
Table of Contents

1. Introduction

Our analysis aims to understand and predict parking availability across 57 distinct roads over a four-month period. The dataset includes information on 13,439,520 parking slots and captures various influencing factors such as weather conditions, transportation options, and nearby facilities like restaurants and schools. By analyzing these variables, we seek to identify patterns and key determinants of parking availability. This analysis will provide actionable insights for optimizing parking management through dynamic pricing, improving infrastructure, and enhancing the overall user experience. Understanding these dynamics will help us develop effective strategies to ensure better parking availability for users.

2. Data Loading and Merging

- Loading datasets
- Displaying Sample Data
- Merging three datasets

```python
# Importing required libraries
import pandas as pd
import numpy as np
import seaborn as sns
```

```python
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score
from sklearn.linear_model import LinearRegression

# Load datasets
ground_df = pd.read_csv('groundtruth.csv')
weather_df = pd.read_csv('weather_features.csv')
road_df = pd.read_csv('road_features.csv')

ground_df.head()
```

```
   Unnamed: 0  road_segment_id            timestamp  max_capacity
occupied  \
0           0            20026  2019-03-01 06:00:00             7
3
1           1            20026  2019-03-01 06:09:00             7
4
2           2            20026  2019-03-01 06:11:00             7
4
3           3            20026  2019-03-01 06:19:00             7
3
4           4            20026  2019-03-01 06:20:00             7
3

   available
0          4
1          3
2          3
3          4
4          4
```

```python
weather_df.head()
```

```
   Unnamed: 0  road_segment_id            timestamp  tempC
windspeedKmph  \
0           0            20026  2019-03-01 06:00:00     24
18
1           1            20026  2019-03-01 06:09:00     24
18
2           2            20026  2019-03-01 06:11:00     24
18
3           3            20026  2019-03-01 06:19:00     24
18
4           4            20026  2019-03-01 06:20:00     24
18
```

```
   precipMM
0       0.0
1       0.0
2       0.0
3       0.0
4       0.0

road_df.head()

   Unnamed: 0  road_segment_id  commercial  residential
transportation  \
0           0            20026        58.0           32
0
1       21960            20057        92.0           14
0
2       43920            20069        35.0            5
1
3       65880            20190        33.0            7
1
4       87840            20198        73.0            4
1

   schools  eventsites  restaurant  shopping  office  supermarket  \
0        4           2         100       100      65           63
1        0           2         100       100     100           66
2        0           1         100       100      43           21
3        0           1         100       100      65           26
4        0           2         100       100      40           10

   num_off_street_parking  off_street_capa
0                       4              462
1                       4              335
2                       4              442
3                       7              719
4                       4              277

# Merge groundtruth with weather_features on road_segment_id and
timestamp
merged_df = pd.merge(ground_df, weather_df, on=['road_segment_id',
'timestamp'])

# Merge the result with road_features on road_segment_id
df = pd.merge(merged_df, road_df, on='road_segment_id')

df.head()

   Unnamed: 0_x  road_segment_id           timestamp  max_capacity
occupied  \
0             0            20026  2019-03-01 06:00:00             7
3
```

```
1             1            20026  2019-03-01 06:09:00             7
4
2             2            20026  2019-03-01 06:11:00             7
4
3             3            20026  2019-03-01 06:19:00             7
3
4             4            20026  2019-03-01 06:20:00             7
3

   available  Unnamed: 0_y  tempC  windspeedKmph  precipMM  ...
residential  \
0          4             0     24             18       0.0  ...
32
1          3             1     24             18       0.0  ...
32
2          3             2     24             18       0.0  ...
32
3          4             3     24             18       0.0  ...
32
4          4             4     24             18       0.0  ...
32

   transportation  schools  eventsites  restaurant  shopping
office  \
0               0        4           2         100       100      65

1               0        4           2         100       100      65

2               0        4           2         100       100      65

3               0        4           2         100       100      65

4               0        4           2         100       100      65


   supermarket  num_off_street_parking  off_street_capa
0           63                       4              462
1           63                       4              462
2           63                       4              462
3           63                       4              462
4           63                       4              462

[5 rows x 22 columns]
```

3. Data Preprocessing I

- Convert timestamp
- Extract few columns
- Checking duplicates

- Remove unnecessary columns
- Checking missing values
- Checking outliers
- Checking data quality issues

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1251720 entries, 0 to 1251719
Data columns (total 22 columns):
 #   Column                 Non-Null Count    Dtype  
---  ------                 --------------    -----  
 0   Unnamed: 0_x           1251720 non-null  int64  
 1   road_segment_id        1251720 non-null  int64  
 2   timestamp              1251720 non-null  object 
 3   max_capacity           1251720 non-null  int64  
 4   occupied               1251720 non-null  int64  
 5   available              1251720 non-null  int64  
 6   Unnamed: 0_y           1251720 non-null  int64  
 7   tempC                  1251720 non-null  int64  
 8   windspeedKmph          1251720 non-null  int64  
 9   precipMM               1251720 non-null  float64
 10  Unnamed: 0             1251720 non-null  int64  
 11  commercial             1229760 non-null  float64
 12  residential            1251720 non-null  int64  
 13  transportation         1251720 non-null  int64  
 14  schools                1251720 non-null  int64  
 15  eventsites             1251720 non-null  int64  
 16  restaurant             1251720 non-null  int64  
 17  shopping               1251720 non-null  int64  
 18  office                 1251720 non-null  int64  
 19  supermarket            1251720 non-null  int64  
 20  num_off_street_parking  1251720 non-null  int64  
 21  off_street_capa        1251720 non-null  int64  
dtypes: float64(2), int64(19), object(1)
memory usage: 210.1+ MB
```

3.1 Convert Timestamp

```
# Convert timestamp
df['timestamp'] = pd.to_datetime(df['timestamp'])
```

3.2 Creating New Features

```
# Extract the date part of the timestamp
df['date'] = df['timestamp'].dt.date

# Extract the time part of the timestamp
df['time'] = df['timestamp'].dt.time
```

3.3 Checing Duplicates

```
# Check for duplicates
duplicates = df.duplicated(subset=['road_segment_id', 'timestamp'])
print(f"Number of duplicate rows: {duplicates.sum()}")
```

```
Number of duplicate rows: 0
```

3.4 Remove unnecessary columns

```
# Remove the unnecessary columns
df = df.drop(['Unnamed: 0_x', 'Unnamed: 0_y', 'Unnamed: 0'], axis =
'columns')

df.shape
```

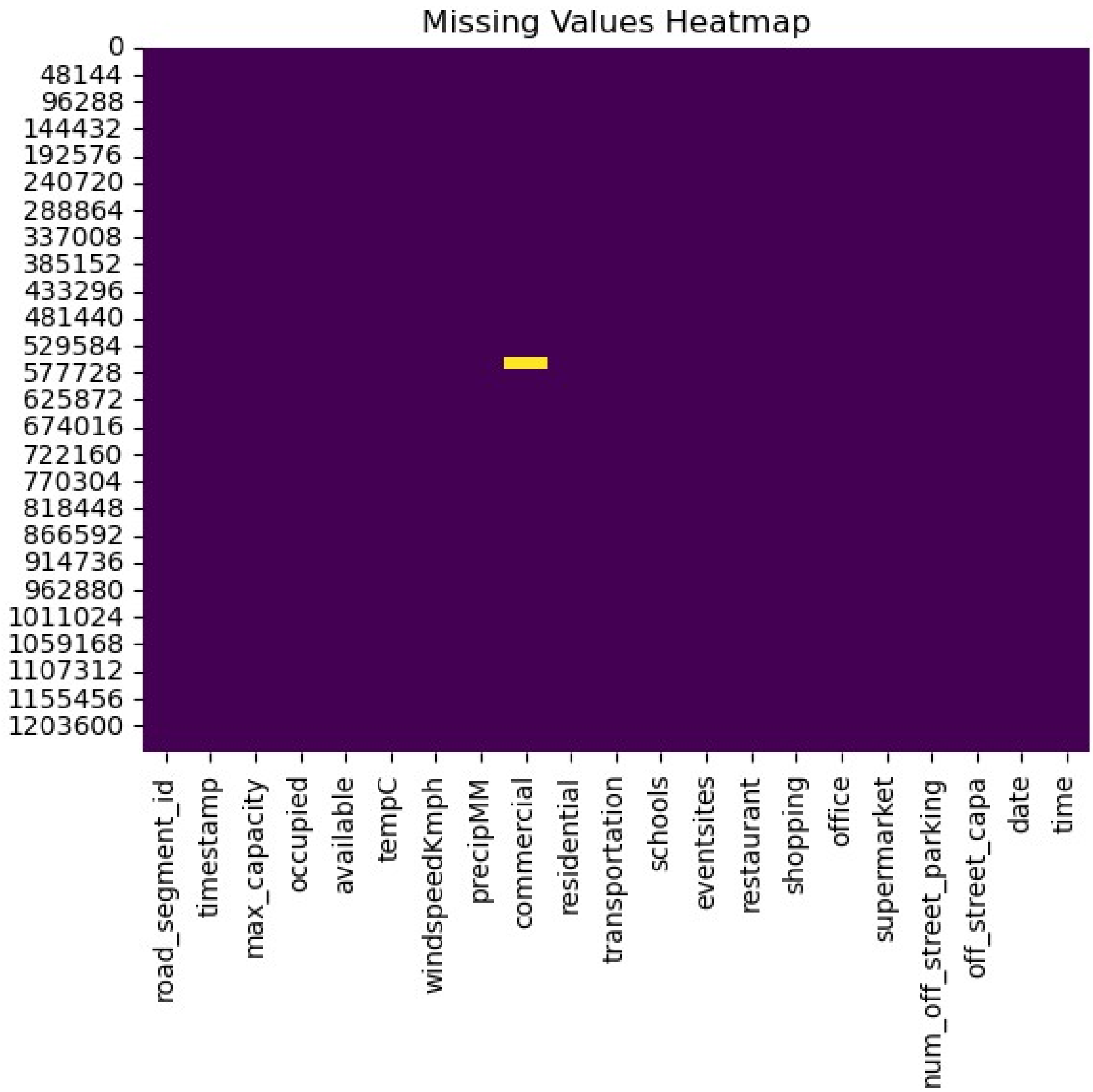
```
(1251720, 21)
```

3.5 Handling Missing Values

```
# Checking the null values
df.isnull().sum()
```

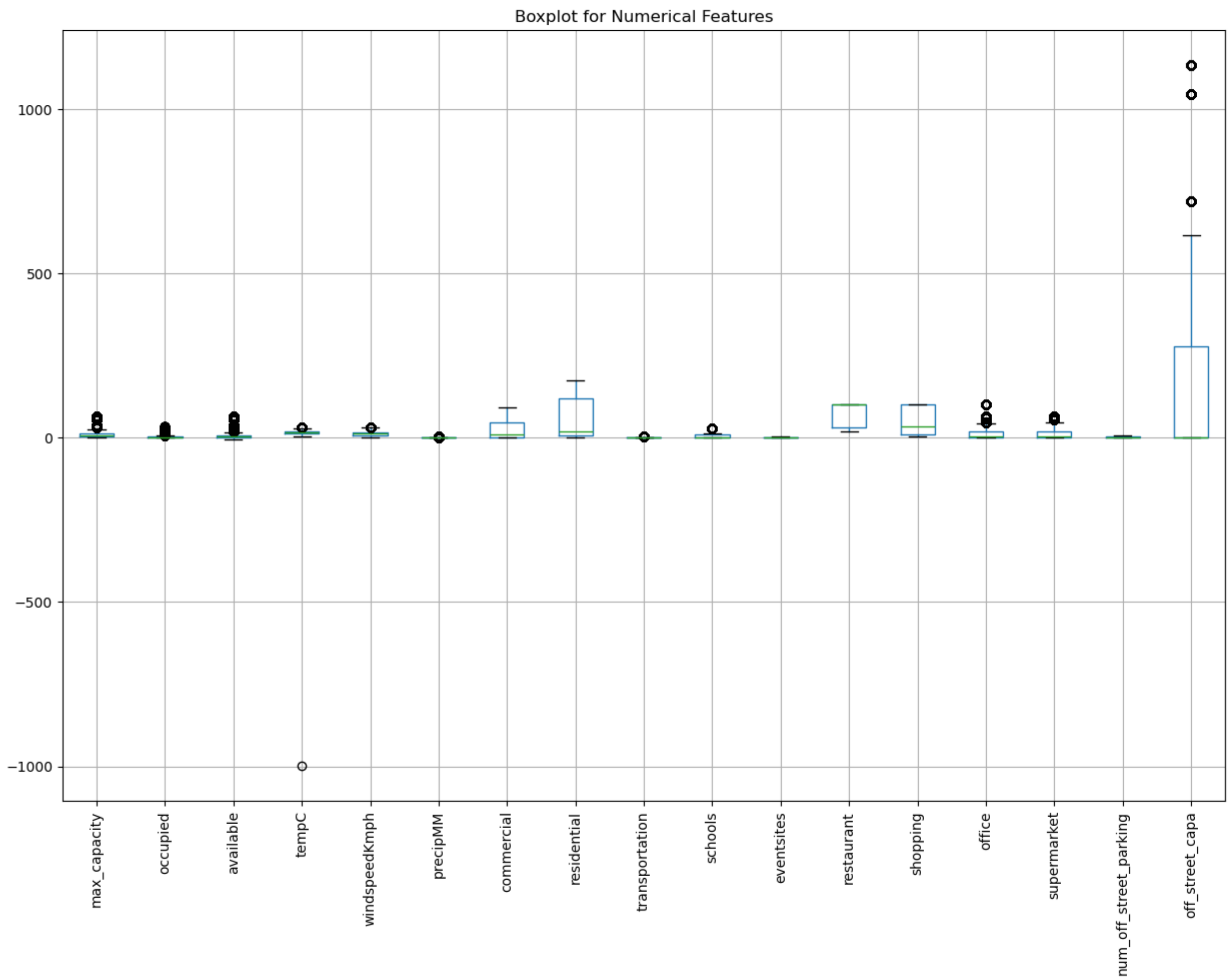
```
road_segment_id            0
timestamp                  0
max_capacity               0
occupied                   0
available                  0
tempC                      0
windspeedKmph              0
precipMM                   0
commercial             21960
residential                0
transportation             0
schools                    0
eventsites                 0
restaurant                 0
shopping                   0
office                     0
supermarket                0
num_off_street_parking     0
off_street_capa            0
date                       0
time                       0
dtype: int64
```

```
# Visualize missing values
sns.heatmap(df.isnull(), cbar=False, cmap='viridis')
plt.title('Missing Values Heatmap')
plt.show()
```

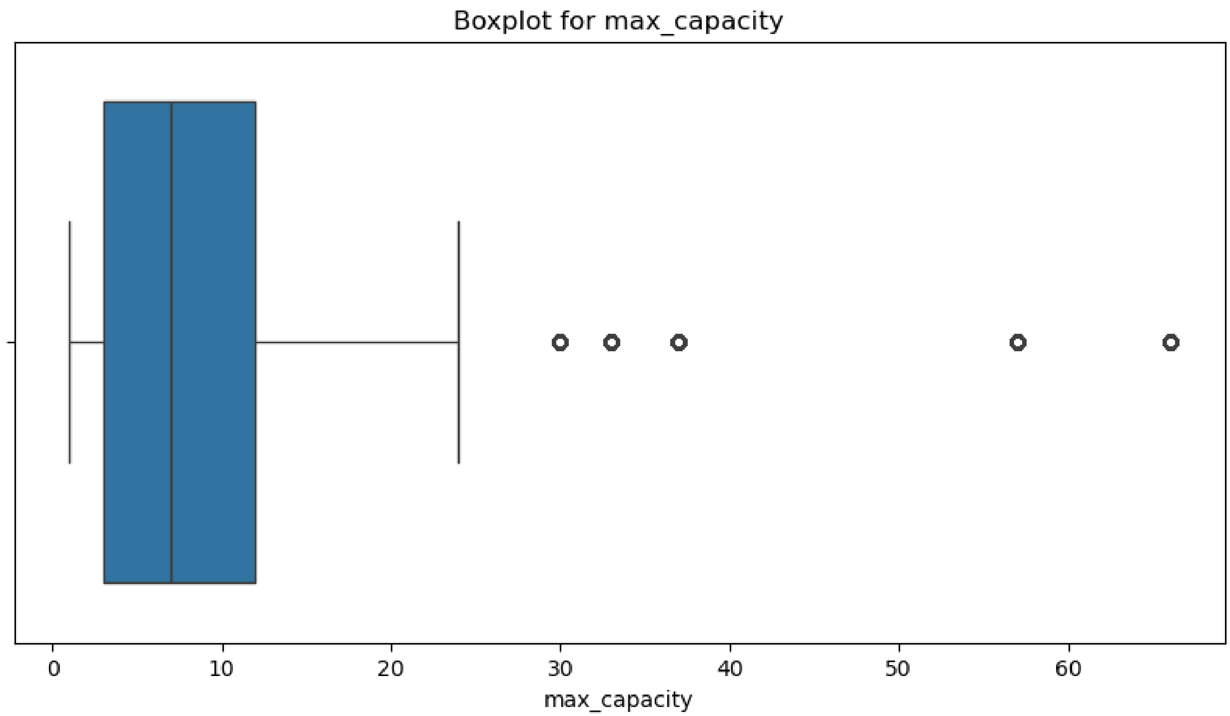


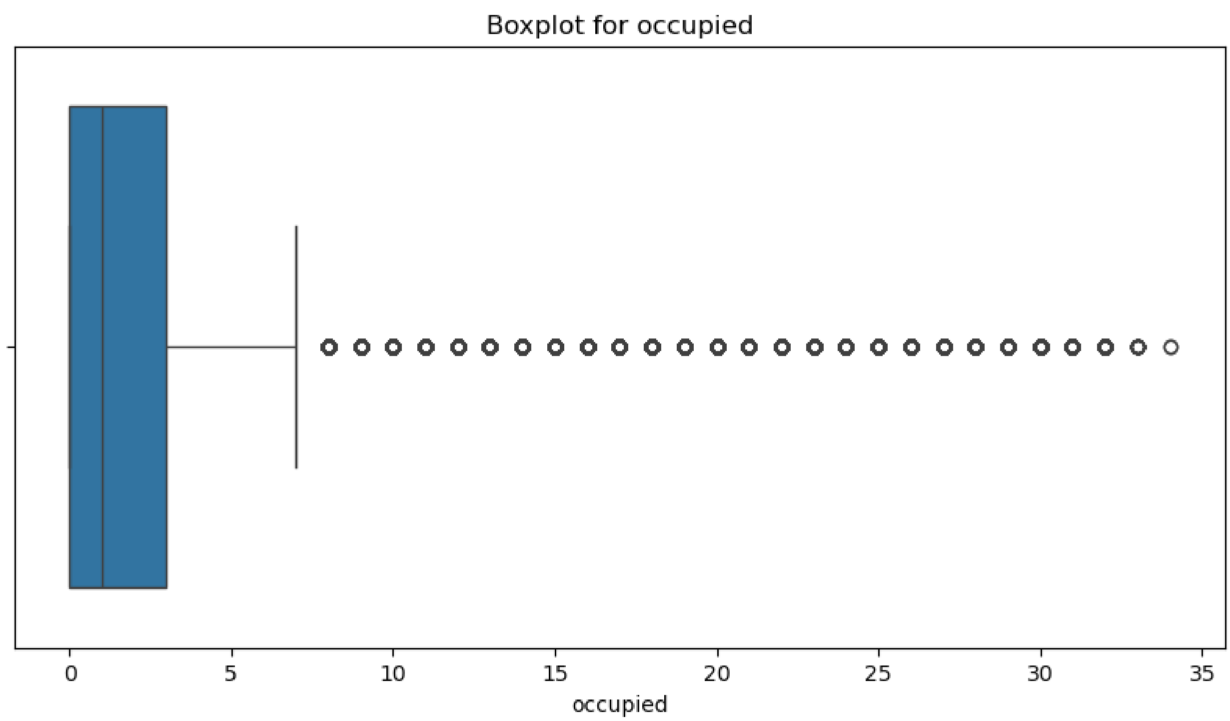
3.6 Outlier Detection

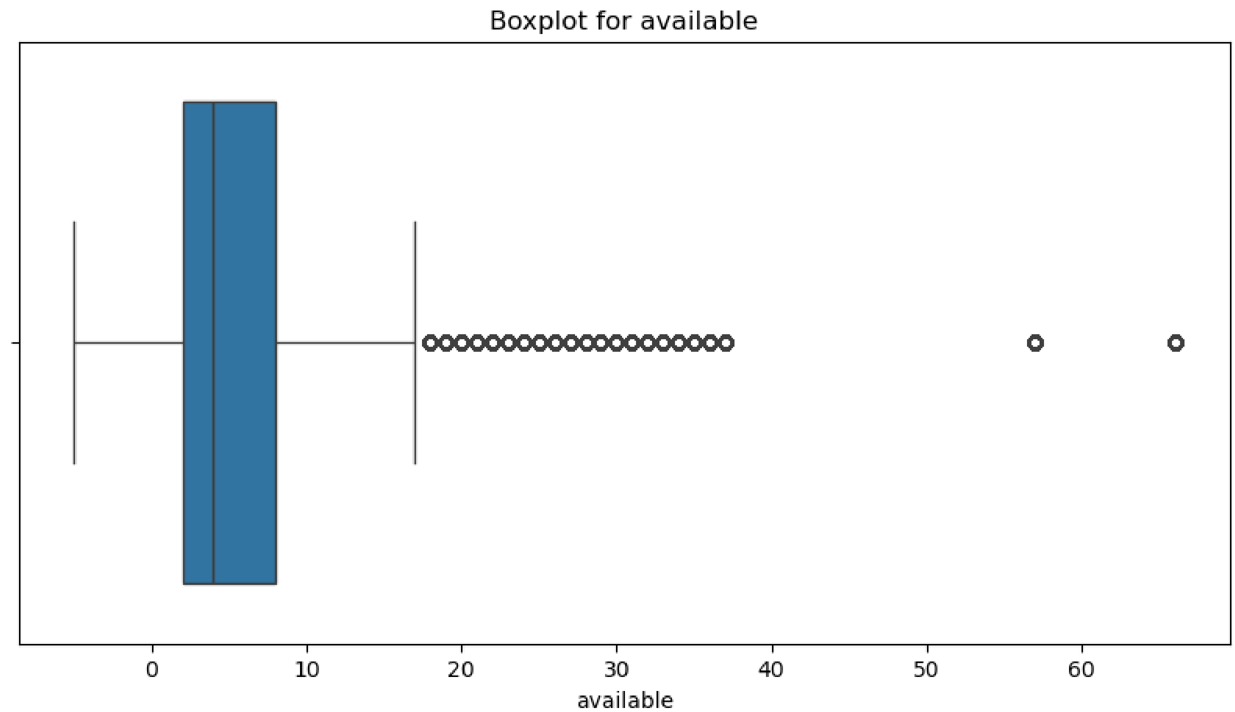
```
# Boxplot for numerical features to detect outliers
numerical_features = ['max_capacity', 'occupied', 'available',
'tempC', 'windspeedKmph', 'precipMM',
                      'commercial', 'residential', 'transportation',
'schools', 'eventsites',
                      'restaurant', 'shopping', 'office',
'supermarket', 'num_off_street_parking', 'off_street_capa']

