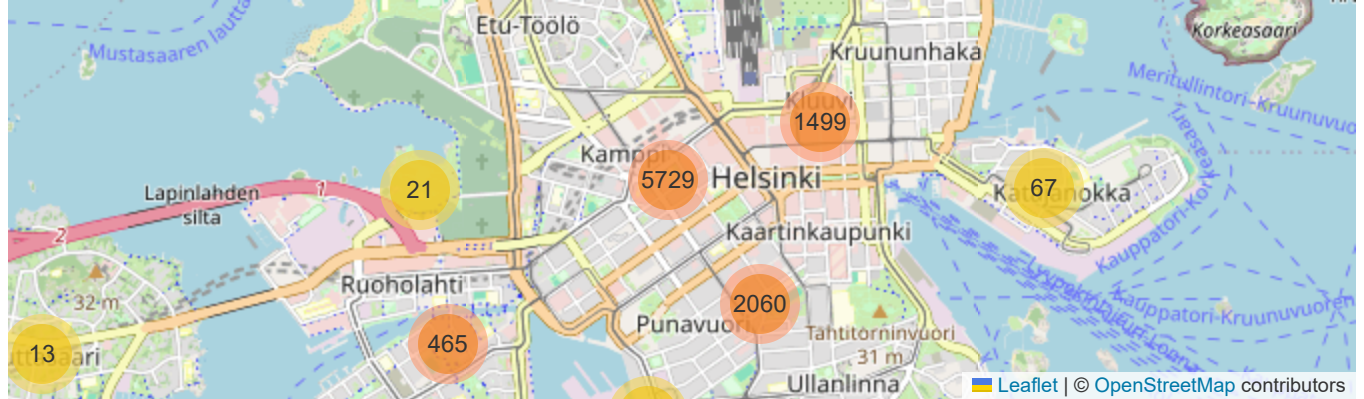
Use MarkerCluster to group nearby markers
marker_cluster = MarkerCluster().add_to(m)

Add points to the marker cluster
for coord **in** coords:
 folium.Marker(location=coord).add_to(marker_cluster)

Display the map
m

Out[59]:





Users

```
In [55]: #import folium
#from folium.plugins import MarkerCluster

# Create a map centered at Helsinki (blue placeholder)
m = folium.Map(location=[60.1756, 24.9342], zoom_start=13)

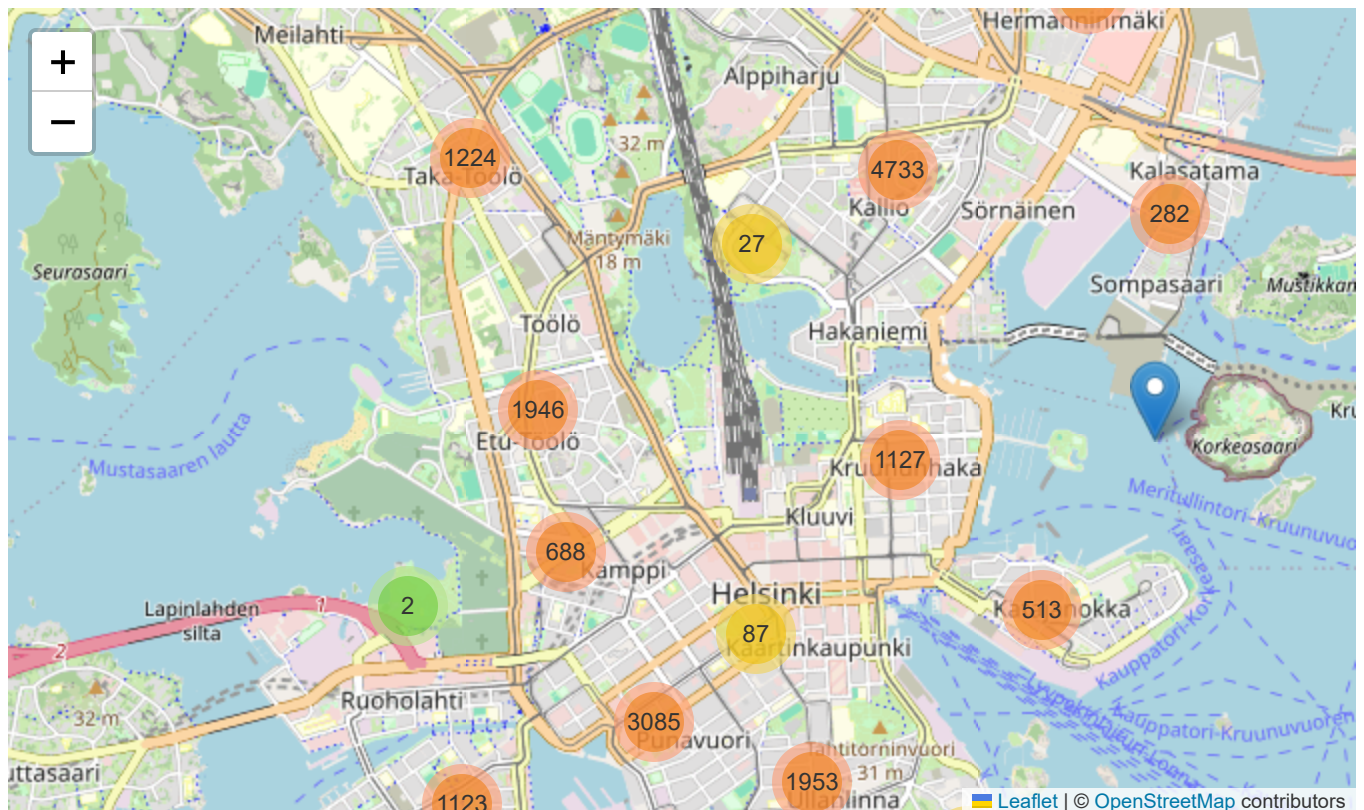
# Define Venue Coordinates
coords = zip(data["user_lat"], data["user_lon"])

# Use MarkerCluster to group nearby markers
marker_cluster = MarkerCluster().add_to(m)

# Add points to the marker cluster
for coord in coords:
    folium.Marker(location=coord).add_to(marker_cluster)

# Display the map
m
```

Out[55]:



Distributions

Three variables carry information about **orders' delivery time**

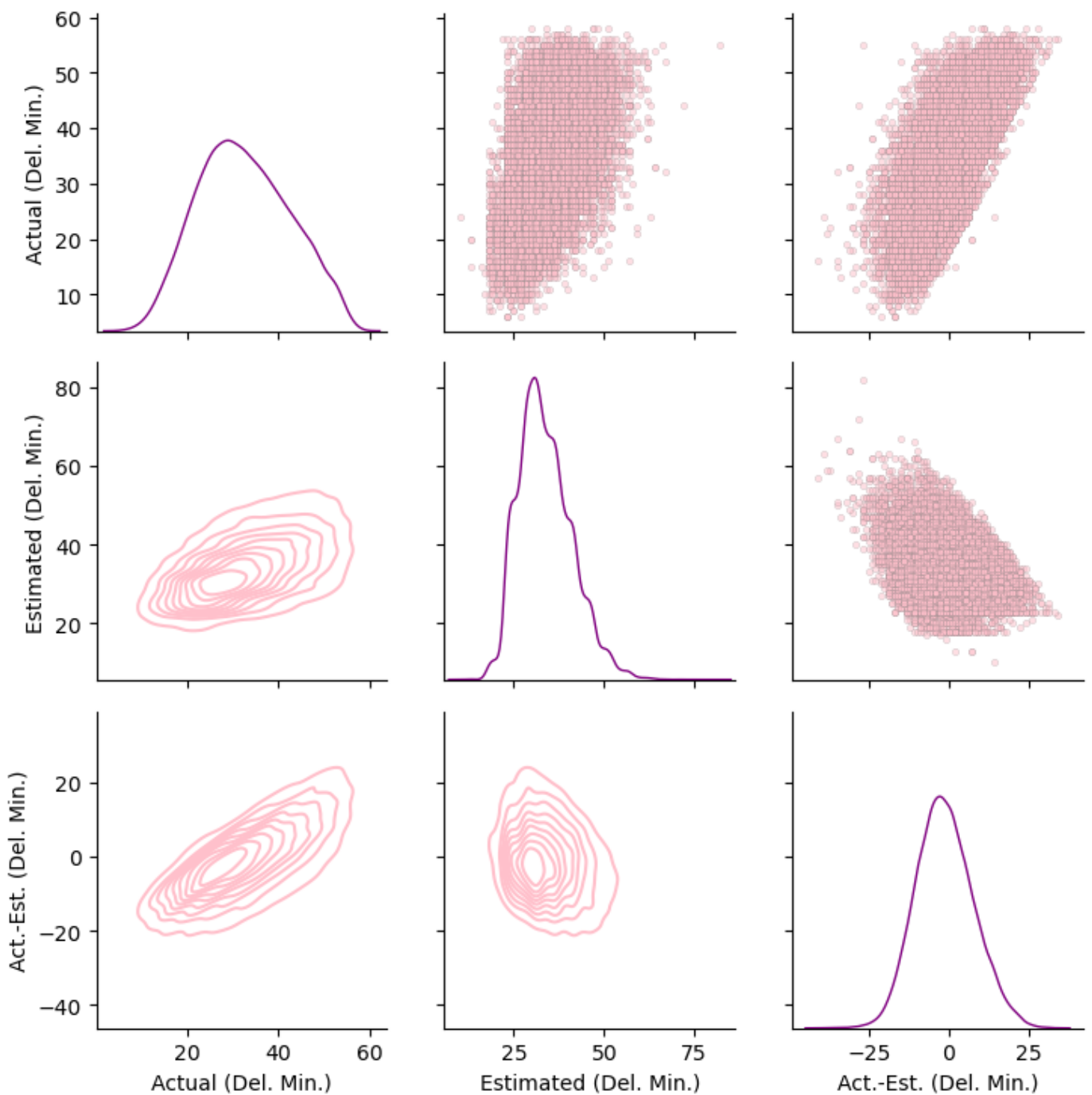
1. "ACTUAL_DELIVERY_MINUTES"
2. "ESTIMATED_DELIVERY_MINUTES",
3. "ACTUAL_DELIVERY_MINUTES - ESTIMATED_DELIVERY_MINUTES"

We can look at their single **distributions** (diagonal). Are they **gaussians**? Are they **skewed**?

What's the relation between each variable and the others (scatterplots and kdeplot, off-diagonal)

We don't see anything particularly surprising. The **(Actual - Estimated Delivery Minutes) variable is gaussian** and **centered below the 0**. Times are calculated so that **the user doesn't experience delays, on average**.

```
In [111... # import seaborn as sns
sub_data = data[["ACTUAL_DELIVERY_MINUTES",
                 "ESTIMATED_DELIVERY_MINUTES",
                 "ACTUAL_DELIVERY_MINUTES - ESTIMATED_DELIVERY_MINUTES"]]
sub_data.columns = ["Actual (Del. Min.)", "Estimated (Del. Min.)", "Act.-Est. (Del. Min.)"]
g = sns.PairGrid(sub_data)
g.map_upper(sns.scatterplot, alpha=0.5, s=10, edgecolor='grey', color = 'pink')
g.map_lower(sns.kdeplot, color = 'pink')
g.map_diag(sns.kdeplot, lw=1, legend=False, color = 'purple')
plt.show()
```



In [114]: `sub_data.describe()`

Out[114]:

	Actual (Del. Min.)	Estimated (Del. Min.)	Act.-Est. (Del. Min.)
count	18706.000000	18706.000000	18706.000000
mean	32.608254	33.809313	-1.201058
std	10.018879	7.340283	8.979834
min	6.000000	10.000000	-41.000000
25%	25.000000	28.000000	-7.000000
50%	32.000000	33.000000	-2.000000
75%	40.000000	38.000000	5.000000
max	58.000000	82.000000	34.000000

Time Series

We can look for interesting **patterns** across time. Should we focus on **weekly/daily/hourly trends**?

Some **variables** with interesting behaviours could be:

1. (Actual - Estimated) Delivery Minutes (Delay)

- Do delays happen more often in certain weekdays/hours of day/day of month?
- What's the time series like for the total window of time in the data? Are there patterns we can predict?

1. Number of Orders

- How does the number of orders depend on weekdays/hours of day/day of month?
- What's the time series like for the total window of time in the data? Are there patterns we can predict?

1. Other

- Should we expect any relation between time and coordinates or user-venue distance?

```
In [244... # Convert into datetime format
data["Datetime"] = pd.to_datetime(data["TIMESTAMP"])

# Define new dataframe, for convenience
time_df = pd.DataFrame({})
time_df["date"] = data["Datetime"]
time_df["minute"] = data["Datetime"].dt.minute
time_df["hour"] = data["Datetime"].dt.hour
time_df["day"] = data["Datetime"].dt.day
time_df["month"] = data["Datetime"].dt.month
time_df["year"] = data["Datetime"].dt.year

time_df["Delay"] = data["ACTUAL_DELIVERY_MINUTES - ESTIMATED_DELIVERY_MINUTES"]
time_df["Counts"] = len(time_df) * [1]

time_df
```

Out[244]:

	date	minute	hour	day	month	year	Delay	Counts
0	2020-08-01 06:07:00	7	6	1	8	2020	-19	1
1	2020-08-01 06:17:00	17	6	1	8	2020	-7	1
2	2020-08-01 06:54:00	54	6	1	8	2020	-17	1
3	2020-08-01 07:09:00	9	7	1	8	2020	-2	1
4	2020-08-01 07:10:00	10	7	1	8	2020	-1	1
...
18701	2020-09-30 19:27:00	27	19	30	9	2020	-1	1
18702	2020-09-30 19:36:00	36	19	30	9	2020	-8	1
18703	2020-09-30 19:39:00	39	19	30	9	2020	-14	1

18704	2020-09-30 19:42:00	42	19	30	9	2020	-11	1
18705	2020-09-30 20:04:00	4	20	30	9	2020	-7	1

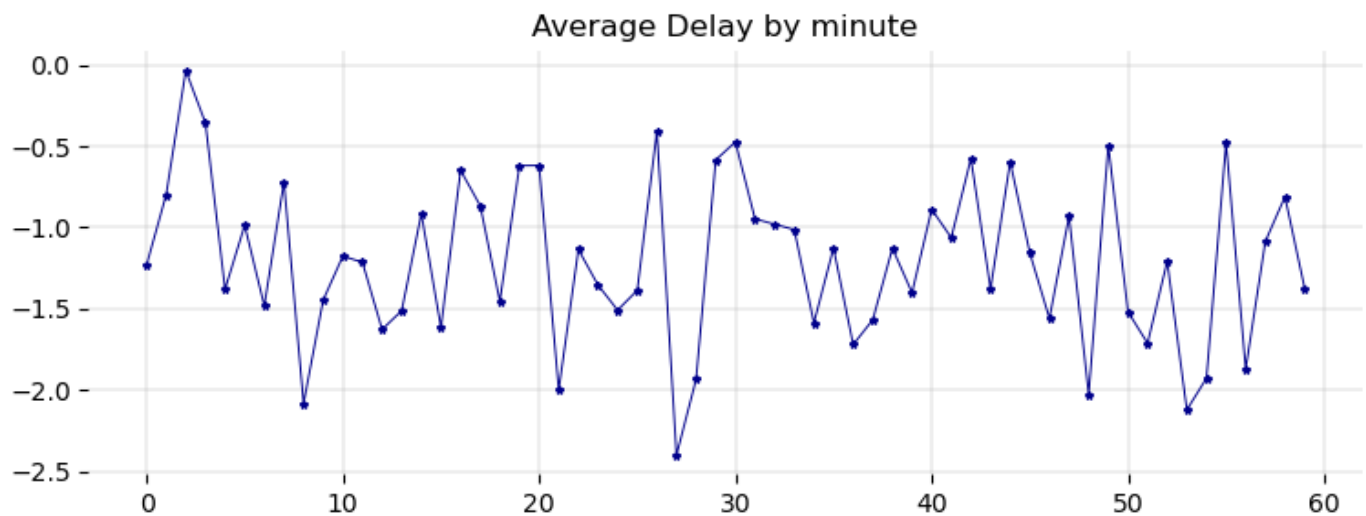
18706 rows × 8 columns

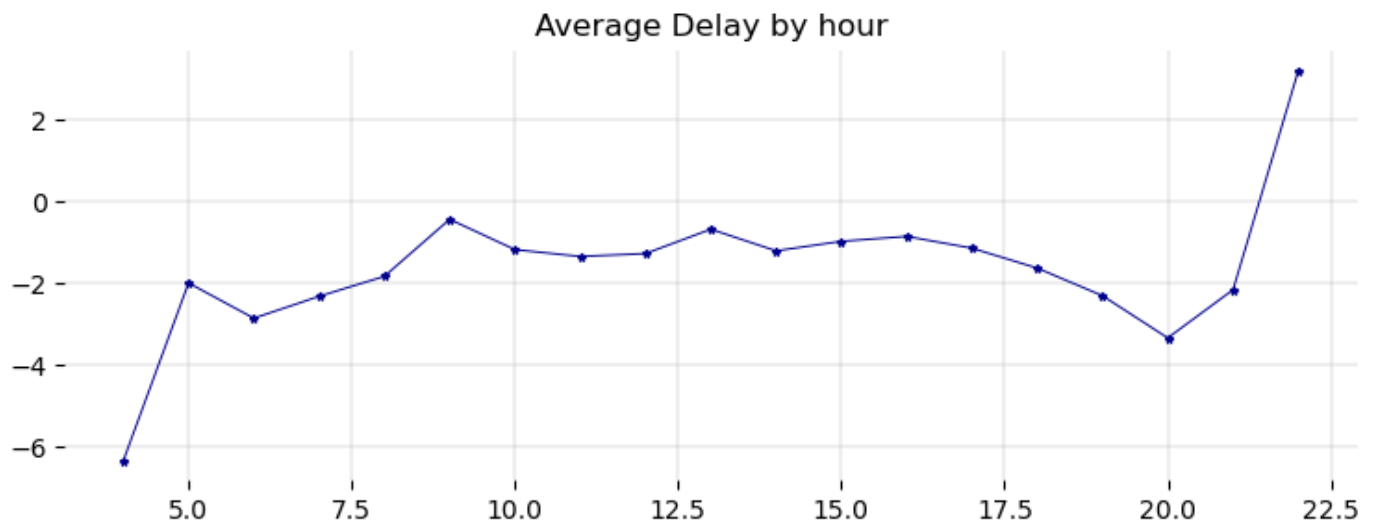
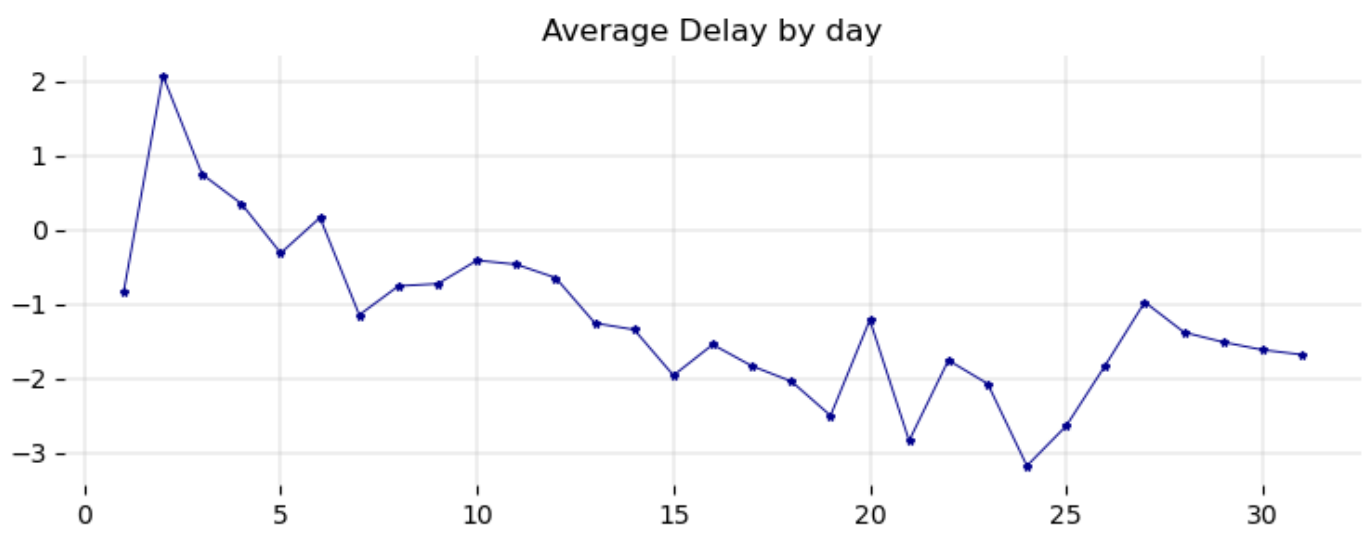
Delays

```
In [245... def time_series_plotter(granularity = 'day'):
    result_df = time_df.groupby([granularity]).agg({'Delay': 'mean'}).reset_index()
    plt.figure(figsize = (9,3))
    plt.plot(result_df[[granularity]], result_df["Delay"], linewidth = 0.69, color = 'd',
             marker = '*', markersize = 3.1)
    plt.title(f"Average Delay by {granularity}")
    plt.grid(True, linewidth = 0.3)
    plt.box(False)
    plt.show()

def time_series_plotter_counts(granularity = 'day'):
    result_df = time_df.groupby([granularity]).agg({'Counts': 'sum'}).reset_index()
    plt.figure(figsize = (9,3))
    plt.plot(result_df[[granularity]], result_df["Counts"], linewidth = 0.69, color = 'd',
             marker = '*', markersize = 3.1)
    plt.title(f"Nr. of Orders by {granularity}")
    plt.grid(True, linewidth = 0.3)
    plt.box(False)
    plt.show()

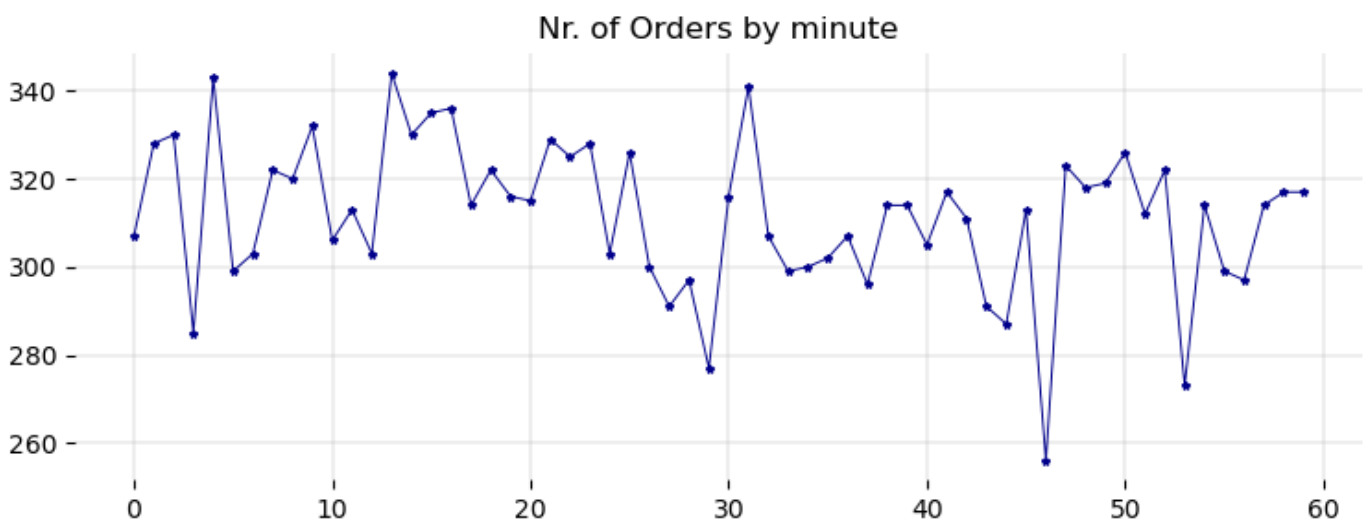
time_series_plotter('minute')
time_series_plotter('day')
time_series_plotter('hour')
```

