

Sensors

June 27, 2023

```
[ ]: import numpy as np
import pandas as pd
import random
from sklearn.preprocessing import PolynomialFeatures

#New! for Legendre
from scipy.special import legendre
from sklearn.metrics import r2_score #for r-squared

import matplotlib.dates as mdates
import matplotlib.pyplot as plt
from matplotlib import rc

from tqdm import tqdm

# Set default font to 'Times New Roman'
rc('font', family='Times New Roman')
```

0.1 Data Pre Processing and Visualization

0.1.1 Load Data

```
[ ]: path = '/Users/Farid/Downloads/woolsey-selected/'

sensor_interest_1 = pd.read_csv('./Data/sensor_interest_1 737433.txt')
print('sensor_interest_1: ', sensor_interest_1.shape)

sensor_interest_2 = pd.read_csv('./Data/sensor_interest_2 764848.txt')
print('sensor_interest_2: ', sensor_interest_2.shape)

sensor_interest_3 = pd.read_csv('./Data/sensor_interest_3 764632.txt')
print('sensor_interest_3: ', sensor_interest_3.shape)
```

```
sensor_interest_1: (9216, 38)
sensor_interest_2: (9216, 38)
sensor_interest_3: (9216, 38)
```

0.1.2 Visualize the Data

```
[ ]: from datetime import datetime, timedelta

# Define the starting date
start_date = datetime(2018, 10, 1) # start from 1st October 2023

# Define the number of days
n_days = 3

# Create the list of days
days = [(start_date + timedelta(days=i)).strftime('%m/%d') for i in
         range(n_days)]
print('days: ', days)
```

days: ['10/01', '10/02', '10/03']

```
[ ]: #####

sensor_interest = sensor_interest_1
sensor_id = 737433
#####

##### Subplots
#####

# Calculate number of rows required for subplots
n = len(days)
nrows = n // 2 if n % 2 == 0 else n // 2 + 1

# Initialize figure and axes for subplots
fig, axs = plt.subplots(nrows=nrows, ncols=2, figsize=(10, nrows*5),
                        constrained_layout=True)
axs = axs.flatten() # flatten array to make indexing easier

fig.suptitle(f'Traffic measured at sensor {sensor_id}', fontsize=14,
            weight='bold')

for i, day in enumerate(days):
    ax = axs[i] # current subplot

    time_series_data = sensor_interest[sensor_interest['Time'].str.
    startswith(day)]
    time_series_data['Time'] = pd.to_datetime(time_series_data['Time'])

    # Filter out data outside of 7 AM to 7 PM
```

```

time_series_data = time_series_data[(time_series_data['Time'].dt.hour >= 7)
↳ & (time_series_data['Time'].dt.hour <= 19)]

# y values
traffic = time_series_data['10']

# x values - use 'Time' values
time = time_series_data['Time']

# Create scatter plot
ax.plot(time, traffic)

# Set x-axis format and locator
hours = mdates.DateFormatter('%I %p')
hour_locator = mdates.HourLocator(interval=2) # put a tick on every 2 hours
ax.xaxis.set_major_locator(hour_locator)
ax.xaxis.set_major_formatter(hours)

# Adjust x limits to start slightly before 7 AM and end at 7 PM
start_time = time.min().replace(hour=6, minute=50, second=0) # 10 minutes
↳ before 7 AM
end_time = time.max().replace(hour=20, minute=10, second=0)
ax.set_xlim(start_time, end_time)

# Set axis titles
ax.set_xlabel('Time (hour)')
ax.set_ylabel('Traffic')
ax.set_title('Traffic from 7 am to 7 pm, '+day)

# If there are more subplots than days (i.e. an even number of subplots),
↳ remove the extra one
if len(days) % 2 != 0:
    fig.delaxes(axes[-1])

plt.show()

##### Additional 1-plot
#####

# Define a list of markers
markers = ['o', 'v', '^', '<', '>', '1', '2', '3', '4', '8', 's', 'p', '*',
↳ 'h', 'H', '+', 'x', 'D', 'd', '|', '_', '.', ',']

fig, ax = plt.subplots(figsize=(10, 5))

for i, day in enumerate(days):

```

```

time_series_data = sensor_interest[sensor_interest['Time'].str.
↳startswith(day)]
time_series_data['Time'] = pd.to_datetime(time_series_data['Time'])

# Filter out data outside of 7 AM to 7 PM
time_series_data = time_series_data[(time_series_data['Time'].dt.hour >= 7)
↳& (time_series_data['Time'].dt.hour <= 19)]

# y values
traffic = time_series_data['10']

# Plot the data for all series with different markers for each day
if n_days < 10:
    ax.plot(np.arange(len(traffic)), traffic, label=day,
↳marker=markers[i%len(markers)])
else:
    ax.plot(np.arange(len(traffic)), traffic, label=day) # Use modulus to
↳prevent out of index errors

# Set x-axis ticks and labels
x_ticks = np.linspace(0, len(traffic), 7) # generate 7 evenly spaced x-axis
↳locations
time_labels = ['7 AM', '9 AM', '11 AM', '1 PM', '3 PM', '5 PM', '7 PM'] #
↳corresponding time labels
ax.set_xticks(x_ticks)
ax.set_xticklabels(time_labels)

# Adjust x limits to start slightly before 7 AM and end at 7 PM
start_time = np.arange(len(traffic)).min() # 10 minutes before 7 AM
end_time = np.arange(len(traffic)).max() # 10 minutes after 7 PM
ax.set_xlim(start_time, end_time)

# Set labels and title for the combined plot
ax.set_xlabel('Time (hour)')
ax.set_ylabel('Traffic')
ax.set_title(f'Traffic for all the selected days at sensor {sensor_id}',
↳fontsize=14, weight='bold')
ax.legend()

plt.show()

```

/var/folders/l0/ytttdmtl97n7fd1v82xdlzb7c0000gn/T/ipykernel_99916/4105916518.py:25: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: <https://pandas.pydata.org/pandas->

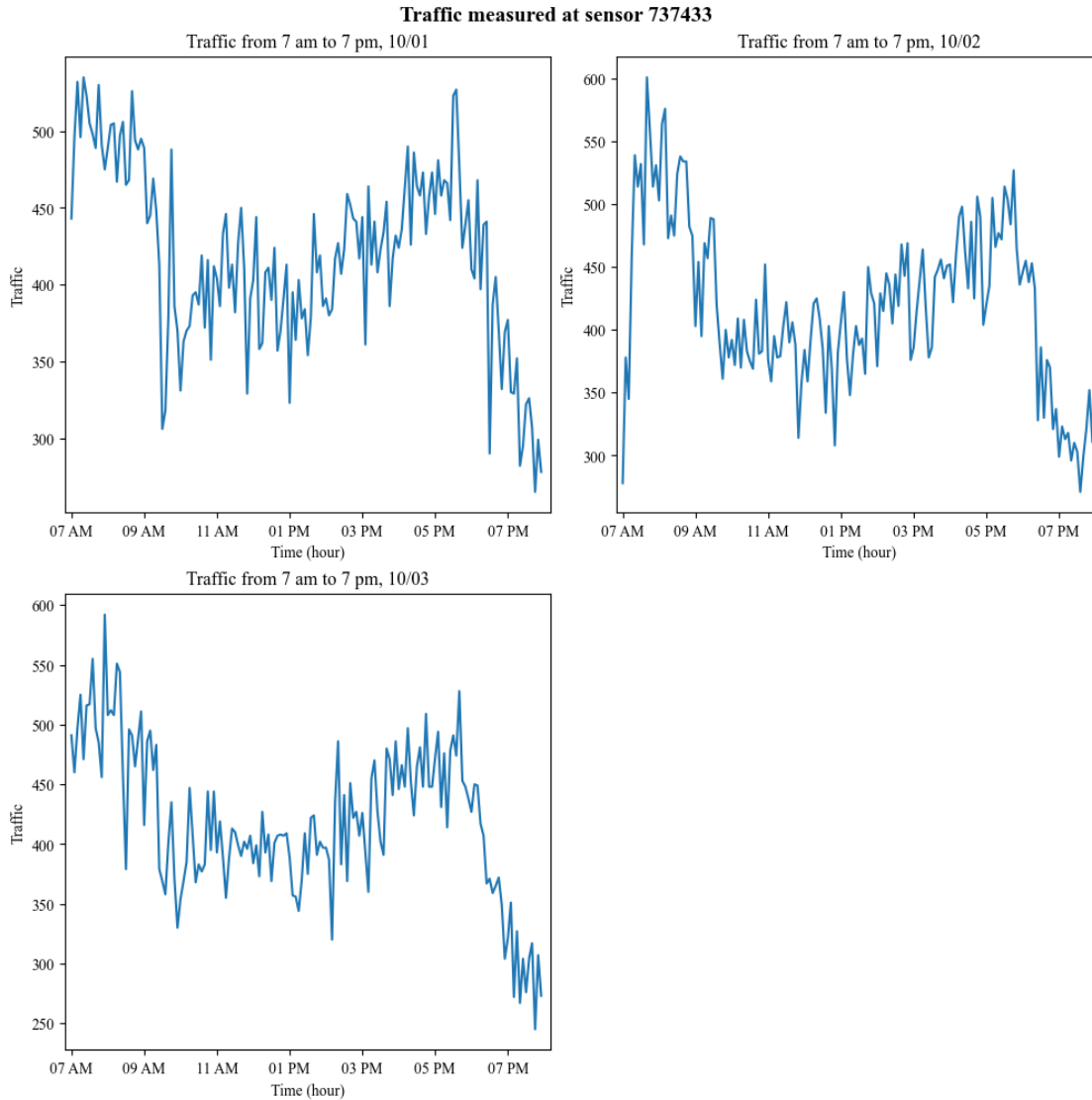
```
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
    time_series_data['Time'] = pd.to_datetime(time_series_data['Time'])
/var/folders/l0/yttldmtl97n7fd1v82xdlzb7c0000gn/T/ipykernel_99916/4105916518.py:2
5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
    time_series_data['Time'] = pd.to_datetime(time_series_data['Time'])
/var/folders/l0/yttldmtl97n7fd1v82xdlzb7c0000gn/T/ipykernel_99916/4105916518.py:2
5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
    time_series_data['Time'] = pd.to_datetime(time_series_data['Time'])
```



```
/var/folders/l0/yttddmtl97n7fd1v82xdlzb7c0000gn/T/ipykernel_99916/4105916518.py:7
```

```
2: SettingWithCopyWarning:
```

```
A value is trying to be set on a copy of a slice from a DataFrame.
```

```
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

```
time_series_data['Time'] = pd.to_datetime(time_series_data['Time'])
```

```
/var/folders/l0/yttddmtl97n7fd1v82xdlzb7c0000gn/T/ipykernel_99916/4105916518.py:7
```

```
2: SettingWithCopyWarning:
```

```
A value is trying to be set on a copy of a slice from a DataFrame.
```

```
Try using .loc[row_indexer,col_indexer] = value instead
```

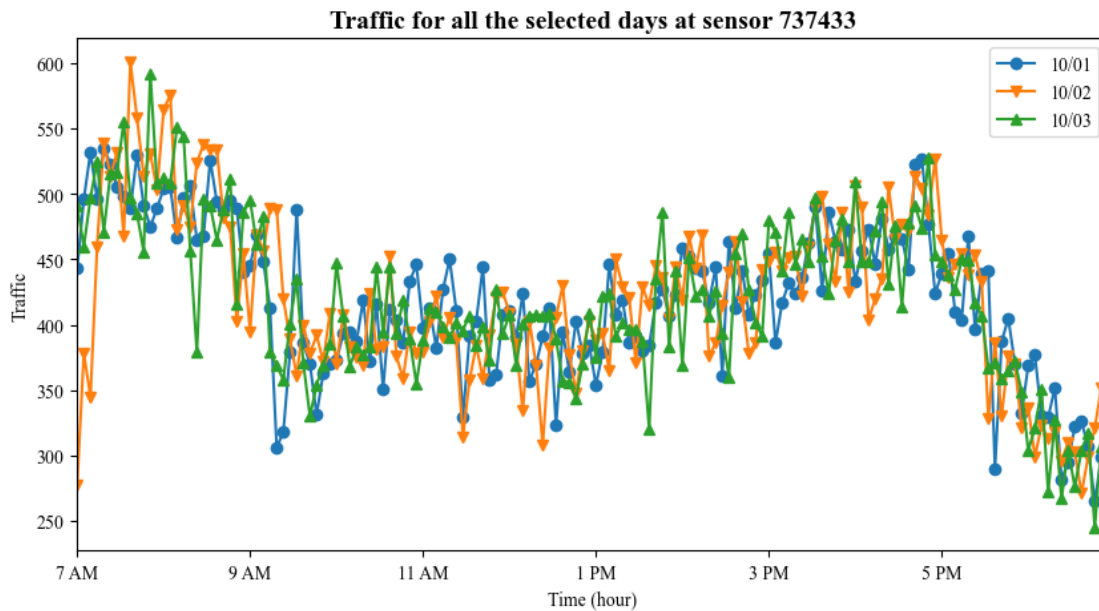
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
time_series_data['Time'] = pd.to_datetime(time_series_data['Time'])
```