plt.figure(figsize=(15, 10))
df[numerical_features].boxplot()
plt.xticks(rotation=90)
plt.title('Boxplot for Numerical Features')
plt.show()
```



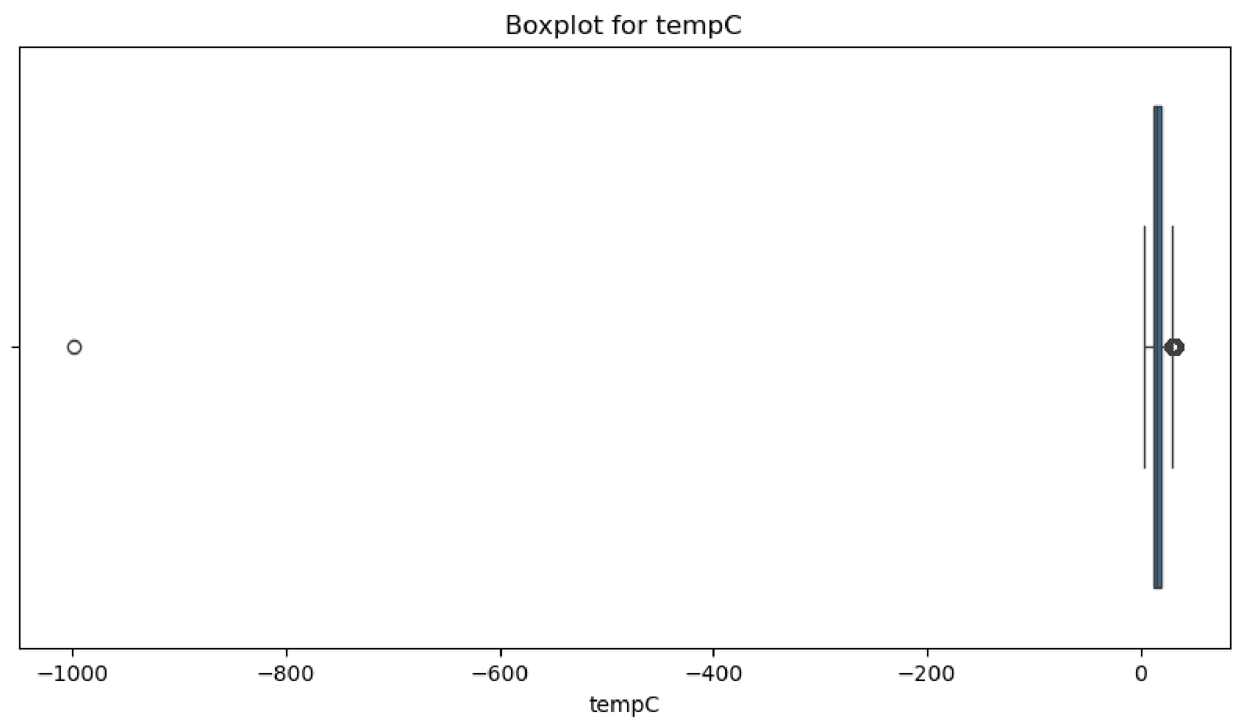