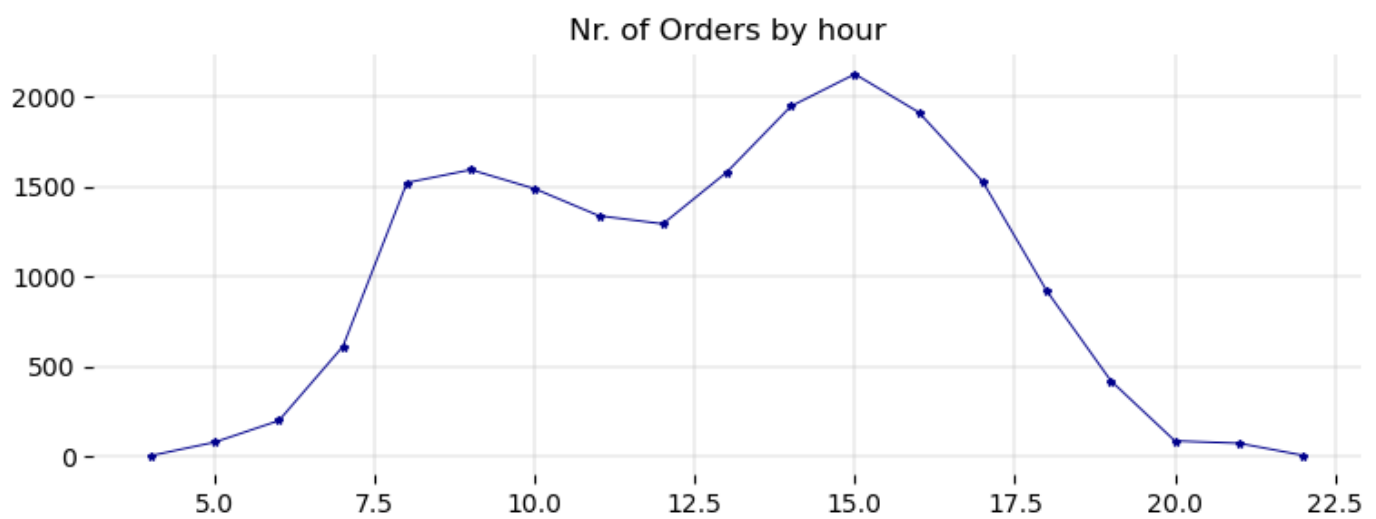




Orders

```
In [246... time_series_plotter_counts('minute')  
time_series_plotter_counts('hour')  
time_series_plotter_counts('day')
```





```
In [247... # This is needed for the resampling in the following plots. Set the "date" column as the
time_df_n = time_df
time_df_n.set_index('date', inplace=True)
```

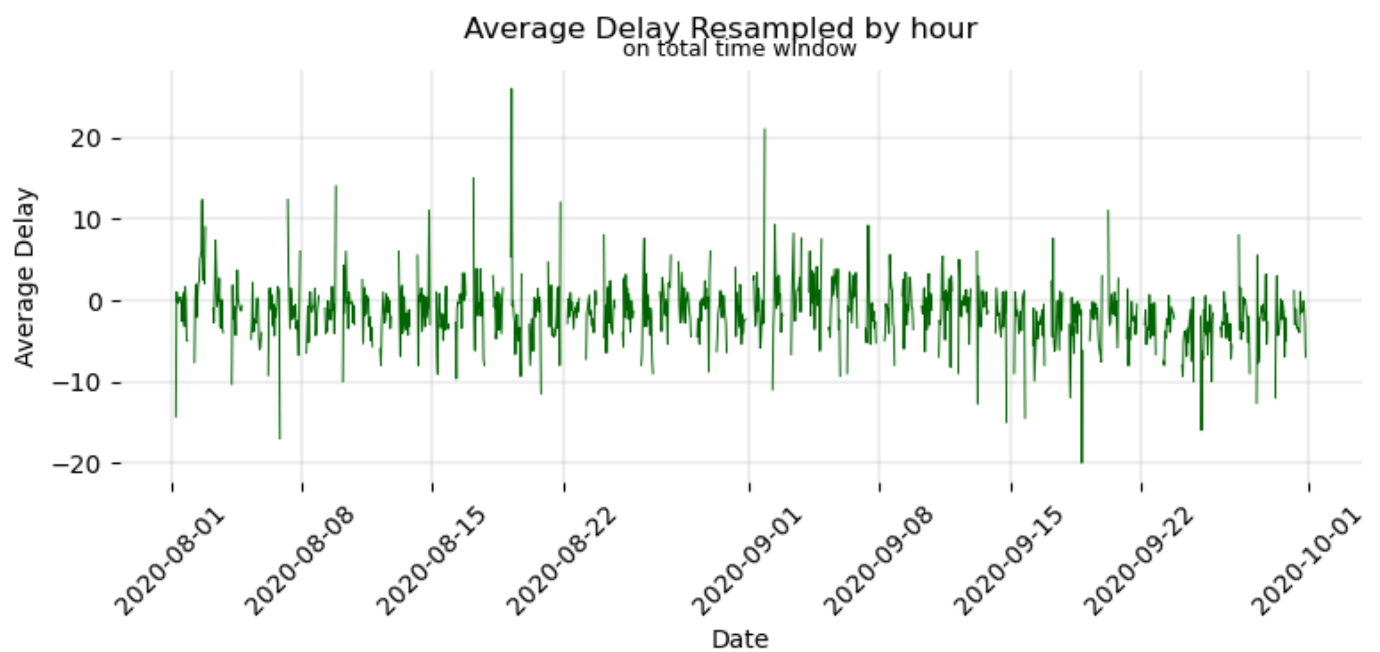
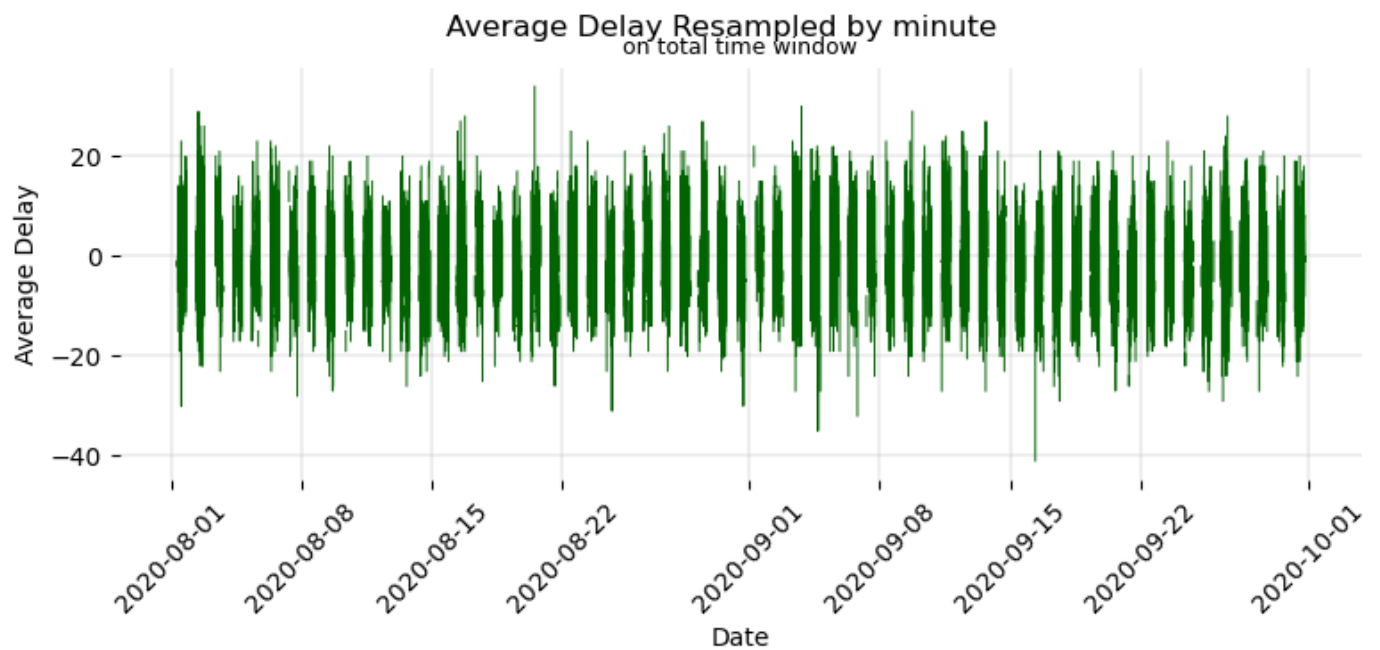
Delays

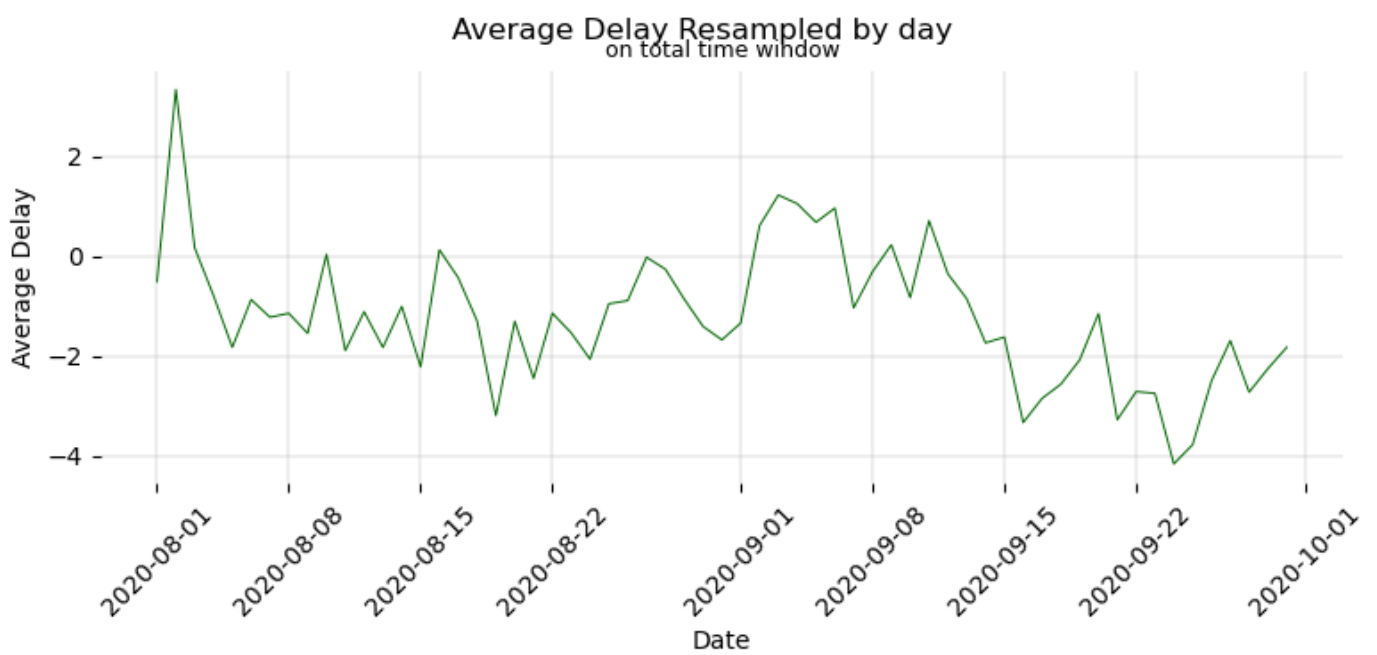
```
In [301... def timeseries_plotter(resampled_by = 'day', indicator = 'mean'):
    dictio = {'minute': 'T', 'hour': 'H', "day": 'D', 'month': 'M'}

    # Resample by day and calculate the mean delay for each day
    if indicator == 'mean':
        resampled_df = time_df_n.resample(dictio[resampled_by]).mean()
    elif indicator == 'sum':
        resampled_df = time_df_n.resample(dictio[resampled_by]).sum()

    plt.figure(figsize = (9,3))
    # Plot the resampled data
    plt.plot(resampled_df.index, resampled_df['Delay'], linewidth = 0.69, color = 'darkg
    plt.xlabel('Date')
    plt.ylabel('Average Delay')
    plt.suptitle(f'Average Delay Resampled by {resampled_by}')
    plt.title('on total time window', fontsize = 9)
    plt.xticks(rotation = 45)
    plt.grid(True, linewidth = 0.3)
    plt.box(False)
    plt.show()
```

```
'''  
timeseries_plotter('minute')  
timeseries_plotter('hour')  
timeseries_plotter('day')  
'''  
  
timeseries_plotter('minute', indicator = 'sum')  
timeseries_plotter('hour', indicator = 'sum')  
timeseries_plotter('day', indicator = 'sum')  
'''
```





```
Out[301]: "\ntimeseries_plotter('minute', indicator = 'sum')\ntimeseries_plotter('hour', indicator
= 'sum')\ntimeseries_plotter('day', indicator = 'sum')\n"
```

Orders

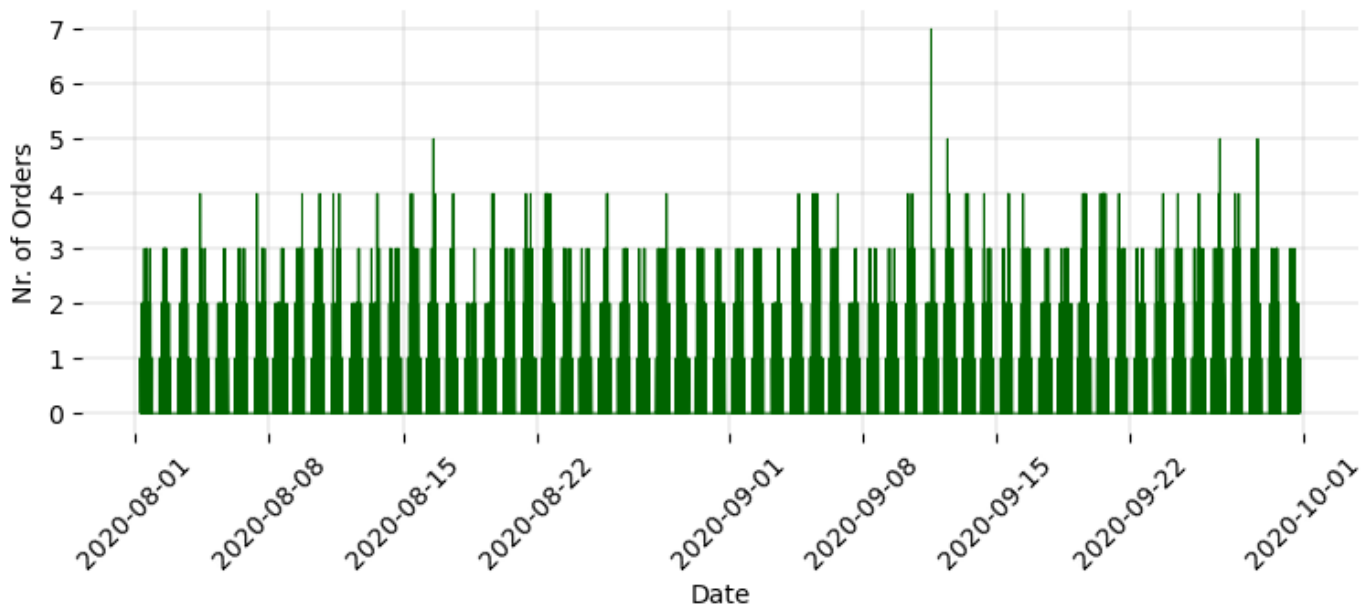
```
In [302... def timeseries_plotter_counts(resampled_by = 'day'):
    dictio = {'minute': 'T', 'hour': 'H', "day": 'D', 'month': 'M'}

    # Resample by day and calculate the mean delay for each day
    resampled_df = time_df_n.resample(dictio[resampled_by]).sum()

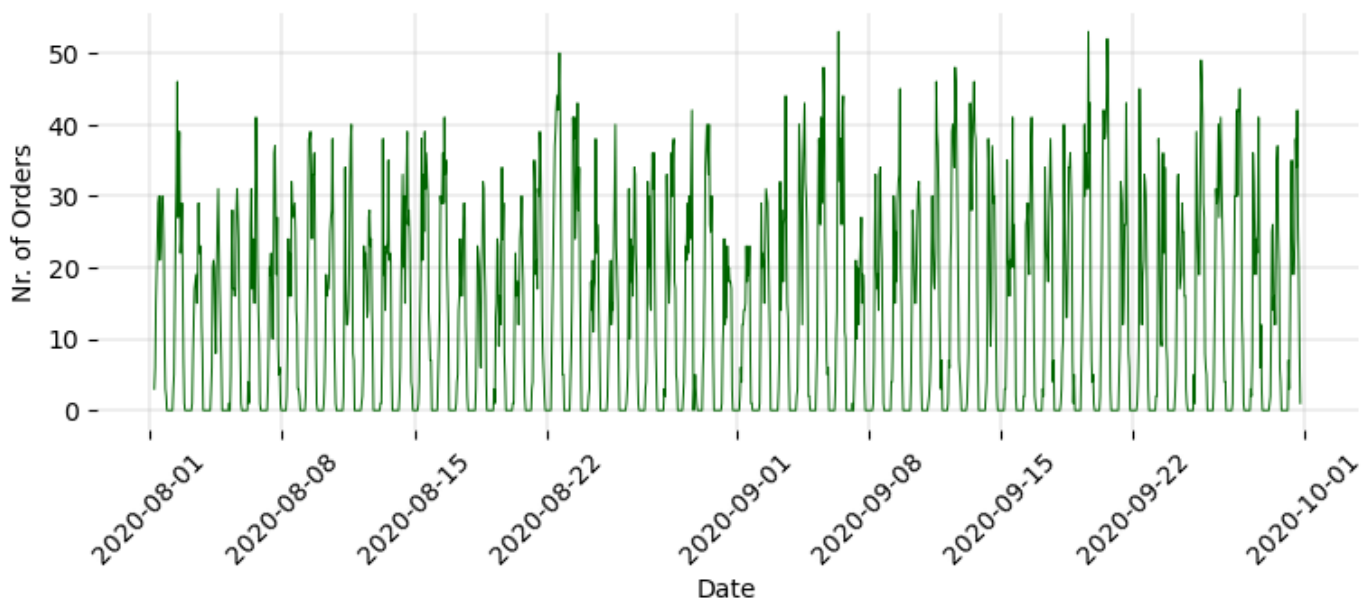
    plt.figure(figsize = (9,3))
    # Plot the resampled data
    plt.plot(resampled_df.index, resampled_df['Counts'], linewidth = 0.69, color = 'dark
    plt.xlabel('Date')
    plt.ylabel('Nr. of Orders')
    plt.suptitle(f'Nr. of Orders Resampled by {resampled_by}')
    plt.title('on total time window', fontsize = 9)
    plt.xticks(rotation = 45)
    plt.grid(True, linewidth = 0.3)
    plt.box(False)
    plt.show()

timeseries_plotter_counts('minute')
timeseries_plotter_counts('hour')
timeseries_plotter_counts('day')
```