/var/folders/l0/yttmtl97n7fd1v82xdlzb7c0000gn/T/ipykernel_99916/4105916518.py:72: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
time_series_data['Time'] = pd.to_datetime(time_series_data['Time'])
```



```
[ ]: day = "10/23"
#####

time_series_data = sensor_interest[sensor_interest['Time'].str.startswith(day)]

# Ensure 'Time' column is in datetime format
time_series_data['Time'] = pd.to_datetime(time_series_data['Time'])

# Filter out data outside of 7 AM to 7 PM
time_series_data = time_series_data[(time_series_data['Time'].dt.hour >= 7) &
    ↪ (time_series_data['Time'].dt.hour <= 19)]

# y values
traffic = time_series_data['10']
```

```

# x values - use 'Time' values
time = time_series_data['Time']

fig, ax = plt.subplots()

# Create scatter plot
ax.plot(time, traffic)

# Set x-axis format and locator
hours = mdates.DateFormatter('%I %p')
hour_locator = mdates.HourLocator(interval=2) # put a tick on every 2 hours
ax.xaxis.set_major_locator(hour_locator)
ax.xaxis.set_major_formatter(hours)

# Adjust x limits to start slightly before 7 AM and end at 7 PM
start_time = time.min().replace(hour=6, minute=50, second=0) # 10 minutes
↳ before 7 AM
end_time = time.max().replace(hour=20, minute=10, second=0)
ax.set_xlim(start_time, end_time)

# Set axis titles
ax.set_xlabel('Time (hour)')
ax.set_ylabel('Traffic')
ax.set_title('Traffic from 7 am to 7 pm, '+day)

plt.show()

```

```

/var/folders/l0/ytttdmtl97n7fd1v82xdlzb7c0000gn/T/ipykernel_99916/1469223246.py:8
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

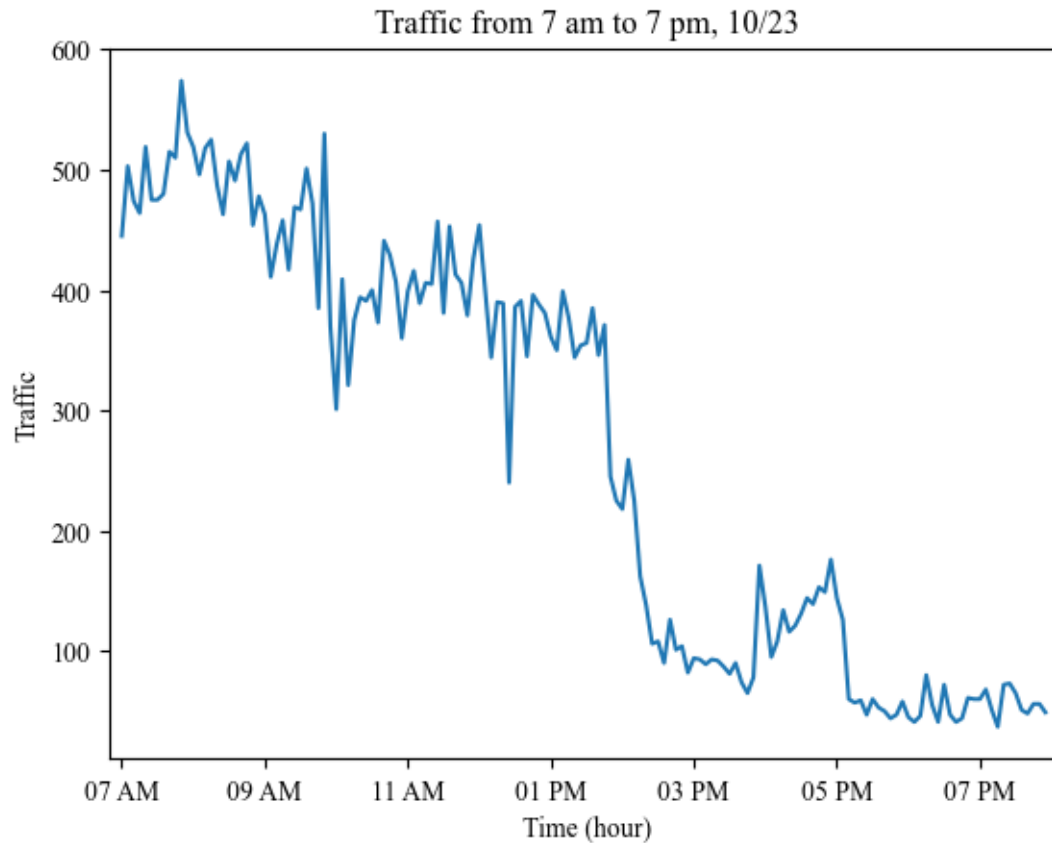
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```

time_series_data['Time'] = pd.to_datetime(time_series_data['Time'])

```

1 Traffic Prediction

1.1 Functions

```
[ ]: def generate_multi_legendre_design_matrix_(x_initial, polynomial_order):
    if np.isscalar(x_initial):
        x_initial = np.array([[x_initial]])

    # Ensure x_initial is a 2D numpy array
    x_initial = np.atleast_2d(x_initial)

    # N is the number of observations,      num_vars is the number of input
    ↪ variables
    N, n_input_vars = x_initial.shape

    # Number of terms in the expansion for each variable (x1^0, x1^1, x1^2, ...)
    n_expansion_terms = polynomial_order + 1
```

```

# Total number of terms in the expansion
total_expansion_terms = n_expansion_terms ** n_input_vars

# Initialize design matrix
design_matrix = np.empty((N, total_expansion_terms), dtype='float64')

# Loop over each data point
for i in range(N):
    col_index = 0 # just a counter
    # Loop over all combinations of polynomial orders for each variable
    for terms in np.ndindex(*([n_expansion_terms]*n_input_vars)): #####
    ↪CHECK
        product = 1.0
        # Calculate the product of Legendre polynomials for this
    ↪combination of terms
        for var in range(n_input_vars):
            P_j = legendre(terms[var])
            product *= P_j(x_initial[i, var])
        # Store result in the design matrix
        design_matrix[i, col_index] = product
        col_index += 1

return design_matrix

```

```

[ ]: #####
    ↪ #####
#####
    ↪ #####
#### This one goes up until the parameters that do not exceed the polynomial
    ↪order ####
#####
    ↪ #####
#####
    ↪ #####

import numpy as np
from numpy.polynomial.legendre import Legendre
from sklearn.preprocessing import MinMaxScaler

def generate_multi_legendre_design_matrix(x_initial, polynomial_order):
    x_initial = np.atleast_2d(x_initial)
    n_input_vars = x_initial.shape[1]

```

```

    # Generate multi-index for which the sum of the indices is <= polynomial_order
    indices = np.indices((polynomial_order + 1,) * n_input_vars).
    reshape(n_input_vars, -1)
    indices = indices[:, np.sum(indices, axis=0) <= polynomial_order]

    # Initialize design matrix
    design_matrix = np.empty((x_initial.shape[0], indices.shape[1]),
    dtype='float64')

    # Compute product of variables raised to the power of indices
    for row in range(x_initial.shape[0]):
        for col, idx in enumerate(indices.T):
            product = 1
            for var, power in enumerate(idx):
                if power != 0:
                    P_j = Legendre.basis(deg=power)
                    product *= P_j(x_initial[row, var])
                else:
                    product *= 1
            design_matrix[row, col] = product

    return design_matrix

```

```

[ ]: xx = np.array([[1,2],[1,2],[1,2]])
print('xx: ', xx)

print('generate_multi_legendre_design_matrix_: \n',
    generate_multi_legendre_design_matrix_(xx,2))
print('\ngenerate_multi_legendre_design_matrix: \n',
    generate_multi_legendre_design_matrix(xx,2))

print('\ngenerate_multi_legendre_design_matrix: ',
    generate_multi_legendre_design_matrix_(xx,2).shape)
print('\ngenerate_multi_legendre_design_matrix: ',
    generate_multi_legendre_design_matrix(xx,2).shape)

```

```

xx:  [[1 2]
      [1 2]
      [1 2]]
generate_multi_legendre_design_matrix_:
[[1.  2.  5.5 1.  2.  5.5 1.  2.  5.5]
 [1.  2.  5.5 1.  2.  5.5 1.  2.  5.5]
 [1.  2.  5.5 1.  2.  5.5 1.  2.  5.5]]

generate_multi_legendre_design_matrix:

```

```
[[1.  2.  5.5 1.  2.  1. ]
 [1.  2.  5.5 1.  2.  1. ]
 [1.  2.  5.5 1.  2.  1. ]]
```

```
generate_multi_legendre_design_matrix_: (3, 9)
```

```
generate_multi_legendre_design_matrix: (3, 6)
```

1.1.1 Predictive Algorithm

```
[ ]: def online_kaczmarz_legendre_multiple(x_initial, target_values,
      ↪ polynomial_order, weights=None):

    # Initialize MinMaxScaler to normalize to range [-1,1]
    # scaler = MinMaxScaler(feature_range=(-1, 1))
    # x_initial = ( x_initial - x_initial.min() ) / ( x_initial.max() -
    ↪ x_initial.min() )

    design_matrix = generate_multi_legendre_design_matrix(x_initial,
    ↪ polynomial_order)

    if weights is None:
        # initialize the weights to be the number of columns in the design
    ↪ matrix
        weight_predictions = np.random.rand(design_matrix.shape[1])
    else:
        weight_predictions = weights

    beta_parameter = 0

    for i in range (design_matrix.shape[0]):
        a = design_matrix[i, :]
        #a = ( a_0 - a_0.min() ) / ( a_0.max() - a_0.min() )

        weight_predictions = weight_predictions + ((target_values[i] - np.
    ↪ dot(a, weight_predictions)) / np.linalg.norm(a)**2) * a.T

        #####
        # weight_predictions = (weight_predictions + a.min() ) * ( a.max() - a.
    ↪ min() )
        #####

    # This is for beta
```

```

        # Note: you may want to uncomment this if you want to compute
        ↪beta_parameter
        # residual_errors = target_values - design_matrix @ weight_predictions
        # sse = residual_errors.T @ residual_errors
        # beta_parameter = sse / ( - polynomial_order)

    return weight_predictions, beta_parameter

```

1.2 1. Sensor 737433 (traffic increase after fire)

1.2.1 Load the data of the sensor of interest, and the m closest sensors.