```
# Detailed boxplot for each feature
for feature in numerical_features:
    plt.figure(figsize=(10, 5))
    sns.boxplot(x=df[feature])
    plt.title(f'Boxplot for {feature}')
    plt.show()
```


Boxplot for max_capacity
0
10
20
30
40
50
60
max_capacity

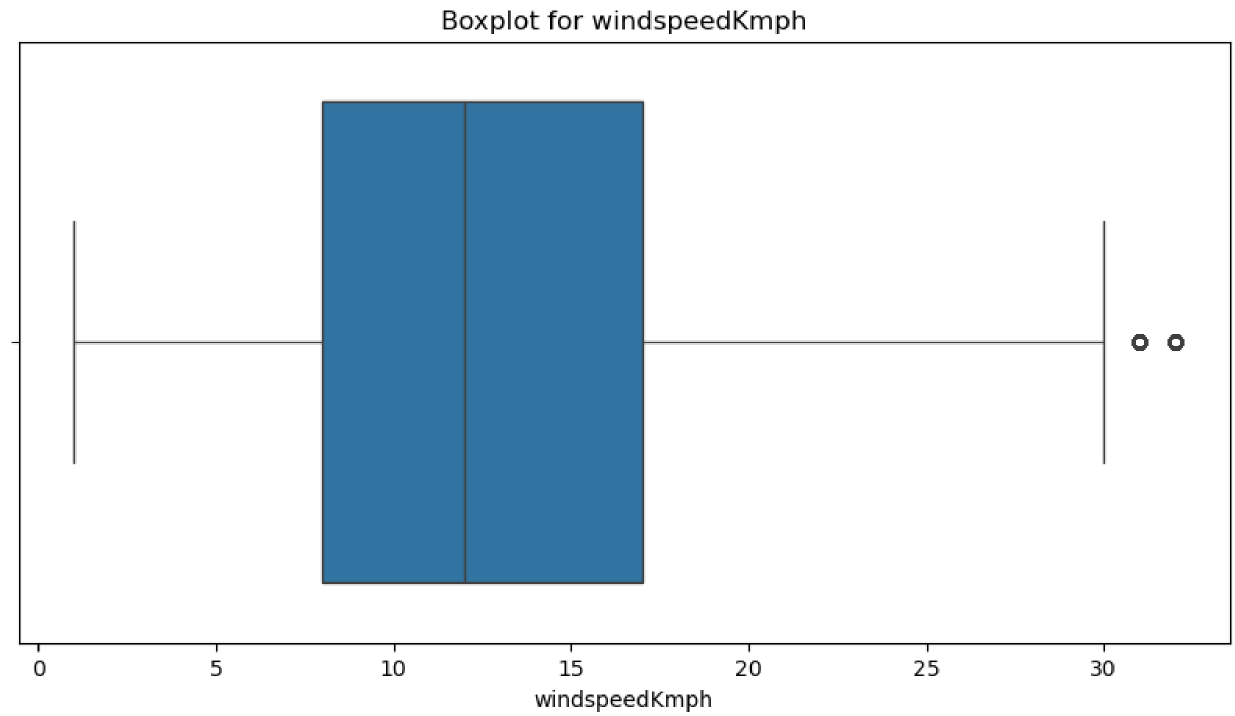

Boxplot for occupied
0
5
10
15
20
25
30
35
occupied



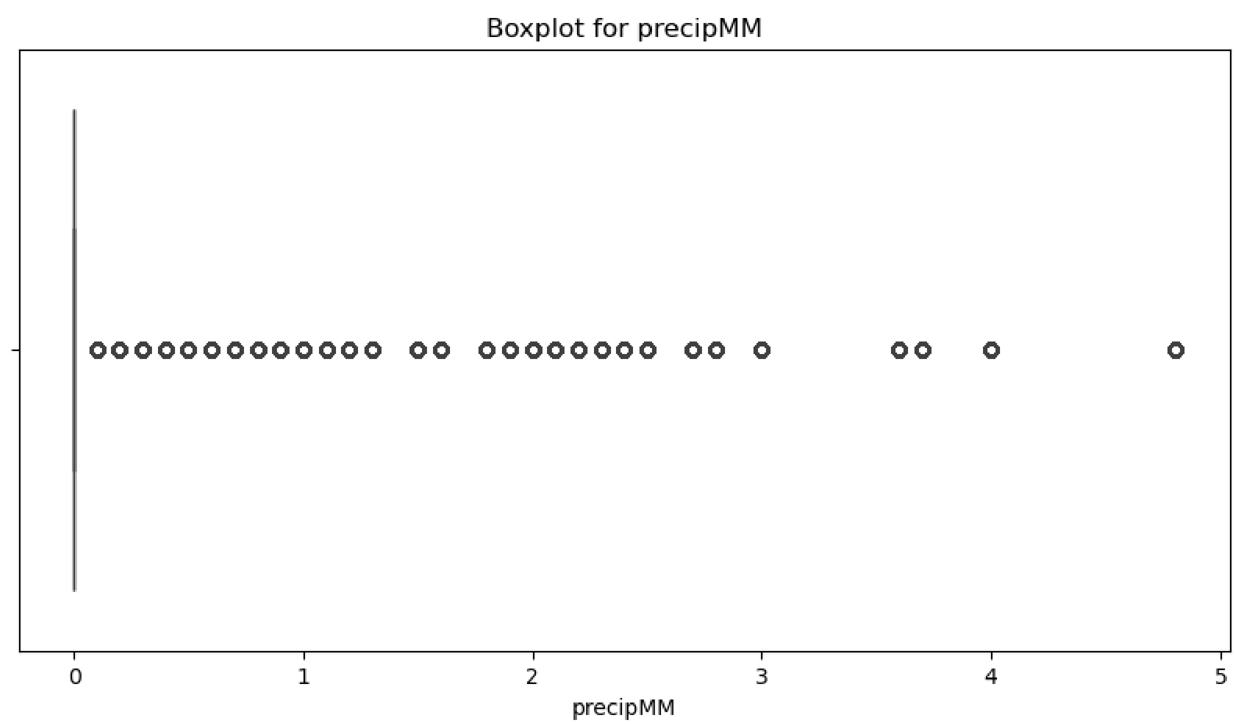
Boxplot for available
0
10
20
30
40
50
60
available



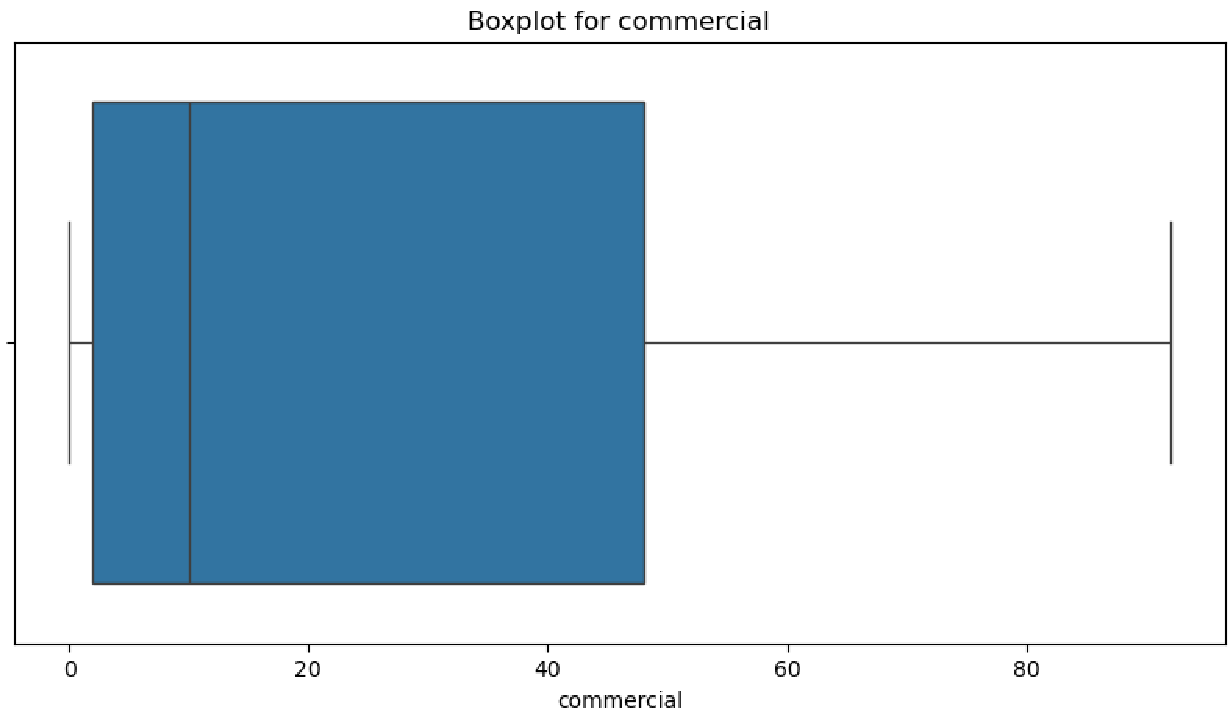
Boxplot for tempC
−1000
−800
−600
−400
−200
0
tempC

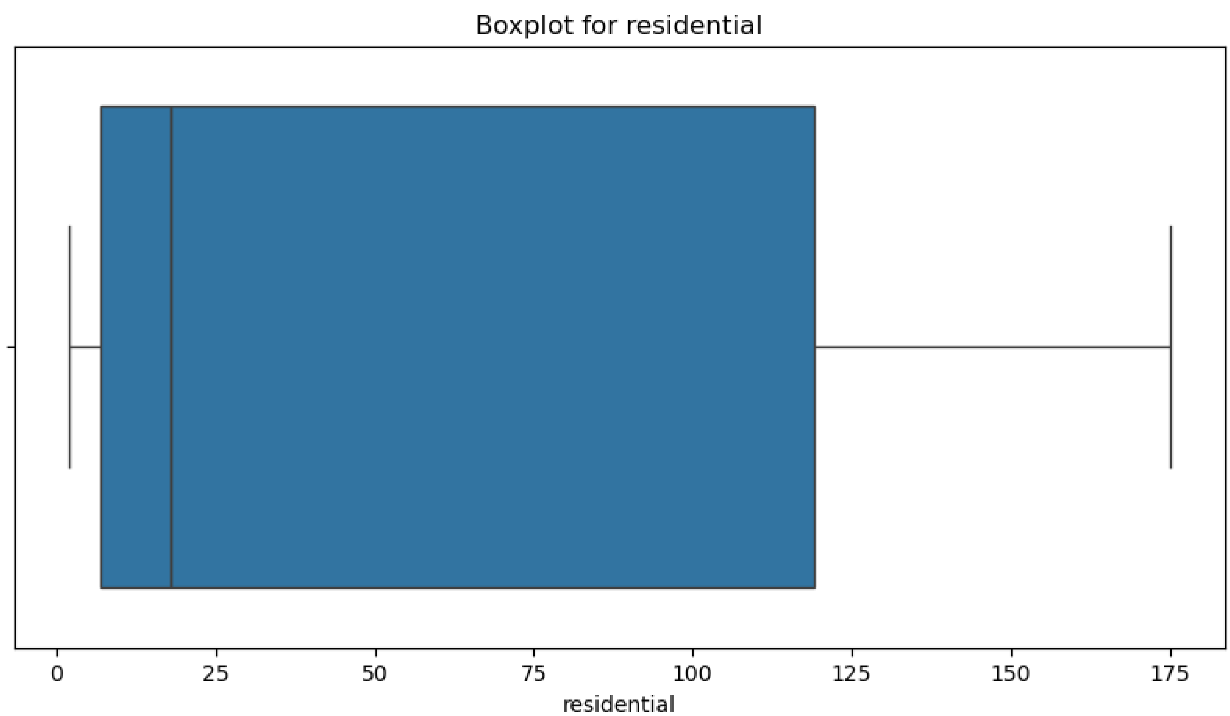


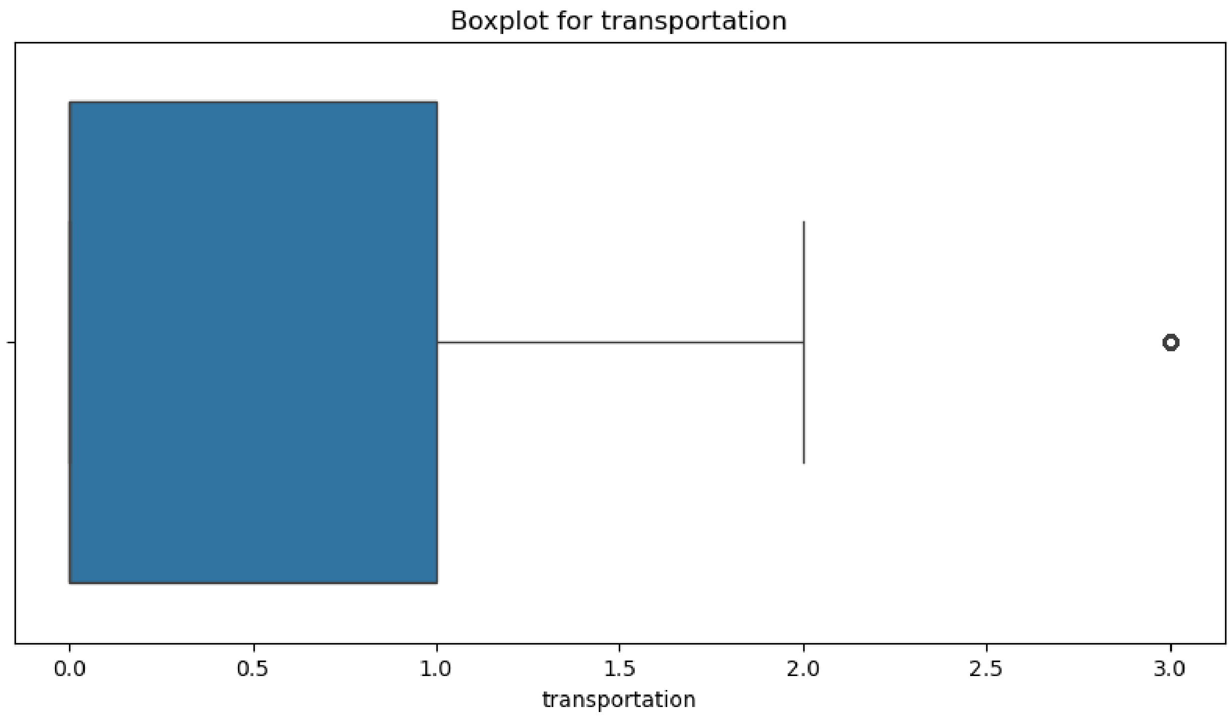
Boxplot for windspeedKmph
0
5
10
15
20
25
30
windspeedKmph

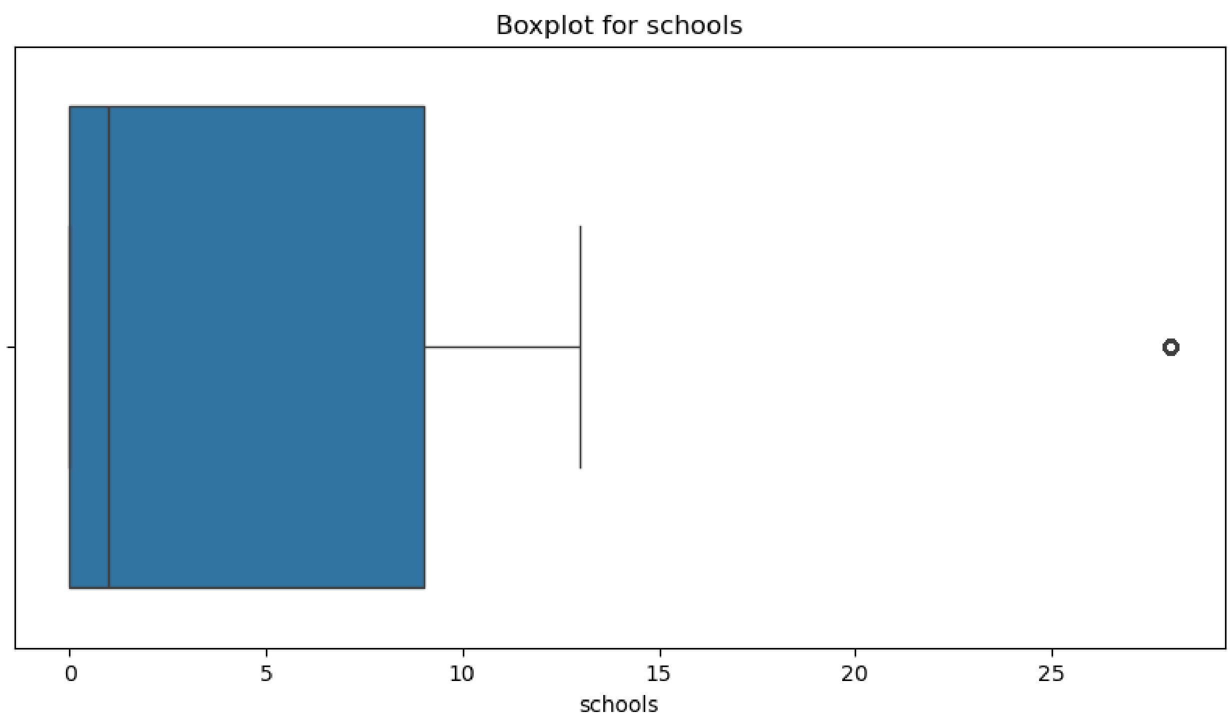


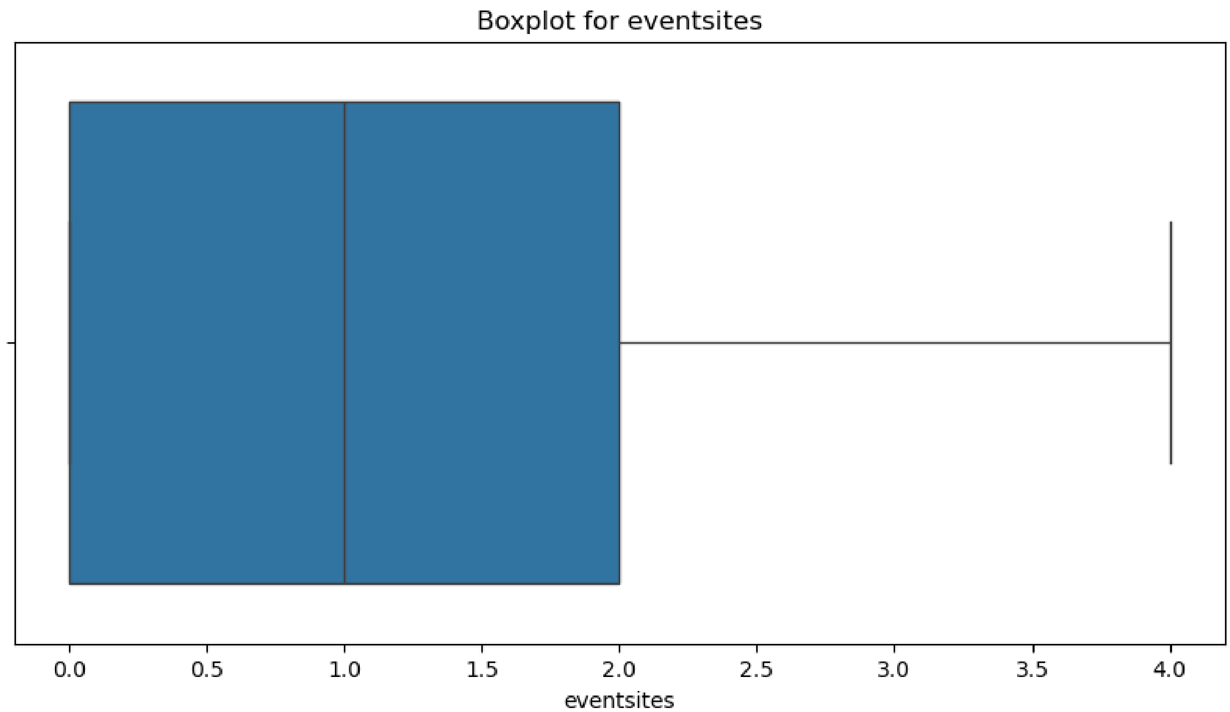
Boxplot for precipMM
0
1
2
3
4
5
precipMM

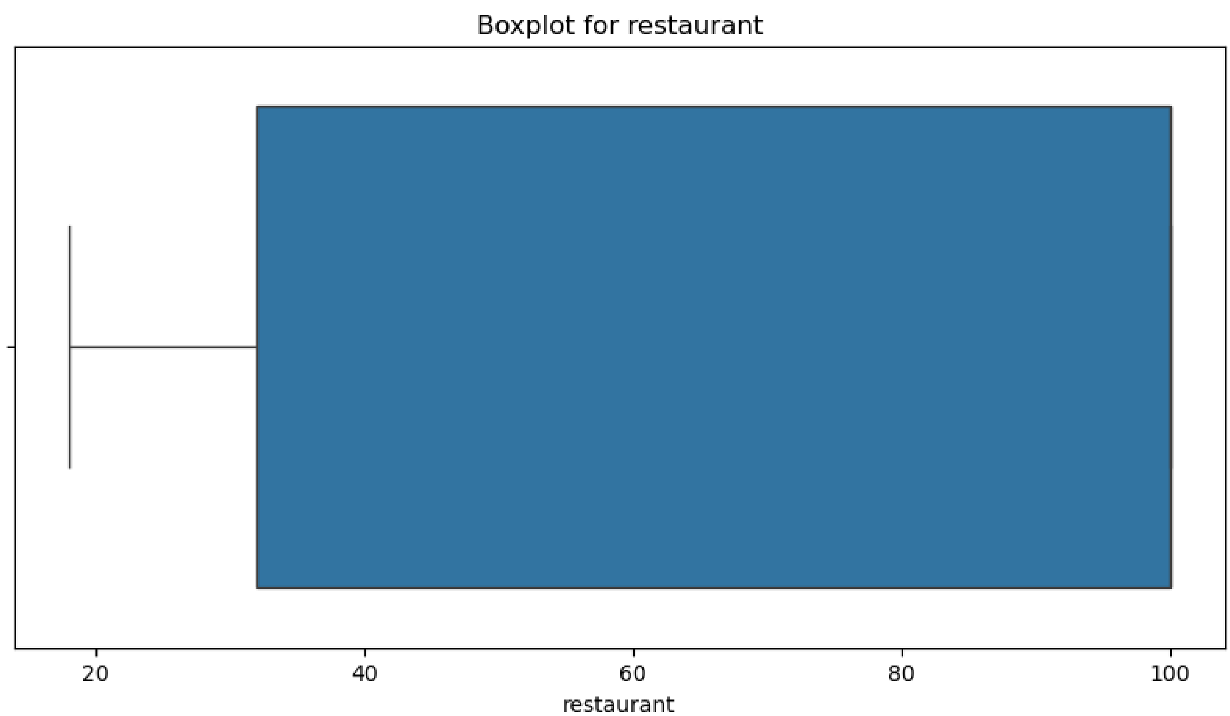

Boxplot for commercial
0
20
40
60
80
commercial

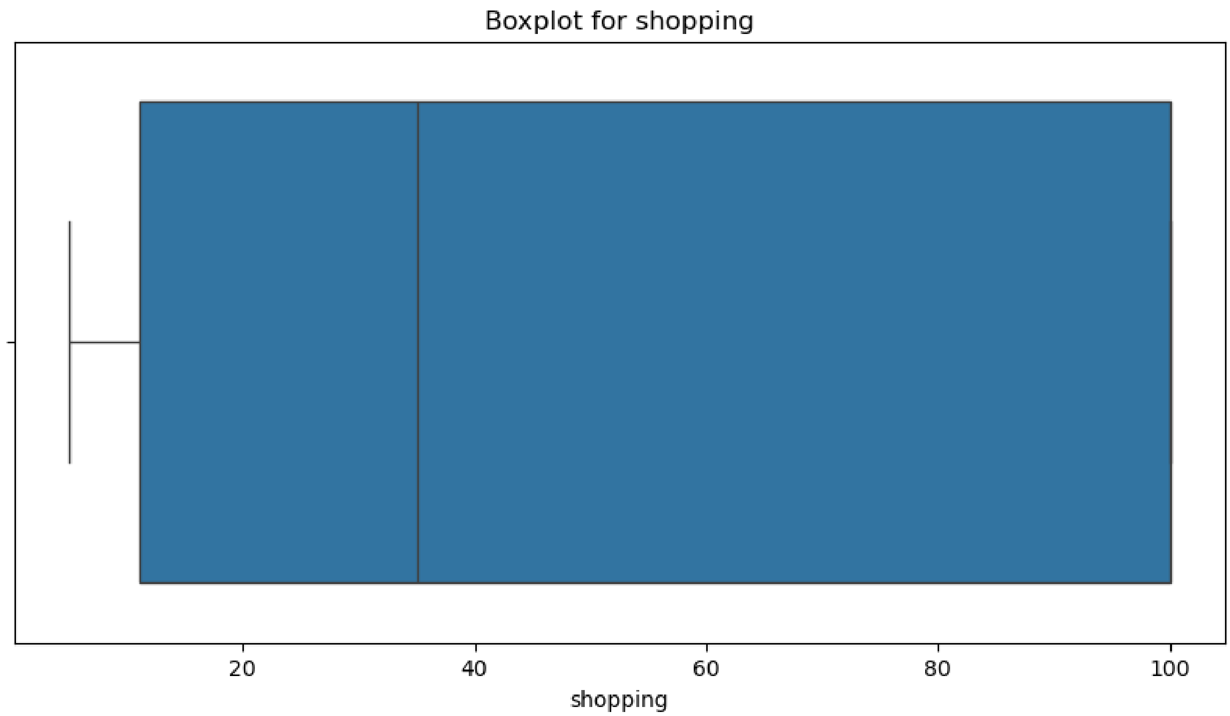

Boxplot for residential
0
25
50
75
100
125
150
175
residential

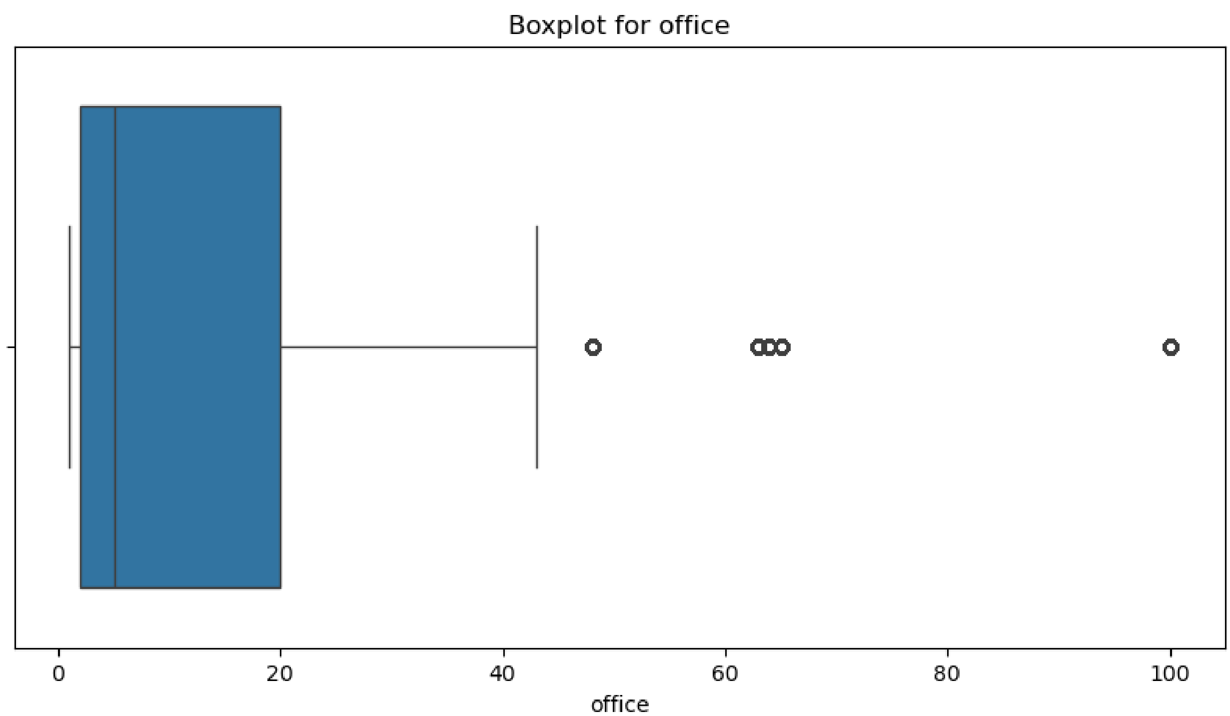

Boxplot for transportation
0.0
0.5
1.0
1.5
2.0
2.5
3.0
transportation

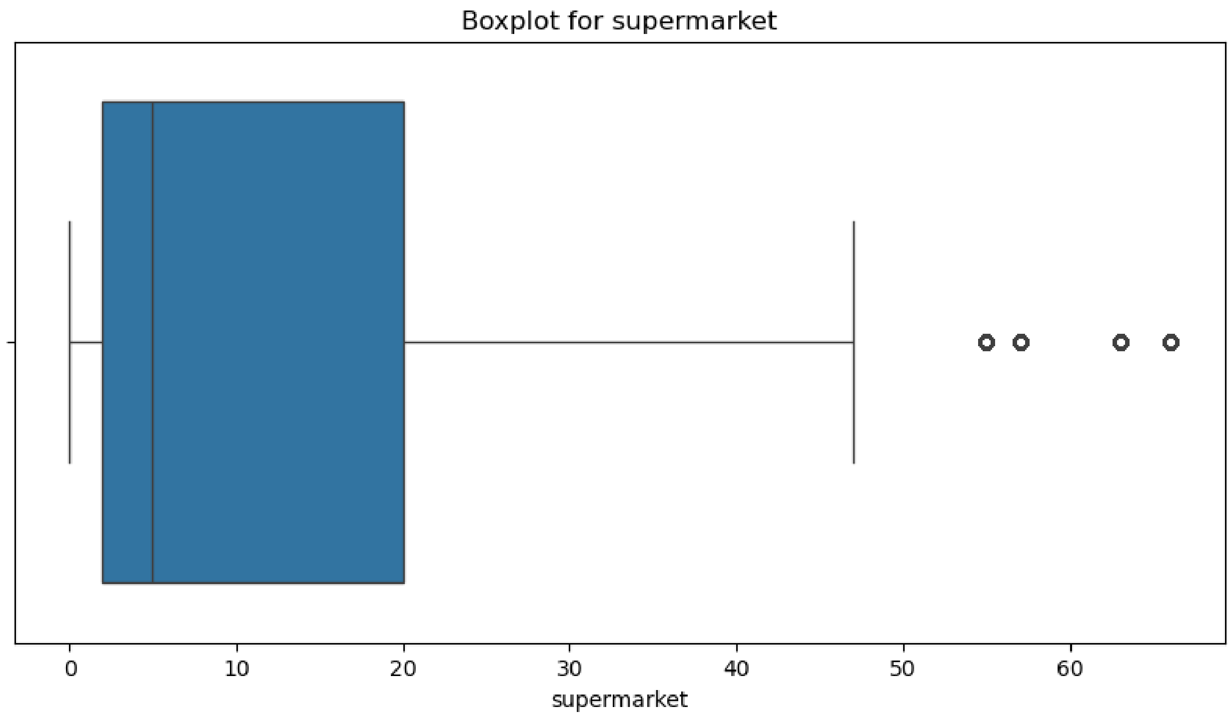

Boxplot for schools
0
5
10
15
20
25
schools

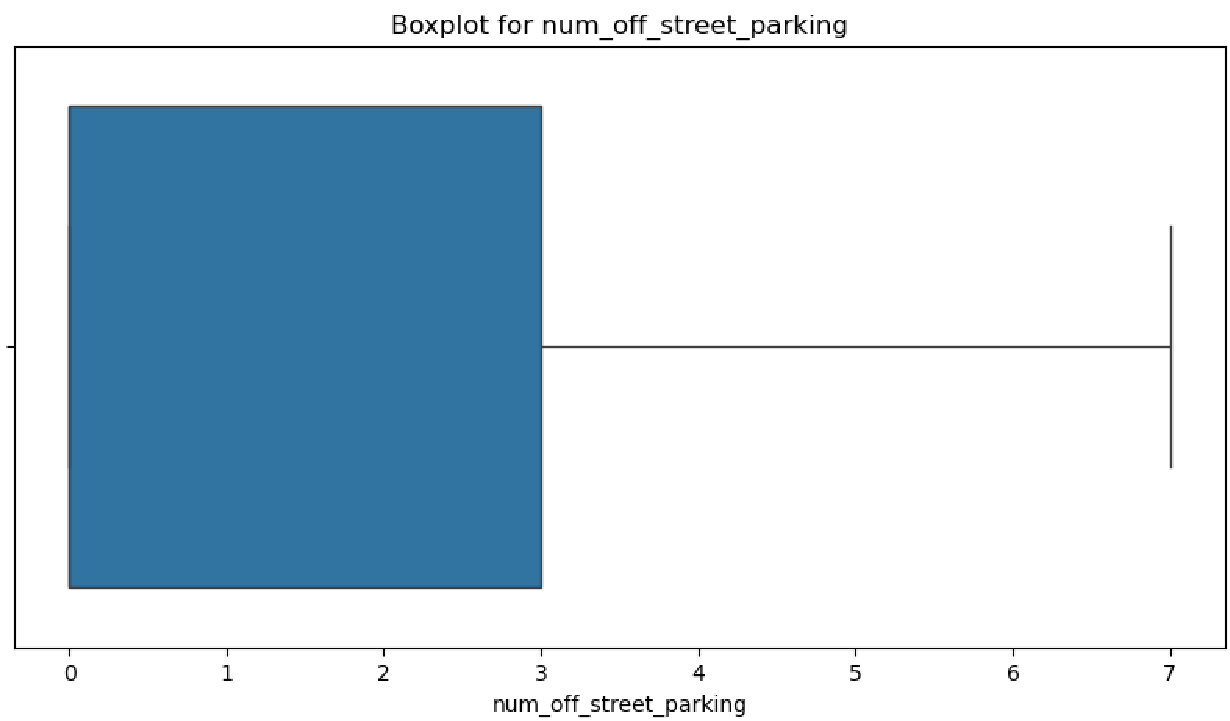

Boxplot for eventsites
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
eventsites

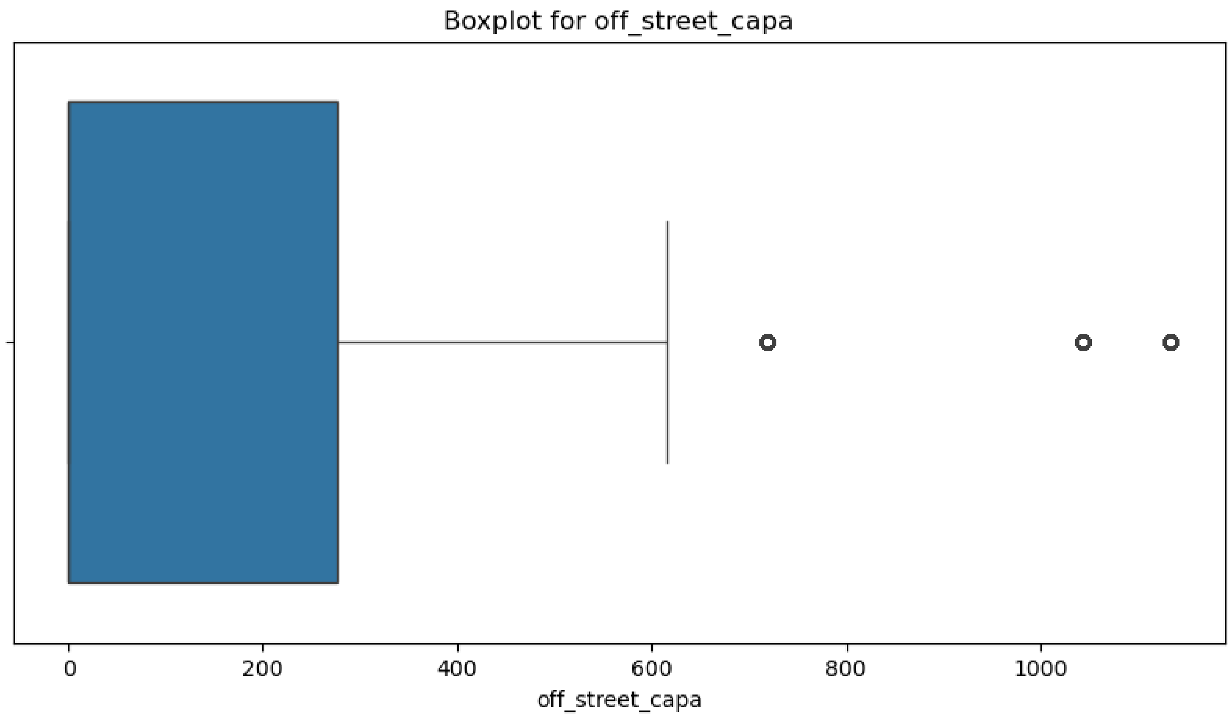

Boxplot for restaurant
20
40
60
80
100
restaurant


Boxplot for shopping
20
40
60
80
100
shopping


Boxplot for office
0
20
40
60
80
100
office


Boxplot for supermarket
0
10
20
30
40
50
60
supermarket


Boxplot for num_off_street_parking
0
1
2
3
4
5
6
7
num_off_street_parking