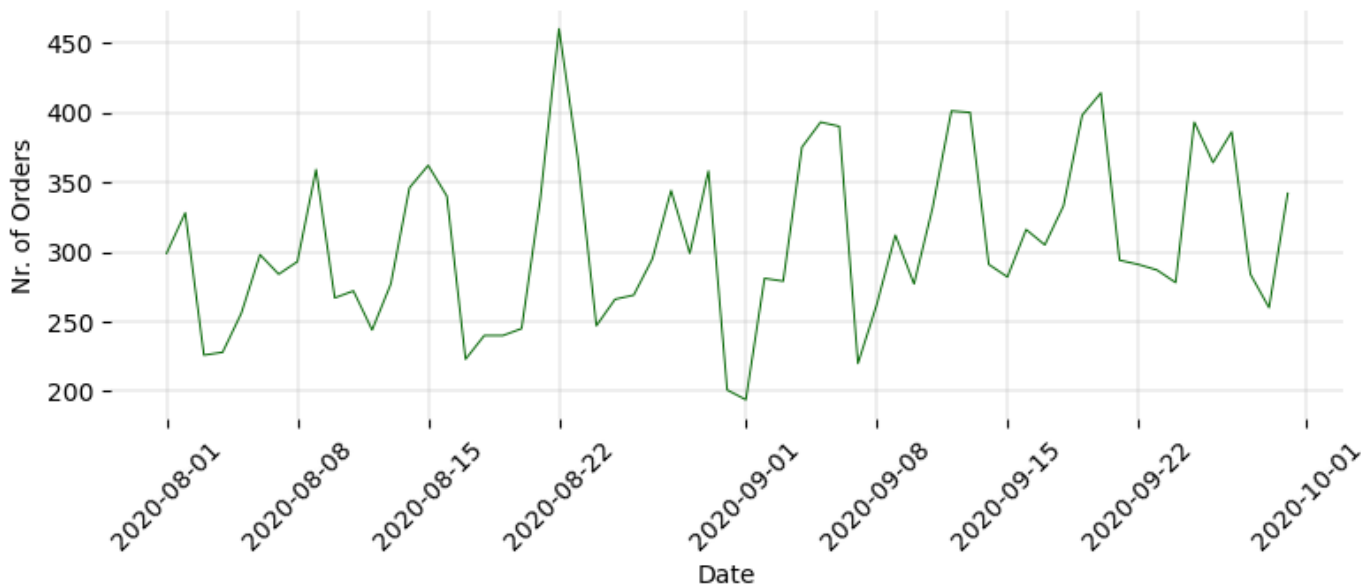
Nr. of Orders Resampled by minute
on total time window



Nr. of Orders Resampled by hour
on total time window



Nr. of Orders Resampled by day
on total time window



Interactive Dashboards

Links for the dashboards

- [EDA 1](#)
 - [EDA 2](#)
 - [EDA 3](#)
-

Orders and delays time trends



Analysis of Delays (Actual - Estimated Delivery Time > 0)

- Exploring **distributions** for **actual and estimated delivery times**, as well as their **difference**.
- The latter appears to have a gaussian distribution with average lower than zero. **Most of the times users don't experience delays**
- Are delays linked to specific venues? How are they impacted by venues popularity or location?



MODEL

Some variables are an obvious choice for a **prediction task**.

For instance, there's no doubt about the benefit and the need of forecasting the number of orders received in a day/hour.

Aim

- The EDA showed some interesting trends/patterns but didn't suggest any unexpected target variable.
- The best way to use our data is to predict a **well defined variable**, the knowledge of which is of obvious **utility**.
- **We thus focus on the average delay** (Actual - Estimated Delivery Minutes).

We try to complete the following **task**:

PREDICT THE AVERAGE DELAY IN THE NEXT DAY/HOUR

Benefits

This could be helpful for many reasons. For example:

- the company could encourage a **higher number of couriers** in those day/hours where more **delays are expected**, countering the latter by properly distributing deliveries.
- the app could **estimate higher delivery times**, in order not to disappoint users. In this case users would just be 'conscious' about the longer waiting times.

Approach

- After defining our predictive goal, we will **model the time series** considering both **endogenous and exogenous features**.
-

SARIMAX

Seasonal **Auto**Regressive Integrated **Moving Average** with Hexogenous features

!Remember!

The SARIMAX model is defined by the order parameters (p, d, q) for the ARIMA part and (P, D, Q, s) for the SARIMA part:

- **p**: The order of the AutoRegressive (AR) part. It represents the number of lags of the dependent variable to be used as predictors.
 - **d**: The degree of differencing. It indicates how many times the data have had past values subtracted to make the series stationary.
 - **q**: The order of the Moving Average (MA) part. It signifies the number of lagged forecast errors that should go into the ARIMA model.
 - **P**: The order of the seasonal part of the AutoRegressive (AR) model.
 - **D**: The degree of seasonal differencing.
 - **Q**: The order of the seasonal part of the Moving Average (MA) model.
 - **s**: The length of the seasonal cycle.
-

1. We can work with **daily or hourly** delays. We choose **hourly** time series since we have a good number of samples.
 2. **We expect periodicity/seasonality**. At least we should observe trends on a **24-hours basis**
 3. We can expect delays to be influenced by **hexogenous features**, such as **weather condition** or number of orders.
 - We rely on **precipitations** assuming this feature is known in advance when performing the forecast. Weathermen are reliable nowadays :)
 - We also consider **weekday and hour** of the day as hexogenous features (for example we know orders are not delivered in certain hours: that is additional information that the model may not completely capture in the naked time series).
-

We will find good orders for the model by looking at the Time Series **Autocorrelation** and **Partial Autocorrelation** for different lags.

The presence of 'high' (outside confidence interval) correlation will suggest the parameters for the SARIMAX model.

```

In [576... #import pandas as pd
#import matplotlib.pyplot as plt
from statsmodels.tsa.stattools import acf, pacf
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

resampled_df = time_df_n.resample('H').sum()
#resampled_df = time_df_n.resample('D').mean()

def correloplotter(x):
    # Compute the autocorrelation function (ACF)
    acf_vals = x#acf(x)
    pacf_vals = x#pacf(x)

    # Plot the ACF
    plot_acf(acf_vals, lags=30)
    plt.ylim([-1.3,1.3])
    plt.grid(linewidth = 0.1)
    #plt.xticks(range(0,20))
    plt.box(True)
    plt.gca().spines['right'].set_visible(False)
    plt.gca().spines['top'].set_visible(False)
    # Set the width of the axes
    plt.gca().spines['left'].set_linewidth(0.31)
    plt.gca().spines['bottom'].set_linewidth(0.31)

    # Plot the PACF
    plot_pacf(pacf_vals, lags =27)
    plt.ylim([-1.3,1.3])
    plt.grid(linewidth = 0.1)
    plt.box(True)
    plt.gca().spines['right'].set_visible(False)
    plt.gca().spines['top'].set_visible(False)
    # Set the width of the axes
    plt.gca().spines['left'].set_linewidth(0.31)
    plt.gca().spines['bottom'].set_linewidth(0.31)

    plt.show()

```

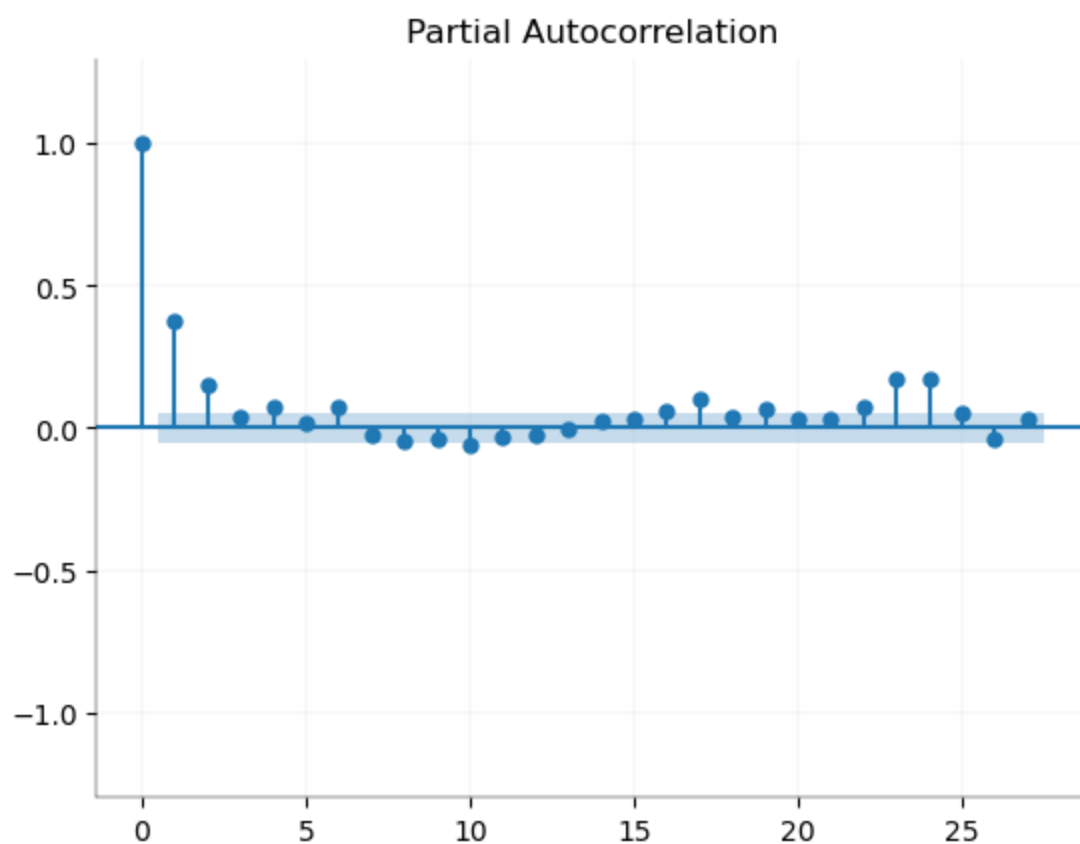
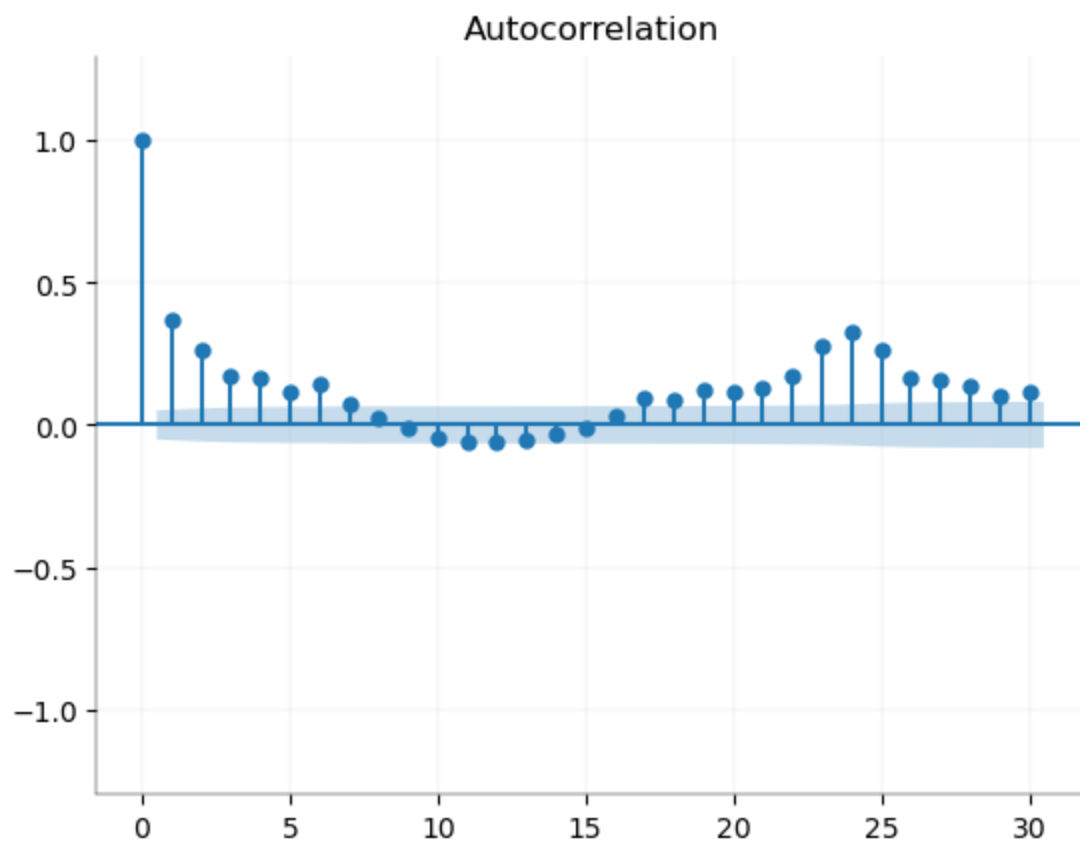
```

In [577... correloplotter(resampled_df['Delay'])

```

C:\Users\diesi\anaconda3\lib\site-packages\statsmodels\graphics\tsaplots.py:348: FutureWarning:

The default method 'yw' can produce PACF values outside of the [-1,1] interval. After 0.13, the default will change to unadjusted Yule-Walker ('ywm'). You can use this method now by setting method='ywm'.

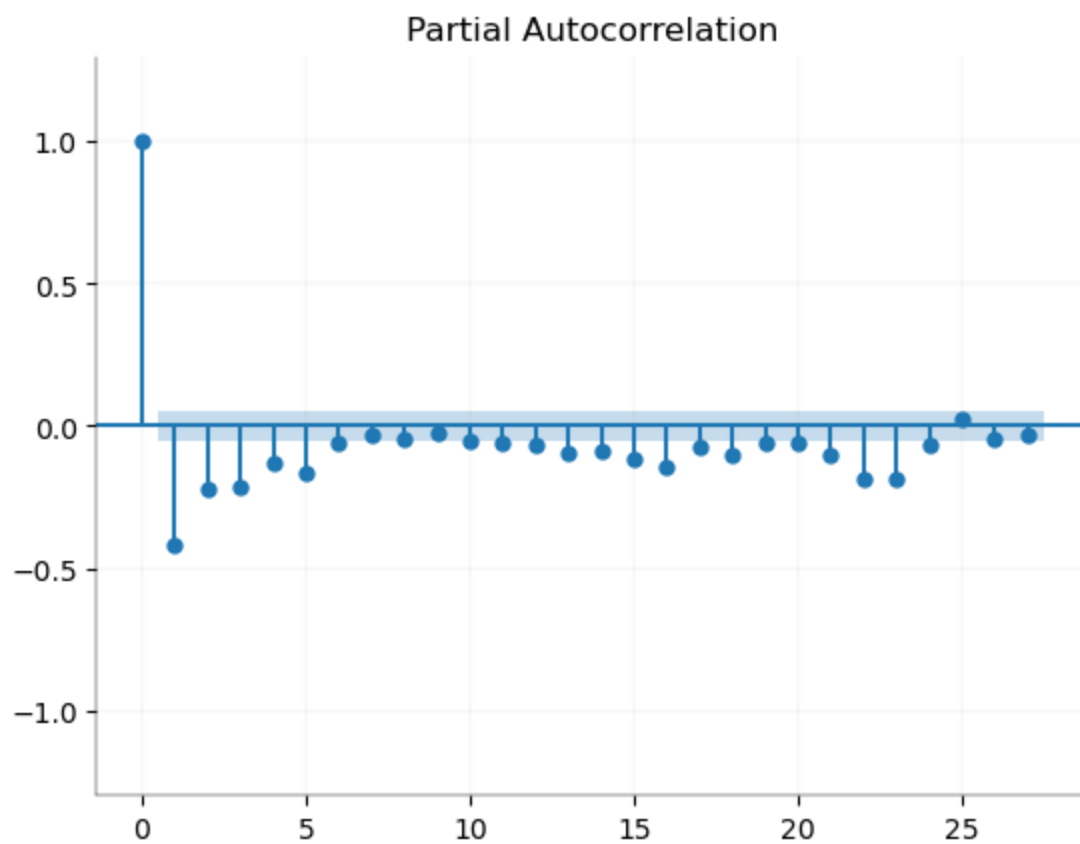
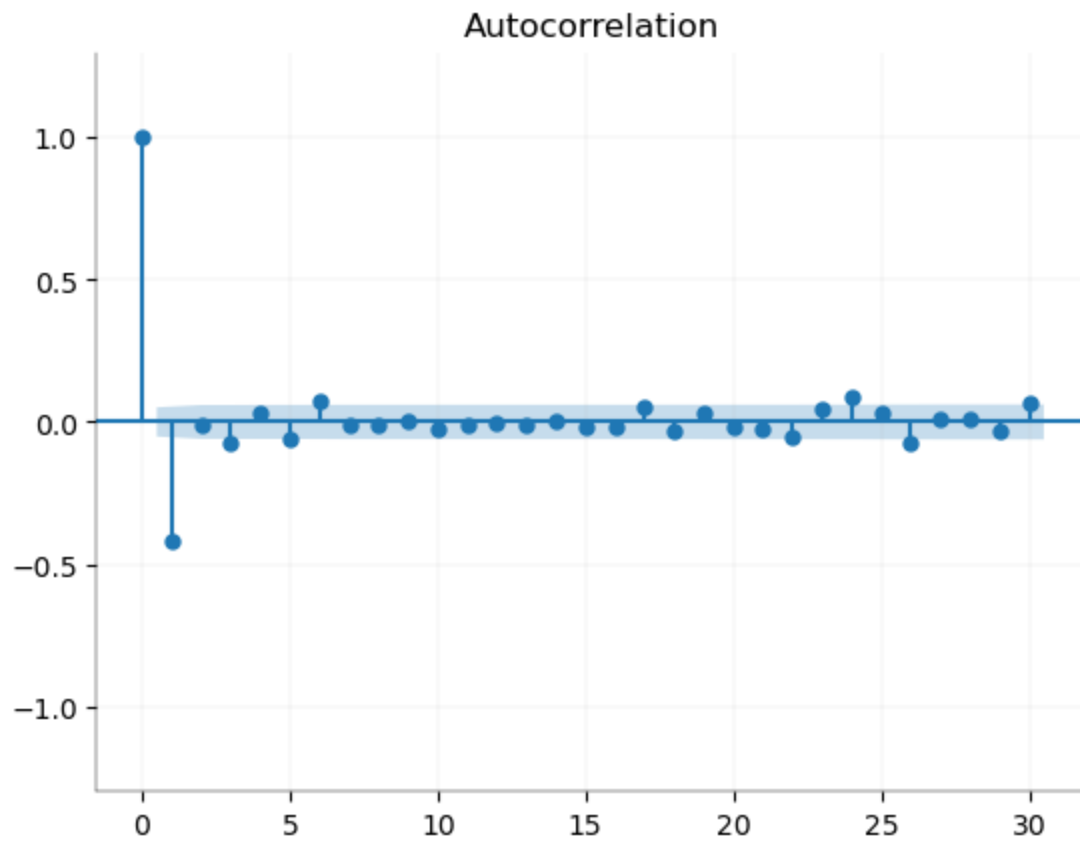


```
In [578... resampled_df['delay_diff'] = resampled_df['Delay'].diff()  
resampled_df_dropna = resampled_df.dropna()  
  
correloplotter(resampled_df_dropna['delay_diff'])
```

C:\Users\diesi\anaconda3\lib\site-packages\statsmodels\graphics\tsaplots.py:348: FutureWarning:

The default method 'yw' can produce PACF values outside of the [-1,1] interval. After 0.13, the default will change to unadjusted Yule-Walker ('ywm'). You can use this method no

w by setting method='ywm'.