```

[ ]: ## m=4

sensor_1_ = pd.read_csv('./Data/sensor_interest_1 737433.txt')
print('sensor_1: ', sensor_1_.shape)

sensor_1_m_1_ = pd.read_csv('./Data/sensor_1_m_8 772564.txt')
sensor_1_m_2_ = pd.read_csv('./Data/sensor_1_m_9 775975.txt')
sensor_1_m_3_ = pd.read_csv('./Data/sensor_1_m_11 775961.txt')
sensor_1_m_4_ = pd.read_csv('./Data/sensor_1_m_14 775949.txt')

```

sensor_1: (13248, 38)

1.2.2 Filter out the measurements that are outside the time intervals of interest.

We want to see the measurements from *7 am to 7 pm*

```

[ ]: # Ensure 'Time' column is in datetime format
sensor_1['Time'] = pd.to_datetime(sensor_1['Time'])
sensor_1_m_1['Time'] = pd.to_datetime(sensor_1_m_1['Time'])
sensor_1_m_2['Time'] = pd.to_datetime(sensor_1_m_2['Time'])
sensor_1_m_3['Time'] = pd.to_datetime(sensor_1_m_3['Time'])
sensor_1_m_4['Time'] = pd.to_datetime(sensor_1_m_4['Time'])

# Filter out data outside of 7 AM to 7 PM
sensor_1 = sensor_1[(sensor_1['Time'].dt.hour >= 7) & (sensor_1['Time'].dt.
    ↪hour < 19)]
sensor_1_m_1 = sensor_1_m_1[(sensor_1_m_1['Time'].dt.hour >= 7) &
    ↪(sensor_1_m_1['Time'].dt.hour < 19)]
sensor_1_m_2 = sensor_1_m_2[(sensor_1_m_2['Time'].dt.hour >= 7) &
    ↪(sensor_1_m_2['Time'].dt.hour < 19)]
sensor_1_m_3 = sensor_1_m_3[(sensor_1_m_3['Time'].dt.hour >= 7) &
    ↪(sensor_1_m_3['Time'].dt.hour < 19)]

```

```
sensor_1_m_4 = sensor_1_m_4[(sensor_1_m_4['Time'].dt.hour >= 7) &
↪(sensor_1_m_4['Time'].dt.hour < 19)]
```

```
# Reset the indices
```

```
sensor_1 = sensor_1.reset_index(drop=True)
sensor_1_m_1 = sensor_1_m_1.reset_index(drop=True)
sensor_1_m_2 = sensor_1_m_2.reset_index(drop=True)
sensor_1_m_3 = sensor_1_m_3.reset_index(drop=True)
sensor_1_m_4 = sensor_1_m_4.reset_index(drop=True)
```

```
print('sensor_1: ', sensor_1.shape)
print('sensor_1_m_1: ', sensor_1_m_1.shape)
print('sensor_1_m_2: ', sensor_1_m_2.shape)
print('sensor_1_m_3: ', sensor_1_m_3.shape)
print('sensor_1_m_4: ', sensor_1_m_4.shape)
```

```
sensor_1: (6624, 38)
sensor_1_m_1: (6623, 38)
sensor_1_m_2: (6624, 38)
sensor_1_m_3: (6624, 34)
sensor_1_m_4: (6624, 34)
```

1.2.3 Generate the matrix as per the specifications in the paper.

Each row will have the measurements of traffic from the sensor of interest and the m-closest sensors.

- The rows will include traffic information of the t-1, t-2,..., t-r observations.
- The rows are organized by sensor, and by timestep: [sensor of interest @ t-1,...,sensor of interest @ t-r, ... , m-closest sensor @ t-1,...,m-closest sensor @ t-r]

```
[ ]: r = 3 # set r to any value

# Minimum number of rows across all dataframes
min_rows = min(sensor_1.shape[0], sensor_1_m_1.shape[0], sensor_1_m_2.shape[0],
↪sensor_1_m_3.shape[0], sensor_1_m_4.shape[0])

# Initialize an empty list to store all row vectors
row_vectors = []

# Iterate over each index from r to min_rows
for i in tqdm(range(r, min_rows)):
    # Generate a list of indexes you're interested in. In this case, it's [i-r,
↪i-r+1, ..., i]

    ind = list(range(i+1, i-r, -1))
    indexes = list(range(i, i-r, -1))
```

```

# Get the desired elements
sensor_1_traffic = sensor_1.loc[ind, '10'].values
sensor_1_m_1_traffic = sensor_1_m_1.loc[indexes, '10'].values
sensor_1_m_2_traffic = sensor_1_m_2.loc[indexes, '10'].values
sensor_1_m_3_traffic = sensor_1_m_3.loc[indexes, '10'].values
sensor_1_m_4_traffic = sensor_1_m_4.loc[indexes, '10'].values

# Concatenate them into a 1x5 row vector
row_vector = np.concatenate([sensor_1_traffic, sensor_1_m_1_traffic,
↪sensor_1_m_2_traffic, sensor_1_m_3_traffic, sensor_1_m_4_traffic])

# Append the row vector to our list
row_vectors.append(row_vector)

# Convert our list of row vectors into a 2D numpy array
traffic_737433 = pd.DataFrame(row_vectors)
traffic_737433

```

100% | 6620/6620 [00:10<00:00, 610.22it/s]

```

[ ]:

```

	0	1	2	3	4	5	6	7	8	9	
0	535.0	496.0	532.0	496.0	445.0	406.0	452.0	86.0	74.0	38.0	\
1	523.0	535.0	496.0	532.0	459.0	445.0	406.0	60.0	86.0	74.0	
2	505.0	523.0	535.0	496.0	437.0	459.0	445.0	80.0	60.0	86.0	
3	498.0	505.0	523.0	535.0	497.0	437.0	459.0	49.0	80.0	60.0	
4	489.0	498.0	505.0	523.0	464.0	497.0	437.0	55.0	49.0	80.0	
...	
6615	354.0	374.0	356.0	393.0	308.0	311.0	379.0	124.0	130.0	191.0	
6616	368.0	354.0	374.0	356.0	318.0	308.0	311.0	110.0	124.0	130.0	
6617	333.0	368.0	354.0	374.0	378.0	318.0	308.0	160.0	110.0	124.0	
6618	349.0	333.0	368.0	354.0	321.0	378.0	318.0	106.0	160.0	110.0	
6619	335.0	349.0	333.0	368.0	337.0	321.0	378.0	140.0	106.0	160.0	
	10	11	12	13	14	15					
0	68.0	50.0	32.0	88.0	86.0	93.0					
1	50.0	68.0	50.0	108.0	88.0	86.0					
2	64.0	50.0	68.0	90.0	108.0	88.0					
3	54.0	64.0	50.0	85.0	90.0	108.0					
4	47.0	54.0	64.0	65.0	85.0	90.0					
...					
6615	100.0	106.0	156.0	42.0	55.0	34.0					
6616	93.0	100.0	106.0	57.0	42.0	55.0					
6617	128.0	93.0	100.0	44.0	57.0	42.0					
6618	81.0	128.0	93.0	46.0	44.0	57.0					
6619	126.0	81.0	128.0	42.0	46.0	44.0					

[6620 rows x 16 columns]

1.2.4 Tests - Sensor 737433

Estimation

```
[ ]: #####
####    Definition of "Hyperparameters"
#####
days = 1  # Max=31.97 (available data)
t = int( (60/5)*12 * days)
t = traffic_737433.shape[0]

#t = traffic_737433.shape[0] # Number of points to be tested on, and times the
    ↪ coefficients will be updated.
    # The coefficients w are calculatd for each of these points, the idea
    ↪ is to simulate an on-line stream of data.

X = traffic_737433.iloc[:t, 1:]

"""
    Update this if using more input variables, # the function is handling a
    ↪ 15-dimensional, second order polynomial.
"""

polynomial_degree = 2
"""
    USING Total (vs. Max) EXPANCTION TERMS
    Number of terms in the weights matrix:

"""

target_values = traffic_737433.iloc[:t, 0]
# Generate Y as target_values (real Y's)

# Initialize weights and estimations
weights_over_time = []
y_hat = []

noise = np.random.normal(scale= 10 , size=(t))

#####
####    Online estimation of coefficients
#####
```



```

for i in tqdm(range(t)):
    x_i = X.iloc[i, :]

    # Normalize and scale to -1,1 the input:
    x_i = ( x_i - x_i.min() ) / ( x_i.max() - x_i.min() ) * 2 - 1

    weight_predictions, _ = online_kaczmarz_legendre_multiple(x_i,
↳ [target_values[i] + noise[i]], polynomial_degree)

    #De-normalize rescale the weights:
    weight_predictions = (((weight_predictions + 1) / 2) * ( x_i.max() - x_i.
↳ min() ) + x_i.min() )

    # Use predicted weights to compute y_hat
    y_predictions = generate_multi_legendre_design_matrix(x_i,
↳ polynomial_degree) @ weight_predictions.T

    # Store the values of predicted y and estimated weights
    y_hat.append(y_predictions)
    weights_over_time.append(weight_predictions)

print("Done carajo")

```

100%| | 6620/6620 [4:40:45<00:00, 2.54s/it]

Done carajo

```
[ ]: for_plot=int((60/5)*12*(31+8))
```

```

[ ]: weights_over_time = np.array(weights_over_time)
y_hat_ = np.array(y_hat) #####
print('y_hat: ', y_hat_.shape)

print('weights_over_time: ', weights_over_time.shape)

weight = weights_over_time[-1]
Weights = pd.DataFrame({
    'Estimated_Weights': weight
})

# Style DataFrame
# Weights.style.format("{:.4f}")

print('Weights: ', Weights.shape)

```

```
y_hat: (6620, 1)
weights_over_time: (6620, 136)
Weights: (136, 1)
```

Results

```
[ ]: #####
#### Results
#####

Predicted_Values = y_hat_.flatten()
print('Predicted_Values: ', Predicted_Values.shape)
Real_Values = target_values
print('Real_Values: ', Real_Values.shape)
difference = (Real_Values-Predicted_Values).T

Y = pd.DataFrame({
    'Predicted_Values': Predicted_Values,
    'Real_Values': Real_Values,
    'Difference': difference
})

# Style DataFrame
Y[-10:].style.format("{:.4f}")
```

```
Predicted_Values: (6620,)
Real_Values: (6620,)
```

```
[ ]: <pandas.io.formats.style.Styler at 0x165a8e7a0>
```

Plots

```
[ ]: # Plot the accuracy
plt.figure(figsize=(8, 6))

r2 = r2_score(target_values, y_hat_)
print('r2: ', r2)

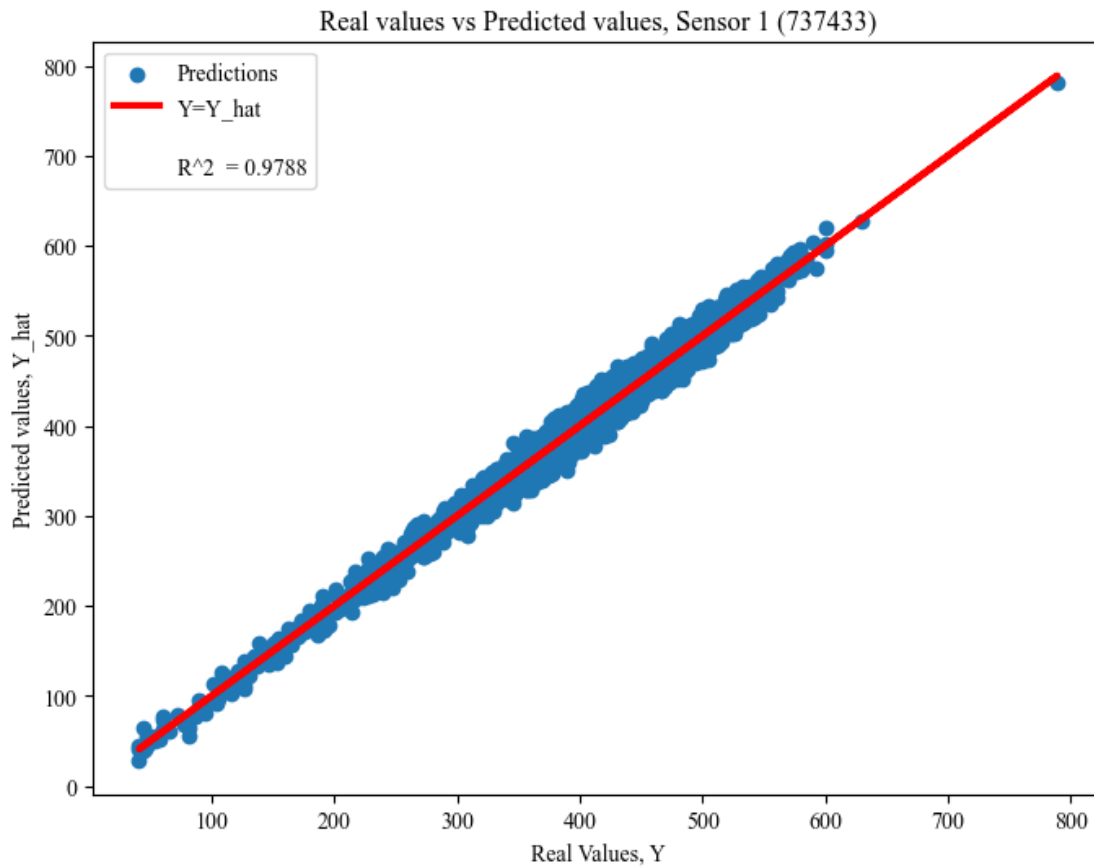
plt.scatter(target_values, y_hat_, label='Predictions')
plt.plot(target_values, target_values, color='red', linewidth = 3,
        label=f'Y=Y_hat')
plt.scatter(target_values, target_values, marker='', label=f'\nR^2 = {r2:.4f}')

plt.xlabel('Real Values, Y')
plt.ylabel('Predicted values, Y_hat')
plt.title('Real values vs Predicted values, Sensor 1 (737433)')
plt.legend()
```