```
def count_outliers(df):

    outliers = {}
    total_points = df.shape[0]

    for column in df.select_dtypes(include=['float64',
'int64']).columns:
        # Calculate Q1 and Q3
        Q1 = df[column].quantile(0.25)
        Q3 = df[column].quantile(0.75)

        # Calculate IQR
        IQR = Q3 - Q1

        # Define outlier boundaries
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR

        # Count outliers
        num_outliers = df[(df[column] < lower_bound) | (df[column] >
upper_bound)].shape[0]
        percentage_outliers = (num_outliers / total_points) * 100

        outliers[column] = [num_outliers, percentage_outliers]

    # Convert dictionary to df
    outliers_df = pd.DataFrame.from_dict(outliers, orient='index',
```

```
columns=['Number of Outliers', 'Percentage of Outliers'])

    return outliers_df

outliers_df = count_outliers(df)
outliers_df
```

```
                        Number of Outliers  Percentage of Outliers
road_segment_id                     109800                8.771930
max_capacity                        109800                8.771930
occupied                             97081                7.755808
available                           160035               12.785208
tempC                                11629                0.929042
windspeedKmph                         2052                0.163934
precipMM                            284544               22.732240
commercial                               0                0.000000
residential                              0                0.000000
transportation                      219600               17.543860
schools                              21960                1.754386
eventsites                               0                0.000000
restaurant                               0                0.000000
shopping                                 0                0.000000
office                              131760               10.526316
supermarket                          87840                7.017544
num_off_street_parking                   0                0.000000
off_street_capa                      65880                5.263158
```

3.7 Data Quality issues

```
# Identifying negative values

def identify_negative_values(df, columns):
    negative_rows = df[(df[columns] < 0).any(axis=1)]
    return negative_rows

count_based_columns = ['max_capacity', 'occupied', 'available',
'windspeedKmph', 'precipMM',
                      'commercial', 'residential', 'transportation',
'schools', 'eventsites',
                      'restaurant', 'shopping', 'office',
'supermarket', 'num_off_street_parking', 'off_street_capa']

negative_values_df = identify_negative_values(df, count_based_columns)
negative_values_df
```

```
         road_segment_id           timestamp  max_capacity
occupied  \
7425               20026 2019-04-11 09:46:00             7         8

8178               20026 2019-04-15 12:32:00             7         8
```

```
12103              20026 2019-05-07 09:38:00             7         8

13917              20026 2019-05-17 10:45:00             7         9

16318              20026 2019-05-30 15:54:00             7         8

...                  ...                 ...           ...       ...

1228924            22942 2019-06-26 11:21:00             2         3

1228966            22942 2019-06-26 14:52:00             2         3

1229101            22942 2019-06-27 11:08:00             2         3

1229165            22942 2019-06-27 16:27:00             2         3

1229354            22942 2019-06-28 17:13:00             2         3


         available  tempC  windspeedKmph  precipMM  commercial
residential  \
7425            -1     14              4       0.0        58.0
32
8178            -1     23             13       0.0        58.0
32
12103           -1     13             15       0.0        58.0
32
13917           -2     14              7       0.0        58.0
32
16318           -1     11             18       0.0        58.0
32
...            ...    ...            ...       ...         ...
...
1228924         -1     12              8       0.0        20.0
10
1228966         -1     13              8       0.0        20.0
10
1229101         -1     13             17       0.0        20.0
10
1229165         -1     13             15       0.0        20.0
10
1229354         -1     13             20       0.0        20.0
10

         ...  schools  eventsites  restaurant  shopping  office
supermarket  \
7425     ...        4           2         100       100      65
63
8178     ...        4           2         100       100      65
```

```
63
12103    ...       4          2         100       100      65
63
13917    ...       4          2         100       100      65
63
16318    ...       4          2         100       100      65
63
...      ...     ...        ...         ...       ...     ...
...
1228924  ...       0          1         100       100      15
22
1228966  ...       0          1         100       100      15
22
1229101  ...       0          1         100       100      15
22
1229165  ...       0          1         100       100      15
22
1229354  ...       0          1         100       100      15
22

         num_off_street_parking  off_street_capa        date      time

7425                          4              462  2019-04-11  09:46:00

8178                          4              462  2019-04-15  12:32:00

12103                         4              462  2019-05-07  09:38:00

13917                         4              462  2019-05-17  10:45:00

16318                         4              462  2019-05-30  15:54:00

...                         ...              ...         ...       ...

1228924                       5             1133  2019-06-26  11:21:00

1228966                       5             1133  2019-06-26  14:52:00

1229101                       5             1133  2019-06-27  11:08:00

1229165                       5             1133  2019-06-27  16:27:00

1229354                       5             1133  2019-06-28  17:13:00


[1353 rows x 21 columns]

def count_negative_values(df, columns):
    negative_values = {}
    total_points = df.shape[0]
```

```
    for column in columns:
        # Count negative values
        num_negative_values = (df[column] < 0).sum()
        percentage_negative_values = (num_negative_values /
total_points) * 100

        negative_values[column] = [num_negative_values,
percentage_negative_values]

    # Convert dictionary to df
    negative_values_df = pd.DataFrame.from_dict(negative_values,
orient='index', columns=['Number of Negative Values', 'Percentage of
Negative Values'])

    return negative_values_df

negative_values_df = count_negative_values(df, count_based_columns)
negative_values_df
```

```
                        Number of Negative Values  \
max_capacity                                    0
occupied                                        0
available                                    1353
windspeedKmph                                   0
precipMM                                        0
commercial                                      0
residential                                     0
transportation                                  0
schools                                         0
eventsites                                      0
restaurant                                      0
shopping                                        0
office                                          0
supermarket                                     0
num_off_street_parking                          0
off_street_capa                                 0

                        Percentage of Negative Values
max_capacity                                 0.000000
occupied                                     0.000000
available                                    0.108091
windspeedKmph                                0.000000
precipMM                                     0.000000
commercial                                   0.000000
residential                                  0.000000
transportation                               0.000000
schools                                      0.000000
eventsites                                   0.000000
restaurant                                   0.000000
shopping                                     0.000000
```

```
office                                                      0.000000
supermarket                                                 0.000000
num_off_street_parking                                      0.000000
off_street_capa                                             0.000000
```

3.8 Summary of Findings

```
data_issues = [
    {
        "Problem/Logical Issue": "Missing values",
        "Affected Variable/s": "commercial",
        "Number of Observations": 21960,
        "Potential Issues": "Missing values can lead to inaccurate
analysis and model predictions.",
        "Handling Technique/s": "Imputation techniques such as filling
missing values with mean, median, or using interpolation."
    },
    {
        "Problem/Logical Issue": "Outliers",
        "Affected Variable/s": "Available, precipMM, transportation,
off_street_capa",
        "Number of Observations": "Various (see above)",
        "Potential Issues": "Outliers can distort the model training
process and lead to poor predictions.",
        "Handling Technique/s": "Identifying and removing outliers
using statistical methods like the cap value method."
    },
    {
        "Problem/Logical Issue": "Duplicates",
        "Affected Variable/s": "None",
        "Number of Observations": 0,
        "Potential Issues": "Multiple entries for the same
road_segment_id and timestamp can skew results.",
        "Handling Technique/s": "Identifying and removing duplicate
records to ensure each observation is unique."
    },
    {
        "Problem/Logical Issue": "Data quality issue 1",
        "Affected Variable/s": "occupied, available, max_capacity",
        "Number of Observations": "available: 1353",
        "Potential Issues": "sum of occupied and available should
always equal max capacity.As a result of that we found 1,353 negative
values in available.",
        "Handling Technique/s": "Replaced by 0"
    },
    {
        "Problem/Logical Issue": "Data quality issue 2",
        "Affected Variable/s": "tempC",
        "Number of Observations": "1",
```

```
        "Potential Issues": "mistake",
        "Handling Technique/s": "Replaced by 0/ mean"
    }
]


df_issues = pd.DataFrame(data_issues)
df_issues

  Problem/Logical Issue                                Affected
Variable/s  \
0        Missing values
commercial
1              Outliers  Available, precipMM, transportation,
off_stree...
2            Duplicates
None
3  Data quality issue 1                  occupied, available,
max_capacity
4  Data quality issue 2
tempC

  Number of Observations                                   Potential
Issues  \
0                  21960  Missing values can lead to inaccurate
analysis...
1    Various (see above)  Outliers can distort the model training
proces...
2                      0  Multiple entries for the same
road_segment_id ...
3        available: 1353  sum of occupied and available should always
eq...
4                      1
mistake

                                Handling Technique/s
0  Imputation techniques such as filling missing ...
1  Identifying and removing outliers using statis...
2  Identifying and removing duplicate records to ...
3                                       Replaced by 0
4                                 Replaced by 0/ mean
```

4. Exploratory Data Analysis (EDA)

- Basic statistics
- Univariate Analysis
- Bivariate Analysis
- Multivariate Analysis

4.1 Basic Statistics

```python
pd.set_option('display.float_format', '{:.2f}'.format)

# Basic statistics
df.describe()
```

```
       road_segment_id                      timestamp  max_capacity  \
count       1251720.00                        1251720    1251720.00   
mean          22097.02  2019-05-01 01:29:30.076503040         10.74   
min           20026.00            2019-03-01 06:00:00          1.00   
25%           21943.00            2019-03-31 13:31:15          3.00   
50%           22277.00            2019-05-01 01:31:00          7.00   
75%           22622.00            2019-05-31 13:26:30         12.00   
max           23277.00            2019-06-30 20:59:00         66.00   
std             738.07                            NaN         12.66   

        occupied  available       tempC  windspeedKmph    precipMM  
commercial  \
count 1251720.00 1251720.00 1251720.00     1251720.00 1251720.00  
1229760.00   
mean        2.41       8.32       15.63          12.75        0.10  
23.14   
min         0.00      -5.00     -999.00           1.00        0.00  
0.00   
25%         0.00       2.00       12.00           8.00        0.00  
2.00   
50%         1.00       4.00       15.00          12.00        0.00  
10.00   
75%         3.00       8.00       19.00          17.00        0.00  
48.00   
max        34.00      66.00       32.00          32.00        4.80  
92.00   
std         3.90      12.15        5.10           6.43        0.37  
26.91   

       residential  transportation    schools  eventsites  restaurant  
\
count   1251720.00      1251720.00 1251720.00  1251720.00  1251720.00   

mean         54.70            0.79       4.00        1.00       69.53   

min           2.00            0.00       0.00        0.00       18.00   

25%           7.00            0.00       0.00        0.00       32.00   

50%          18.00            0.00       1.00        1.00      100.00   

75%         119.00            1.00       9.00        2.00      100.00   

max         175.00            3.00      28.00        4.00      100.00   
```

```
std          60.37            1.15        5.33         1.08        33.62


        shopping      office  supermarket  num_off_street_parking  \
count 1251720.00 1251720.00   1251720.00              1251720.00
mean       54.82       15.70        13.30                    1.23
min         5.00        1.00         0.00                    0.00
25%        11.00        2.00         2.00                    0.00
50%        35.00        5.00         5.00                    0.00
75%       100.00       20.00        20.00                    3.00
max       100.00      100.00        66.00                    7.00
std        42.04       21.07        17.15                    1.82

       off_street_capa
count       1251720.00
mean            161.51
min               0.00
25%               0.00
50%               0.00
75%             277.00
max            1133.00
std             265.22
```

```python
df['max_capacity'].sum()
```

```
13439520
```

```python
df['road_segment_id'].nunique()
```

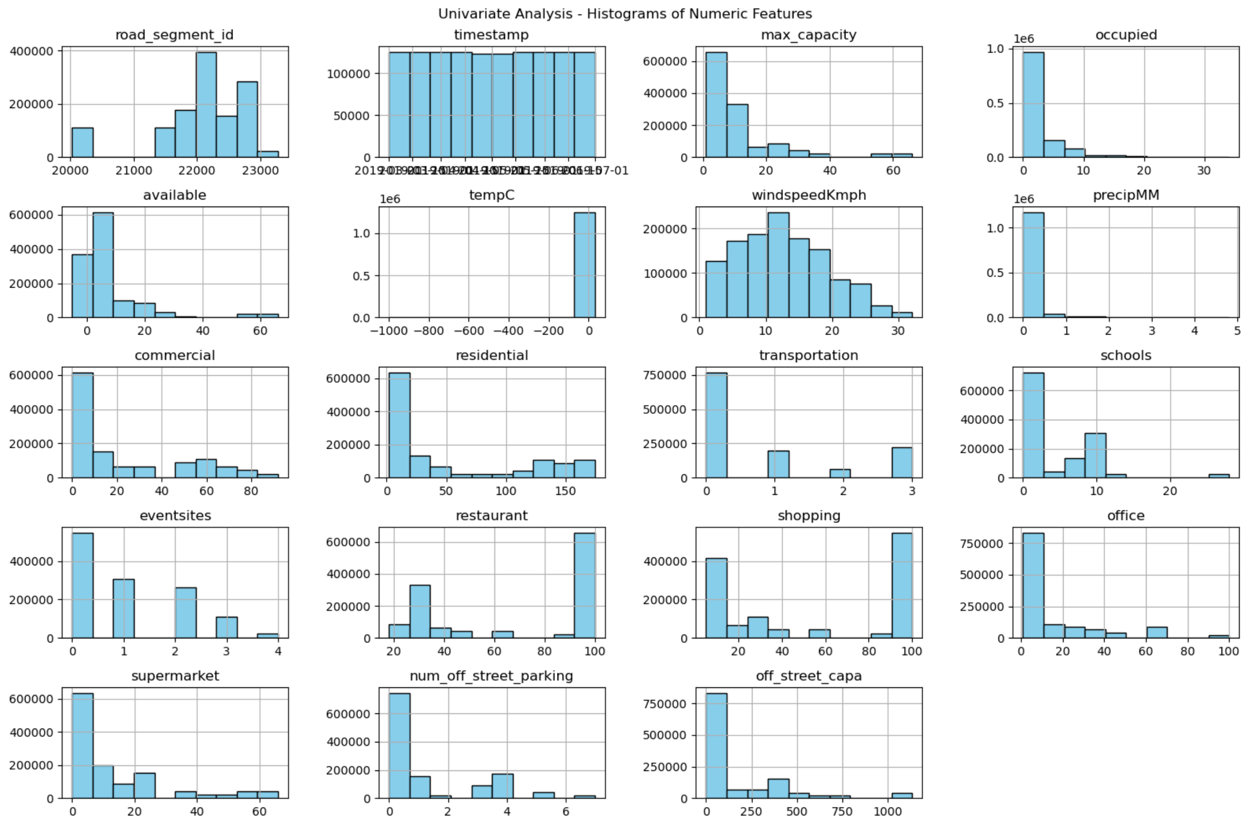
```
57
```

```python
df.shape
```

```
(1251720, 21)
```

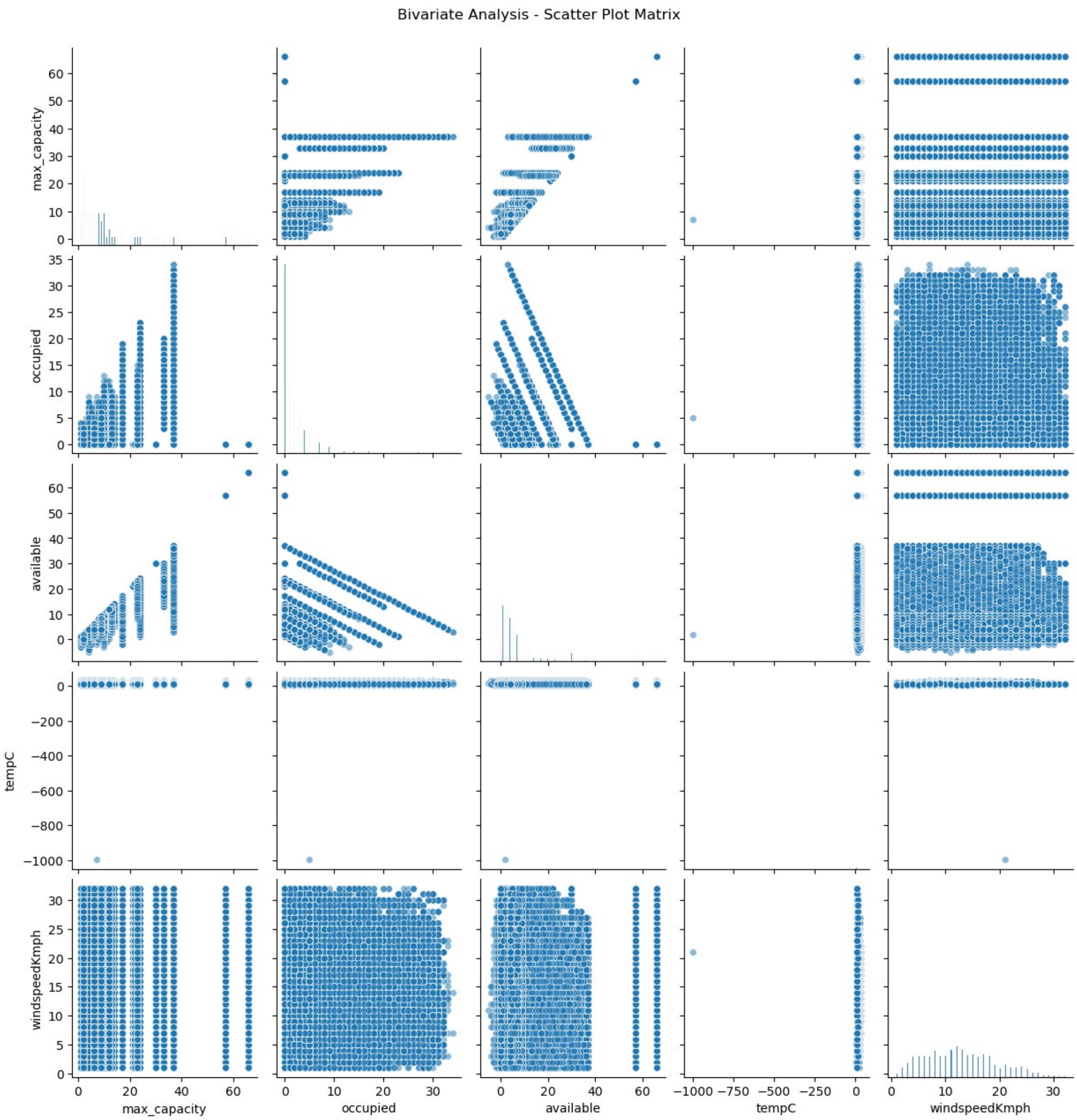
4.2 Univariate Analysis