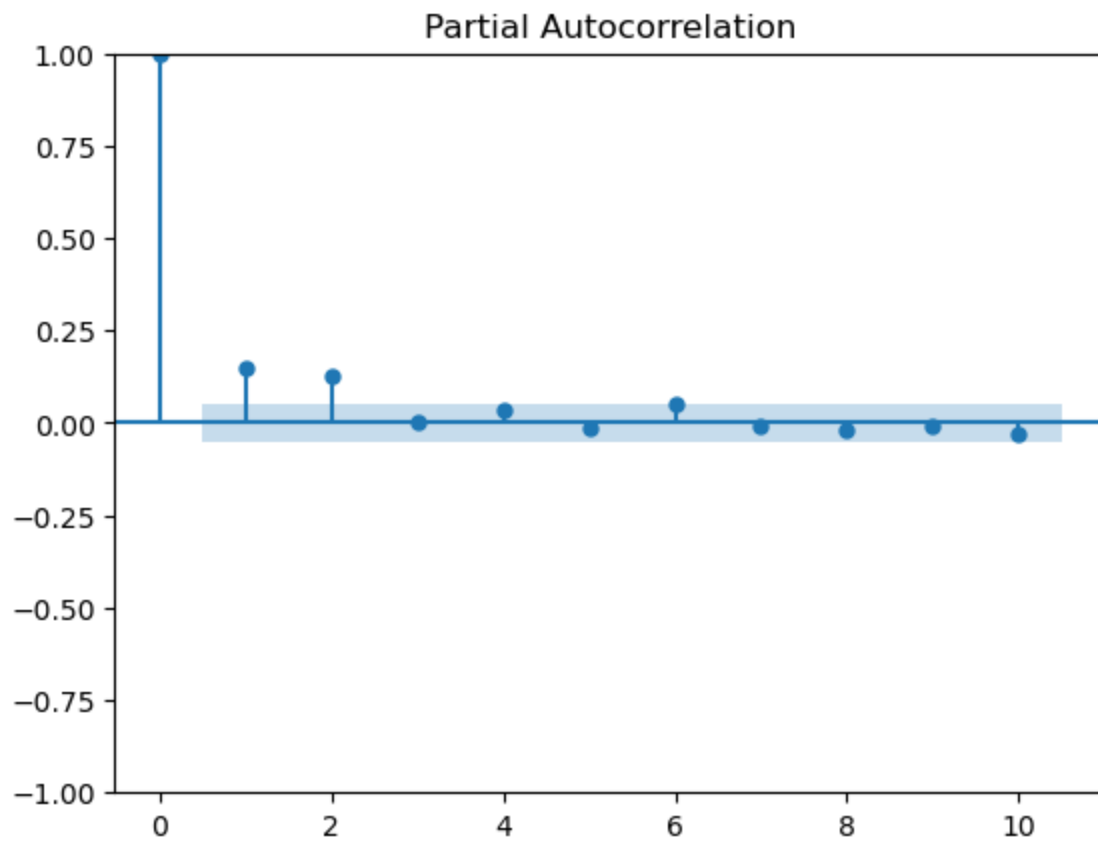
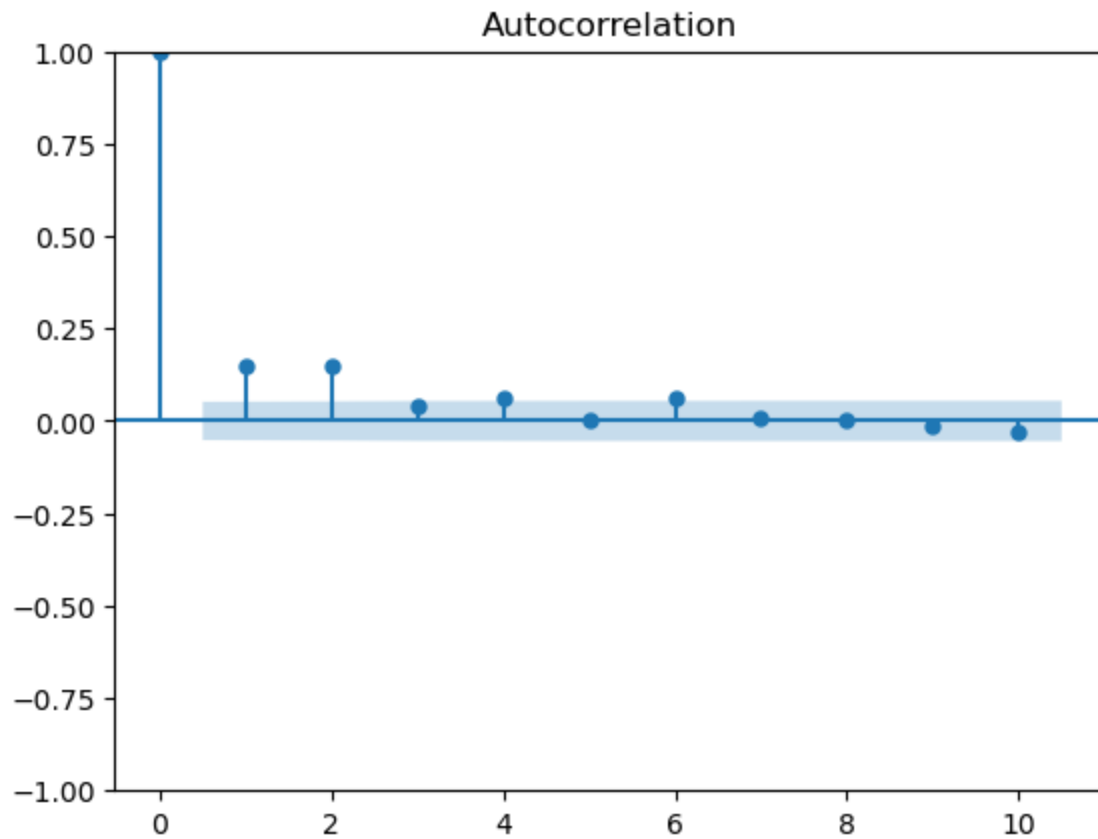


Sarima

```
In [537... # ACF and PACF plots for seasonal component
seasonal_diff = resampled_df['Delay'].diff(24).dropna()

plot_acf(seasonal_diff, lags=10, zero=True)
plt.show()
```

```
plot_pacf(seasonal_diff, lags=10, zero=True)  
plt.show()
```



Analysis

Let's analyze the findings:

Original Series:

- ACF shows significant spikes at lags 1, 2, 3, 4, 5, 6, and 16 to 27.
- PACF shows significant spikes at lags 1 and 2.

Differencing (non-seasonal):

- ACF after differencing shows significant spikes at lags 1, 6, and 24.
- PACF after differencing shows significant spikes at lags 1, 2, 3, 4, 5, and 16 to 24.

Seasonal Differencing (s=24):

- ACF after seasonal differencing shows significant spikes at lags 1 and 2.
- PACF after seasonal differencing shows significant spikes at lags 1 and 2.

Deductions:

- Considering the ACF and PACF spikes after non-seasonal differencing, it seems there is a seasonal component with a period of 24 hours, as one could expect.

Suggested Orders:

Based on the observations, a SARIMA model may be appropriate. The suggested orders could be as follows:

- **Seasonal Order (S):** 24 (since the data is hourly and the seasonality is observed every 24 hours).
- **Autoregressive Order (p):** Consider values around 2 for both the non-seasonal and seasonal components based on the PACF.
- **Integrated Order (d):** 1 for the non-seasonal component (since differencing at lag 1 shows significance).
- **Seasonal Integrated Order (D):** 1 for the seasonal component (since seasonal differencing at lag 24 shows significance).
- **Moving Average Order (q):** Consider values around 2 for both the non-seasonal and seasonal components based on the ACF.

Model

Dataframe creation. We will have:

- **Target Variable** -> *Average Delay*
Target Variable and time series variable
- **Hex. Features** -> *weekday (number from 1 to 7), hour of the day (1 to 24), Rain (precipitaiothn in mm)*
We could use categorical features but we retain the numerical form

Additional considerations:

- **order** = (2, 1, 2)
- **seasonal_order** = (2, 1, 2, 24)
- We handle **null values** (for hours where there are no orders at all) by replacing them with the average hourly delay across the whole series (= -1.5)

```

In [736... # Define new dataframe, for convenience
time_df = pd.DataFrame({})
time_df["date"] = data["Datetime"]
time_df["minute"] = data["Datetime"].dt.minute
time_df["hour"] = data["Datetime"].dt.hour
time_df["day"] = data["Datetime"].dt.day
time_df["month"] = data["Datetime"].dt.month
time_df["year"] = data["Datetime"].dt.year
time_df["weekday"] = data["Datetime"].dt.weekday

time_df["Delay"] = data["ACTUAL_DELIVERY_MINUTES - ESTIMATED_DELIVERY_MINUTES"]
time_df["Counts"] = len(time_df)*[1]
time_df["Rain"] = data["PRECIPITATION"]

# This is needed for the resampling in the following plots. Set the "date" column as the
time_df_n = time_df
time_df_n.set_index('date', inplace=True)

# Resample by considering hourly sum of delays
resampled_df = time_df_n.resample('H').sum()
#resampled_df = time_df_n.resample('D').mean()

#print(resampled_df['Delay'].dropna().mean())

for column in resampled_df.columns:
    if column != 'Counts':
        # Perform the division only when "Counts" is not 0, otherwise set the result to
        resampled_df[column] = np.where(
            resampled_df["Counts"] != 0,
            resampled_df[column] / resampled_df["Counts"], -1.5) # or 0)

```

```

In [737... train_size = int(len(resampled_df) * 0.9) # 95% for training, 5% for testing
train, test = resampled_df[:train_size], resampled_df[train_size:]

```

```

In [738... from statsmodels.tsa.statespace.sarimax import SARIMAX

### HOURLY FORECAST ###
order = (2, 1, 2) # Non-seasonal component
seasonal_order = (2, 1, 2, 24) # Seasonal component

'''
### DAILY FORECAST ###
order = (2, 1, 1) # Non-seasonal component
seasonal_order = (2, 1, 2, 7) # Seasonal component
'''

'''
order = (3, 1, 3) # Non-seasonal component
seasonal_order = (2, 1, 2, 24) # Seasonal component
'''

# Fit the SARIMA model
sarima_model = SARIMAX(train['Delay'],
                        order=order, exog=train[['hour', 'weekday', 'Rain']],
                        seasonal_order=seasonal_order,
                        method_kwargs={'maxiter':1000})
fitted_sarima_model = sarima_model.fit()

# Forecast on the test set
sarima_predictions = fitted_sarima_model.get_forecast(len(test), exog=test[['hour', 'week

```


erWarning:

Non-stationary starting autoregressive parameters found. Using zeros as starting parameters.

C:\Users\diesi\anaconda3\lib\site-packages\statsmodels\tsa\statespace\sarimax.py:978: UserWarning:

Non-invertible starting MA parameters found. Using zeros as starting parameters.

C:\Users\diesi\anaconda3\lib\site-packages\statsmodels\base\model.py:604: ConvergenceWarning:

Maximum Likelihood optimization failed to converge. Check mle_retvals

In [767...

```
# Calculate RMSE (Root Mean Squared Error)
rmse = sqrt(mean_squared_error(test['Delay'], sarima_predictions.predicted_mean))
print(f'Root Mean Squared Error (RMSE): {rmse}')

# Plotting the results
plt.figure(figsize=(10, 6))

# Plot training data
plt.plot(train.index, train['Delay'], label='Train', color='gray', linewidth = 0.31)

# Plot actual test data
plt.plot(test.index, test['Delay'], label='Actual', color='green', linewidth = 0.31)

# Plot predicted values
plt.plot(test.index, sarima_predictions.predicted_mean, label='Predicted', color='red',

# Plot confidence intervals
ci = sarima_predictions.conf_int()
plt.fill_between(test.index, ci['lower Delay'], ci['upper Delay'], color='pink', alpha=0

plt.title('SARIMA Model: Actual vs. Predicted Values')
plt.xlabel('Date')
plt.ylabel('Delay')
plt.xticks(rotation=45)
plt.legend()
plt.box(True)
plt.gca().spines['right'].set_visible(False)
plt.gca().spines['top'].set_visible(False)
# Set the width of the axes
plt.gca().spines['left'].set_linewidth(0.31)
plt.gca().spines['bottom'].set_linewidth(0.31)
plt.grid(linewidth = 0.1)
plt.show()

#####
### DETAIL ###
#####

# Plotting the results
plt.figure(figsize=(10, 6))

# Plot training data
plt.plot(train.index[-24*3:], train['Delay'][-24*3:], label='Train', color='gray', linew

# Plot actual test data
plt.plot(test.index, test['Delay'], label='Actual', color='green', linewidth = 0.31)

# Plot predicted values
plt.plot(test.index, sarima_predictions.predicted_mean, label='Predicted', color='red',
```

```

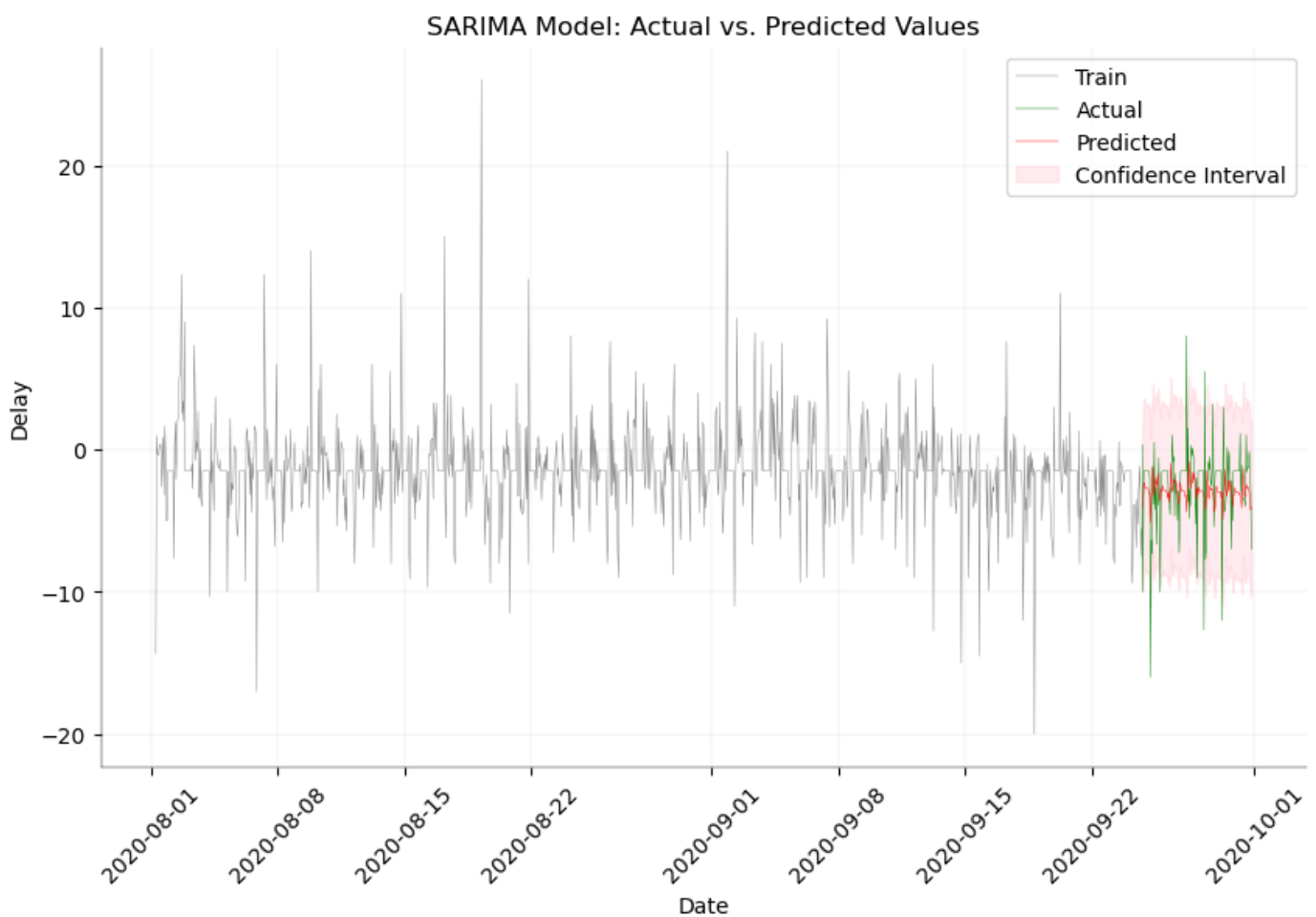
# Plot confidence intervals
ci = sarima_predictions.conf_int()
plt.fill_between(test.index, ci['lower Delay'], ci['upper Delay'], color='pink', alpha=0.5)

plt.title('SARIMA Model: Actual vs. Predicted Values (Detail)')
plt.xlabel('Date')
plt.ylabel('Delay')
plt.xticks(rotation=45)
plt.legend()
plt.box(True)
plt.gca().spines['right'].set_visible(False)
plt.gca().spines['top'].set_visible(False)
# Set the width of the axes
plt.gca().spines['left'].set_linewidth(0.31)
plt.gca().spines['bottom'].set_linewidth(0.31)

plt.grid(linewidth = 0.1)
plt.show()

```

Root Mean Squared Error (RMSE): 2.9221514974542764



SARIMA Model: Actual vs. Predicted Values (Detail)



Diagnostic (below)

Dsitribution

- No trend observed
- No deviation from gaussian distribution, except for a narrower peak of the KDE.

Q-Q Plot:

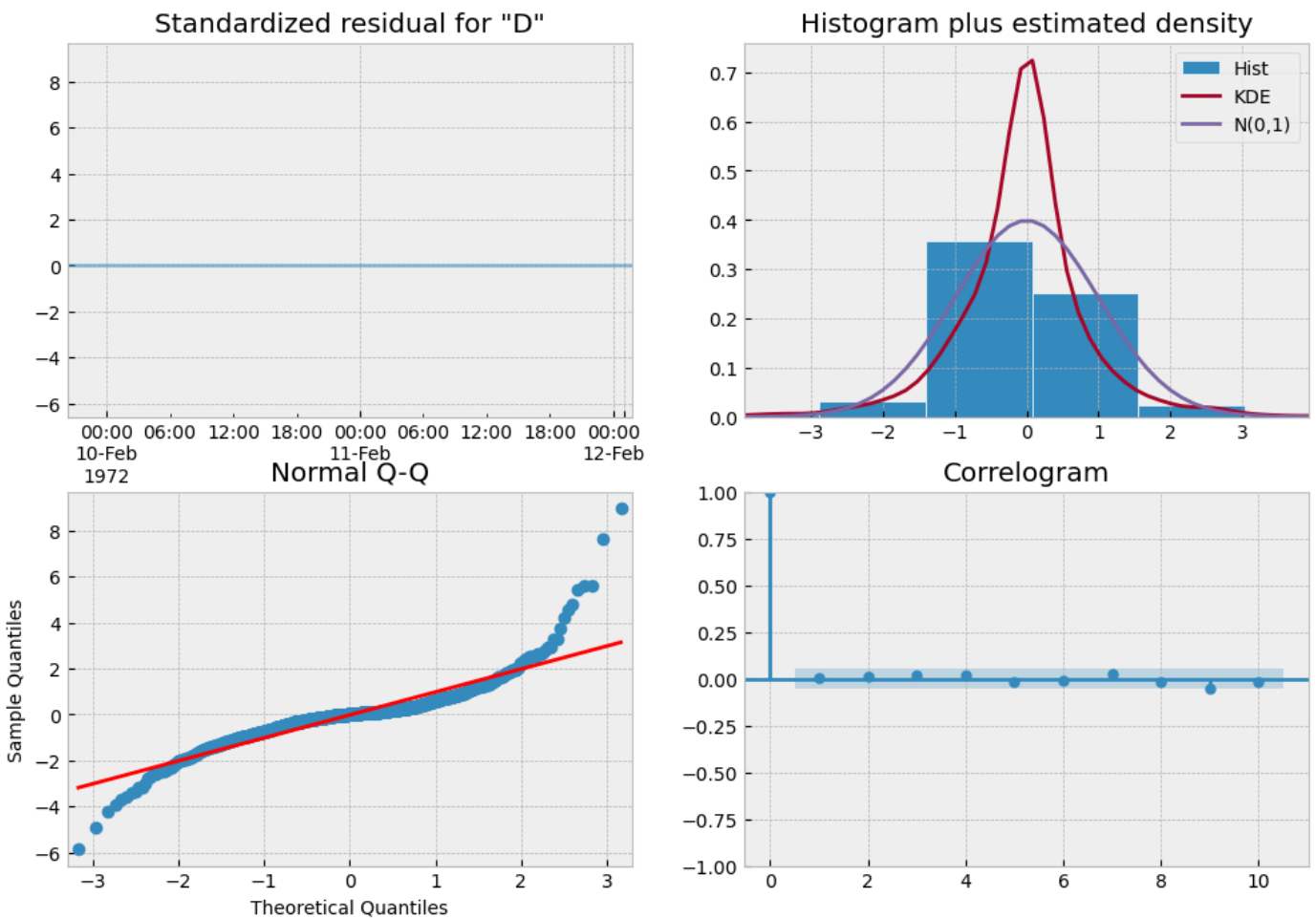
- The small "s" shape around the diagonal line in the Q-Q plot may indicate slight deviations from normality.