```
plt.savefig('./figures/traffic_sensor_1.png')

plt.show()
```

r2: 0.9788321254962971



[]:

[]: *# Plot the traffic*

```
number_days = 1
n = int(t/days * number_days)

plt.figure(figsize=(8, 6))

plt.plot(Y['Real_Values'][-n:], linewidth=1, label='Real Traffic')
plt.plot(Y['Predicted_Values'][-n:], color='red', linestyle='dotted',
        label='Predicted Traffic')
```

```

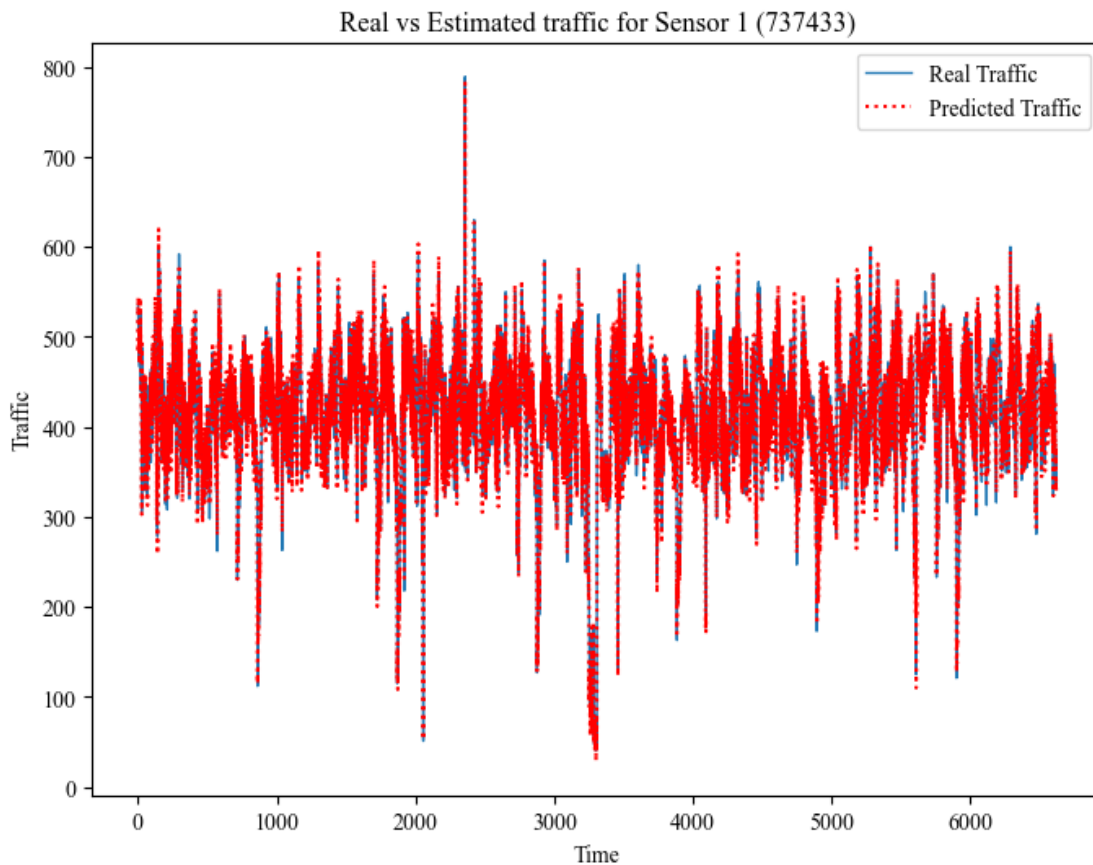
# plt.scatter(Y[-n:].index, Y['Predicted_Values'][-n:], marker='x', color =
↳ 'black', label='Predicted Traffic')

plt.xlabel('Time')
plt.ylabel('Traffic')
plt.title('Real vs Estimated traffic for Sensor 1 (737433)')
plt.legend()

plt.savefig('./Figures/traffic_sensor_1.png')

plt.show()

```



```

[ ]: ## Day Before Ignition

# Extract data and generate time values
# n = int(t / days)
n = 31 + 7

num_entries = len(Y['Real_Values'][(144*(n-1)+1):144*(n)])

```

```

time_range = pd.date_range(start='7:00', end='19:00', freq='5min')
time_values = np.tile(time_range, num_entries // len(time_range) + 1)[:
    ↪num_entries]

# Prepare plot data
plot_df = pd.DataFrame({
    'Time': time_values,
    'Real_Values': Y['Real_Values'][(144*(n-1)+1):144*(n)].values,
    'Predicted_Values': Y['Predicted_Values'][(144*(n-1)+1):144*(n)].values
})

# Plot data
fig, ax = plt.subplots(figsize=(10, 6))
ax.plot('Time', 'Real_Values', data=plot_df, linewidth=1, color='red',
    ↪label='Real Traffic')
ax.plot('Time', 'Predicted_Values', data=plot_df, linestyle=':',
    ↪label='Predicted Traffic')

# Set x-axis format and locator
ax.xaxis.set_major_locator(mdates.HourLocator(interval=2))
ax.xaxis.set_major_formatter(mdates.DateFormatter('%I %p'))

# Set x limits and titles
ax.set_xlim(plot_df['Time'].min() - pd.Timedelta(minutes=30), plot_df['Time'].
    ↪max() + pd.Timedelta(minutes=30))
ax.set(xlabel='Time of day', ylabel='Traffic flow', title='Real vs Estimated
    ↪traffic for Sensor 1 (737433) from 7 am to 7 pm \n Online-Kaczmarz')
ax.legend()

plt.savefig('./Figures/before ignition - Increase.png')

plt.show()

## Day After Ignition

# Extract data and generate time values
# n = int(t / days)
n = 31 + 9

num_entries = len(Y['Real_Values'][(144*(n-1)+1):144*(n)])
time_range = pd.date_range(start='7:00', end='19:00', freq='5min')
time_values = np.tile(time_range, num_entries // len(time_range) + 1)[:
    ↪num_entries]

```

```

# Prepare plot data
plot_df = pd.DataFrame({
    'Time': time_values,
    'Real_Values': Y['Real_Values'][(144*(n-1)+1):144*(n)].values,
    'Predicted_Values': Y['Predicted_Values'][(144*(n-1)+1):144*(n)].values
})

# Plot data
fig, ax = plt.subplots(figsize=(10, 6))
ax.plot('Time', 'Real_Values', data=plot_df, linewidth=1, color='red',
        ↪label='Real Traffic')
ax.plot('Time', 'Predicted_Values', data=plot_df, linestyle=':',
        ↪label='Predicted Traffic')

# Set x-axis format and locator
ax.xaxis.set_major_locator(mdates.HourLocator(interval=2))
ax.xaxis.set_major_formatter(mdates.DateFormatter('%I %p'))

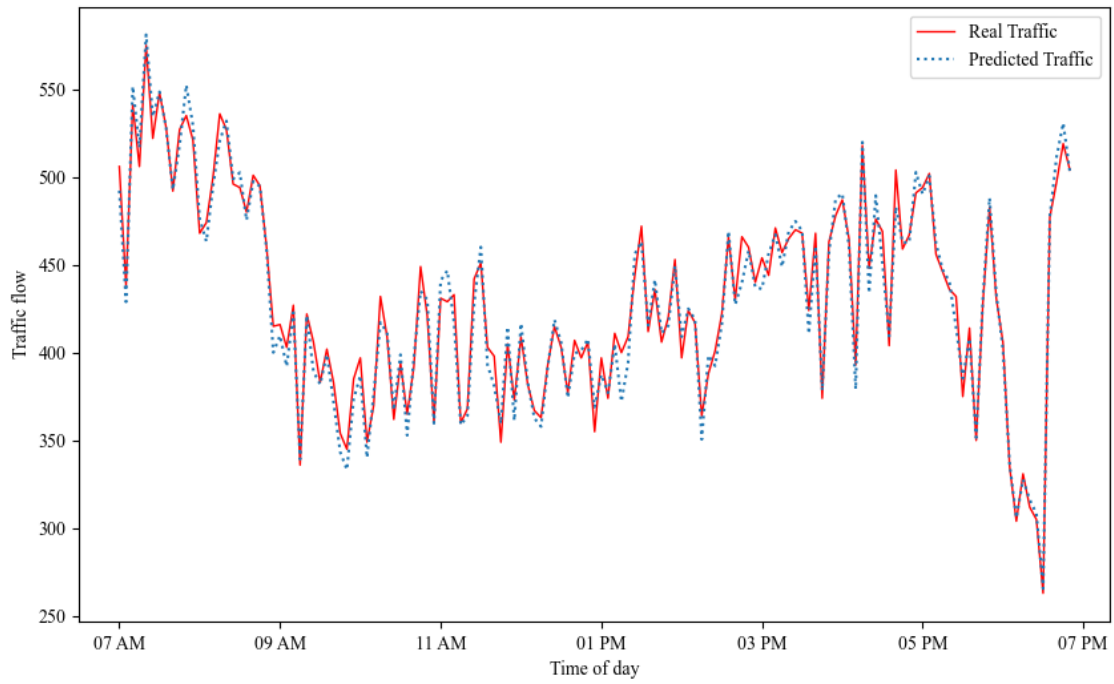
# Set x limits and titles
ax.set_xlim(plot_df['Time'].min() - pd.Timedelta(minutes=30), plot_df['Time'].
        ↪max() + pd.Timedelta(minutes=30))
ax.set(xlabel='Time of day', ylabel='Traffic flow', title='Real vs Estimated
        ↪traffic for Sensor 1 (737433) from 7 am to 7 pm \n Online-Kaczmarz')
ax.legend()

plt.savefig('./Figures/after ignition - Increase.png')

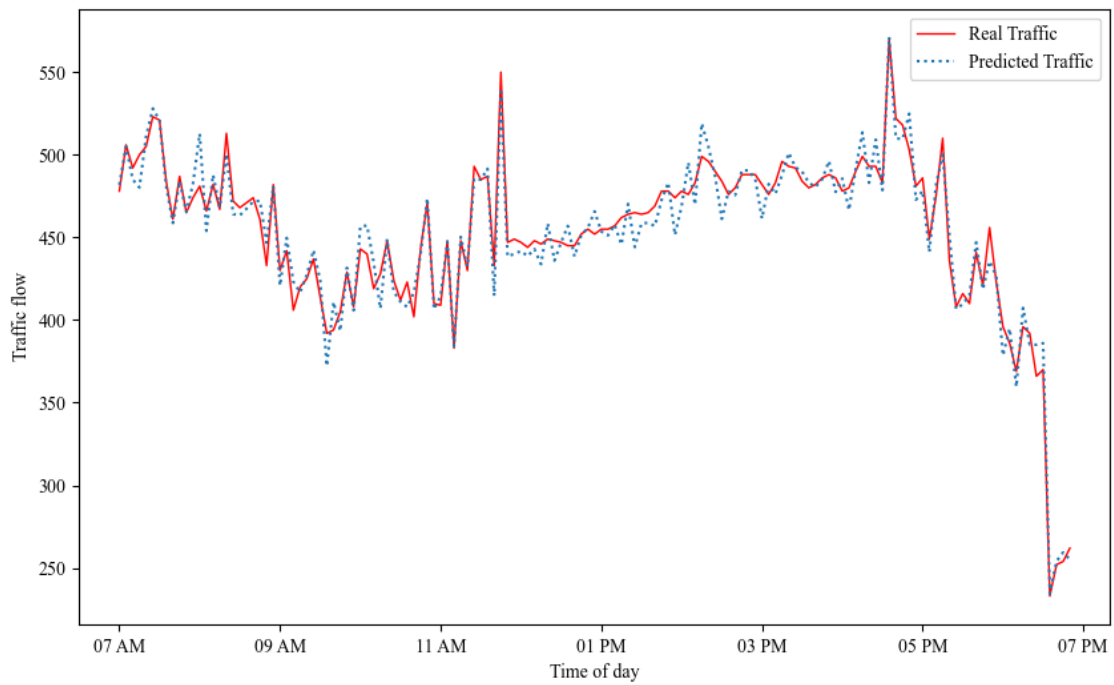
plt.show()

```

Real vs Estimated traffic for Sensor 1 (737433) from 7 am to 7 pm
Online-Kaczmarz



Real vs Estimated traffic for Sensor 1 (737433) from 7 am to 7 pm
Online-Kaczmarz



1.3 2. Sensor 764848 (traffic decrease after fire)

1.3.1 Load the data of the sensor of interest, and the m closest sensors.