```python
# Histograms for each numeric column
def plot_histograms(df):
    df.hist(bins=10, figsize=(15, 10), color='skyblue',
edgecolor='black')
    plt.suptitle('Univariate Analysis - Histograms of Numeric
Features')
    plt.tight_layout()
    plt.show()

plot_histograms(df)
```



4.3 Bivariate Analysis

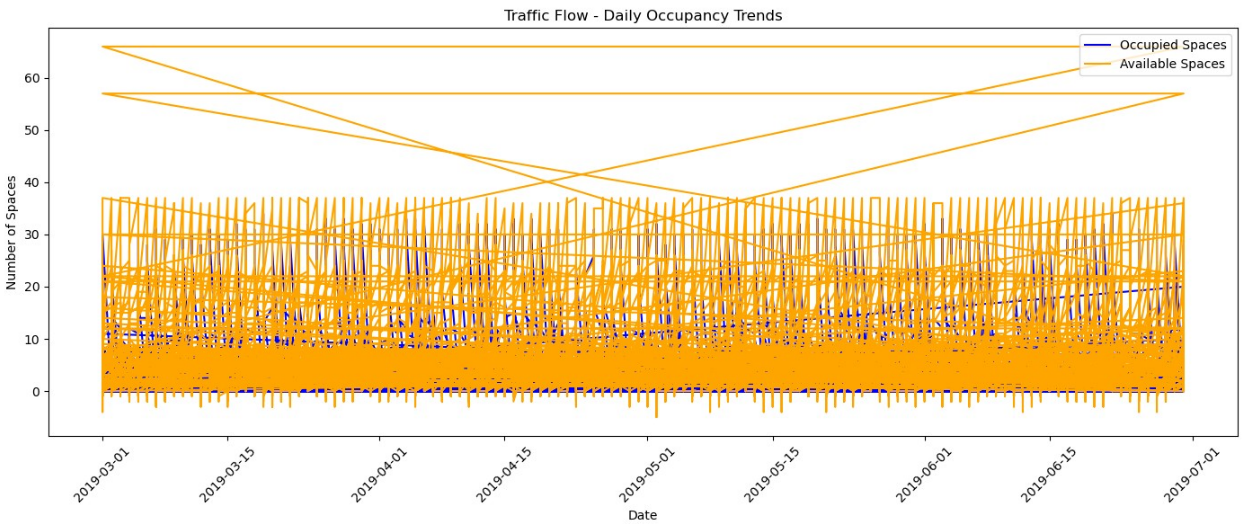
```python
# Scatter plot matrix
def plot_scatter_matrix(df, features):
    sns.pairplot(df[features], plot_kws={'alpha':0.5, 's':30})
    plt.suptitle('Bivariate Analysis - Scatter Plot Matrix', y=1.02)
    plt.show()

plot_scatter_matrix(df, ['max_capacity', 'occupied', 'available',
'tempC', 'windspeedKmph'])
```




```
# Traffic Flow and Capacity Utilization
# Plot daily occupancy trends to identify peak and low times
plt.figure(figsize=(14, 6))
plt.plot(df['date'], df['occupied'], label='Occupied Spaces',
color='blue')
plt.plot(df['date'], df['available'], label='Available Spaces',
color='orange')
plt.xlabel('Date')
plt.ylabel('Number of Spaces')
plt.title('Traffic Flow - Daily Occupancy Trends')
plt.legend()
```

```
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

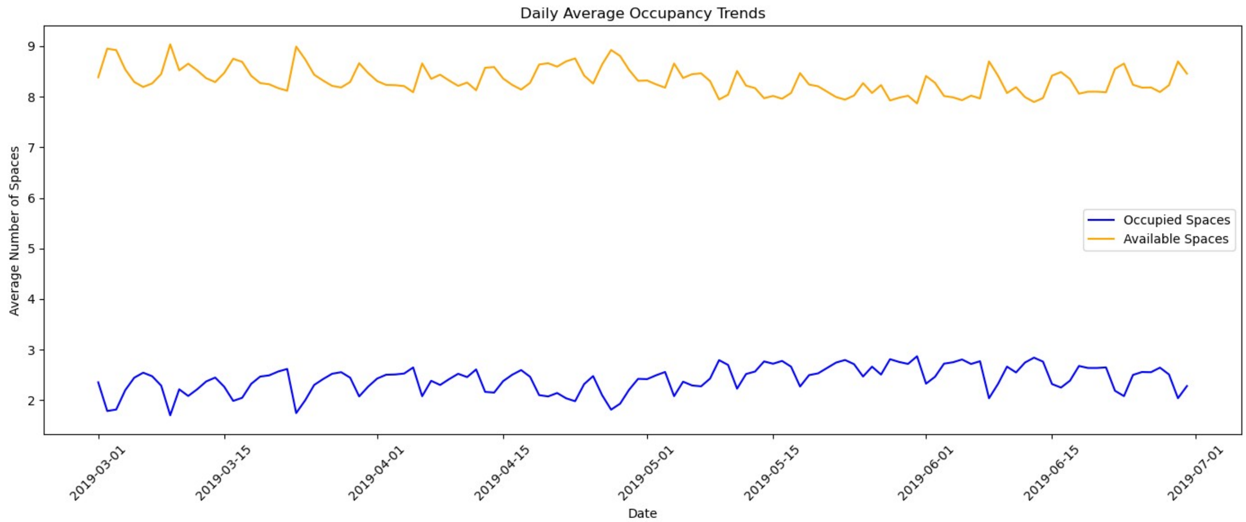
```
C:\Users\lahir\AppData\Local\Temp\ipykernel_17740\307938723.py:11:
UserWarning: Creating legend with loc="best" can be slow with large
amounts of data.
  plt.tight_layout()
C:\Users\lahir\anaconda3\Lib\site-packages\IPython\core\
pylabtools.py:170: UserWarning: Creating legend with loc="best" can be
slow with large amounts of data.
  fig.canvas.print_figure(bytes_io, **kw)
```



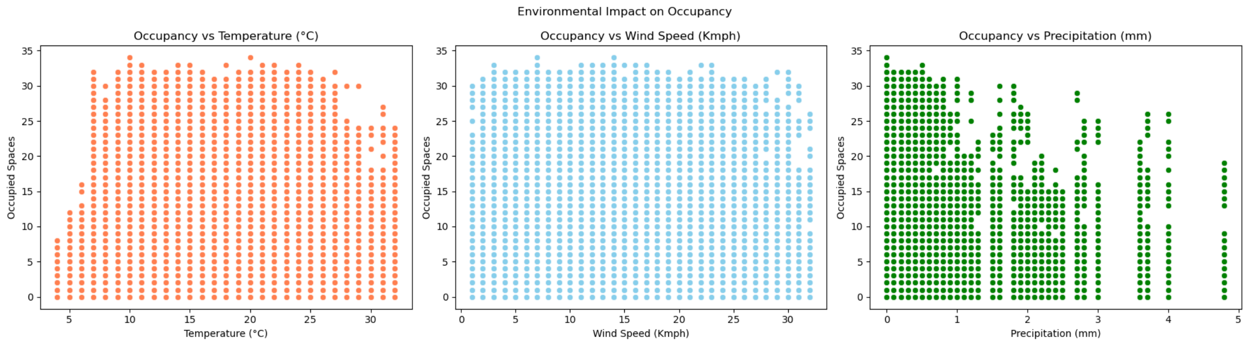
Cant interprete the above graph and therefore grouping the data

```
# Daily Average Occupancy Trends
# Grouping data by day to calculate daily averages of occupied and
available spaces
df['date'] = df['timestamp'].dt.date
daily_avg = df.groupby('date').agg({'occupied': 'mean', 'available':
'mean'})

# Plot daily trends with the aggregated data
plt.figure(figsize=(14, 6))
plt.plot(daily_avg.index, daily_avg['occupied'], label='Occupied
Spaces', color='blue')
plt.plot(daily_avg.index, daily_avg['available'], label='Available
Spaces', color='orange')
plt.xlabel('Date')
plt.ylabel('Average Number of Spaces')
plt.title('Daily Average Occupancy Trends')
plt.legend()
plt.xticks(rotation=45)
```

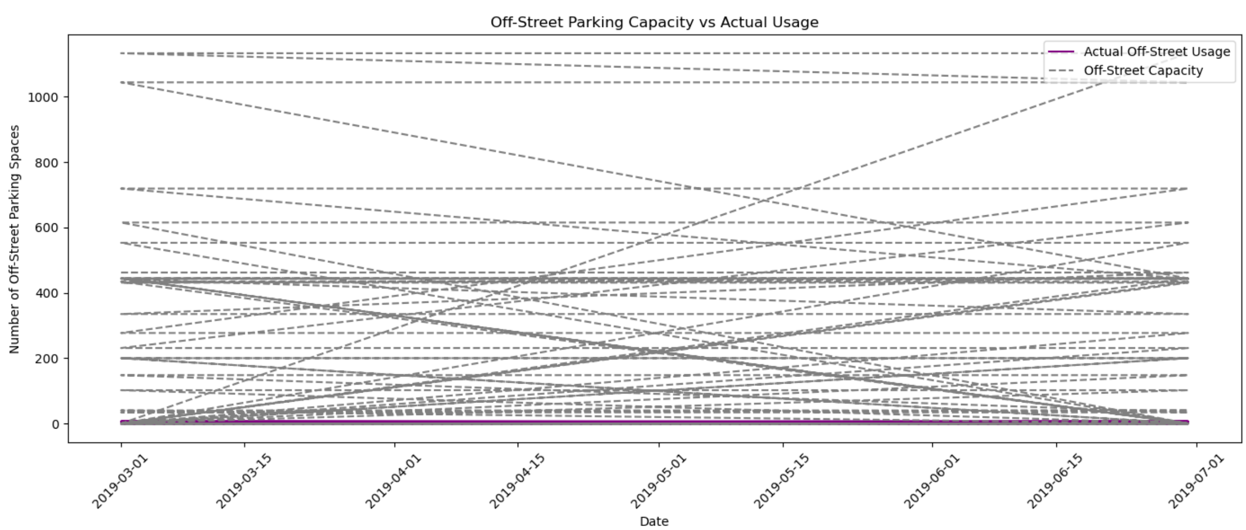
```
plt.tight_layout()
plt.show()
```



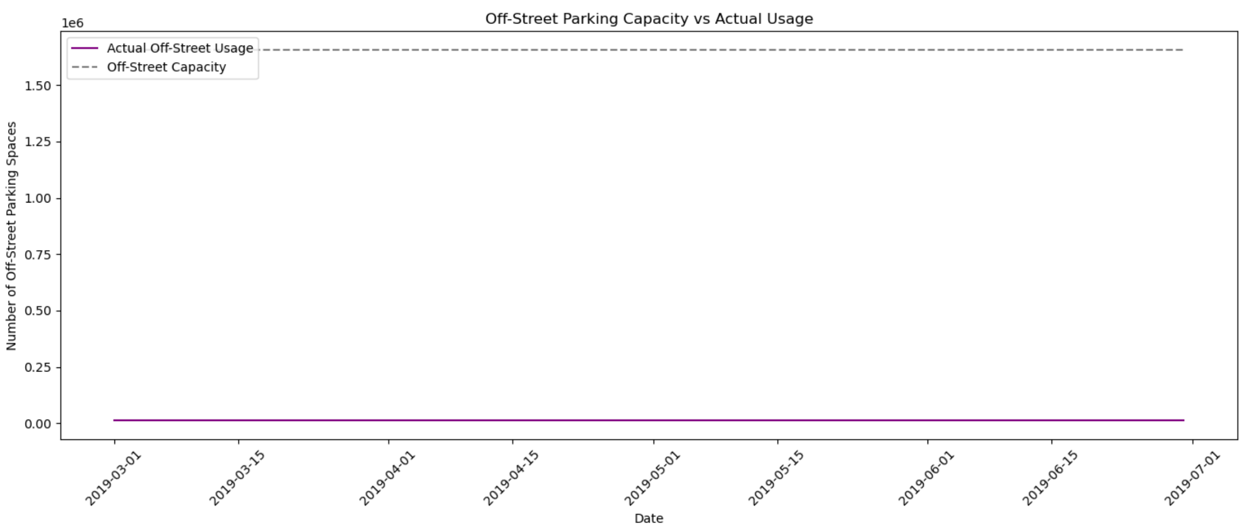

```
# Temporally removing the outlier
df2= df[df['tempC'] != -999]

# Environmental Impact on Usage
# Scatter plot of occupancy vs temperature, wind speed, and
precipitation
fig, axs = plt.subplots(1, 3, figsize=(18, 5))

sns.scatterplot(x=df2['tempC'], y=df2['occupied'], ax=axs[0],
color='coral')
axs[0].set_title('Occupancy vs Temperature (°C)')
axs[0].set_xlabel('Temperature (°C)')
axs[0].set_ylabel('Occupied Spaces')

sns.scatterplot(x=df['windspeedKmph'], y=df['occupied'], ax=axs[1],
color='skyblue')
axs[1].set_title('Occupancy vs Wind Speed (Kmph)')
axs[1].set_xlabel('Wind Speed (Kmph)')
axs[1].set_ylabel('Occupied Spaces')

sns.scatterplot(x=df['precipMM'], y=df['occupied'], ax=axs[2],
color='green')
axs[2].set_title('Occupancy vs Precipitation (mm)')
axs[2].set_xlabel('Precipitation (mm)')
axs[2].set_ylabel('Occupied Spaces')

plt.suptitle('Environmental Impact on Occupancy')
plt.tight_layout()
plt.show()
```




```
# Off-street Parking Capacity vs Occupancy
plt.figure(figsize=(14, 6))
plt.plot(df['date'], df['num_off_street_parking'], label='Actual Off-
Street Usage', color='purple')
plt.plot(df['date'], df['off_street_capa'], label='Off-Street
Capacity', color='gray', linestyle='--')
plt.xlabel('Date')
plt.ylabel('Number of Off-Street Parking Spaces')
plt.title('Off-Street Parking Capacity vs Actual Usage')
plt.legend()
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

C:\Users\lahir\AppData\Local\Temp\ipykernel_17740\2958170429.py:10:
UserWarning: Creating legend with loc="best" can be slow with large
amounts of data.
  plt.tight_layout()
C:\Users\lahir\anaconda3\Lib\site-packages\IPython\core\
pylabtools.py:170: UserWarning: Creating legend with loc="best" can be
slow with large amounts of data.
  fig.canvas.print_figure(bytes_io, **kw)
```



```python
# Off-Street Parking Capacity vs Actual Usage
# Aggregate data by date (for example, by summing up the
'num_off_street_parking' and 'off_street_capa')
daily_data = df.groupby('date').agg({
    'num_off_street_parking': 'sum',
    'off_street_capa': 'sum'
}).reset_index()

# Plot the aggregated data
plt.figure(figsize=(14, 6))
plt.plot(daily_data['date'], daily_data['num_off_street_parking'],
label='Actual Off-Street Usage', color='purple')
plt.plot(daily_data['date'], daily_data['off_street_capa'],
label='Off-Street Capacity', color='gray', linestyle='--')

plt.xlabel('Date')
plt.ylabel('Number of Off-Street Parking Spaces')
plt.title('Off-Street Parking Capacity vs Actual Usage')
plt.legend(loc='upper left')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```




```python
# Check the unique date counts
date_counts = df['date'].value_counts()
print("Unique date counts:\n", date_counts)
```

```
Unique date counts:
 date
2019-03-01    10260
2019-05-31    10260
2019-05-29    10260
2019-05-28    10260
```

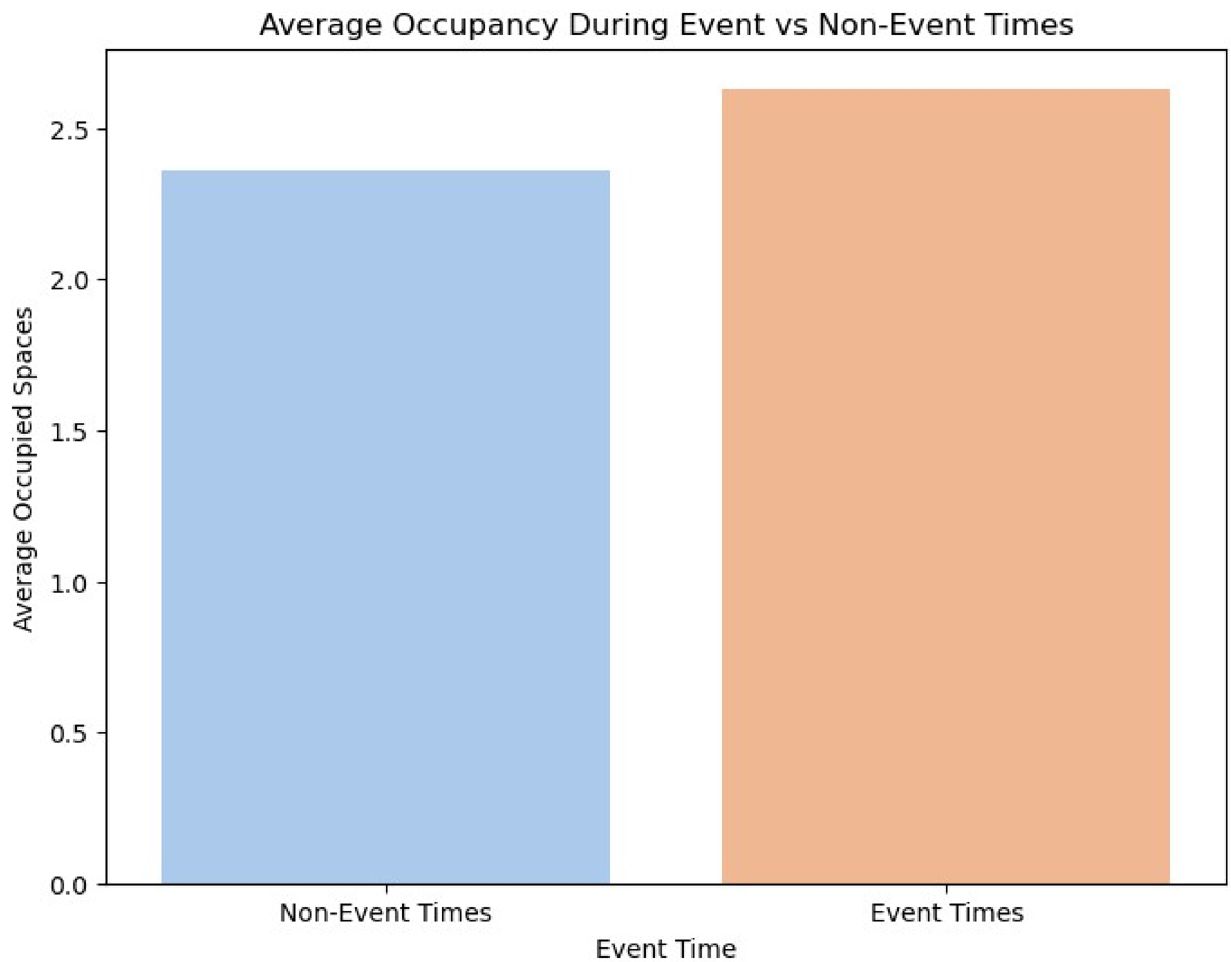
```
2019-05-27    10260
                ...
2019-04-06    10260
2019-04-05    10260
2019-04-04    10260
2019-04-03    10260
2019-06-30    10260
Name: count, Length: 122, dtype: int64

# Define the time range for events
# Assume events occur between 18:00 and 20:59
start_time = pd.to_datetime('18:00:00').time()
end_time = pd.to_datetime('20:59:00').time()

# Filter the DataFrame for times between 18:00 and 20:59
df_events = df[(df['time'] >= start_time) & (df['time'] <= end_time)]
df_events

         road_segment_id           timestamp  max_capacity
occupied  \
144                20026 2019-03-01 18:03:00             7          2

145                20026 2019-03-01 18:05:00             7          2

146                20026 2019-03-01 18:12:00             7          0

147                20026 2019-03-01 18:18:00             7          0

148                20026 2019-03-01 18:22:00             7          1

...                  ...                 ...           ...        ...