This is not uncommon at the tails of the distribution.

Correlogram:

- No spikes just outside the confidence band in the correlogram
- The model likely won't benefit from changes in the orders

```
In [819... plt.style.use('bmh') #ggplot')
fitted_sarima_model.plot_diagnostics(figsize=(12, 8))
plt.show()
plt.style.use('default')
```



Results

- The **model captures** global behaviours and **patterns**
- **High values for hourly delay fail to be predicted**, sometimes even trespassing outside of the 95% confidence band.
- **RMSE** is approx **2.9**

Deep Learning with LSTMs

Long Short Term Memory Recurrent Neural Networks

Model 1 (Vanilla LSTM)

Dataframe creation. We will have:

- **Target Variable** -> *Average Delay*. Target Variable and time series variable
- **Features**

1. *weekday (number from 1 to 7), hour of the day (1 to 24), Rain (precipitaiothn in mm)*

We could use categorical features but we retain the numerical form

2. **Past values of the target variable**, up to a fixed number (LOOKBACK).

We **set it to 24** but alternative values should be considered

Additional considerations:

- 27 features for one target variable. In addition the lstm will be sensitive to sequential patterns
 - We handle **null values** (for hours where there are no orders at all) by replacing them with the average hourly delay across the whole series (= -1.5)
-

```
In [773... import tensorflow.keras as keras
from tensorflow.keras.layers import Input, Bidirectional, LSTM, Dense
import tensorflow as tf

from sklearn.metrics import mean_squared_error
```

```
In [793... # Define new dataframe, for convenience
time_df = pd.DataFrame({})
time_df["date"] = data["Datetime"]
time_df["minute"] = data["Datetime"].dt.minute
time_df["hour"] = data["Datetime"].dt.hour
time_df["day"] = data["Datetime"].dt.day
time_df["month"] = data["Datetime"].dt.month
time_df["year"] = data["Datetime"].dt.year
time_df["weekday"] = data["Datetime"].dt.weekday

time_df["Delay"] = data["ACTUAL_DELIVERY_MINUTES - ESTIMATED_DELIVERY_MINUTES"]
time_df["Counts"] = len(time_df)*[1]
time_df["Rain"] = data["PRECIPITATION"]

# This is needed for the resampling in the following plots. Set the "date" column as the
time_df_n = time_df
time_df_n.set_index('date', inplace=True)

# Resample by considering hourly sum of delays
resampled_df = time_df_n.resample('H').sum()
#resampled_df = time_df_n.resample('D').mean()

#print(resampled_df['Delay'].dropna().mean())

for column in resampled_df.columns:
    if column != 'Counts':
        # Perform the division only when "Counts" is not 0, otherwise set the result to
        resampled_df[column] = np.where(
            resampled_df["Counts"] != 0,
            resampled_df[column] / resampled_df["Counts"], -1.5) # or 0)
```

```
In [794... hex_df = resampled_df[['hour', 'weekday', 'Rain']]
del_df = resampled_df["Delay"]
```

```
In [795... # Set the lookback period to 24. This is the number of previous time steps
# to use as input variables to predict the next time period.
LOOKBACK = 24

# Define a function to wrap the data
def wrap_data(df, lookback):
    # Initialize an empty list to store the dataset
    dataset = []

    # Loop over the DataFrame from 'lookback' to the end of the DataFrame
    for index in range(lookback, len(df)+1):
        features = {
            f"col_{i}": float(val) for i, val in enumerate(
```

```

        df.iloc[index-lookback:index].values
    )
}

# Convert the dictionary to a DataFrame and append it to the 'dataset' list
row = pd.DataFrame.from_dict([features])

# Set the index of the row to be the index of the last period in the lookback window
row.index = [df.index[index-1]]

# Append the row to the dataset
dataset.append(row)

# Return a DataFrame obtained by concatenating all the DataFrames in the 'dataset' list
return pd.concat(dataset, axis=0)

```

```

In [796... # Obtained features by lagging target variable
dataset = wrap_data(del_df, lookback=LOOKBACK)
# Target Variable
dataset = dataset.join(del_df.shift(-1))
# Hex. Features
dataset = pd.concat([dataset, hex_df], axis = 1)

```

```

In [799... dataset = dataset.dropna()

```

```

In [800... callback = tf.keras.callbacks.EarlyStopping(monitor='loss', patience=3)

def create_model():
    input_layer = Input(shape=(LOOKBACK + len(hex_df.columns), 1))
    recurrent = Bidirectional(LSTM(100, activation="tanh"))(input_layer)
    output_layer = Dense(1)(recurrent)
    model = keras.models.Model(inputs=input_layer, outputs=output_layer)
    model.compile(
        loss='mse', optimizer=keras.optimizers.Adagrad(),
        metrics=[
            keras.metrics.RootMeanSquaredError(),
            keras.metrics.MeanAbsoluteError()
        ])
    return model

model = create_model()

```

```

In [801... from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(
    dataset.drop(columns="Delay"),
    dataset["Delay"],
    shuffle=False, test_size = 0.1)

```

```

In [802... model.fit(X_train, y_train, epochs=1000, callbacks=[callback])

```

```

Epoch 1/1000
41/41 [=====] - 3s 16ms/step - loss: 10.7438 - root_mean_square
d_error: 3.2778 - mean_absolute_error: 2.2524
Epoch 2/1000
41/41 [=====] - 1s 15ms/step - loss: 9.6810 - root_mean_squared
_error: 3.1114 - mean_absolute_error: 1.9822
Epoch 3/1000
41/41 [=====] - 1s 14ms/step - loss: 9.2782 - root_mean_squared
_error: 3.0460 - mean_absolute_error: 1.8392
Epoch 4/1000
41/41 [=====] - 1s 15ms/step - loss: 9.1602 - root_mean_squared
_error: 3.0266 - mean_absolute_error: 1.8040
Epoch 5/1000