```
[ ]: ## m=4

sensor_2_ = pd.read_csv('./Data/sensor_interest_2 764848.txt')
print('sensor_2: ', sensor_2_.shape)

sensor_2_m_1_ = pd.read_csv('./Data/sensor_2_m_2 771475.txt')
sensor_2_m_2_ = pd.read_csv('./Data/sensor_2_m_4 771410.txt')
sensor_2_m_3_ = pd.read_csv('./Data/sensor_2_m_7 771421.txt')
sensor_2_m_4_ = pd.read_csv('./Data/sensor_2_m_9 771463.txt')
```

sensor_2: (13248, 38)

1.3.2 Filter out the measurements that are outside the time intervals of interest.

We want to see the measurements from *7 am to 7 pm*

```
[ ]: # Ensure 'Time' column is in datetime format
sensor_2_['Time'] = pd.to_datetime(sensor_2_['Time'])
sensor_2_m_1_['Time'] = pd.to_datetime(sensor_2_m_1_['Time'])
sensor_2_m_2_['Time'] = pd.to_datetime(sensor_2_m_2_['Time'])
sensor_2_m_3_['Time'] = pd.to_datetime(sensor_2_m_3_['Time'])
sensor_2_m_4_['Time'] = pd.to_datetime(sensor_2_m_4_['Time'])

# Filter out data outside of 7 AM to 7 PM
sensor_2 = sensor_2_[(sensor_2_['Time'].dt.hour >= 7) & (sensor_2_['Time'].dt.
    ↳hour < 19)]
sensor_2_m_1 = sensor_2_m_1_[(sensor_2_m_1_['Time'].dt.hour >= 7) &
    ↳(sensor_2_m_1_['Time'].dt.hour < 19)]
sensor_2_m_2 = sensor_2_m_2_[(sensor_2_m_2_['Time'].dt.hour >= 7) &
    ↳(sensor_2_m_2_['Time'].dt.hour < 19)]
sensor_2_m_3 = sensor_2_m_3_[(sensor_2_m_3_['Time'].dt.hour >= 7) &
    ↳(sensor_2_m_3_['Time'].dt.hour < 19)]
sensor_2_m_4 = sensor_2_m_4_[(sensor_2_m_4_['Time'].dt.hour >= 7) &
    ↳(sensor_2_m_4_['Time'].dt.hour < 19)]

# Reset the indices
sensor_2 = sensor_2.reset_index(drop=True)
sensor_2_m_1 = sensor_2_m_1.reset_index(drop=True)
sensor_2_m_2 = sensor_2_m_2.reset_index(drop=True)
sensor_2_m_3 = sensor_2_m_3.reset_index(drop=True)
sensor_2_m_4 = sensor_2_m_4.reset_index(drop=True)
```



```

print('sensor_2: ', sensor_2.shape)
print('sensor_2_m_1: ', sensor_2_m_1.shape)
print('sensor_2_m_2: ', sensor_2_m_2.shape)
print('sensor_2_m_3: ', sensor_2_m_3.shape)
print('sensor_2_m_4: ', sensor_2_m_4.shape)

```

```

sensor_2: (6624, 38)
sensor_2_m_1: (6624, 34)
sensor_2_m_2: (6624, 34)
sensor_2_m_3: (6624, 34)
sensor_2_m_4: (6623, 34)

```

1.3.3 Generate the matrix as per the specifications in the paper.

Each row will have the measurements of traffic from the sensor of interest and the m-closest sensors.

- The rows will include traffic information of the t-1, t-2,..., t-r observations.
- The rows are organized by sensor, and by timestep: [sensor of interest @ t-1,...,sensor of interest @ t-r, ... , m-closest sensor @ t-1,...,m-closest sensor @ t-r]

```

[ ]: r = 3 # set r to any value

# Minimum number of rows across all dataframes
min_rows = min(sensor_2.shape[0], sensor_2_m_1.shape[0], sensor_2_m_2.shape[0],
               ↪ sensor_2_m_3.shape[0], sensor_2_m_4.shape[0])

# Initialize an empty list to store all row vectors
row_vectors = []

# Iterate over each index from r to min_rows
for i in tqdm(range(r, min_rows)):
    # Generate a list of indexes you're interested in. In this case, it's [i-r,
    ↪ i-r+1, ..., i]

    # ind = list(range(i-r, i+1))
    # indexes = list(range(i-r+1, i+1))

    ind = list(range(i+1, i-r, -1))
    indexes = list(range(i, i-r, -1))

    # Get the desired elements
    sensor_2_traffic = sensor_2.loc[ind, '10'].values
    sensor_2_m_1_traffic = sensor_2_m_1.loc[indexes, '10'].values
    sensor_2_m_2_traffic = sensor_2_m_2.loc[indexes, '10'].values
    sensor_2_m_3_traffic = sensor_2_m_3.loc[indexes, '10'].values

```

```

sensor_2_m_4_traffic = sensor_2_m_4.loc[indexes, '10'].values

# Concatenate them into a 1x5 row vector
row_vector = np.concatenate([sensor_2_traffic, sensor_2_m_1_traffic,
↪sensor_2_m_2_traffic, sensor_2_m_3_traffic, sensor_2_m_4_traffic])

# Append the row vector to our list
row_vectors.append(row_vector)

# Convert our list of row vectors into a 2D numpy array
traffic_764848 = pd.DataFrame(row_vectors)
traffic_764848

```

100% | 6620/6620 [00:10<00:00, 607.51it/s]

```

[ ]:
    0      1      2      3      4      5      6      7      8      9  \
0   529.0  500.0  415.0  399.0  322.0  295.0  308.0  159.0  158.0  179.0
1   542.0  529.0  500.0  415.0  344.0  322.0  295.0  202.0  159.0  158.0
2   526.0  542.0  529.0  500.0  326.0  344.0  322.0  188.0  202.0  159.0
3   507.0  526.0  542.0  529.0  333.0  326.0  344.0  183.0  188.0  202.0
4   514.0  507.0  526.0  542.0  410.0  333.0  326.0  218.0  183.0  188.0
...   ...   ...   ...   ...   ...   ...   ...   ...   ...
6615  413.0  380.0  360.0  356.0  141.0  188.0  173.0  134.0  138.0  176.0
6616  393.0  413.0  380.0  360.0  139.0  141.0  188.0  126.0  134.0  138.0
6617  391.0  393.0  413.0  380.0  150.0  139.0  141.0  111.0  126.0  134.0
6618  405.0  391.0  393.0  413.0  145.0  150.0  139.0  144.0  111.0  126.0
6619  294.0  405.0  391.0  393.0  159.0  145.0  150.0  173.0  144.0  111.0

    10     11     12     13     14     15
0   203.0  149.0  182.0  292.0  276.0  268.0
1   185.0  203.0  149.0  296.0  292.0  276.0
2   196.0  185.0  203.0  288.0  296.0  292.0
3   185.0  196.0  185.0  286.0  288.0  296.0
4   235.0  185.0  196.0  357.0  286.0  288.0
...   ...   ...   ...   ...   ...   ...
6615  152.0  161.0  199.0  127.0  131.0  184.0
6616  158.0  152.0  161.0  139.0  127.0  131.0
6617  122.0  158.0  152.0  128.0  139.0  127.0
6618  176.0  122.0  158.0  146.0  128.0  139.0
6619  198.0  176.0  122.0  119.0  146.0  128.0

```

[6620 rows x 16 columns]

1.3.4 Tests - Sensor 764848

Estimation

[]:

```
#####
####    Definition of "Hyperparameters"
#####
days = 1    # Max=31.97 (available data)
t = int( (60/5)*12 * days)
t = traffic_764848.shape[0]

#t = traffic_737433.shape[0] # Number of points to be tested on, and times the
    ↪ coefficients will be updated.
    # The coefficients w are calculated for each of these points, the idea
    ↪ is to simulate an on-line stream of data.

X = traffic_764848.iloc[:t, 1:]

"""
    Update this if using more input variables, # the function is handling a
    ↪ 15-dimensional, second order polynomial.
"""

polynomial_degree = 2
"""
    USING Total (vs. Max) EXPANCTION TERMS
    Number of terms in the weights matrix:

    """

target_values = traffic_764848.iloc[:t, 0]
# Generate Y as target_values (real Y's)

# Initialize weights and estimations
weights_over_time = []
y_hat = []

noise = np.random.normal(scale= 10 , size=(t))

#####
####    Online estimation of coefficients
#####

for i in tqdm(range(t)):
    x_i = X.iloc[i, :]

    # Normalize and scale to -1,1 the input:
    x_i = ( x_i - x_i.min() ) / ( x_i.max() - x_i.min() ) * 2 - 1
```

```

weight_predictions, _ = online_kaczmarz_legendre_multiple(x_i,
↳[target_values[i] + noise[i]], polynomial_degree)

#De-normalize rescale the weights:
weight_predictions = (((weight_predictions + 1) / 2) * ( x_i.max() - x_i.
↳min() ) + x_i.min() )

# Use predicted weights to compute y_hat
y_predictions = generate_multi_legendre_design_matrix(x_i,
↳polynomial_degree) @ weight_predictions.T

# Store the values of predicted y and estimated weights
y_hat.append(y_predictions)
weights_over_time.append(weight_predictions)

print("Done carajo")

```

100%| | 6620/6620 [4:47:21<00:00, 2.60s/it]

Done carajo

```

[ ]: weights_over_time = np.array(weights_over_time)
y_hat_ = np.array(y_hat) #####
print('y_hat: ', y_hat_.shape)

print('weights_over_time: ', weights_over_time.shape)

weight = weights_over_time[-1]
Weights = pd.DataFrame({
    'Estimated_Weights': weight
})

# Style DataFrame
# Weights.style.format("{:,.4f}")

print('Weights: ', Weights.shape)

```

```

y_hat: (6620, 1)
weights_over_time: (6620, 136)
Weights: (136, 1)

```

Results

```

[ ]: #####
    ###      Results

```

```
#####

Predicted_Values = y_hat_.flatten()
print('Predicted_Values: ', Predicted_Values.shape)
Real_Values = traffic_764848.iloc[:, 0]
print('Real_Values: ', Real_Values.shape)
difference = (Real_Values-Predicted_Values).T

Y = pd.DataFrame({
    'Predicted_Values': Predicted_Values,
    'Real_Values': Real_Values,
    'Difference': difference
})

# Style DataFrame
Y[-10:].style.format("{:.4f}")
```

```
Predicted_Values: (6620,)
Real_Values: (6620,)
```

```
[ ]: <pandas.io.formats.style.Styler at 0x1661057b0>
```

Plots

```
[ ]: # Plot the accuracy
plt.figure(figsize=(8, 6))

r2 = r2_score(target_values, y_hat_)
print('r2: ', r2)