1251715            23277 2019-06-30 20:36:00             9          5

1251716            23277 2019-06-30 20:44:00             9          5

1251717            23277 2019-06-30 20:46:00             9          5

1251718            23277 2019-06-30 20:52:00             9          5

1251719            23277 2019-06-30 20:59:00             9          5


         available  tempC  windspeedKmph  precipMM  commercial
residential  \
144              5     29              9      0.00       58.00
32
145              5     29              9      0.00       58.00
32
146              7     29              9      0.00       58.00
32
```

```
147                7     29                 9      0.00       58.00
32
148                6     29                 9      0.00       58.00
32
...              ...    ...               ...       ...         ...
...
1251715            4      9                18      0.00       11.00
16
1251716            4      9                18      0.00       11.00
16
1251717            4      9                18      0.00       11.00
16
1251718            4      9                18      0.00       11.00
16
1251719            4      9                18      0.00       11.00
16

         ...  schools  eventsites  restaurant  shopping  office
supermarket  \
144      ...        4           2         100       100      65
63
145      ...        4           2         100       100      65
63
146      ...        4           2         100       100      65
63
147      ...        4           2         100       100      65
63
148      ...        4           2         100       100      65
63
...      ...      ...         ...         ...       ...     ...
...
1251715  ...        1           1         100       100       2
7
1251716  ...        1           1         100       100       2
7
1251717  ...        1           1         100       100       2
7
1251718  ...        1           1         100       100       2
7
1251719  ...        1           1         100       100       2
7

         num_off_street_parking  off_street_capa        date      time

144                           4              462  2019-03-01  18:03:00

145                           4              462  2019-03-01  18:05:00

146                           4              462  2019-03-01  18:12:00
```

```
147                               4              462  2019-03-01  18:18:00
148                               4              462  2019-03-01  18:22:00
...                             ...              ...         ...       ...
1251715                           0                0  2019-06-30  20:36:00
1251716                           0                0  2019-06-30  20:44:00
1251717                           0                0  2019-06-30  20:46:00
1251718                           0                0  2019-06-30  20:52:00
1251719                           0                0  2019-06-30  20:59:00

[250344 rows x 21 columns]
```

```python
# Event Impacts and Temporal Patterns Analysis

# Create a column to simulate events; assume events occur during specific hours across days
df['is_event_time'] = df['time'].apply(lambda t: 1 if t.hour in [18, 19, 20] else 0)  # Events in the evening

# Average Occupancy During Event vs Non-Event Times
# Calculate average occupancy for event and non-event times
event_vs_non_event = df.groupby('is_event_time')['occupied'].mean()
event_vs_non_event.index = ['Non-Event Times', 'Event Times']

# Plot event vs non-event time occupancy
plt.figure(figsize=(8, 6))
sns.barplot(x=event_vs_non_event.index, y=event_vs_non_event.values, palette='pastel')
plt.xlabel('Event Time')
plt.ylabel('Average Occupied Spaces')
plt.title('Average Occupancy During Event vs Non-Event Times')
plt.show()
```

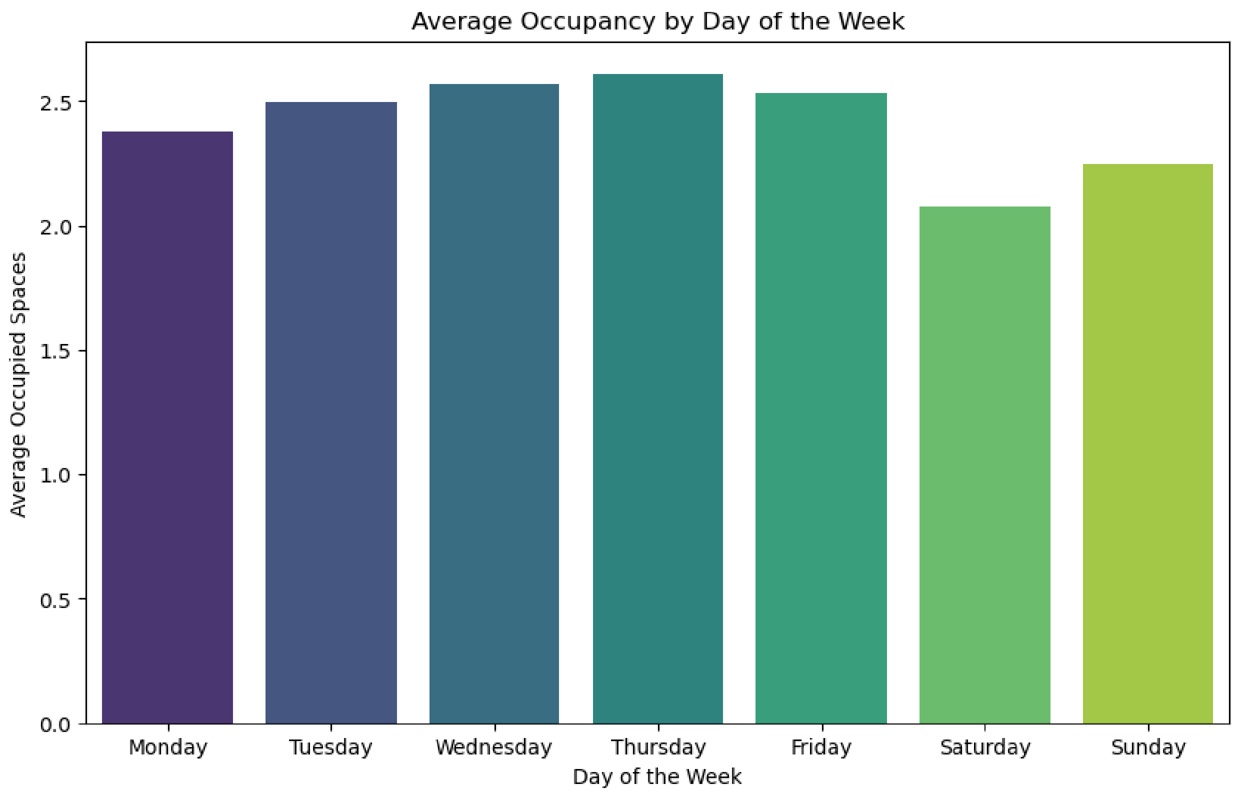
```
C:\Users\lahir\AppData\Local\Temp\ipykernel_17740\1450093152.py:8: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=event_vs_non_event.index, y=event_vs_non_event.values, palette='pastel')
```




```
# Average Occupancy by Day of the Week
# Convert 'timestamp' to datetime
df['timestamp'] = pd.to_datetime(df['timestamp'], errors='coerce')

# Temporal Patterns: Weekly and Daily Trends
# Extract day of the week and hour of the day for temporal pattern
analysis
df['day_of_week'] = df['timestamp'].dt.day_name()
df['hour_of_day'] = df['timestamp'].dt.hour

# Average occupancy by day of the week
avg_occupancy_by_day = df.groupby('day_of_week')
['occupied'].mean().reindex(
    ["Monday", "Tuesday", "Wednesday", "Thursday", "Friday",
"Saturday", "Sunday"]
)

# Plot
plt.figure(figsize=(10, 6))
sns.barplot(x=avg_occupancy_by_day.index,
```

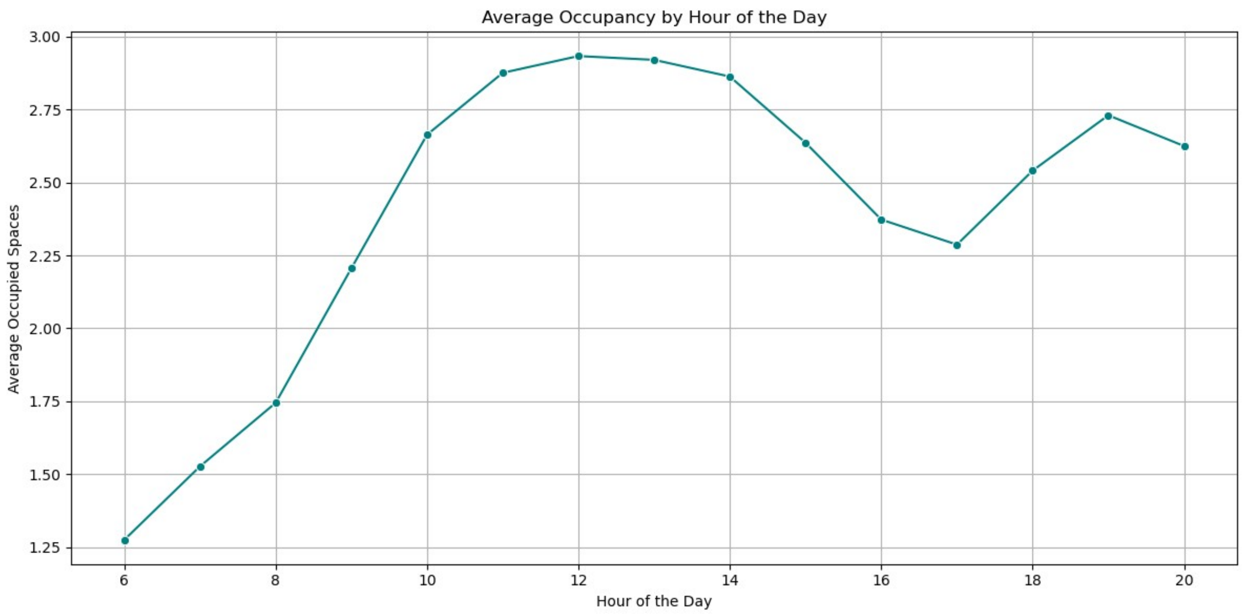
```
y=avg_occupancy_by_day.values, palette='viridis')
plt.xlabel('Day of the Week')
plt.ylabel('Average Occupied Spaces')
plt.title('Average Occupancy by Day of the Week')
plt.show()
```

```
C:\Users\lahir\AppData\Local\Temp\ipykernel_17740\3574020592.py:17:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x=avg_occupancy_by_day.index,
y=avg_occupancy_by_day.values, palette='viridis')
```

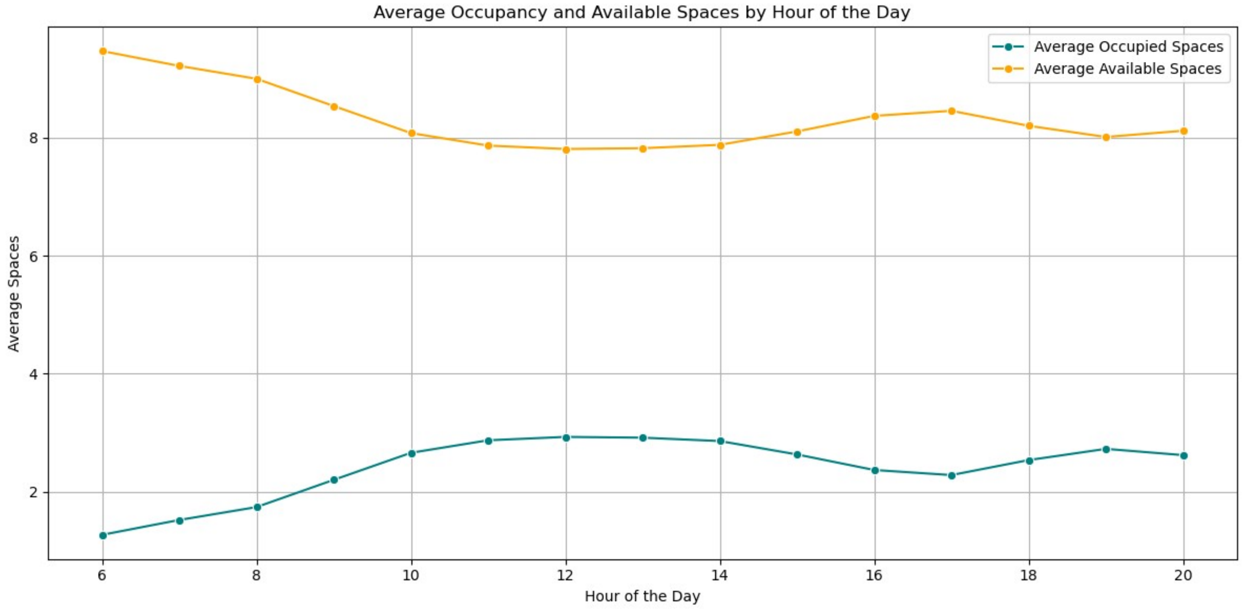



```
# Average occupancy by hour of the day
avg_occupancy_by_hour = df.groupby('hour_of_day')['occupied'].mean()

# Plot average occupancy by hour of the day
plt.figure(figsize=(12, 6))
sns.lineplot(x=avg_occupancy_by_hour.index,
y=avg_occupancy_by_hour.values, marker='o', color='teal')
plt.xlabel('Hour of the Day')
plt.ylabel('Average Occupied Spaces')
```

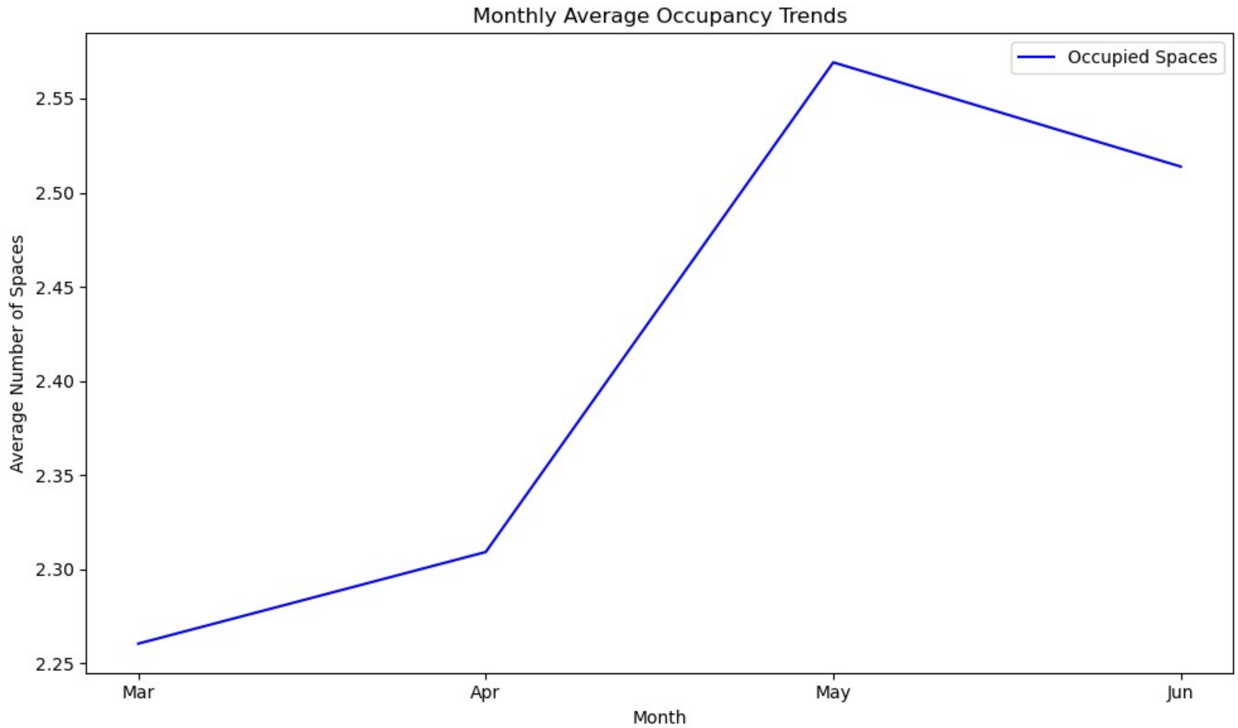
```
plt.title('Average Occupancy by Hour of the Day')
plt.grid()
plt.tight_layout()
plt.show()
```



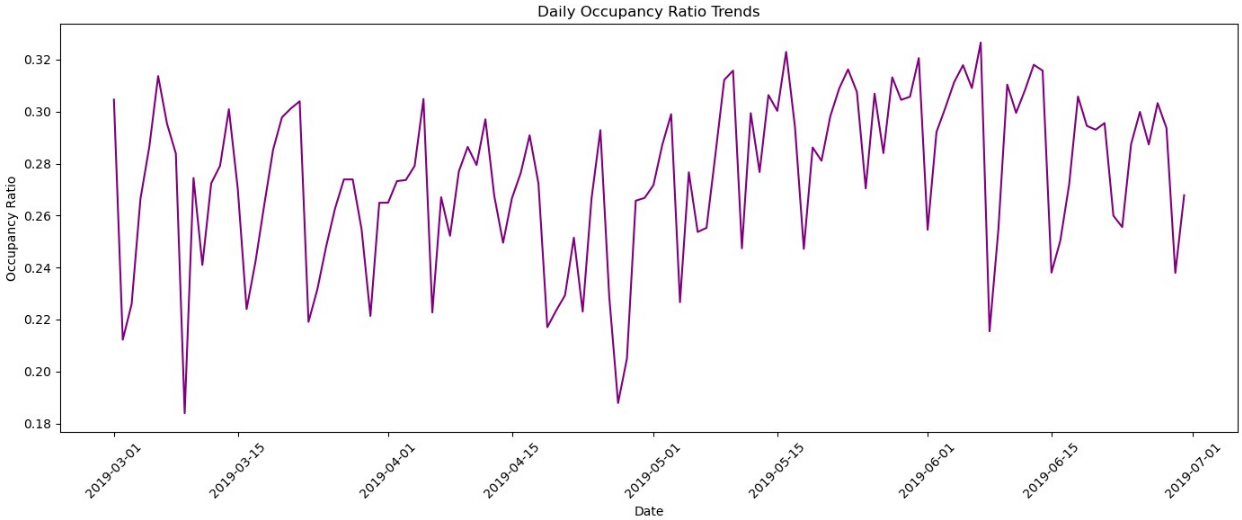

```
# Calculate average occupancy and available spaces by hour of the day
avg_occupancy_by_hour = df.groupby('hour_of_day')['occupied'].mean()
avg_available_by_hour = df.groupby('hour_of_day')['available'].mean()

# Plot average occupancy and available spaces by hour of the day
plt.figure(figsize=(12, 6))
sns.lineplot(x=avg_occupancy_by_hour.index,
y=avg_occupancy_by_hour.values, marker='o', color='teal',
label='Average Occupied Spaces')
sns.lineplot(x=avg_available_by_hour.index,
y=avg_available_by_hour.values, marker='o', color='orange',
label='Average Available Spaces')