```



```
41/41 [=====] - 1s 15ms/step - loss: 9.1281 - root_mean_squared
_error: 3.0213 - mean_absolute_error: 1.8053
Epoch 6/1000
41/41 [=====] - 1s 15ms/step - loss: 9.1179 - root_mean_squared
_error: 3.0196 - mean_absolute_error: 1.8082
Epoch 7/1000
41/41 [=====] - 1s 15ms/step - loss: 9.1098 - root_mean_squared
_error: 3.0182 - mean_absolute_error: 1.8056
Epoch 8/1000
41/41 [=====] - 1s 15ms/step - loss: 9.1030 - root_mean_squared
_error: 3.0171 - mean_absolute_error: 1.8041
Epoch 9/1000
41/41 [=====] - 1s 15ms/step - loss: 9.0964 - root_mean_squared
_error: 3.0160 - mean_absolute_error: 1.8019
Epoch 10/1000
41/41 [=====] - 1s 16ms/step - loss: 9.0915 - root_mean_squared
_error: 3.0152 - mean_absolute_error: 1.8046
Epoch 11/1000
41/41 [=====] - 1s 15ms/step - loss: 9.0844 - root_mean_squared
_error: 3.0140 - mean_absolute_error: 1.7959
Epoch 12/1000
41/41 [=====] - 1s 15ms/step - loss: 9.0816 - root_mean_squared
_error: 3.0136 - mean_absolute_error: 1.8027
Epoch 13/1000
41/41 [=====] - 1s 14ms/step - loss: 9.0766 - root_mean_squared
_error: 3.0127 - mean_absolute_error: 1.7968
Epoch 14/1000
41/41 [=====] - 1s 14ms/step - loss: 9.0719 - root_mean_squared
_error: 3.0120 - mean_absolute_error: 1.7925
Epoch 15/1000
41/41 [=====] - 1s 15ms/step - loss: 9.0686 - root_mean_squared
_error: 3.0114 - mean_absolute_error: 1.7939
Epoch 16/1000
41/41 [=====] - 1s 14ms/step - loss: 9.0641 - root_mean_squared
_error: 3.0107 - mean_absolute_error: 1.7914
Epoch 17/1000
41/41 [=====] - 1s 15ms/step - loss: 9.0588 - root_mean_squared
_error: 3.0098 - mean_absolute_error: 1.7914
Epoch 18/1000
41/41 [=====] - 1s 15ms/step - loss: 9.0564 - root_mean_squared
_error: 3.0094 - mean_absolute_error: 1.7905
Epoch 19/1000
41/41 [=====] - 1s 15ms/step - loss: 9.0528 - root_mean_squared
_error: 3.0088 - mean_absolute_error: 1.7907
Epoch 20/1000
41/41 [=====] - 1s 21ms/step - loss: 9.0473 - root_mean_squared
_error: 3.0079 - mean_absolute_error: 1.7892
Epoch 21/1000
41/41 [=====] - 1s 22ms/step - loss: 9.0450 - root_mean_squared
_error: 3.0075 - mean_absolute_error: 1.7889
Epoch 22/1000
41/41 [=====] - 1s 24ms/step - loss: 9.0414 - root_mean_squared
_error: 3.0069 - mean_absolute_error: 1.7905
Epoch 23/1000
41/41 [=====] - 1s 23ms/step - loss: 9.0390 - root_mean_squared
_error: 3.0065 - mean_absolute_error: 1.7881
Epoch 24/1000
41/41 [=====] - 1s 20ms/step - loss: 9.0367 - root_mean_squared
_error: 3.0061 - mean_absolute_error: 1.7862
Epoch 25/1000
41/41 [=====] - 1s 22ms/step - loss: 9.0328 - root_mean_squared
_error: 3.0055 - mean_absolute_error: 1.7861
Epoch 26/1000
41/41 [=====] - 1s 22ms/step - loss: 9.0315 - root_mean_squared
_error: 3.0052 - mean_absolute_error: 1.7851
Epoch 27/1000
```

```
41/41 [=====] - 1s 21ms/step - loss: 9.0250 - root_mean_squared
_error: 3.0042 - mean_absolute_error: 1.7815
Epoch 28/1000
41/41 [=====] - 1s 19ms/step - loss: 9.0229 - root_mean_squared
_error: 3.0038 - mean_absolute_error: 1.7843
Epoch 29/1000
41/41 [=====] - 1s 20ms/step - loss: 9.0201 - root_mean_squared
_error: 3.0034 - mean_absolute_error: 1.7834
Epoch 30/1000
41/41 [=====] - 1s 22ms/step - loss: 9.0170 - root_mean_squared
_error: 3.0028 - mean_absolute_error: 1.7823
Epoch 31/1000
41/41 [=====] - 1s 20ms/step - loss: 9.0142 - root_mean_squared
_error: 3.0024 - mean_absolute_error: 1.7845
Epoch 32/1000
41/41 [=====] - 1s 19ms/step - loss: 9.0133 - root_mean_squared
_error: 3.0022 - mean_absolute_error: 1.7805
Epoch 33/1000
41/41 [=====] - 1s 20ms/step - loss: 9.0098 - root_mean_squared
_error: 3.0016 - mean_absolute_error: 1.7791
Epoch 34/1000
41/41 [=====] - 1s 21ms/step - loss: 9.0070 - root_mean_squared
_error: 3.0012 - mean_absolute_error: 1.7797
Epoch 35/1000
41/41 [=====] - 1s 22ms/step - loss: 9.0053 - root_mean_squared
_error: 3.0009 - mean_absolute_error: 1.7754
Epoch 36/1000
41/41 [=====] - 1s 21ms/step - loss: 9.0022 - root_mean_squared
_error: 3.0004 - mean_absolute_error: 1.7763
Epoch 37/1000
41/41 [=====] - 1s 20ms/step - loss: 9.0003 - root_mean_squared
_error: 3.0000 - mean_absolute_error: 1.7750
Epoch 38/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9977 - root_mean_squared
_error: 2.9996 - mean_absolute_error: 1.7782
Epoch 39/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9956 - root_mean_squared
_error: 2.9993 - mean_absolute_error: 1.7723
Epoch 40/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9935 - root_mean_squared
_error: 2.9989 - mean_absolute_error: 1.7757
Epoch 41/1000
41/41 [=====] - 1s 22ms/step - loss: 8.9909 - root_mean_squared
_error: 2.9985 - mean_absolute_error: 1.7761
Epoch 42/1000
41/41 [=====] - 1s 22ms/step - loss: 8.9903 - root_mean_squared
_error: 2.9984 - mean_absolute_error: 1.7746
Epoch 43/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9872 - root_mean_squared
_error: 2.9979 - mean_absolute_error: 1.7760
Epoch 44/1000
41/41 [=====] - 1s 22ms/step - loss: 8.9849 - root_mean_squared
_error: 2.9975 - mean_absolute_error: 1.7731
Epoch 45/1000
41/41 [=====] - 1s 21ms/step - loss: 8.9820 - root_mean_squared
_error: 2.9970 - mean_absolute_error: 1.7740
Epoch 46/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9804 - root_mean_squared
_error: 2.9967 - mean_absolute_error: 1.7715
Epoch 47/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9781 - root_mean_squared
_error: 2.9964 - mean_absolute_error: 1.7721
Epoch 48/1000
41/41 [=====] - 1s 19ms/step - loss: 8.9761 - root_mean_squared
_error: 2.9960 - mean_absolute_error: 1.7693
Epoch 49/1000
```

```
41/41 [=====] - 1s 21ms/step - loss: 8.9750 - root_mean_squared
_error: 2.9958 - mean_absolute_error: 1.7700
Epoch 50/1000
41/41 [=====] - 1s 19ms/step - loss: 8.9722 - root_mean_squared
_error: 2.9954 - mean_absolute_error: 1.7688
Epoch 51/1000
41/41 [=====] - 1s 19ms/step - loss: 8.9699 - root_mean_squared
_error: 2.9950 - mean_absolute_error: 1.7695
Epoch 52/1000
41/41 [=====] - 1s 21ms/step - loss: 8.9674 - root_mean_squared
_error: 2.9946 - mean_absolute_error: 1.7684
Epoch 53/1000
41/41 [=====] - 1s 23ms/step - loss: 8.9676 - root_mean_squared
_error: 2.9946 - mean_absolute_error: 1.7684
Epoch 54/1000
41/41 [=====] - 1s 21ms/step - loss: 8.9641 - root_mean_squared
_error: 2.9940 - mean_absolute_error: 1.7656
Epoch 55/1000
41/41 [=====] - 1s 22ms/step - loss: 8.9628 - root_mean_squared
_error: 2.9938 - mean_absolute_error: 1.7650
Epoch 56/1000
41/41 [=====] - 1s 22ms/step - loss: 8.9609 - root_mean_squared
_error: 2.9935 - mean_absolute_error: 1.7644
Epoch 57/1000
41/41 [=====] - 1s 21ms/step - loss: 8.9579 - root_mean_squared
_error: 2.9930 - mean_absolute_error: 1.7651
Epoch 58/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9572 - root_mean_squared
_error: 2.9929 - mean_absolute_error: 1.7626
Epoch 59/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9538 - root_mean_squared
_error: 2.9923 - mean_absolute_error: 1.7636
Epoch 60/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9532 - root_mean_squared
_error: 2.9922 - mean_absolute_error: 1.7637
Epoch 61/1000
41/41 [=====] - 1s 22ms/step - loss: 8.9510 - root_mean_squared
_error: 2.9918 - mean_absolute_error: 1.7644
Epoch 62/1000
41/41 [=====] - 1s 23ms/step - loss: 8.9508 - root_mean_squared
_error: 2.9918 - mean_absolute_error: 1.7590
Epoch 63/1000
41/41 [=====] - 1s 21ms/step - loss: 8.9487 - root_mean_squared
_error: 2.9914 - mean_absolute_error: 1.7578
Epoch 64/1000
41/41 [=====] - 1s 22ms/step - loss: 8.9473 - root_mean_squared
_error: 2.9912 - mean_absolute_error: 1.7583
Epoch 65/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9459 - root_mean_squared
_error: 2.9910 - mean_absolute_error: 1.7583
Epoch 66/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9448 - root_mean_squared
_error: 2.9908 - mean_absolute_error: 1.7607
Epoch 67/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9433 - root_mean_squared
_error: 2.9905 - mean_absolute_error: 1.7575
Epoch 68/1000
41/41 [=====] - 1s 21ms/step - loss: 8.9416 - root_mean_squared
_error: 2.9902 - mean_absolute_error: 1.7580
Epoch 69/1000
41/41 [=====] - 1s 21ms/step - loss: 8.9394 - root_mean_squared
_error: 2.9899 - mean_absolute_error: 1.7578
Epoch 70/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9383 - root_mean_squared
_error: 2.9897 - mean_absolute_error: 1.7586
Epoch 71/1000
```

```
41/41 [=====] - 1s 23ms/step - loss: 8.9364 - root_mean_squared
_error: 2.9894 - mean_absolute_error: 1.7571
Epoch 72/1000
41/41 [=====] - 1s 21ms/step - loss: 8.9359 - root_mean_squared
_error: 2.9893 - mean_absolute_error: 1.7571
Epoch 73/1000
41/41 [=====] - 1s 21ms/step - loss: 8.9328 - root_mean_squared
_error: 2.9888 - mean_absolute_error: 1.7576
Epoch 74/1000
41/41 [=====] - 1s 21ms/step - loss: 8.9316 - root_mean_squared
_error: 2.9886 - mean_absolute_error: 1.7553
Epoch 75/1000
41/41 [=====] - 1s 21ms/step - loss: 8.9308 - root_mean_squared
_error: 2.9884 - mean_absolute_error: 1.7566
Epoch 76/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9293 - root_mean_squared
_error: 2.9882 - mean_absolute_error: 1.7524
Epoch 77/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9287 - root_mean_squared
_error: 2.9881 - mean_absolute_error: 1.7551
Epoch 78/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9257 - root_mean_squared
_error: 2.9876 - mean_absolute_error: 1.7550
Epoch 79/1000
41/41 [=====] - 1s 21ms/step - loss: 8.9248 - root_mean_squared
_error: 2.9874 - mean_absolute_error: 1.7555
Epoch 80/1000
41/41 [=====] - 1s 24ms/step - loss: 8.9232 - root_mean_squared
_error: 2.9872 - mean_absolute_error: 1.7531
Epoch 81/1000
41/41 [=====] - 1s 26ms/step - loss: 8.9218 - root_mean_squared
_error: 2.9869 - mean_absolute_error: 1.7518
Epoch 82/1000
41/41 [=====] - 1s 25ms/step - loss: 8.9211 - root_mean_squared
_error: 2.9868 - mean_absolute_error: 1.7549
Epoch 83/1000
41/41 [=====] - 1s 25ms/step - loss: 8.9186 - root_mean_squared
_error: 2.9864 - mean_absolute_error: 1.7535
Epoch 84/1000
41/41 [=====] - 1s 21ms/step - loss: 8.9179 - root_mean_squared
_error: 2.9863 - mean_absolute_error: 1.7514
Epoch 85/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9159 - root_mean_squared
_error: 2.9860 - mean_absolute_error: 1.7496
Epoch 86/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9147 - root_mean_squared
_error: 2.9858 - mean_absolute_error: 1.7515
Epoch 87/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9140 - root_mean_squared
_error: 2.9856 - mean_absolute_error: 1.7476
Epoch 88/1000
41/41 [=====] - 1s 21ms/step - loss: 8.9132 - root_mean_squared
_error: 2.9855 - mean_absolute_error: 1.7524
Epoch 89/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9112 - root_mean_squared
_error: 2.9852 - mean_absolute_error: 1.7469
Epoch 90/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9103 - root_mean_squared
_error: 2.9850 - mean_absolute_error: 1.7510
Epoch 91/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9080 - root_mean_squared
_error: 2.9846 - mean_absolute_error: 1.7535
Epoch 92/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9092 - root_mean_squared
_error: 2.9848 - mean_absolute_error: 1.7519
Epoch 93/1000
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41/41 [=====] - 1s 20ms/step - loss: 8.9064 - root_mean_squared
_error: 2.9844 - mean_absolute_error: 1.7518
Epoch 94/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9060 - root_mean_squared
_error: 2.9843 - mean_absolute_error: 1.7474
Epoch 95/1000
41/41 [=====] - 1s 21ms/step - loss: 8.9035 - root_mean_squared
_error: 2.9839 - mean_absolute_error: 1.7492
Epoch 96/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9032 - root_mean_squared
_error: 2.9838 - mean_absolute_error: 1.7464
Epoch 97/1000
41/41 [=====] - 1s 20ms/step - loss: 8.9009 - root_mean_squared
_error: 2.9834 - mean_absolute_error: 1.7494
Epoch 98/1000
41/41 [=====] - 1s 19ms/step - loss: 8.8996 - root_mean_squared
_error: 2.9832 - mean_absolute_error: 1.7499
Epoch 99/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8987 - root_mean_squared
_error: 2.9831 - mean_absolute_error: 1.7458
Epoch 100/1000
41/41 [=====] - 1s 22ms/step - loss: 8.8974 - root_mean_squared
_error: 2.9828 - mean_absolute_error: 1.7469
Epoch 101/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8971 - root_mean_squared
_error: 2.9828 - mean_absolute_error: 1.7478
Epoch 102/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8955 - root_mean_squared
_error: 2.9825 - mean_absolute_error: 1.7461
Epoch 103/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8942 - root_mean_squared
_error: 2.9823 - mean_absolute_error: 1.7461
Epoch 104/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8929 - root_mean_squared
_error: 2.9821 - mean_absolute_error: 1.7459
Epoch 105/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8926 - root_mean_squared
_error: 2.9821 - mean_absolute_error: 1.7470
Epoch 106/1000
41/41 [=====] - 1s 22ms/step - loss: 8.8929 - root_mean_squared
_error: 2.9821 - mean_absolute_error: 1.7494
Epoch 107/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8894 - root_mean_squared
_error: 2.9815 - mean_absolute_error: 1.7476
Epoch 108/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8888 - root_mean_squared
_error: 2.9814 - mean_absolute_error: 1.7442
Epoch 109/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8885 - root_mean_squared
_error: 2.9814 - mean_absolute_error: 1.7451
Epoch 110/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8863 - root_mean_squared
_error: 2.9810 - mean_absolute_error: 1.7493
Epoch 111/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8866 - root_mean_squared
_error: 2.9810 - mean_absolute_error: 1.7475
Epoch 112/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8841 - root_mean_squared
_error: 2.9806 - mean_absolute_error: 1.7494
Epoch 113/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8829 - root_mean_squared
_error: 2.9804 - mean_absolute_error: 1.7473
Epoch 114/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8829 - root_mean_squared
_error: 2.9804 - mean_absolute_error: 1.7415
Epoch 115/1000
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41/41 [=====] - 1s 21ms/step - loss: 8.8819 - root_mean_squared
_error: 2.9802 - mean_absolute_error: 1.7408
Epoch 116/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8809 - root_mean_squared
_error: 2.9801 - mean_absolute_error: 1.7429
Epoch 117/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8796 - root_mean_squared
_error: 2.9799 - mean_absolute_error: 1.7457
Epoch 118/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8786 - root_mean_squared
_error: 2.9797 - mean_absolute_error: 1.7437
Epoch 119/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8766 - root_mean_squared
_error: 2.9794 - mean_absolute_error: 1.7454
Epoch 120/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8758 - root_mean_squared
_error: 2.9792 - mean_absolute_error: 1.7423
Epoch 121/1000
41/41 [=====] - 1s 27ms/step - loss: 8.8759 - root_mean_squared
_error: 2.9792 - mean_absolute_error: 1.7423
Epoch 122/1000
41/41 [=====] - 1s 23ms/step - loss: 8.8742 - root_mean_squared
_error: 2.9790 - mean_absolute_error: 1.7393
Epoch 123/1000
41/41 [=====] - 1s 22ms/step - loss: 8.8735 - root_mean_squared
_error: 2.9788 - mean_absolute_error: 1.7441
Epoch 124/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8724 - root_mean_squared
_error: 2.9787 - mean_absolute_error: 1.7435
Epoch 125/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8715 - root_mean_squared
_error: 2.9785 - mean_absolute_error: 1.7415
Epoch 126/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8711 - root_mean_squared
_error: 2.9784 - mean_absolute_error: 1.7395
Epoch 127/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8697 - root_mean_squared
_error: 2.9782 - mean_absolute_error: 1.7415
Epoch 128/1000
41/41 [=====] - 1s 22ms/step - loss: 8.8691 - root_mean_squared
_error: 2.9781 - mean_absolute_error: 1.7419
Epoch 129/1000
41/41 [=====] - 1s 22ms/step - loss: 8.8678 - root_mean_squared
_error: 2.9779 - mean_absolute_error: 1.7383
Epoch 130/1000
41/41 [=====] - 1s 25ms/step - loss: 8.8665 - root_mean_squared
_error: 2.9777 - mean_absolute_error: 1.7403
Epoch 131/1000
41/41 [=====] - 1s 22ms/step - loss: 8.8677 - root_mean_squared
_error: 2.9779 - mean_absolute_error: 1.7376
Epoch 132/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8653 - root_mean_squared
_error: 2.9775 - mean_absolute_error: 1.7366
Epoch 133/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8644 - root_mean_squared
_error: 2.9773 - mean_absolute_error: 1.7400
Epoch 134/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8635 - root_mean_squared
_error: 2.9772 - mean_absolute_error: 1.7377
Epoch 135/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8623 - root_mean_squared
_error: 2.9770 - mean_absolute_error: 1.7380
Epoch 136/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8623 - root_mean_squared
_error: 2.9770 - mean_absolute_error: 1.7422
Epoch 137/1000
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41/41 [=====] - 1s 23ms/step - loss: 8.8605 - root_mean_squared
_error: 2.9767 - mean_absolute_error: 1.7378
Epoch 138/1000
41/41 [=====] - 1s 23ms/step - loss: 8.8595 - root_mean_squared
_error: 2.9765 - mean_absolute_error: 1.7421
Epoch 139/1000
41/41 [=====] - 1s 22ms/step - loss: 8.8579 - root_mean_squared
_error: 2.9762 - mean_absolute_error: 1.7401
Epoch 140/1000
41/41 [=====] - 1s 22ms/step - loss: 8.8584 - root_mean_squared
_error: 2.9763 - mean_absolute_error: 1.7426
Epoch 141/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8564 - root_mean_squared
_error: 2.9760 - mean_absolute_error: 1.7393
Epoch 142/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8557 - root_mean_squared
_error: 2.9759 - mean_absolute_error: 1.7393
Epoch 143/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8554 - root_mean_squared
_error: 2.9758 - mean_absolute_error: 1.7365
Epoch 144/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8551 - root_mean_squared
_error: 2.9757 - mean_absolute_error: 1.7397
Epoch 145/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8537 - root_mean_squared
_error: 2.9755 - mean_absolute_error: 1.7386
Epoch 146/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8539 - root_mean_squared
_error: 2.9755 - mean_absolute_error: 1.7357
Epoch 147/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8529 - root_mean_squared
_error: 2.9754 - mean_absolute_error: 1.7368
Epoch 148/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8504 - root_mean_squared
_error: 2.9750 - mean_absolute_error: 1.7353
Epoch 149/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8506 - root_mean_squared
_error: 2.9750 - mean_absolute_error: 1.7359
Epoch 150/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8490 - root_mean_squared
_error: 2.9747 - mean_absolute_error: 1.7383
Epoch 151/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8487 - root_mean_squared
_error: 2.9747 - mean_absolute_error: 1.7405
Epoch 152/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8478 - root_mean_squared
_error: 2.9745 - mean_absolute_error: 1.7342
Epoch 153/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8473 - root_mean_squared
_error: 2.9744 - mean_absolute_error: 1.7369
Epoch 154/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8469 - root_mean_squared
_error: 2.9744 - mean_absolute_error: 1.7349
Epoch 155/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8456 - root_mean_squared
_error: 2.9742 - mean_absolute_error: 1.7390
Epoch 156/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8449 - root_mean_squared
_error: 2.9740 - mean_absolute_error: 1.7385
Epoch 157/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8446 - root_mean_squared
_error: 2.9740 - mean_absolute_error: 1.7326
Epoch 158/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8432 - root_mean_squared
_error: 2.9737 - mean_absolute_error: 1.7322
Epoch 159/1000
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41/41 [=====] - 1s 20ms/step - loss: 8.8424 - root_mean_squared
_error: 2.9736 - mean_absolute_error: 1.7340
Epoch 160/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8420 - root_mean_squared
_error: 2.9736 - mean_absolute_error: 1.7335
Epoch 161/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8419 - root_mean_squared
_error: 2.9735 - mean_absolute_error: 1.7315
Epoch 162/1000
41/41 [=====] - 1s 24ms/step - loss: 8.8399 - root_mean_squared
_error: 2.9732 - mean_absolute_error: 1.7320
Epoch 163/1000
41/41 [=====] - 1s 22ms/step - loss: 8.8382 - root_mean_squared
_error: 2.9729 - mean_absolute_error: 1.7350
Epoch 164/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8379 - root_mean_squared
_error: 2.9729 - mean_absolute_error: 1.7332
Epoch 165/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8370 - root_mean_squared
_error: 2.9727 - mean_absolute_error: 1.7382
Epoch 166/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8371 - root_mean_squared
_error: 2.9727 - mean_absolute_error: 1.7348
Epoch 167/1000
41/41 [=====] - 1s 22ms/step - loss: 8.8368 - root_mean_squared
_error: 2.9727 - mean_absolute_error: 1.7355
Epoch 168/1000
41/41 [=====] - 1s 22ms/step - loss: 8.8349 - root_mean_squared
_error: 2.9724 - mean_absolute_error: 1.7360
Epoch 169/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8341 - root_mean_squared
_error: 2.9722 - mean_absolute_error: 1.7362
Epoch 170/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8334 - root_mean_squared
_error: 2.9721 - mean_absolute_error: 1.7359
Epoch 171/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8324 - root_mean_squared
_error: 2.9719 - mean_absolute_error: 1.7381
Epoch 172/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8321 - root_mean_squared
_error: 2.9719 - mean_absolute_error: 1.7319
Epoch 173/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8310 - root_mean_squared
_error: 2.9717 - mean_absolute_error: 1.7355
Epoch 174/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8317 - root_mean_squared
_error: 2.9718 - mean_absolute_error: 1.7357
Epoch 175/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8315 - root_mean_squared
_error: 2.9718 - mean_absolute_error: 1.7383
Epoch 176/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8297 - root_mean_squared
_error: 2.9715 - mean_absolute_error: 1.7351
Epoch 177/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8289 - root_mean_squared
_error: 2.9713 - mean_absolute_error: 1.7364
Epoch 178/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8281 - root_mean_squared
_error: 2.9712 - mean_absolute_error: 1.7341
Epoch 179/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8267 - root_mean_squared
_error: 2.9710 - mean_absolute_error: 1.7317
Epoch 180/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8257 - root_mean_squared
_error: 2.9708 - mean_absolute_error: 1.7360
Epoch 181/1000
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41/41 [=====] - 1s 20ms/step - loss: 8.8276 - root_mean_squared
_error: 2.9711 - mean_absolute_error: 1.7354
Epoch 182/1000
41/41 [=====] - 1s 22ms/step - loss: 8.8248 - root_mean_squared
_error: 2.9707 - mean_absolute_error: 1.7343
Epoch 183/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8250 - root_mean_squared
_error: 2.9707 - mean_absolute_error: 1.7337
Epoch 184/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8244 - root_mean_squared
_error: 2.9706 - mean_absolute_error: 1.7381
Epoch 185/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8223 - root_mean_squared
_error: 2.9702 - mean_absolute_error: 1.7342
Epoch 186/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8228 - root_mean_squared
_error: 2.9703 - mean_absolute_error: 1.7300
Epoch 187/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8214 - root_mean_squared
_error: 2.9701 - mean_absolute_error: 1.7331
Epoch 188/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8212 - root_mean_squared
_error: 2.9701 - mean_absolute_error: 1.7337
Epoch 189/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8206 - root_mean_squared
_error: 2.9699 - mean_absolute_error: 1.7319
Epoch 190/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8195 - root_mean_squared
_error: 2.9698 - mean_absolute_error: 1.7337
Epoch 191/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8188 - root_mean_squared
_error: 2.9697 - mean_absolute_error: 1.7329
Epoch 192/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8181 - root_mean_squared
_error: 2.9695 - mean_absolute_error: 1.7310
Epoch 193/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8175 - root_mean_squared
_error: 2.9694 - mean_absolute_error: 1.7272
Epoch 194/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8169 - root_mean_squared
_error: 2.9693 - mean_absolute_error: 1.7292
Epoch 195/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8164 - root_mean_squared
_error: 2.9692 - mean_absolute_error: 1.7296
Epoch 196/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8155 - root_mean_squared
_error: 2.9691 - mean_absolute_error: 1.7332
Epoch 197/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8154 - root_mean_squared
_error: 2.9691 - mean_absolute_error: 1.7319
Epoch 198/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8134 - root_mean_squared
_error: 2.9687 - mean_absolute_error: 1.7324
Epoch 199/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8143 - root_mean_squared
_error: 2.9689 - mean_absolute_error: 1.7315
Epoch 200/1000
41/41 [=====] - 1s 22ms/step - loss: 8.8134 - root_mean_squared
_error: 2.9687 - mean_absolute_error: 1.7313
Epoch 201/1000
41/41 [=====] - 1s 22ms/step - loss: 8.8126 - root_mean_squared
_error: 2.9686 - mean_absolute_error: 1.7280
Epoch 202/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8109 - root_mean_squared
_error: 2.9683 - mean_absolute_error: 1.7302
Epoch 203/1000
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41/41 [=====] - 1s 20ms/step - loss: 8.8112 - root_mean_squared
_error: 2.9684 - mean_absolute_error: 1.7291
Epoch 204/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8106 - root_mean_squared
_error: 2.9683 - mean_absolute_error: 1.7312
Epoch 205/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8104 - root_mean_squared
_error: 2.9682 - mean_absolute_error: 1.7311
Epoch 206/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8097 - root_mean_squared
_error: 2.9681 - mean_absolute_error: 1.7290
Epoch 207/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8088 - root_mean_squared
_error: 2.9680 - mean_absolute_error: 1.7342
Epoch 208/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8079 - root_mean_squared
_error: 2.9678 - mean_absolute_error: 1.7308
Epoch 209/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8078 - root_mean_squared
_error: 2.9678 - mean_absolute_error: 1.7279
Epoch 210/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8064 - root_mean_squared
_error: 2.9676 - mean_absolute_error: 1.7320
Epoch 211/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8065 - root_mean_squared
_error: 2.9676 - mean_absolute_error: 1.7249
Epoch 212/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8050 - root_mean_squared
_error: 2.9673 - mean_absolute_error: 1.7276
Epoch 213/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8048 - root_mean_squared
_error: 2.9673 - mean_absolute_error: 1.7282
Epoch 214/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8040 - root_mean_squared
_error: 2.9672 - mean_absolute_error: 1.7298
Epoch 215/1000
41/41 [=====] - 1s 21ms/step - loss: 8.8034 - root_mean_squared
_error: 2.9670 - mean_absolute_error: 1.7278
Epoch 216/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8039 - root_mean_squared
_error: 2.9671 - mean_absolute_error: 1.7276
Epoch 217/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8027 - root_mean_squared
_error: 2.9669 - mean_absolute_error: 1.7307
Epoch 218/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8026 - root_mean_squared
_error: 2.9669 - mean_absolute_error: 1.7309
Epoch 219/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8012 - root_mean_squared
_error: 2.9667 - mean_absolute_error: 1.7271
Epoch 220/1000
41/41 [=====] - 1s 20ms/step - loss: 8.8009 - root_mean_squared
_error: 2.9666 - mean_absolute_error: 1.7286
Epoch 221/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7997 - root_mean_squared
_error: 2.9664 - mean_absolute_error: 1.7265
Epoch 222/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7992 - root_mean_squared
_error: 2.9663 - mean_absolute_error: 1.7258
Epoch 223/1000
41/41 [=====] - 1s 19ms/step - loss: 8.7991 - root_mean_squared
_error: 2.9663 - mean_absolute_error: 1.7266
Epoch 224/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7995 - root_mean_squared
_error: 2.9664 - mean_absolute_error: 1.7277
Epoch 225/1000
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41/41 [=====] - 1s 20ms/step - loss: 8.7983 - root_mean_squared
_error: 2.9662 - mean_absolute_error: 1.7262
Epoch 226/1000
41/41 [=====] - 1s 19ms/step - loss: 8.7971 - root_mean_squared
_error: 2.9660 - mean_absolute_error: 1.7242
Epoch 227/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7970 - root_mean_squared
_error: 2.9660 - mean_absolute_error: 1.7270
Epoch 228/1000
41/41 [=====] - 1s 19ms/step - loss: 8.7959 - root_mean_squared
_error: 2.9658 - mean_absolute_error: 1.7290
Epoch 229/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7976 - root_mean_squared
_error: 2.9661 - mean_absolute_error: 1.7299
Epoch 230/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7950 - root_mean_squared
_error: 2.9656 - mean_absolute_error: 1.7266
Epoch 231/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7948 - root_mean_squared
_error: 2.9656 - mean_absolute_error: 1.7270
Epoch 232/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7931 - root_mean_squared
_error: 2.9653 - mean_absolute_error: 1.7239
Epoch 233/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7926 - root_mean_squared
_error: 2.9652 - mean_absolute_error: 1.7323
Epoch 234/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7924 - root_mean_squared
_error: 2.9652 - mean_absolute_error: 1.7294
Epoch 235/1000
41/41 [=====] - 1s 19ms/step - loss: 8.7918 - root_mean_squared
_error: 2.9651 - mean_absolute_error: 1.7295
Epoch 236/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7923 - root_mean_squared
_error: 2.9652 - mean_absolute_error: 1.7316
Epoch 237/1000
41/41 [=====] - 1s 19ms/step - loss: 8.7917 - root_mean_squared
_error: 2.9651 - mean_absolute_error: 1.7278
Epoch 238/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7903 - root_mean_squared
_error: 2.9649 - mean_absolute_error: 1.7293
Epoch 239/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7900 - root_mean_squared
_error: 2.9648 - mean_absolute_error: 1.7276
Epoch 240/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7884 - root_mean_squared
_error: 2.9645 - mean_absolute_error: 1.7296
Epoch 241/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7882 - root_mean_squared
_error: 2.9645 - mean_absolute_error: 1.7302
Epoch 242/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7885 - root_mean_squared
_error: 2.9645 - mean_absolute_error: 1.7300
Epoch 243/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7869 - root_mean_squared
_error: 2.9643 - mean_absolute_error: 1.7246
Epoch 244/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7861 - root_mean_squared
_error: 2.9641 - mean_absolute_error: 1.7243
Epoch 245/1000
41/41 [=====] - 1s 19ms/step - loss: 8.7862 - root_mean_squared
_error: 2.9642 - mean_absolute_error: 1.7280
Epoch 246/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7857 - root_mean_squared
_error: 2.9641 - mean_absolute_error: 1.7243
Epoch 247/1000
```

```

41/41 [=====] - 1s 19ms/step - loss: 8.7859 - root_mean_squared
_error: 2.9641 - mean_absolute_error: 1.7278
Epoch 248/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7850 - root_mean_squared
_error: 2.9640 - mean_absolute_error: 1.7252
Epoch 249/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7845 - root_mean_squared
_error: 2.9639 - mean_absolute_error: 1.7258
Epoch 250/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7834 - root_mean_squared
_error: 2.9637 - mean_absolute_error: 1.7296
Epoch 251/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7829 - root_mean_squared
_error: 2.9636 - mean_absolute_error: 1.7251
Epoch 252/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7821 - root_mean_squared
_error: 2.9635 - mean_absolute_error: 1.7239
Epoch 253/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7819 - root_mean_squared
_error: 2.9634 - mean_absolute_error: 1.7259
Epoch 254/1000
41/41 [=====] - 1s 19ms/step - loss: 8.7813 - root_mean_squared
_error: 2.9633 - mean_absolute_error: 1.7276
Epoch 255/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7805 - root_mean_squared
_error: 2.9632 - mean_absolute_error: 1.7289
Epoch 256/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7805 - root_mean_squared
_error: 2.9632 - mean_absolute_error: 1.7235
Epoch 257/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7807 - root_mean_squared
_error: 2.9632 - mean_absolute_error: 1.7239
Epoch 258/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7805 - root_mean_squared
_error: 2.9632 - mean_absolute_error: 1.7220
<keras.src.callbacks.History at 0x2b28d615300>

```

Out[802]:

```

In [825.. def show_result(y_test, predicted):
    plt.figure(figsize=(10, 6))
    plt.plot(y_train.index, y_train, '-', label="Train", color='gray', linewidth = 0.31)
    plt.plot(y_test.index, y_test, '-', label="actual", color='green', linewidth = 0.31)
    plt.plot(y_test.index, predicted, '-', label="predicted", color='blue', linewidth =

    plt.title('LSTM Model: Actual vs. Predicted Values (Detail)')
    plt.xlabel('Date')
    plt.ylabel('Delay')
    plt.legend()
    plt.xticks(rotation=45)
    plt.box(True)
    plt.gca().spines['right'].set_visible(False)
    plt.gca().spines['top'].set_visible(False)
    # Set the width of the axes
    plt.gca().spines['left'].set_linewidth(0.31)
    plt.gca().spines['bottom'].set_linewidth(0.31)

    plt.grid(linewidth = 0.1)
    plt.show()

def show_result_detail(y_test, predicted):
    # Plotting the results
    plt.figure(figsize=(10, 6))

    # Plot training data
    #plt.plot(X_train.index[-24*3:], train['Delay'][-24*3:], label='Train', color='gray'