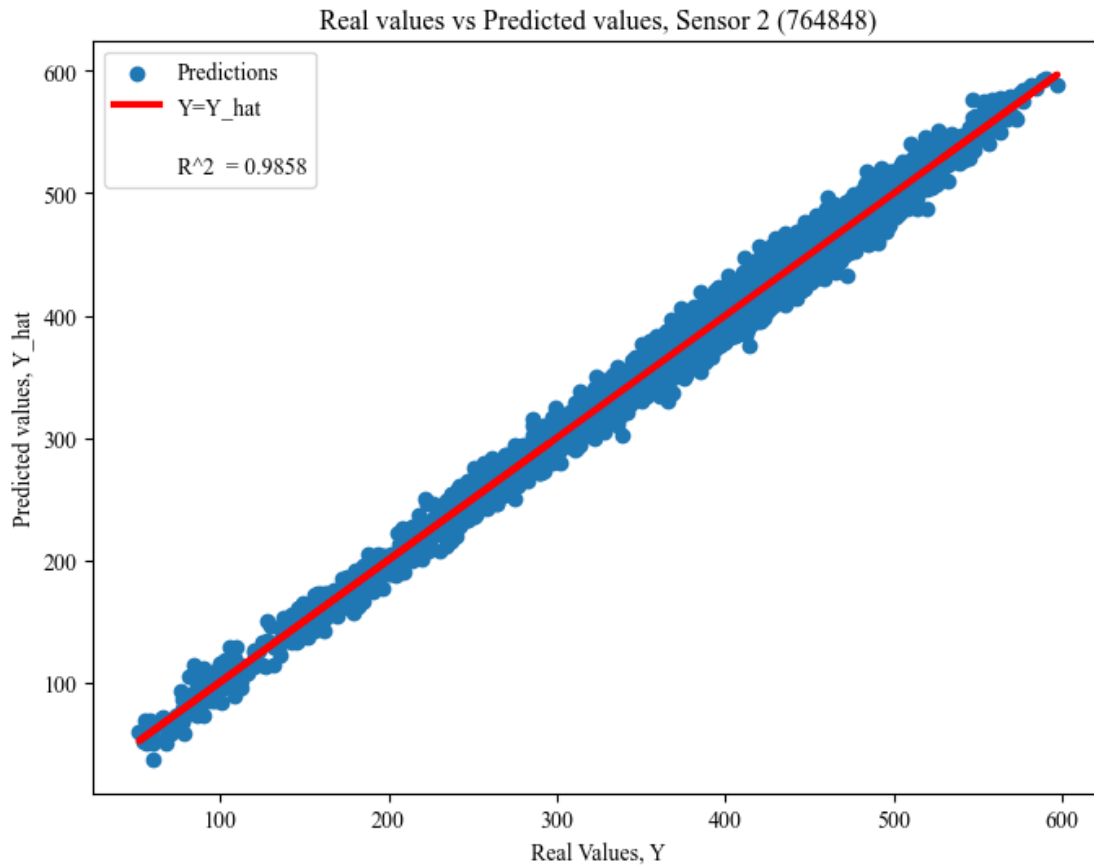
plt.scatter(target_values, y_hat_, label='Predictions')
plt.plot(target_values, target_values, color='red', linewidth = 3,
        label=f'Y=Y_hat')
plt.scatter(target_values, target_values, marker='.', label=f'\nR^2 = {r2:.4f}')

plt.xlabel('Real Values, Y')
plt.ylabel('Predicted values, Y_hat')
plt.title('Real values vs Predicted values, Sensor 2 (764848)')
plt.legend()

plt.savefig('./figures/traffic_sensor_2.png')

plt.show()
```

```
r2: 0.9858336841615297
```



```
[ ]: # Plot the traffic
n = t

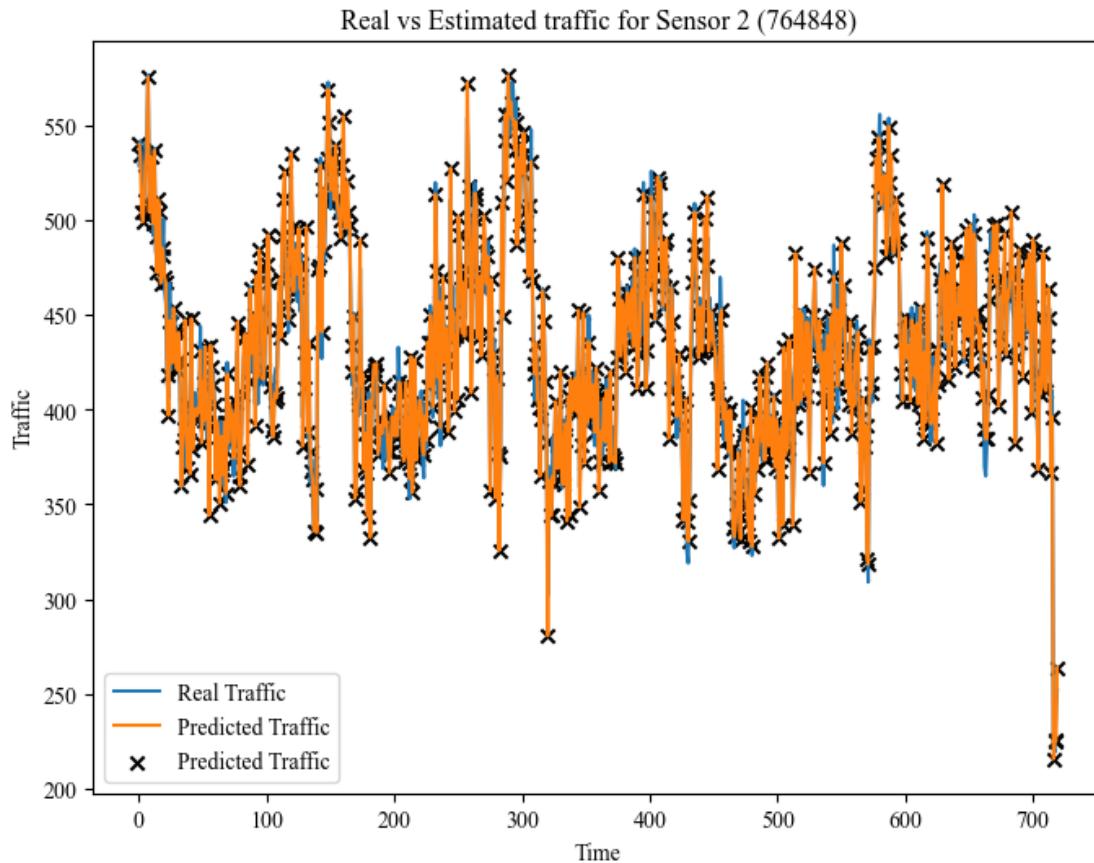
plt.figure(figsize=(8, 6))

plt.plot(Y['Real_Values'][-n:],label='Real Traffic')
plt.plot(Y['Predicted_Values'][-n:],label='Predicted Traffic')
plt.scatter(Y[-n:].index, Y['Predicted_Values'][-n:], marker='x', color =_
    ↪'black',label='Predicted Traffic')

plt.xlabel('Time')
plt.ylabel('Traffic')
plt.title('Real vs Estimated traffic for Sensor 2 (764848)')
plt.legend()

plt.savefig('./Figures/traffic_sensor_2.png')

plt.show()
```



```
[ ]: ## Day Before Ignition

# Extract data and generate time values
# n = int(t / days)
n = 31 + 7

num_entries = len(Y['Real_Values'][(144*(n-1)+1):144*(n)])
time_range = pd.date_range(start='7:00', end='19:00', freq='5min')
time_values = np.tile(time_range, num_entries // len(time_range) + 1)[:
    ↪ num_entries]

# Prepare plot data
plot_df = pd.DataFrame({
    'Time': time_values,
    'Real_Values': Y['Real_Values'][(144*(n-1)+1):144*(n)].values,
    'Predicted_Values': Y['Predicted_Values'][(144*(n-1)+1):144*(n)].values
})

# Plot data
```

```

fig, ax = plt.subplots(figsize=(10, 6))
ax.plot('Time', 'Real_Values', data=plot_df, linewidth=1, color='red',
        ↪label='Real Traffic')
ax.plot('Time', 'Predicted_Values', data=plot_df, linestyle=':',
        ↪label='Predicted Traffic')

# Set x-axis format and locator
ax.xaxis.set_major_locator(mdates.HourLocator(interval=2))
ax.xaxis.set_major_formatter(mdates.DateFormatter('%I %p'))

# Set x limits and titles
ax.set_xlim(plot_df['Time'].min() - pd.Timedelta(minutes=30), plot_df['Time'].
            ↪max() + pd.Timedelta(minutes=30))
ax.set(xlabel='Time of day', ylabel='Traffic flow', title='Real vs Estimated
            ↪traffic for Sensor 2 (764848) from 7 am to 7 pm \n Online-Kaczmarz')
ax.legend()

plt.savefig('./Figures/before ignition - Decrease.png')

plt.show()

## Day After Ignition

# Extract data and generate time values
# n = int(t / days)
n = 31 + 9

num_entries = len(Y['Real_Values'][(144*(n-1)+1):144*(n)])
time_range = pd.date_range(start='7:00', end='19:00', freq='5min')
time_values = np.tile(time_range, num_entries // len(time_range) + 1)[
    ↪num_entries]

# Prepare plot data
plot_df = pd.DataFrame({
    'Time': time_values,
    'Real_Values': Y['Real_Values'][(144*(n-1)+1):144*(n)].values,
    'Predicted_Values': Y['Predicted_Values'][(144*(n-1)+1):144*(n)].values
})

# Plot data
fig, ax = plt.subplots(figsize=(10, 6))
ax.plot('Time', 'Real_Values', data=plot_df, linewidth=1, color='red',
        ↪label='Real Traffic')

```



```

ax.plot('Time', 'Predicted_Values', data=plot_df, linestyle=':',
        label='Predicted Traffic')

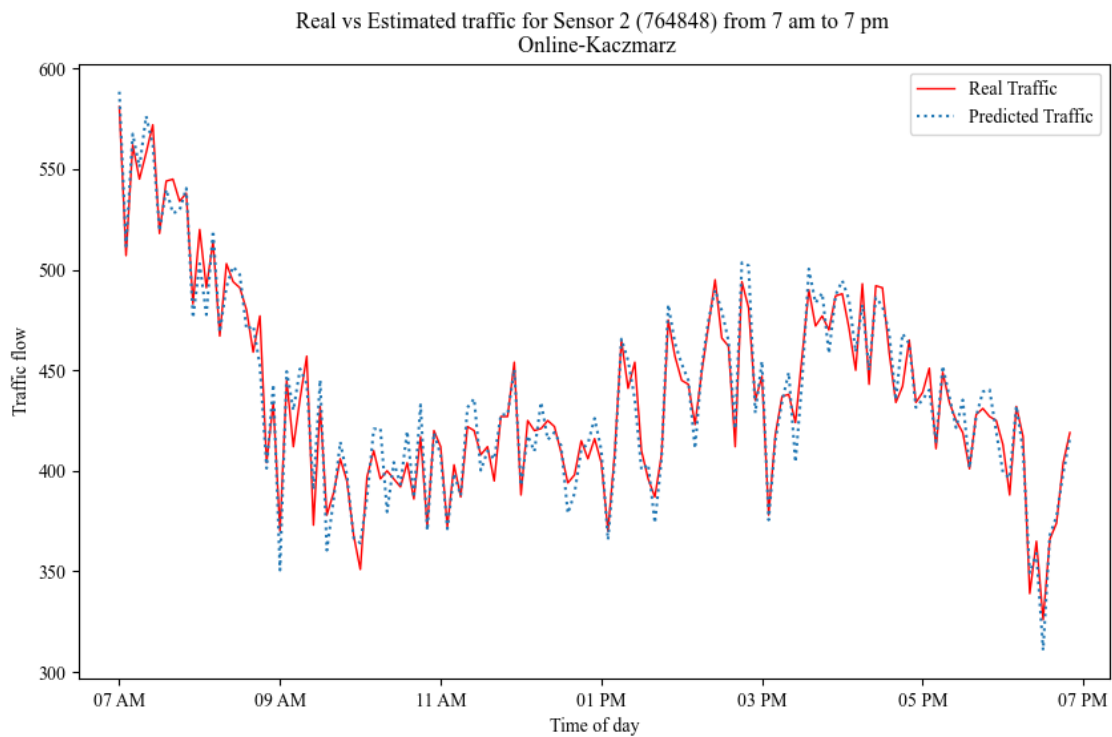
# Set x-axis format and locator
ax.xaxis.set_major_locator(mdates.HourLocator(interval=2))
ax.xaxis.set_major_formatter(mdates.DateFormatter('%I %p'))