# Add labels and title
plt.xlabel('Hour of the Day')
plt.ylabel('Average Spaces')
plt.title('Average Occupancy and Available Spaces by Hour of the Day')
plt.grid()
plt.legend()
plt.tight_layout()
plt.show()
```



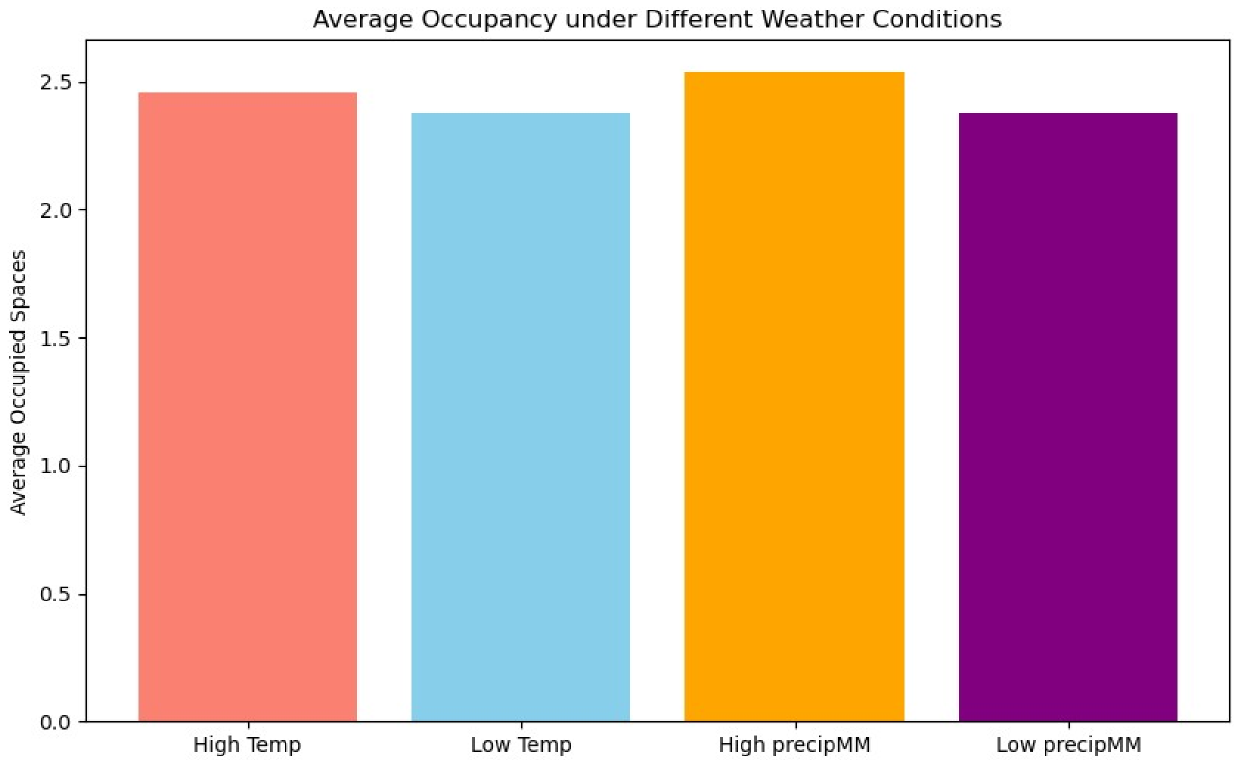

```
# Monthly Average Occupancy Trends
df['month'] = df['timestamp'].dt.month
monthly_avg = df.groupby('month').agg({'occupied': 'mean',
'available': 'mean'})
month_labels = {3: 'Mar', 4: 'Apr', 5: 'May', 6: 'Jun'}

plt.figure(figsize=(10, 6))
plt.plot(monthly_avg.index, monthly_avg['occupied'], label='Occupied
Spaces', color='blue')
#plt.plot(monthly_avg.index, monthly_avg['available'],
label='Available Spaces', color='orange')
plt.xlabel('Month')
plt.ylabel('Average Number of Spaces')
plt.title('Monthly Average Occupancy Trends')
plt.legend()
plt.xticks(monthly_avg.index, [month_labels[m] for m in
monthly_avg.index])
plt.tight_layout()
plt.show()
```




```
# Daily Occupancy Ratio Trends
# Calculate occupancy to availability ratio
df['occupancy_ratio'] = df['occupied'] / (df['occupied'] +
df['available'])

# Group by day and calculate daily occupancy ratio
daily_ratio = df.groupby('date')['occupancy_ratio'].mean()

# Plot the daily occupancy ratio trend
plt.figure(figsize=(14, 6))
plt.plot(daily_ratio.index, daily_ratio.values, label='Occupancy
Ratio', color='purple')
plt.xlabel('Date')
plt.ylabel('Occupancy Ratio')
plt.title('Daily Occupancy Ratio Trends')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



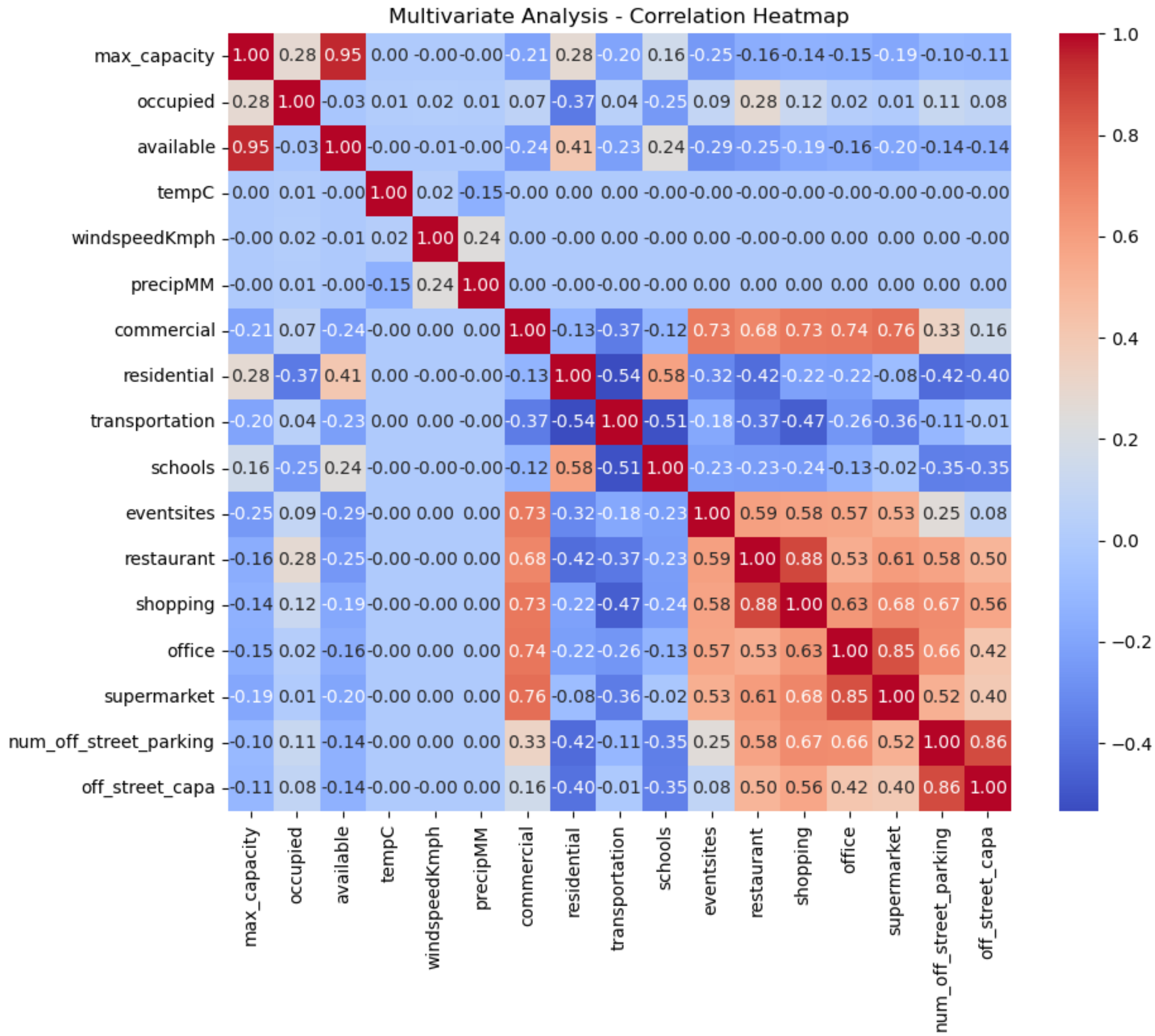

```
# Average Occupancy under Different Weather Conditions
# Divide data into high and low temperature/wind groups
high_temp = df[df['tempC'] > df['tempC'].median()]
low_temp = df[df['tempC'] <= df['tempC'].median()]
high_wind = df[df['precipMM'] > df['precipMM'].median()]
low_wind = df[df['precipMM'] <= df['precipMM'].median()]

# Plot comparison of occupancy under different conditions
plt.figure(figsize=(10, 6))
plt.bar(['High Temp', 'Low Temp', 'High precipMM', 'Low precipMM'],
        [high_temp['occupied'].mean(), low_temp['occupied'].mean(),
high_wind['occupied'].mean(), low_wind['occupied'].mean()],
        color=['salmon', 'skyblue', 'orange', 'purple'])
plt.ylabel('Average Occupied Spaces')
plt.title('Average Occupancy under Different Weather Conditions')
plt.show()
```



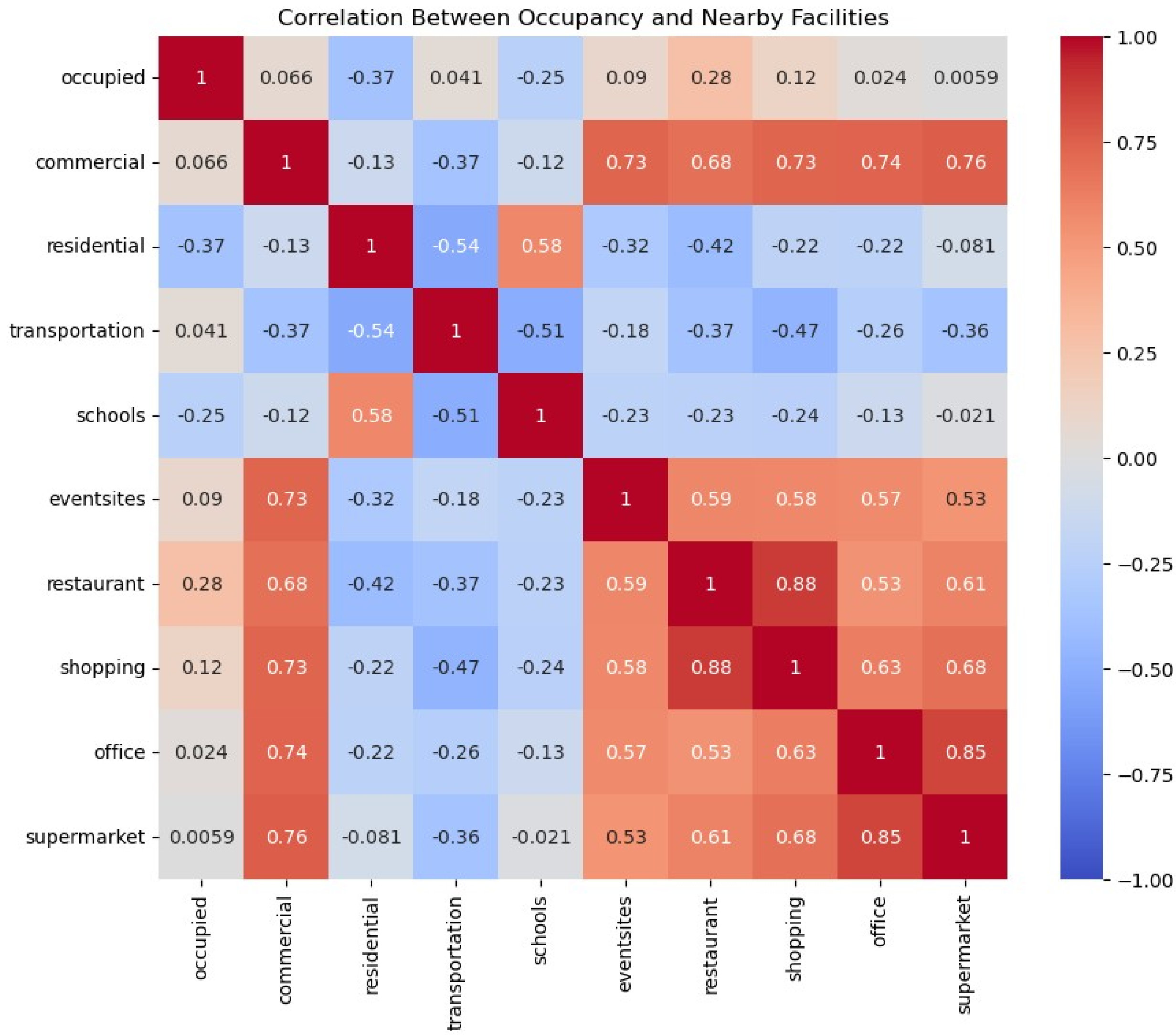

```
df.columns
```

```
Index(['road_segment_id', 'timestamp', 'max_capacity', 'occupied',
'available',
       'tempC', 'windspeedKmph', 'precipMM', 'commercial',
'residential',
       'transportation', 'schools', 'eventsites', 'restaurant',
'shopping',
       'office', 'supermarket', 'num_off_street_parking',
'off_street_capa',
       'date', 'time', 'is_event_time', 'day_of_week', 'hour_of_day',
'month',
       'occupancy_ratio'],
      dtype='object')
```

```
## 4.4 Multivariate Analysis

# Heatmap for correlation
def plot_correlation_heatmap(df):
    corr = df.corr()
    plt.figure(figsize=(10, 8))
    sns.heatmap(corr, annot=True, cmap='coolwarm', fmt=".2f")
    plt.title('Multivariate Analysis - Correlation Heatmap')
    plt.show()

plot_correlation_heatmap(df.iloc[:, 2:-7]) # Considering only the
relevant features
```

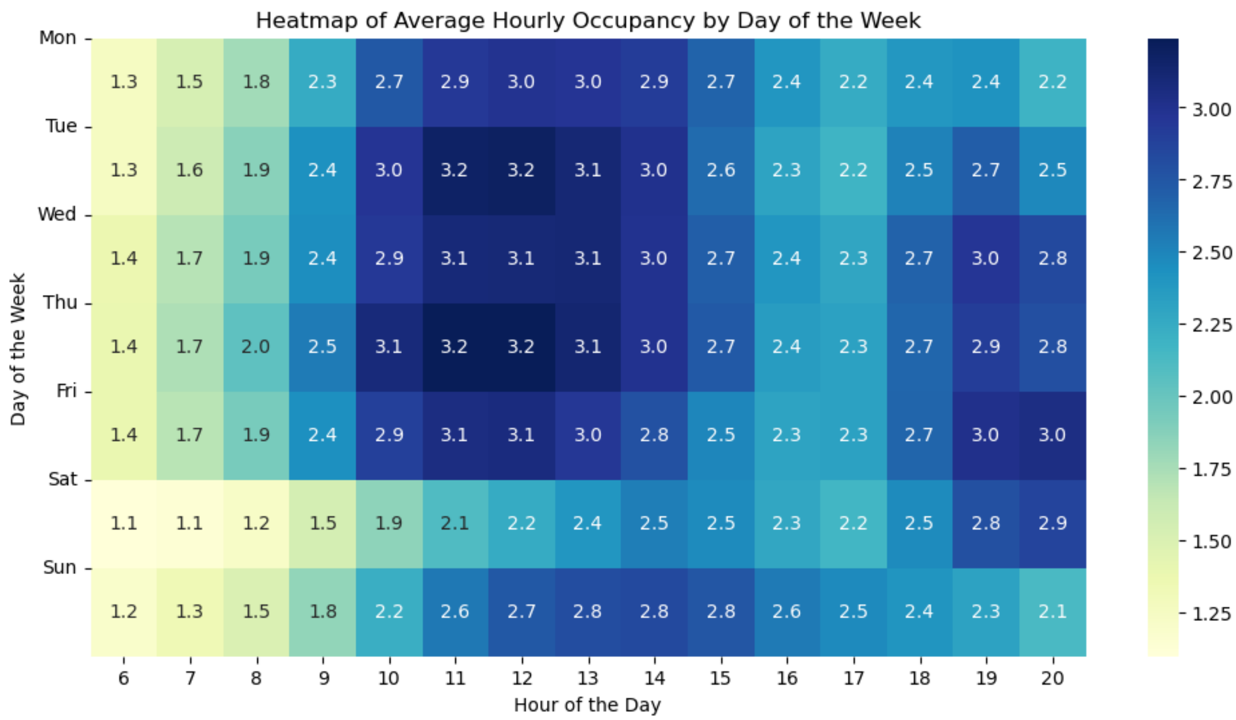



```
# Analyzing the impact of nearby facilities and off-street parking on
occupancy

# Correlation heatmap
plt.figure(figsize=(10, 8))
facilities_cols = ['commercial', 'residential', 'transportation',
'schools', 'eventsites',
                  'restaurant', 'shopping', 'office', 'supermarket']
correlation_matrix = df[['occupied'] + facilities_cols].corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', vmin=-1,
vmax=1)
plt.title('Correlation Between Occupancy and Nearby Facilities')
plt.show()
```



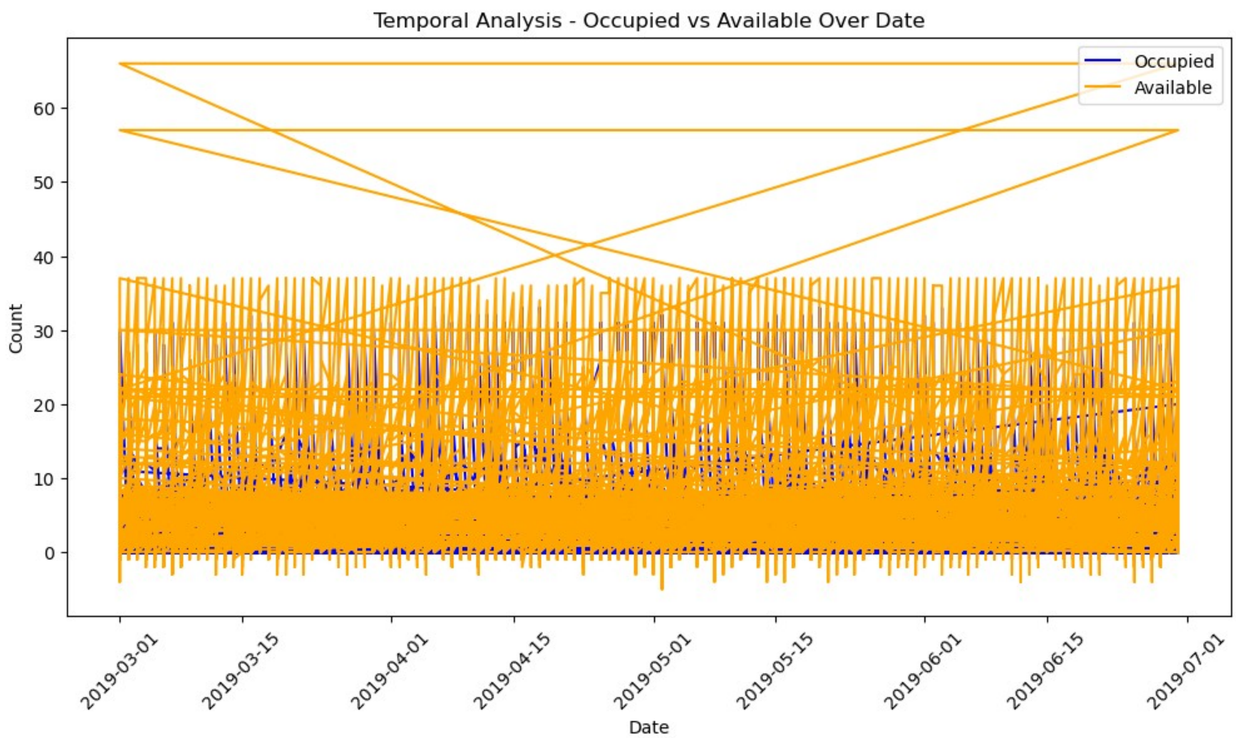

```
# Heatmap of Average Hourly Occupancy by Day of the Week
# Create a pivot table to show average occupancy per hour for each day
of the week
df['day_of_week'] = df['timestamp'].dt.dayofweek
df['hour'] = df['timestamp'].dt.hour
hourly_weekday_pivot = df.pivot_table(values='occupied',
index='day_of_week', columns='hour', aggfunc='mean')

# Plot heatmap
plt.figure(figsize=(12, 6))
sns.heatmap(hourly_weekday_pivot, cmap='YlGnBu', annot=True,
fmt=".1f")
plt.xlabel('Hour of the Day')
plt.ylabel('Day of the Week')
plt.title('Heatmap of Average Hourly Occupancy by Day of the Week')
plt.yticks(ticks=range(7), labels=['Mon', 'Tue', 'Wed', 'Thu', 'Fri',
```

```
'Sat', 'Sun'], rotation=0)
plt.show()
```