```

```

plt.plot(y_train.index[-24*3:], y_train[-24*3:], '-', label="Train", color='gray',
plt.plot(y_test.index, y_test, '-', label="actual", color='green', linewidth = 0.31)
plt.plot(y_test.index, predicted, '-', label="predicted", color='blue', linewidth =

# Plot confidence intervals
#ci = sarima_predictions.conf_int()
#plt.fill_between(test.index, ci['lower Delay'], ci['upper Delay'], color='pink', al

plt.title('LSTM Model: Actual vs. Predicted Values (Detail)')
plt.xlabel('Date')
plt.ylabel('Delay')
plt.xticks(rotation=45)
plt.legend()
plt.box(True)
plt.gca().spines['right'].set_visible(False)
plt.gca().spines['top'].set_visible(False)
# Set the width of the axes
plt.gca().spines['left'].set_linewidth(0.31)
plt.gca().spines['bottom'].set_linewidth(0.31)

plt.grid(linewidth = 0.1)
plt.show()

results_df = pd.DataFrame({'test':y_test,'preds':list(predicted)})
mse = mean_squared_error(results_df.dropna()['test'], results_df.dropna()['preds'])
rmse = mse**(1/2)
print(f'Test RMSE: {rmse}')

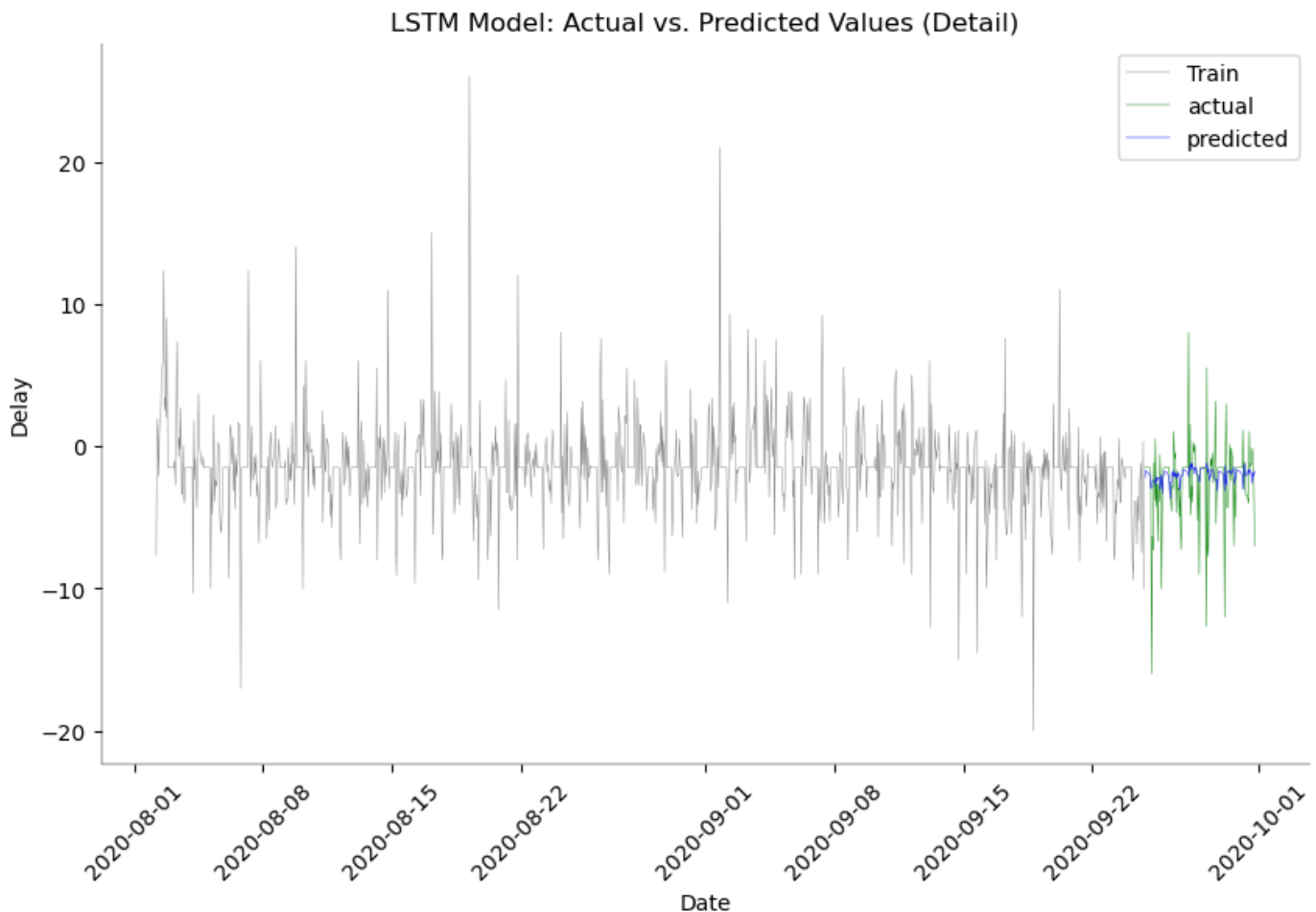
```

```

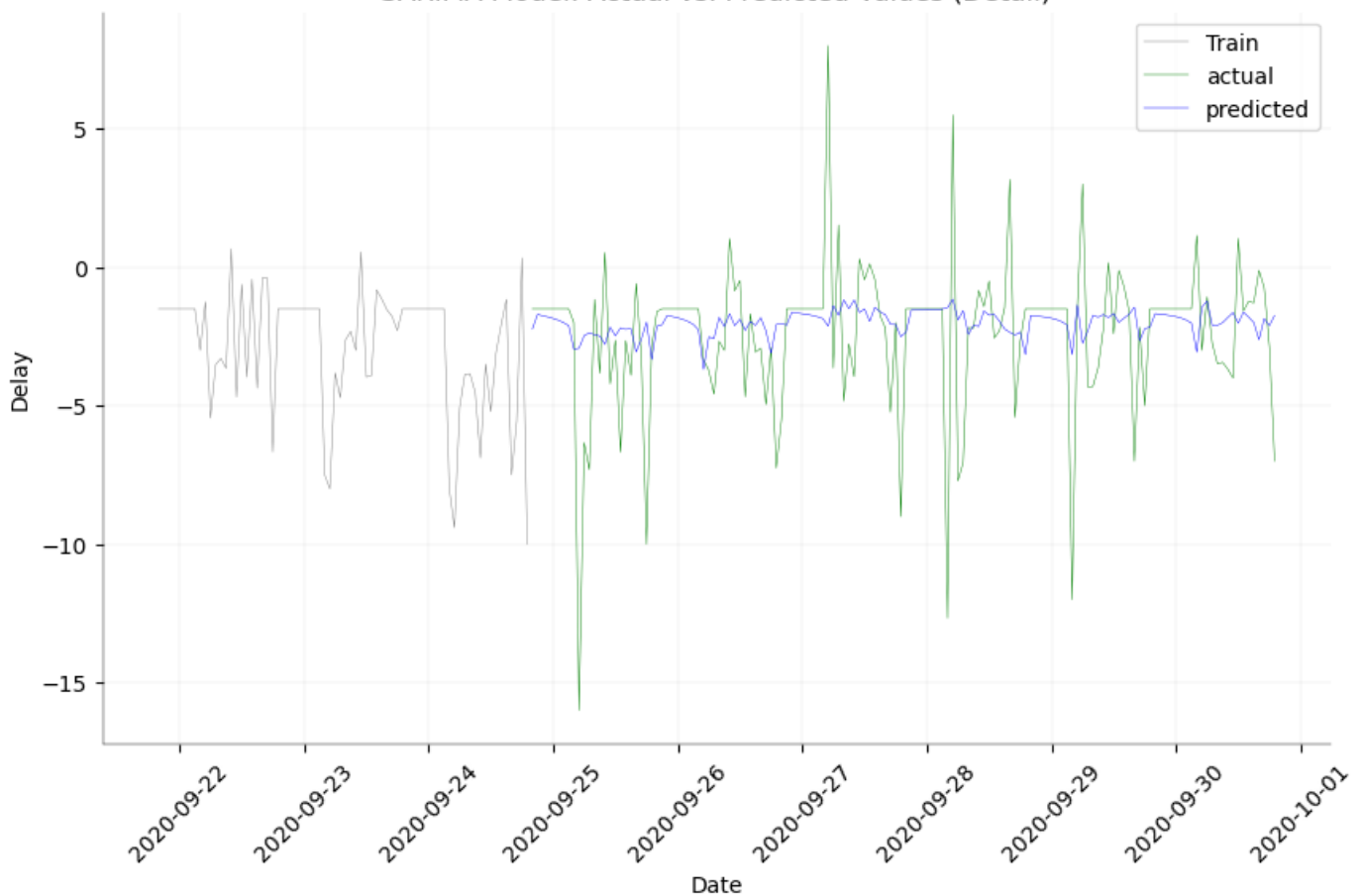
In [816... predicted = model.predict(X_test)
show_result(y_test, predicted)
show_result_detail(y_test, predicted)

```

5/5 [=====] - 0s 6ms/step



SARIMA Model: Actual vs. Predicted Values (Detail)



Test RMSE: 2.8147900311469574

Results

- The **model captures** global behaviours and **patterns**, but not better than SARIMAX.
- **High values for hourly delay fail to be predicted.** The predicted values tend to lay around the mean.
- **RMSE** is approx **2.8**

Further Developements

- Set **different LOOKBACK** values
- **Upgrade LSTM architecture, add layers and parameters** for richer non-linear models.
- Optimize training

Model 2 (Multiple Layers LSTM)

- Adding layers to **Model 1**

```
In [820... def create_complex_model():
    input_layer = Input(shape=(LOOKBACK + len(hex_df.columns), 1))

    # Add multiple LSTM layers with dropout
    lstm1 = Bidirectional(LSTM(100, activation="tanh", return_sequences=True))(input_layer)
    lstm1 = Dropout(0.2)(lstm1)

    lstm2 = Bidirectional(LSTM(50, activation="tanh", return_sequences=True))(lstm1)
```



```

lstm2 = Dropout(0.2)(lstm2)

lstm3 = Bidirectional(LSTM(25, activation="tanh"))(lstm2)
lstm3 = Dropout(0.2)(lstm3)

# Concatenate the output of the last LSTM layer with the input for skip connections
#concat_layer = Concatenate()([lstm3, input_layer])

# Dense layers for final prediction
dense1 = Dense(50, activation='relu')(lstm3)
#dense1 = Dense(50, activation='relu')(concat_layer)
dense1 = Dropout(0.2)(dense1)

dense2 = Dense(25, activation='relu')(dense1)
dense2 = Dropout(0.2)(dense2)

output_layer = Dense(1)(dense2)

model = keras.models.Model(inputs=input_layer, outputs=output_layer)

model.compile(
    loss='mse',
    optimizer=keras.optimizers.Adam(),
    metrics=[
        keras.metrics.RootMeanSquaredError(),
        keras.metrics.MeanAbsoluteError()
    ]
)

return model

model.fit(X_train, y_train, epochs=1000, callbacks=[callback])

```

```

Epoch 1/1000
41/41 [=====] - 1s 15ms/step - loss: 8.7798 - root_mean_squared_error: 2.9631 - mean_absolute_error: 1.7224
Epoch 2/1000
41/41 [=====] - 1s 15ms/step - loss: 8.7784 - root_mean_squared_error: 2.9628 - mean_absolute_error: 1.7238
Epoch 3/1000
41/41 [=====] - 1s 15ms/step - loss: 8.7787 - root_mean_squared_error: 2.9629 - mean_absolute_error: 1.7257
Epoch 4/1000
41/41 [=====] - 1s 15ms/step - loss: 8.7776 - root_mean_squared_error: 2.9627 - mean_absolute_error: 1.7268
Epoch 5/1000
41/41 [=====] - 1s 16ms/step - loss: 8.7783 - root_mean_squared_error: 2.9628 - mean_absolute_error: 1.7249
Epoch 6/1000
41/41 [=====] - 1s 15ms/step - loss: 8.7778 - root_mean_squared_error: 2.9627 - mean_absolute_error: 1.7271
Epoch 7/1000
41/41 [=====] - 1s 14ms/step - loss: 8.7757 - root_mean_squared_error: 2.9624 - mean_absolute_error: 1.7229
Epoch 8/1000
41/41 [=====] - 1s 16ms/step - loss: 8.7759 - root_mean_squared_error: 2.9624 - mean_absolute_error: 1.7238
Epoch 9/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7762 - root_mean_squared_error: 2.9625 - mean_absolute_error: 1.7264
Epoch 10/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7736 - root_mean_squared_error: 2.9620 - mean_absolute_error: 1.7204
Epoch 11/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7733 - root_mean_squared_error: 2.9620 - mean_absolute_error: 1.7220

```

Epoch 12/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7733 - root_mean_squared_error: 2.9620 - mean_absolute_error: 1.7259
Epoch 13/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7734 - root_mean_squared_error: 2.9620 - mean_absolute_error: 1.7270
Epoch 14/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7727 - root_mean_squared_error: 2.9619 - mean_absolute_error: 1.7230
Epoch 15/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7716 - root_mean_squared_error: 2.9617 - mean_absolute_error: 1.7251
Epoch 16/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7702 - root_mean_squared_error: 2.9615 - mean_absolute_error: 1.7291
Epoch 17/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7697 - root_mean_squared_error: 2.9614 - mean_absolute_error: 1.7266
Epoch 18/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7696 - root_mean_squared_error: 2.9614 - mean_absolute_error: 1.7219
Epoch 19/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7691 - root_mean_squared_error: 2.9613 - mean_absolute_error: 1.7240
Epoch 20/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7692 - root_mean_squared_error: 2.9613 - mean_absolute_error: 1.7205
Epoch 21/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7683 - root_mean_squared_error: 2.9611 - mean_absolute_error: 1.7222
Epoch 22/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7677 - root_mean_squared_error: 2.9610 - mean_absolute_error: 1.7203
Epoch 23/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7675 - root_mean_squared_error: 2.9610 - mean_absolute_error: 1.7207
Epoch 24/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7673 - root_mean_squared_error: 2.9610 - mean_absolute_error: 1.7236
Epoch 25/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7664 - root_mean_squared_error: 2.9608 - mean_absolute_error: 1.7233
Epoch 26/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7653 - root_mean_squared_error: 2.9606 - mean_absolute_error: 1.7225
Epoch 27/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7661 - root_mean_squared_error: 2.9608 - mean_absolute_error: 1.7265
Epoch 28/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7647 - root_mean_squared_error: 2.9605 - mean_absolute_error: 1.7254
Epoch 29/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7646 - root_mean_squared_error: 2.9605 - mean_absolute_error: 1.7255
Epoch 30/1000
41/41 [=====] - 1s 23ms/step - loss: 8.7639 - root_mean_squared_error: 2.9604 - mean_absolute_error: 1.7193
Epoch 31/1000
41/41 [=====] - 1s 24ms/step - loss: 8.7633 - root_mean_squared_error: 2.9603 - mean_absolute_error: 1.7220
Epoch 32/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7629 - root_mean_squared_error: 2.9602 - mean_absolute_error: 1.7213
Epoch 33/1000
41/41 [=====] - 1s 26ms/step - loss: 8.7634 - root_mean_squared_error: 2.9603 - mean_absolute_error: 1.7240

```
Epoch 34/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7620 - root_mean_squared
_error: 2.9601 - mean_absolute_error: 1.7220
Epoch 35/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7616 - root_mean_squared
_error: 2.9600 - mean_absolute_error: 1.7246
Epoch 36/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7619 - root_mean_squared
_error: 2.9601 - mean_absolute_error: 1.7227
Epoch 37/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7604 - root_mean_squared
_error: 2.9598 - mean_absolute_error: 1.7222
Epoch 38/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7608 - root_mean_squared
_error: 2.9599 - mean_absolute_error: 1.7229
Epoch 39/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7595 - root_mean_squared
_error: 2.9596 - mean_absolute_error: 1.7239
Epoch 40/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7596 - root_mean_squared
_error: 2.9597 - mean_absolute_error: 1.7261
Epoch 41/1000
41/41 [=====] - 1s 23ms/step - loss: 8.7589 - root_mean_squared
_error: 2.9595 - mean_absolute_error: 1.7226
Epoch 42/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7588 - root_mean_squared
_error: 2.9595 - mean_absolute_error: 1.7263
Epoch 43/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7578 - root_mean_squared
_error: 2.9594 - mean_absolute_error: 1.7218
Epoch 44/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7576 - root_mean_squared
_error: 2.9593 - mean_absolute_error: 1.7211
Epoch 45/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7568 - root_mean_squared
_error: 2.9592 - mean_absolute_error: 1.7206
Epoch 46/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7567 - root_mean_squared
_error: 2.9592 - mean_absolute_error: 1.7182
Epoch 47/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7564 - root_mean_squared
_error: 2.9591 - mean_absolute_error: 1.7211
Epoch 48/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7561 - root_mean_squared
_error: 2.9591 - mean_absolute_error: 1.7194
Epoch 49/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7551 - root_mean_squared
_error: 2.9589 - mean_absolute_error: 1.7232
Epoch 50/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7539 - root_mean_squared
_error: 2.9587 - mean_absolute_error: 1.7222
Epoch 51/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7540 - root_mean_squared
_error: 2.9587 - mean_absolute_error: 1.7204
Epoch 52/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7536 - root_mean_squared
_error: 2.9586 - mean_absolute_error: 1.7203
Epoch 53/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7523 - root_mean_squared
_error: 2.9584 - mean_absolute_error: 1.7160
Epoch 54/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7522 - root_mean_squared
_error: 2.9584 - mean_absolute_error: 1.7231
Epoch 55/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7527 - root_mean_squared
_error: 2.9585 - mean_absolute_error: 1.7215
```

```
Epoch 56/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7515 - root_mean_squared
_error: 2.9583 - mean_absolute_error: 1.7167
Epoch 57/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7524 - root_mean_squared
_error: 2.9584 - mean_absolute_error: 1.7225
Epoch 58/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7504 - root_mean_squared
_error: 2.9581 - mean_absolute_error: 1.7219
Epoch 59/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7500 - root_mean_squared
_error: 2.9580 - mean_absolute_error: 1.7207
Epoch 60/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7493 - root_mean_squared
_error: 2.9579 - mean_absolute_error: 1.7217
Epoch 61/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7497 - root_mean_squared
_error: 2.9580 - mean_absolute_error: 1.7215
Epoch 62/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7480 - root_mean_squared
_error: 2.9577 - mean_absolute_error: 1.7216
Epoch 63/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7484 - root_mean_squared
_error: 2.9578 - mean_absolute_error: 1.7212
Epoch 64/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7466 - root_mean_squared
_error: 2.9575 - mean_absolute_error: 1.7215
Epoch 65/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7465 - root_mean_squared
_error: 2.9574 - mean_absolute_error: 1.7194
Epoch 66/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7473 - root_mean_squared
_error: 2.9576 - mean_absolute_error: 1.7211
Epoch 67/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7457 - root_mean_squared
_error: 2.9573 - mean_absolute_error: 1.7227
Epoch 68/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7462 - root_mean_squared
_error: 2.9574 - mean_absolute_error: 1.7220
Epoch 69/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7453 - root_mean_squared
_error: 2.9573 - mean_absolute_error: 1.7170
Epoch 70/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7449 - root_mean_squared
_error: 2.9572 - mean_absolute_error: 1.7196
Epoch 71/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7431 - root_mean_squared
_error: 2.9569 - mean_absolute_error: 1.7164
Epoch 72/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7432 - root_mean_squared
_error: 2.9569 - mean_absolute_error: 1.7244
Epoch 73/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7436 - root_mean_squared
_error: 2.9570 - mean_absolute_error: 1.7218
Epoch 74/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7426 - root_mean_squared
_error: 2.9568 - mean_absolute_error: 1.7226
Epoch 75/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7429 - root_mean_squared
_error: 2.9568 - mean_absolute_error: 1.7213
Epoch 76/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7416 - root_mean_squared
_error: 2.9566 - mean_absolute_error: 1.7178
Epoch 77/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7401 - root_mean_squared
_error: 2.9564 - mean_absolute_error: 1.7186
```