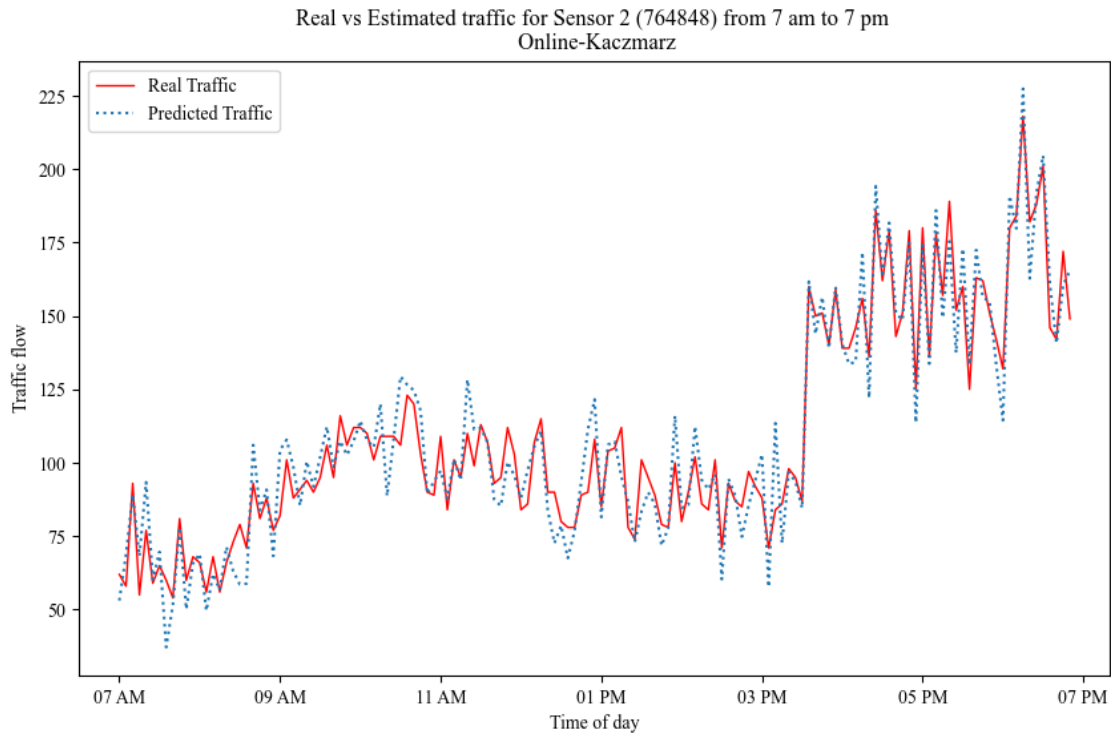
# Set x limits and titles
ax.set_xlim(plot_df['Time'].min() - pd.Timedelta(minutes=30), plot_df['Time'].
            max() + pd.Timedelta(minutes=30))
ax.set(xlabel='Time of day', ylabel='Traffic flow', title='Real vs Estimated
            traffic for Sensor 2 (764848) from 7 am to 7 pm \n Online-Kaczmarz')
ax.legend()

plt.savefig('./Figures/after ignition - Decrease.png')

plt.show()

```





1.4 3. Sensor 764632 (traffic changes after fire)

1.4.1 Load the data of the sensor of interest, and the m closest sensors.

```
[ ]: ## m=4

sensor_3_ = pd.read_csv('./Data/sensor_interest_3 764632.txt')
print('sensor_3: ', sensor_3_.shape)

sensor_3_m_1_ = pd.read_csv('./Data/sensor_3_m_3 764958.txt')
sensor_3_m_2_ = pd.read_csv('./Data/sensor_3_m_6 764181.txt')
sensor_3_m_3_ = pd.read_csv('./Data/sensor_3_m_8 765100.txt')
sensor_3_m_4_ = pd.read_csv('./Data/sensor_3_m_11 760892.txt')
```

sensor_3: (13248, 38)

1.4.2 Filter out the measurements that are outside the time intervals of interest.

We want to see the measurements from *7 am to 7 pm*

```
[ ]: # Ensure 'Time' column is in datetime format
sensor_3['Time'] = pd.to_datetime(sensor_3['Time'])
sensor_3_m_1['Time'] = pd.to_datetime(sensor_3_m_1['Time'])
sensor_3_m_2['Time'] = pd.to_datetime(sensor_3_m_2['Time'])
sensor_3_m_3['Time'] = pd.to_datetime(sensor_3_m_3['Time'])
sensor_3_m_4['Time'] = pd.to_datetime(sensor_3_m_4['Time'])

# Filter out data outside of 7 AM to 7 PM
sensor_3 = sensor_3[(sensor_3['Time'].dt.hour >= 7) & (sensor_3['Time'].dt.
    ↳hour < 19)]
sensor_3_m_1 = sensor_3_m_1[(sensor_3_m_1['Time'].dt.hour >= 7) &↳
    ↳ (sensor_3_m_1['Time'].dt.hour < 19)]
sensor_3_m_2 = sensor_3_m_2[(sensor_3_m_2['Time'].dt.hour >= 7) &↳
    ↳ (sensor_3_m_2['Time'].dt.hour < 19)]
sensor_3_m_3 = sensor_3_m_3[(sensor_3_m_3['Time'].dt.hour >= 7) &↳
    ↳ (sensor_3_m_3['Time'].dt.hour < 19)]
sensor_3_m_4 = sensor_3_m_4[(sensor_3_m_4['Time'].dt.hour >= 7) &↳
    ↳ (sensor_3_m_4['Time'].dt.hour < 19)]

# Reset the indices
sensor_3 = sensor_3.reset_index(drop=True)
sensor_3_m_1 = sensor_3_m_1.reset_index(drop=True)
sensor_3_m_2 = sensor_3_m_2.reset_index(drop=True)
sensor_3_m_3 = sensor_3_m_3.reset_index(drop=True)
sensor_3_m_4 = sensor_3_m_4.reset_index(drop=True)

print('sensor_3: ', sensor_3.shape)
print('sensor_3_m_1: ', sensor_3_m_1.shape)
print('sensor_3_m_2: ', sensor_3_m_2.shape)
print('sensor_3_m_3: ', sensor_3_m_3.shape)
print('sensor_3_m_4: ', sensor_3_m_4.shape)
```

```
sensor_3: (6624, 38)
sensor_3_m_1: (6624, 38)
sensor_3_m_2: (6624, 38)
sensor_3_m_3: (6624, 38)
sensor_3_m_4: (6624, 38)
```

1.4.3 Generate the matrix as per the specifications in the paper.

Each row will have the measurements of traffic from the sensor of interest and the m-closest sensors.

- The rows will include traffic information of the t-1, t-2,..., t-r observations.
- The rows are organized by sensor, and by timestep: [sensor of interest @ t-1,...,sensor of interest @ t-r, ... , m-closest sensor @ t-1,...,m-closest sensor @ t-r]

```

[ ]: r = 3 # set r to any value

# Minimum number of rows across all dataframes
min_rows = min(sensor_3.shape[0], sensor_3_m_1.shape[0], sensor_3_m_2.shape[0],
↳ sensor_3_m_3.shape[0], sensor_3_m_4.shape[0])

# Initialize an empty list to store all row vectors
row_vectors = []

# Iterate over each index from r to min_rows
for i in tqdm(range(r, min_rows-1)):
    # Generate a list of indexes you're interested in. In this case, it's [i-r,
↳ i-r+1, ..., i]

    # ind = list(range(i-r, i+1))
    # indexes = list(range(i-r+1, i+1))

    ind = list(range(i+1, i-r, -1))
    indexes = list(range(i, i-r, -1))

    # Get the desired elements
    sensor_3_traffic = sensor_3.loc[ind, '10'].values
    sensor_3_m_1_traffic = sensor_3_m_1.loc[indexes, '10'].values
    sensor_3_m_2_traffic = sensor_3_m_2.loc[indexes, '10'].values
    sensor_3_m_3_traffic = sensor_3_m_3.loc[indexes, '10'].values
    sensor_3_m_4_traffic = sensor_3_m_4.loc[indexes, '10'].values

    # Concatenate them into a 1xr*5 row vector
    row_vector = np.concatenate([sensor_3_traffic, sensor_3_m_1_traffic,
↳ sensor_3_m_2_traffic, sensor_3_m_3_traffic, sensor_3_m_4_traffic])

    # Append the row vector to our list
    row_vectors.append(row_vector)

# Convert our list of row vectors into a 2D numpy array
traffic_764632 = pd.DataFrame(row_vectors)
traffic_764632

```

100%| | 6620/6620 [00:12<00:00, 529.83it/s]

```

[ ]:
0    224.0  258.0  228.0  205.0  487.0  435.0  447.0  478.0  436.0  379.0  \
1    248.0  224.0  258.0  228.0  540.0  487.0  435.0  462.0  478.0  436.0
2    299.0  248.0  224.0  258.0  539.0  540.0  487.0  450.0  462.0  478.0
3    279.0  299.0  248.0  224.0  518.0  539.0  540.0  457.0  450.0  462.0
4    307.0  279.0  299.0  248.0  489.0  518.0  539.0  409.0  457.0  450.0

```

...
6615	403.0	346.0	419.0	379.0	320.0	323.0	344.0	378.0	432.0	431.0			
6616	406.0	403.0	346.0	419.0	290.0	320.0	323.0	445.0	378.0	432.0			
6617	348.0	406.0	403.0	346.0	337.0	290.0	320.0	466.0	445.0	378.0			
6618	375.0	348.0	406.0	403.0	294.0	337.0	290.0	342.0	466.0	445.0			
6619	343.0	375.0	348.0	406.0	286.0	294.0	337.0	293.0	342.0	466.0			

	10	11	12	13	14	15
0	567.0	557.0	568.0	452.0	434.0	418.0
1	604.0	567.0	557.0	465.0	452.0	434.0
2	593.0	604.0	567.0	515.0	465.0	452.0
3	588.0	593.0	604.0	396.0	515.0	465.0
4	580.0	588.0	593.0	463.0	396.0	515.0

...
6615	401.0	361.0	385.0	408.0	371.0	308.0
6616	349.0	401.0	361.0	325.0	408.0	371.0
6617	371.0	349.0	401.0	346.0	325.0	408.0
6618	366.0	371.0	349.0	343.0	346.0	325.0
6619	413.0	366.0	371.0	380.0	343.0	346.0

[6620 rows x 16 columns]

1.4.4 Tests - Sensor 764632

Estimation

```
[ ]: #####
####    Definition of "Hyperparameters"
#####
days = 1 # Max=31.97 (available data)
t = int( (60/5)*12 * days)
t = traffic_764632.shape[0]

#t = traffic_737433.shape[0] # Number of points to be tested on, and times the
    ↪ coefficients will be updated.
    # The coefficients w are calculatd for each of these points, the idea
    ↪ is to simulate an on-line stream of data.