Epoch 78/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7400 - root_mean_squared_error: 2.9563 - mean_absolute_error: 1.7198
Epoch 79/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7408 - root_mean_squared_error: 2.9565 - mean_absolute_error: 1.7195
Epoch 80/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7390 - root_mean_squared_error: 2.9562 - mean_absolute_error: 1.7235
Epoch 81/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7381 - root_mean_squared_error: 2.9560 - mean_absolute_error: 1.7227
Epoch 82/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7382 - root_mean_squared_error: 2.9560 - mean_absolute_error: 1.7165
Epoch 83/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7380 - root_mean_squared_error: 2.9560 - mean_absolute_error: 1.7208
Epoch 84/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7378 - root_mean_squared_error: 2.9560 - mean_absolute_error: 1.7161
Epoch 85/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7371 - root_mean_squared_error: 2.9559 - mean_absolute_error: 1.7225
Epoch 86/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7368 - root_mean_squared_error: 2.9558 - mean_absolute_error: 1.7198
Epoch 87/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7370 - root_mean_squared_error: 2.9558 - mean_absolute_error: 1.7189
Epoch 88/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7358 - root_mean_squared_error: 2.9556 - mean_absolute_error: 1.7188
Epoch 89/1000
41/41 [=====] - 1s 23ms/step - loss: 8.7351 - root_mean_squared_error: 2.9555 - mean_absolute_error: 1.7182
Epoch 90/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7354 - root_mean_squared_error: 2.9556 - mean_absolute_error: 1.7201
Epoch 91/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7344 - root_mean_squared_error: 2.9554 - mean_absolute_error: 1.7176
Epoch 92/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7349 - root_mean_squared_error: 2.9555 - mean_absolute_error: 1.7196
Epoch 93/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7350 - root_mean_squared_error: 2.9555 - mean_absolute_error: 1.7205
Epoch 94/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7336 - root_mean_squared_error: 2.9553 - mean_absolute_error: 1.7182
Epoch 95/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7343 - root_mean_squared_error: 2.9554 - mean_absolute_error: 1.7170
Epoch 96/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7338 - root_mean_squared_error: 2.9553 - mean_absolute_error: 1.7158
Epoch 97/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7314 - root_mean_squared_error: 2.9549 - mean_absolute_error: 1.7140
Epoch 98/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7311 - root_mean_squared_error: 2.9548 - mean_absolute_error: 1.7193
Epoch 99/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7307 - root_mean_squared_error: 2.9548 - mean_absolute_error: 1.7173

```
Epoch 100/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7307 - root_mean_squared
_error: 2.9548 - mean_absolute_error: 1.7167
Epoch 101/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7306 - root_mean_squared
_error: 2.9548 - mean_absolute_error: 1.7172
Epoch 102/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7300 - root_mean_squared
_error: 2.9547 - mean_absolute_error: 1.7177
Epoch 103/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7291 - root_mean_squared
_error: 2.9545 - mean_absolute_error: 1.7177
Epoch 104/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7296 - root_mean_squared
_error: 2.9546 - mean_absolute_error: 1.7127
Epoch 105/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7289 - root_mean_squared
_error: 2.9545 - mean_absolute_error: 1.7140
Epoch 106/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7281 - root_mean_squared
_error: 2.9543 - mean_absolute_error: 1.7183
Epoch 107/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7281 - root_mean_squared
_error: 2.9543 - mean_absolute_error: 1.7176
Epoch 108/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7276 - root_mean_squared
_error: 2.9543 - mean_absolute_error: 1.7169
Epoch 109/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7269 - root_mean_squared
_error: 2.9541 - mean_absolute_error: 1.7159
Epoch 110/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7259 - root_mean_squared
_error: 2.9540 - mean_absolute_error: 1.7159
Epoch 111/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7262 - root_mean_squared
_error: 2.9540 - mean_absolute_error: 1.7167
Epoch 112/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7256 - root_mean_squared
_error: 2.9539 - mean_absolute_error: 1.7181
Epoch 113/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7244 - root_mean_squared
_error: 2.9537 - mean_absolute_error: 1.7174
Epoch 114/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7239 - root_mean_squared
_error: 2.9536 - mean_absolute_error: 1.7184
Epoch 115/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7245 - root_mean_squared
_error: 2.9537 - mean_absolute_error: 1.7192
Epoch 116/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7236 - root_mean_squared
_error: 2.9536 - mean_absolute_error: 1.7180
Epoch 117/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7236 - root_mean_squared
_error: 2.9536 - mean_absolute_error: 1.7150
Epoch 118/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7228 - root_mean_squared
_error: 2.9534 - mean_absolute_error: 1.7195
Epoch 119/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7226 - root_mean_squared
_error: 2.9534 - mean_absolute_error: 1.7176
Epoch 120/1000
41/41 [=====] - 1s 24ms/step - loss: 8.7222 - root_mean_squared
_error: 2.9533 - mean_absolute_error: 1.7168
Epoch 121/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7216 - root_mean_squared
_error: 2.9532 - mean_absolute_error: 1.7218
```

```
Epoch 122/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7214 - root_mean_squared
_error: 2.9532 - mean_absolute_error: 1.7206
Epoch 123/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7210 - root_mean_squared
_error: 2.9531 - mean_absolute_error: 1.7180
Epoch 124/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7208 - root_mean_squared
_error: 2.9531 - mean_absolute_error: 1.7166
Epoch 125/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7203 - root_mean_squared
_error: 2.9530 - mean_absolute_error: 1.7158
Epoch 126/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7193 - root_mean_squared
_error: 2.9528 - mean_absolute_error: 1.7205
Epoch 127/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7195 - root_mean_squared
_error: 2.9529 - mean_absolute_error: 1.7157
Epoch 128/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7195 - root_mean_squared
_error: 2.9529 - mean_absolute_error: 1.7178
Epoch 129/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7189 - root_mean_squared
_error: 2.9528 - mean_absolute_error: 1.7144
Epoch 130/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7175 - root_mean_squared
_error: 2.9525 - mean_absolute_error: 1.7124
Epoch 131/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7176 - root_mean_squared
_error: 2.9526 - mean_absolute_error: 1.7201
Epoch 132/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7157 - root_mean_squared
_error: 2.9522 - mean_absolute_error: 1.7178
Epoch 133/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7170 - root_mean_squared
_error: 2.9525 - mean_absolute_error: 1.7182
Epoch 134/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7153 - root_mean_squared
_error: 2.9522 - mean_absolute_error: 1.7151
Epoch 135/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7156 - root_mean_squared
_error: 2.9522 - mean_absolute_error: 1.7168
Epoch 136/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7146 - root_mean_squared
_error: 2.9521 - mean_absolute_error: 1.7162
Epoch 137/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7141 - root_mean_squared
_error: 2.9520 - mean_absolute_error: 1.7182
Epoch 138/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7141 - root_mean_squared
_error: 2.9520 - mean_absolute_error: 1.7173
Epoch 139/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7151 - root_mean_squared
_error: 2.9521 - mean_absolute_error: 1.7205
Epoch 140/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7145 - root_mean_squared
_error: 2.9520 - mean_absolute_error: 1.7167
Epoch 141/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7131 - root_mean_squared
_error: 2.9518 - mean_absolute_error: 1.7191
Epoch 142/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7118 - root_mean_squared
_error: 2.9516 - mean_absolute_error: 1.7203
Epoch 143/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7118 - root_mean_squared
_error: 2.9516 - mean_absolute_error: 1.7174
```

```
Epoch 144/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7116 - root_mean_squared
_error: 2.9515 - mean_absolute_error: 1.7148
Epoch 145/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7117 - root_mean_squared
_error: 2.9516 - mean_absolute_error: 1.7201
Epoch 146/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7098 - root_mean_squared
_error: 2.9512 - mean_absolute_error: 1.7177
Epoch 147/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7107 - root_mean_squared
_error: 2.9514 - mean_absolute_error: 1.7162
Epoch 148/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7087 - root_mean_squared
_error: 2.9510 - mean_absolute_error: 1.7201
Epoch 149/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7090 - root_mean_squared
_error: 2.9511 - mean_absolute_error: 1.7169
Epoch 150/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7083 - root_mean_squared
_error: 2.9510 - mean_absolute_error: 1.7168
Epoch 151/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7076 - root_mean_squared
_error: 2.9509 - mean_absolute_error: 1.7207
Epoch 152/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7087 - root_mean_squared
_error: 2.9510 - mean_absolute_error: 1.7174
Epoch 153/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7072 - root_mean_squared
_error: 2.9508 - mean_absolute_error: 1.7183
Epoch 154/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7066 - root_mean_squared
_error: 2.9507 - mean_absolute_error: 1.7149
Epoch 155/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7076 - root_mean_squared
_error: 2.9509 - mean_absolute_error: 1.7169
Epoch 156/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7055 - root_mean_squared
_error: 2.9505 - mean_absolute_error: 1.7147
Epoch 157/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7058 - root_mean_squared
_error: 2.9506 - mean_absolute_error: 1.7158
Epoch 158/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7049 - root_mean_squared
_error: 2.9504 - mean_absolute_error: 1.7144
Epoch 159/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7051 - root_mean_squared
_error: 2.9504 - mean_absolute_error: 1.7133
Epoch 160/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7038 - root_mean_squared
_error: 2.9502 - mean_absolute_error: 1.7137
Epoch 161/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7042 - root_mean_squared
_error: 2.9503 - mean_absolute_error: 1.7184
Epoch 162/1000
41/41 [=====] - 1s 23ms/step - loss: 8.7033 - root_mean_squared
_error: 2.9501 - mean_absolute_error: 1.7134
Epoch 163/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7026 - root_mean_squared
_error: 2.9500 - mean_absolute_error: 1.7105
Epoch 164/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7019 - root_mean_squared
_error: 2.9499 - mean_absolute_error: 1.7130
Epoch 165/1000
41/41 [=====] - 1s 20ms/step - loss: 8.7027 - root_mean_squared
_error: 2.9500 - mean_absolute_error: 1.7141
```



```

Epoch 166/1000
41/41 [=====] - 1s 21ms/step - loss: 8.7011 - root_mean_squared
_error: 2.9498 - mean_absolute_error: 1.7159
Epoch 167/1000
41/41 [=====] - 1s 25ms/step - loss: 8.7002 - root_mean_squared
_error: 2.9496 - mean_absolute_error: 1.7149
Epoch 168/1000
41/41 [=====] - 1s 22ms/step - loss: 8.7005 - root_mean_squared
_error: 2.9497 - mean_absolute_error: 1.7151
Epoch 169/1000
41/41 [=====] - 1s 28ms/step - loss: 8.6993 - root_mean_squared
_error: 2.9495 - mean_absolute_error: 1.7150
Epoch 170/1000
41/41 [=====] - 1s 24ms/step - loss: 8.7009 - root_mean_squared
_error: 2.9497 - mean_absolute_error: 1.7174
Epoch 171/1000
41/41 [=====] - 1s 21ms/step - loss: 8.6999 - root_mean_squared
_error: 2.9496 - mean_absolute_error: 1.7172
Epoch 172/1000
41/41 [=====] - 1s 27ms/step - loss: 8.6989 - root_mean_squared
_error: 2.9494 - mean_absolute_error: 1.7146
Epoch 173/1000
41/41 [=====] - 1s 22ms/step - loss: 8.6982 - root_mean_squared
_error: 2.9493 - mean_absolute_error: 1.7169
Epoch 174/1000
41/41 [=====] - 1s 22ms/step - loss: 8.6982 - root_mean_squared
_error: 2.9493 - mean_absolute_error: 1.7164
Epoch 175/1000
41/41 [=====] - 1s 21ms/step - loss: 8.6970 - root_mean_squared
_error: 2.9491 - mean_absolute_error: 1.7144
Epoch 176/1000
41/41 [=====] - 1s 21ms/step - loss: 8.6972 - root_mean_squared
_error: 2.9491 - mean_absolute_error: 1.7153
Epoch 177/1000
41/41 [=====] - 1s 20ms/step - loss: 8.6967 - root_mean_squared
_error: 2.9490 - mean_absolute_error: 1.7152
Epoch 178/1000
41/41 [=====] - 1s 21ms/step - loss: 8.6951 - root_mean_squared
_error: 2.9487 - mean_absolute_error: 1.7182
Epoch 179/1000
41/41 [=====] - 1s 23ms/step - loss: 8.6965 - root_mean_squared
_error: 2.9490 - mean_absolute_error: 1.7142
Epoch 180/1000
41/41 [=====] - 1s 21ms/step - loss: 8.6941 - root_mean_squared
_error: 2.9486 - mean_absolute_error: 1.7163
Epoch 181/1000
41/41 [=====] - 1s 23ms/step - loss: 8.6942 - root_mean_squared
_error: 2.9486 - mean_absolute_error: 1.7170
Epoch 182/1000
41/41 [=====] - 1s 21ms/step - loss: 8.6959 - root_mean_squared
_error: 2.9489 - mean_absolute_error: 1.7134
Epoch 183/1000
41/41 [=====] - 1s 21ms/step - loss: 8.6943 - root_mean_squared
_error: 2.9486 - mean_absolute_error: 1.7125
<keras.src.callbacks.History at 0x2b2c266c7c0>

```

Out[820]:

```

In [826... predicted = model.predict(X_test)
show_result(y_test, predicted)
show_result_detail(y_test, predicted)

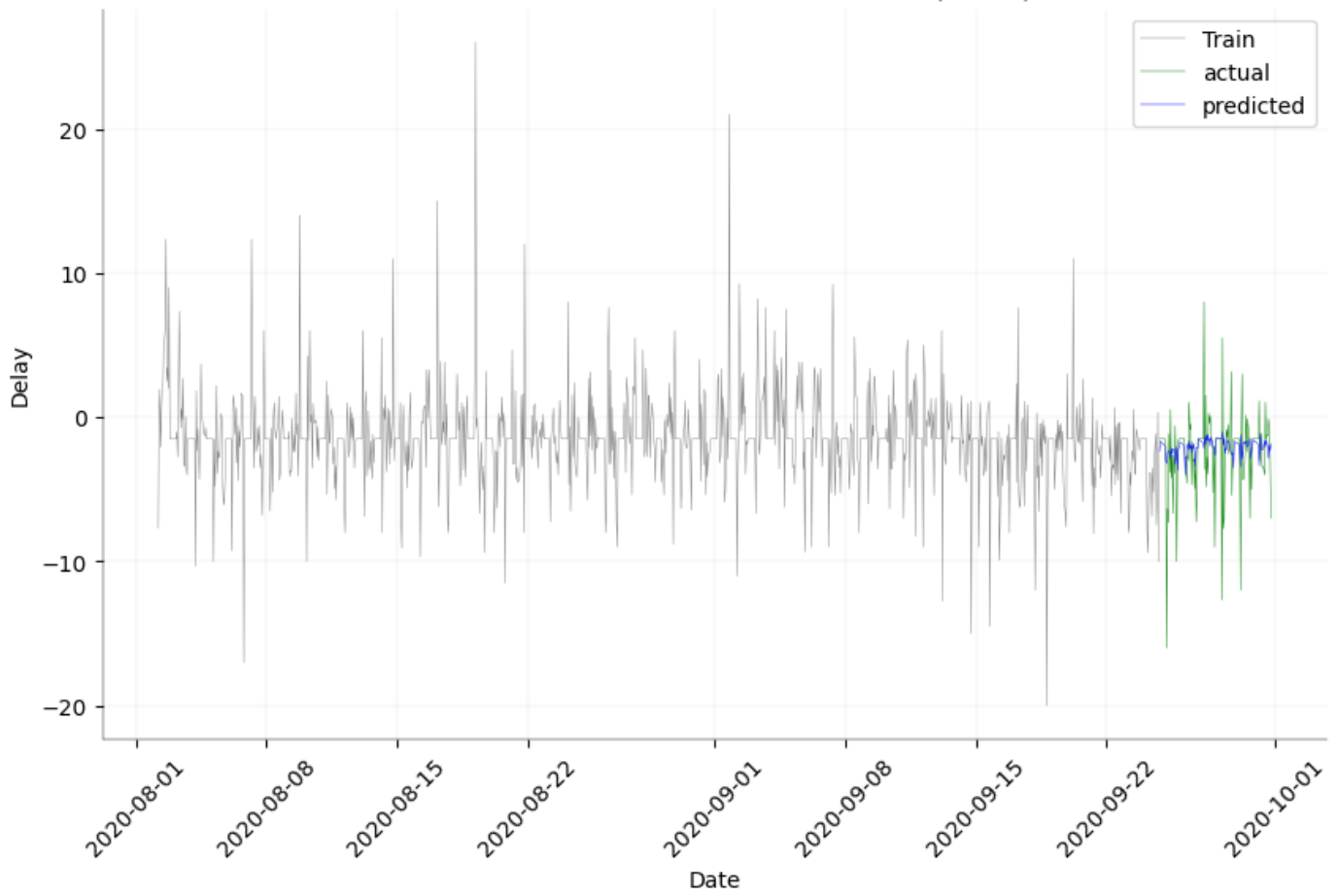
```

```

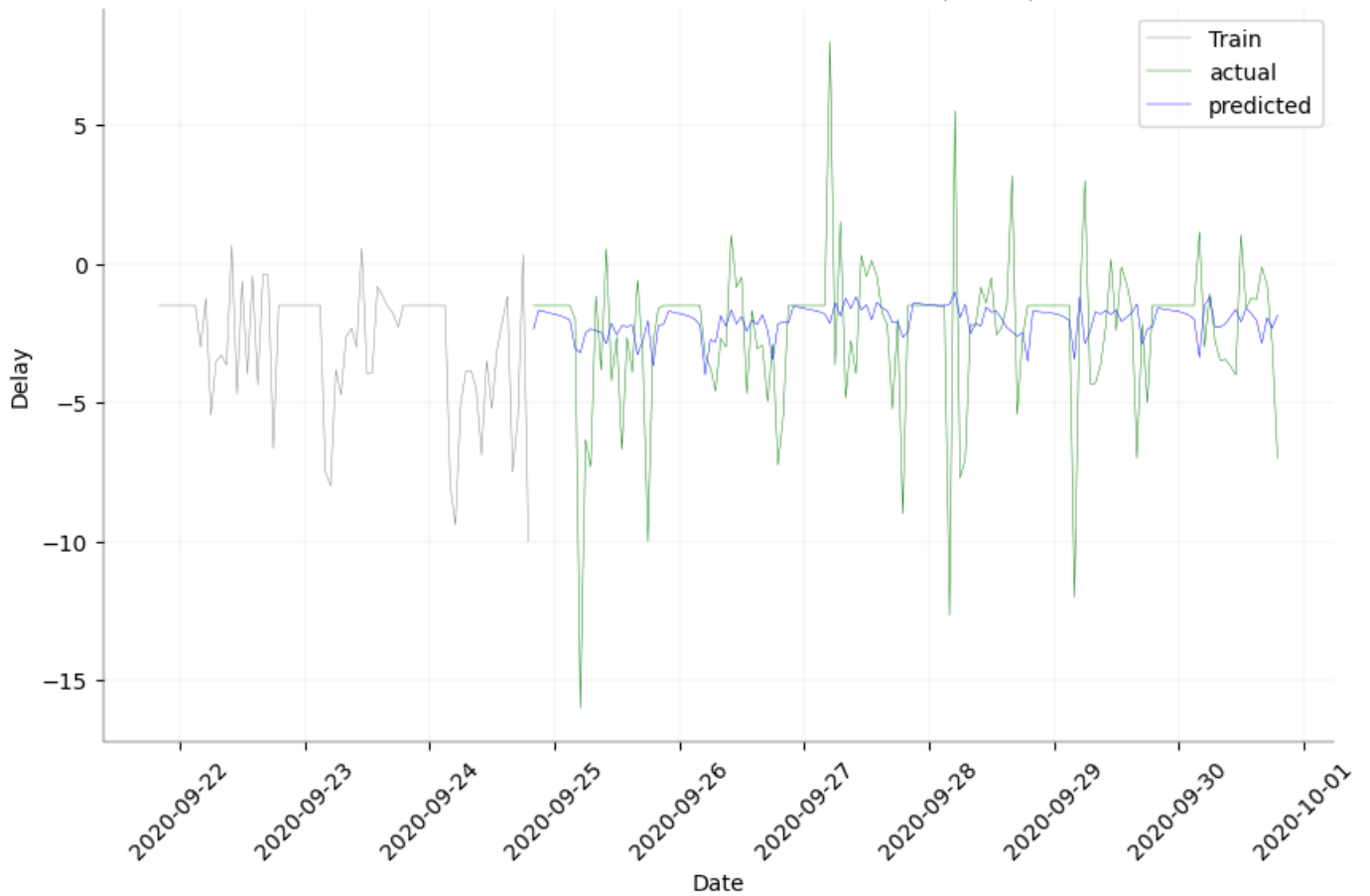
5/5 [=====] - 0s 9ms/step

```

LSTM Model: Actual vs. Predicted Values (Detail)



LSTM Model: Actual vs. Predicted Values (Detail)



Test RMSE: 2.797925942229235

Results

- The **model captures** global behaviours and **patterns**, but not better than SARIMAX.
 - **High values for hourly delay fail to be predicted.** The predicted values tend to lay around the mean.
 - **RMSE** is approx **2.8**
-

Further Developements

- Set **different LOOKBACK** values
 - **Upgrade LSTM architecture, add layers and parameters** for richer non-linear models.
 - Optimize training
-

CONCLUSIONS AND FURTHER DEVELOPMENTS

- **Forecasting daily delays** rather than hourly ones would be reasonable, and **likely yield better results.** **More data is needed** in order to do that.
- SARIMAX and LSTM models should be **optimized** by **tuning parameters** and modifying **architectures.**
- **Anomaly detection** could be employed to predict **spikes in the delivery time.**
- **More advanced models** should be considered. LSTMs could be replaced by **Transformers.**

#!pip freeze