X = traffic_764632.iloc[:t, 1:]

"""
    Update this if using more input variables, # the function is handling a
    ↪ 15-dimensional, second order polynomial.
"""

polynomial_degree = 2
"""
```

USING Total (vs. Max) EXPANCTION TERMS
Number of terms in the weights matrix:

"""

```
target_values = traffic_764632.iloc[:, 0]
# Generate Y as target_values (real Y's)
```

```
# Initialize weights and estimations
weights_over_time = []
y_hat = []
```

```
noise = np.random.normal(scale= 10 , size=(t))
```

```
#####
###      Online estimation of coefficients
#####
```

```
for i in tqdm(range(t)):
    x_i = X.iloc[i, :]
```

```
    # Normalize and scale to -1,1 the input:
```

```
    x_i = ( x_i - x_i.min() ) / ( x_i.max() - x_i.min() ) * 2 - 1
```

```
    weight_predictions, _ = online_kaczmarz_legendre_multiple(x_i,
↳ [target_values[i] + noise[i]], polynomial_degree)
```

```
    #De-normalize rescale the weights:
```

```
    weight_predictions = (((weight_predictions + 1) / 2) * ( x_i.max() - x_i.
↳ min() ) + x_i.min() )
```

```
    # Use predicted weights to compute y_hat
```

```
    y_predictions = generate_multi_legendre_design_matrix(x_i,
↳ polynomial_degree) @ weight_predictions.T
```

```
    # Store the values of predicted y and estimated weights
```

```
    y_hat.append(y_predictions)
    weights_over_time.append(weight_predictions)
```

```
print("Done carajo")
```

3% | 204/6620 [09:27<5:05:30, 2.86s/it]

```
[ ]: weights_over_time = np.array(weights_over_time)
y_hat_ = np.array(y_hat) #####
print('y_hat: ', y_hat_.shape)

print('weights_over_time: ', weights_over_time.shape)

weight = weights_over_time[-1]
Weights = pd.DataFrame({
    'Estimated_Weights': weight
})

# Style DataFrame
# Weights.style.format("{:.4f}")

print('Weights: ', Weights.shape)
```

```
y_hat: (720, 1)
weights_over_time: (720, 136)
Weights: (136, 1)
```

Results

```
[ ]: #####
#### Results
#####

Predicted_Values = y_hat_.flatten()
print('Predicted_Values: ', Predicted_Values.shape)
Real_Values = target_values
print('Real_Values: ', Real_Values.shape)
difference = (Real_Values-Predicted_Values).T

Y = pd.DataFrame({
    'Predicted_Values': Predicted_Values,
    'Real_Values': Real_Values,
    'Difference': difference
})

# Style DataFrame
Y[-10:].style.format("{:.4f}")
```

```
Predicted_Values: (720,)
Real_Values: (720,)
```

```
[ ]: <pandas.io.formats.style.Styler at 0x161b5b7f0>
```

Plots

```
[ ]: # Plot the accuracy
plt.figure(figsize=(8, 6))

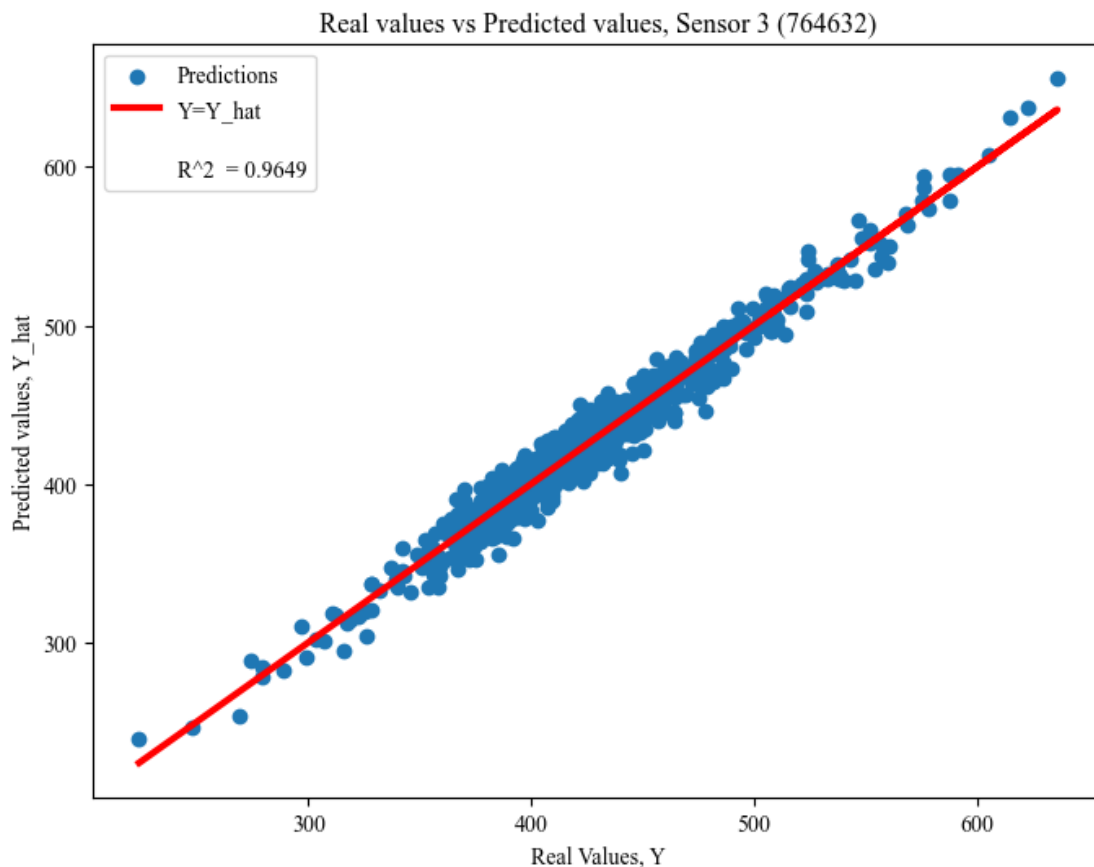
r2 = r2_score(target_values, y_hat_)
print('r2: ', r2)

plt.scatter(target_values, y_hat_, label='Predictions')
plt.plot(target_values, target_values, color='red', linewidth = 3,
         label=f'Y=Y_hat')
plt.scatter(target_values, target_values, marker='', label=f'\nR^2 = {r2:.4f}')

plt.xlabel('Real Values, Y')
plt.ylabel('Predicted values, Y_hat')
plt.title('Real values vs Predicted values, Sensor 3 (764632)')
plt.legend()

plt.show()
```

r2: 0.9649484225792238




```
[ ]: # Plot the traffic
n = t

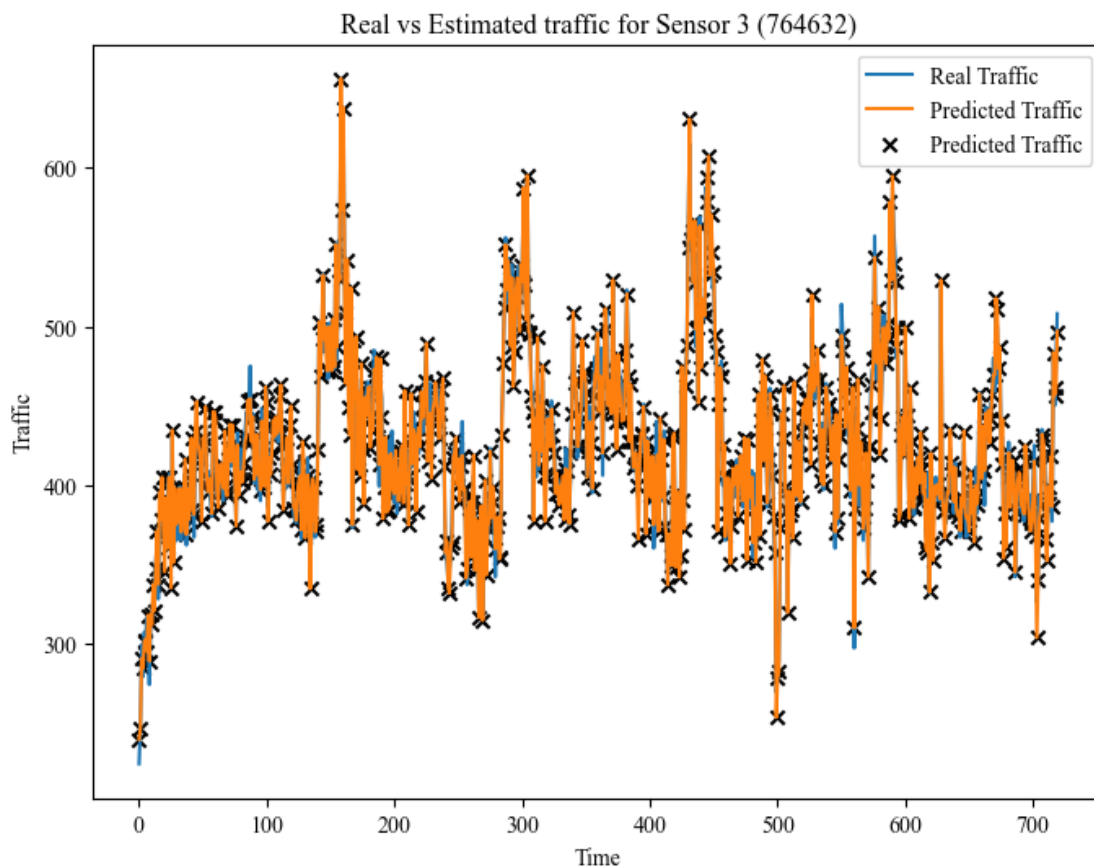
plt.figure(figsize=(8, 6))

plt.plot(Y['Real_Values'][-n:],label='Real Traffic')
plt.plot(Y['Predicted_Values'][-n:],label='Predicted Traffic')
plt.scatter(Y[-n:].index, Y['Predicted_Values'][-n:], marker='x', color = 'black',label='Predicted Traffic')

plt.xlabel('Time')
plt.ylabel('Traffic')
plt.title('Real vs Estimated traffic for Sensor 3 (764632)')
plt.legend()

plt.savefig('./Figures/traffic_sensor_3.png')

plt.show()
```



```

[ ]: ## Day Before Ignition

# Extract data and generate time values
# n = int(t / days)
n = 31 + 7

num_entries = len(Y['Real_Values'][(144*(n-1)+1):144*(n)])
time_range = pd.date_range(start='7:00', end='19:00', freq='5min')
time_values = np.tile(time_range, num_entries // len(time_range) + 1)[:
    ↪num_entries]

# Prepare plot data
plot_df = pd.DataFrame({
    'Time': time_values,
    'Real_Values': Y['Real_Values'][(144*(n-1)+1):144*(n)].values,
    'Predicted_Values': Y['Predicted_Values'][(144*(n-1)+1):144*(n)].values
})

# Plot data
fig, ax = plt.subplots(figsize=(10, 6))
ax.plot('Time', 'Real_Values', data=plot_df, linewidth=1, color='red', ↪
    ↪label='Real Traffic')
ax.plot('Time', 'Predicted_Values', data=plot_df, linestyle=':', ↪
    ↪label='Predicted Traffic')

# Set x-axis format and locator
ax.xaxis.set_major_locator(mdates.HourLocator(interval=2))
ax.xaxis.set_major_formatter(mdates.DateFormatter('%I %p'))

# Set x limits and titles
ax.set_xlim(plot_df['Time'].min() - pd.Timedelta(minutes=30), plot_df['Time'].
    ↪max() + pd.Timedelta(minutes=30))
ax.set(xlabel='Time of day', ylabel='Traffic flow', title='Real vs Estimated ↪
    ↪traffic for Sensor 3 (764632) from 7 am to 7 pm \n Online-Kaczmarz')
ax.legend()

plt.savefig('./Figures/before ignition - Change.png')

plt.show()

## Day After Ignition

# Extract data and generate time values
# n = int(t / days)
n = 31 + 9

```

```

num_entries = len(Y['Real_Values'][(144*(n-1)+1):144*(n)])
time_range = pd.date_range(start='7:00', end='19:00', freq='5min')
time_values = np.tile(time_range, num_entries // len(time_range) + 1)[:
    ↪num_entries]

# Prepare plot data
plot_df = pd.DataFrame({
    'Time': time_values,
    'Real_Values': Y['Real_Values'][(144*(n-1)+1):144*(n)].values,
    'Predicted_Values': Y['Predicted_Values'][(144*(n-1)+1):144*(n)].values
})

# Plot data
fig, ax = plt.subplots(figsize=(10, 6))
ax.plot('Time', 'Real_Values', data=plot_df, linewidth=1, color='red',
    ↪label='Real Traffic')
ax.plot('Time', 'Predicted_Values', data=plot_df, linestyle=':',
    ↪label='Predicted Traffic')

# Set x-axis format and locator
ax.xaxis.set_major_locator(mdates.HourLocator(interval=2))
ax.xaxis.set_major_formatter(mdates.DateFormatter('%I %p'))

# Set x limits and titles
ax.set_xlim(plot_df['Time'].min() - pd.Timedelta(minutes=30), plot_df['Time'].
    ↪max() + pd.Timedelta(minutes=30))
ax.set(xlabel='Time of day', ylabel='Traffic flow', title='Real vs Estimated
    ↪traffic for Sensor 3 (764632) from 7 am to 7 pm \n Online-Kaczmarz')
ax.legend()

plt.savefig('./Figures/after ignition - Change.png')

plt.show()

```

```

[ ]: s1 = pd.read_csv('./Data/sensor_interest_1 737433.txt')
     s2 = pd.read_csv('./Data/sensor_interest_2 764848.txt')

```

```

[ ]:

```