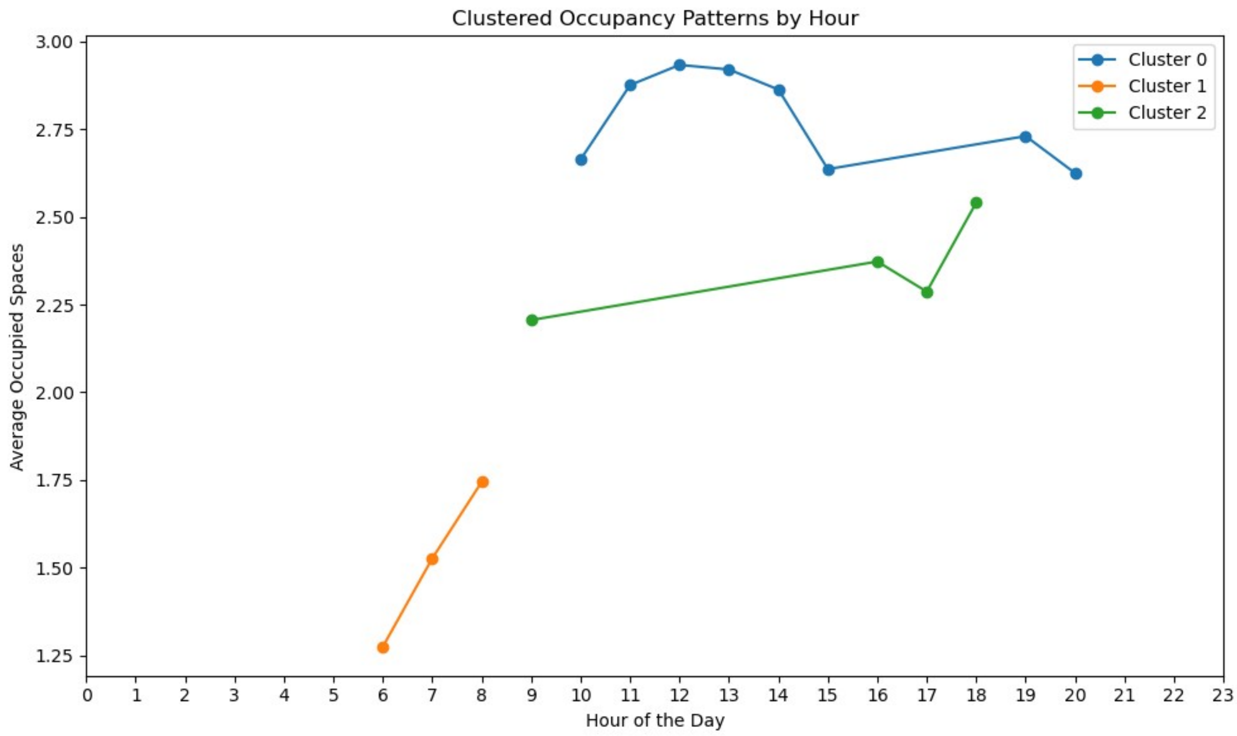

```
# Temporal Analysis
# Line plot for occupied vs available over time
def plot_temporal_trends(df):
    plt.figure(figsize=(12, 6))
    plt.plot(df['date'], df['occupied'], label='Occupied',
color='blue')
    plt.plot(df['date'], df['available'], label='Available',
color='orange')
    plt.xlabel('Date')
    plt.ylabel('Count')
    plt.title('Temporal Analysis - Occupied vs Available Over Date')
    plt.legend()
    plt.xticks(rotation=45)
    plt.show()

plot_temporal_trends(df)
```

```
C:\Users\lahir\anaconda3\Lib\site-packages\IPython\core\
pylabtools.py:170: UserWarning: Creating legend with loc="best" can be
slow with large amounts of data.
  fig.canvas.print_figure(bytes_io, **kw)
```




```
# Cluster Analysis

# Prepare data for clustering by averaging occupancy at each hour of
the day
hourly_pattern = df.groupby('hour_of_day').agg({'occupied': 'mean',
'available': 'mean'})

# Standardize data for clustering
scaler = StandardScaler()
hourly_pattern_scaled = scaler.fit_transform(hourly_pattern)

# Apply k-means clustering
kmeans = KMeans(n_clusters=3,
random_state=0).fit(hourly_pattern_scaled)
hourly_pattern['cluster'] = kmeans.labels_

# Plot hourly patterns by cluster
plt.figure(figsize=(10, 6))
for cluster in range(3):
    subset = hourly_pattern[hourly_pattern['cluster'] == cluster]
    plt.plot(subset.index, subset['occupied'], label=f'Cluster
{cluster}', marker='o')

plt.xlabel('Hour of the Day')
plt.ylabel('Average Occupied Spaces')
plt.title('Clustered Occupancy Patterns by Hour')
plt.legend()
```

```
plt.xticks(range(0, 24))
plt.tight_layout()
plt.show()

C:\Users\lahir\anaconda3\Lib\site-packages\sklearn\cluster\
_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on
Windows with MKL, when there are less chunks than available threads.
You can avoid it by setting the environment variable
OMP_NUM_THREADS=1.
  warnings.warn(
```



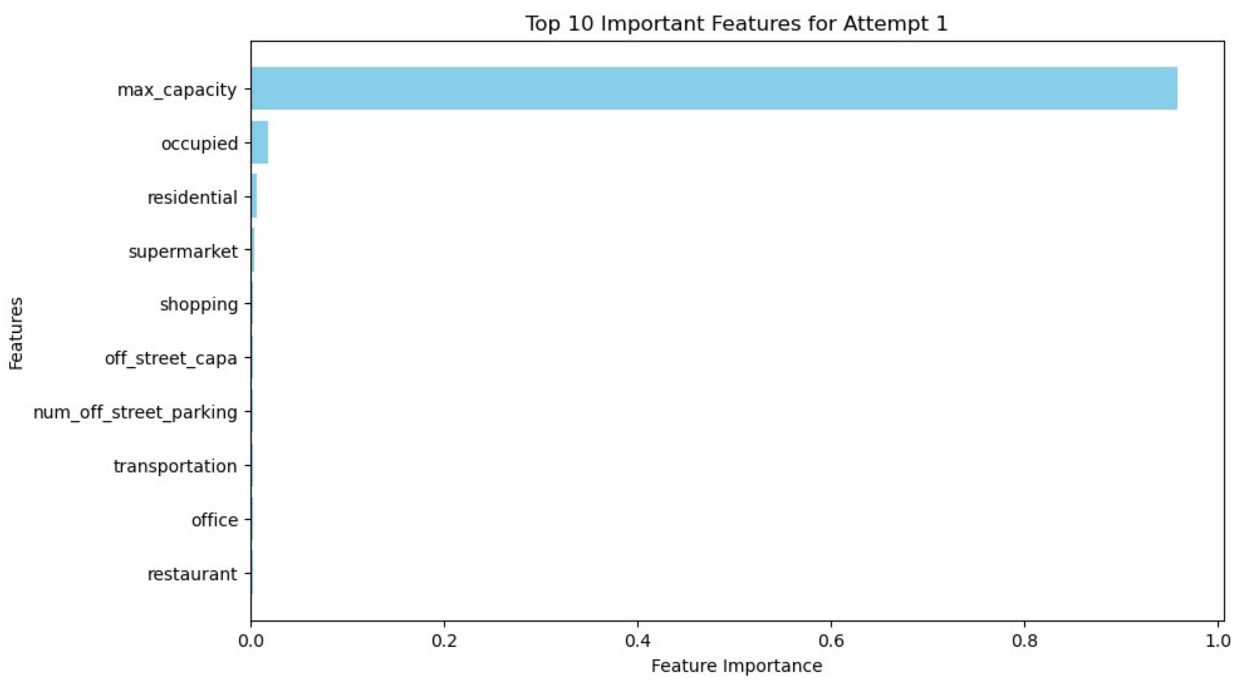
5. Model Training and Evaluation

I ran several experiments with different data preprocessing techniques, as shown in the results graph below. I conducted the experiments without feature engineering, by selecting specific features, by creating new features using lag features and rolling aggregates for max capacity and occupancy, and finally, by performing feature engineering and treating outliers.

```
# Placeholder for results tracking
results = []

# Define a function to train and evaluate a model
def run_experiment(df, features, target, attempt_name, top_n=10):
    # Splitting the data
    X = df[features]
```

```
    y = df[target]
    X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, shuffle=False)

    # Normalization using StandardScaler
    scaler = StandardScaler()
    X_train = scaler.fit_transform(X_train)
    X_test = scaler.transform(X_test)

    # Model training
    model = RandomForestRegressor()
    model.fit(X_train, y_train)

    # Predictions
    predictions = model.predict(X_test)

    # Calculate evaluation metrics
    mae = mean_absolute_error(y_test, predictions)
    rmse = np.sqrt(mean_squared_error(y_test, predictions))
    r2 = r2_score(y_test, predictions)

    # Print metrics
    print(f"Attempt: {attempt_name}")
    print(f"Mean Absolute Error: {mae}")
    print(f"Root Mean Squared Error: {rmse}")
    print(f"R-squared: {r2}")

    # Append metrics to results list
    results.append({
        'Attempt': attempt_name,
        'MAE': mae,
        'RMSE': rmse,
        'R2': r2
        })

    # Get feature importances
    importances = model.feature_importances_
    importance_df = pd.DataFrame({
        'Feature': features,
        'Importance': importances
    }).sort_values(by='Importance', ascending=False)

    # Select the top N most important features
    top_features = importance_df.head(top_n)

    # Plot top important features
    plt.figure(figsize=(10, 6))
    plt.barh(top_features['Feature'], top_features['Importance'],
color='skyblue')
    plt.xlabel('Feature Importance')
```

```
    plt.ylabel('Features')
    plt.title(f'Top {top_n} Important Features for {attempt_name}')
    plt.gca().invert_yaxis()
    plt.show()

# Attempt 1 - Selecting all the features and without doing feature
engineering
attempt1 = ['max_capacity', 'occupied', 'tempC',
       'windspeedKmph', 'precipMM', 'commercial', 'residential',
       'transportation', 'schools', 'eventsites', 'restaurant',
'shopping',
       'office', 'supermarket', 'num_off_street_parking',
'off_street_capa']
run_experiment(df, attempt1, 'available', "Attempt 1")

Attempt: Attempt 1
Mean Absolute Error: 1.0882860783561816
Root Mean Squared Error: 2.089467644245773
R-squared: 0.9151142918809467
```

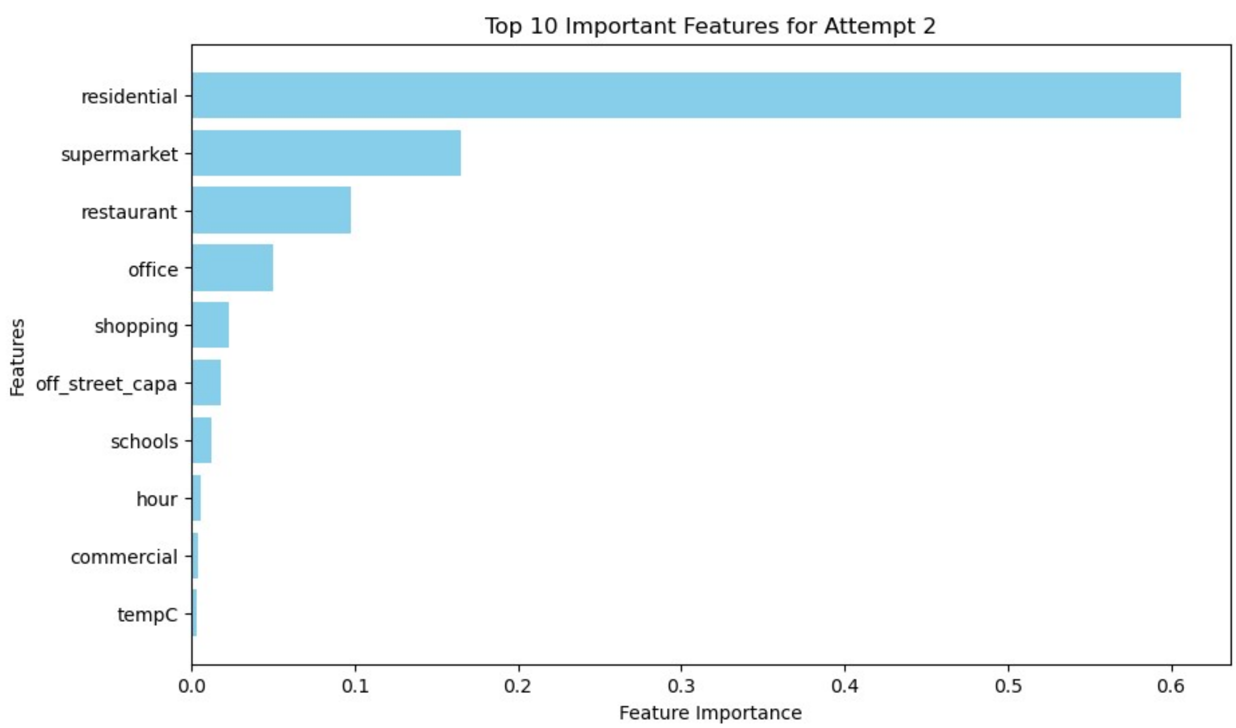



```
# Attempt 2 - Feature Engineering, Preprocessing and selecting
specific features

# Extract useful temporal features from the date and time columns
df['timestamp'] = pd.to_datetime(df['timestamp'])
df['day_of_week'] = df['timestamp'].dt.dayofweek
df['is_weekend'] = df['day_of_week'].apply(lambda x: 1 if x >= 5 else
0)
```

```
df['hour'] = pd.to_datetime(df['timestamp']).dt.hour

# Drop unnecessary columns
#df.drop(columns=['date', 'time'], inplace=True)

df['is_weekend'] = df['day_of_week'].isin([5, 6]).astype(int)
df['hour'] = pd.to_datetime(df['timestamp']).dt.hour

# Replace missing values in 'commercial' column with the median
df['commercial'].fillna(df['commercial'].median(), inplace=True)

# Replace missing or invalid values in 'available' with 0
df['available'].fillna(0, inplace=True)
df['available'] = df['available'].apply(lambda x: 0 if x < 0 else x)

# Replace -999 in 'tempC' column with the average of the column
mean_tempC = df.loc[df['tempC'] != -999, 'tempC'].mean()  # Calculate
mean without -999 values
df['tempC'].replace(-999, mean_tempC, inplace=True)

attempt2 = ['tempC', 'windspeedKmph', 'precipMM', 'commercial',
'residential',
                      'transportation', 'schools', 'eventsites',
'restaurant', 'shopping',
                      'office', 'supermarket',
'num_off_street_parking', 'off_street_capa',
                      'day_of_week', 'is_weekend', 'hour']
run_experiment(df, attempt2, 'available', "Attempt 2")
```

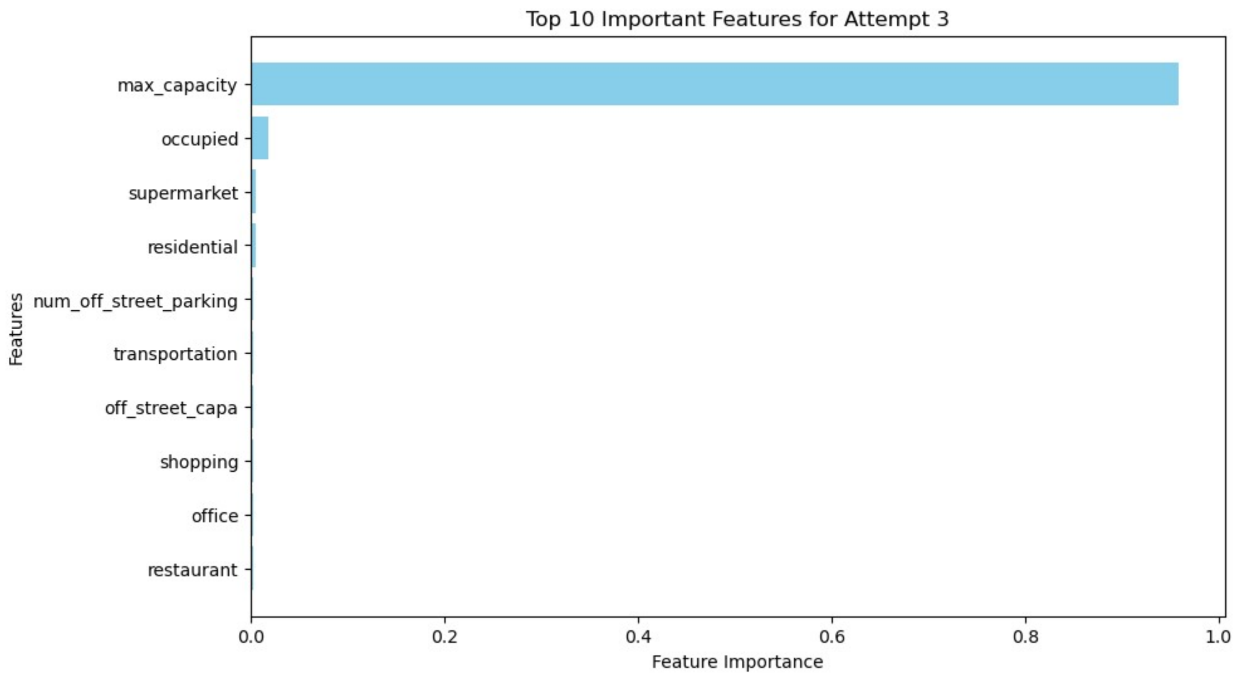
```
C:\Users\lahir\AppData\Local\Temp\ipykernel_17740\1126651581.py:16:
FutureWarning: A value is trying to be set on a copy of a DataFrame or
Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never
work because the intermediate object on which we are setting values
always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try
using 'df.method({col: value}, inplace=True)' or df[col] =
df[col].method(value) instead, to perform the operation inplace on the
original object.


  df['commercial'].fillna(df['commercial'].median(), inplace=True)
C:\Users\lahir\AppData\Local\Temp\ipykernel_17740\1126651581.py:19:
FutureWarning: A value is trying to be set on a copy of a DataFrame or
Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never
work because the intermediate object on which we are setting values
always behaves as a copy.
```

```
For example, when doing 'df[col].method(value, inplace=True)', try
using 'df.method({col: value}, inplace=True)' or df[col] =
df[col].method(value) instead, to perform the operation inplace on the
original object.


  df['available'].fillna(0, inplace=True)
C:\Users\lahir\AppData\Local\Temp\ipykernel_17740\1126651581.py:24:
FutureWarning: A value is trying to be set on a copy of a DataFrame or
Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never
work because the intermediate object on which we are setting values
always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try
using 'df.method({col: value}, inplace=True)' or df[col] =
df[col].method(value) instead, to perform the operation inplace on the
original object.


  df['tempC'].replace(-999, mean_tempC, inplace=True)

Attempt: Attempt 2
Mean Absolute Error: 7.331413768012332
Root Mean Squared Error: 8.661392299071043
R-squared: -0.4586998063368364
```



```
# Attempt 3 - Feature Engineering, Preprocessing and selecting all
features
attempt3 = ['max_capacity', 'occupied','tempC', 'windspeedKmph',
'precipMM', 'commercial',
            'residential', 'transportation', 'schools', 'eventsites',
'restaurant', 'shopping',
                      'office', 'supermarket',
'num_off_street_parking', 'off_street_capa',
                      'day_of_week', 'is_weekend', 'hour']
run_experiment(df, attempt3, 'available', "Attempt 3")
```

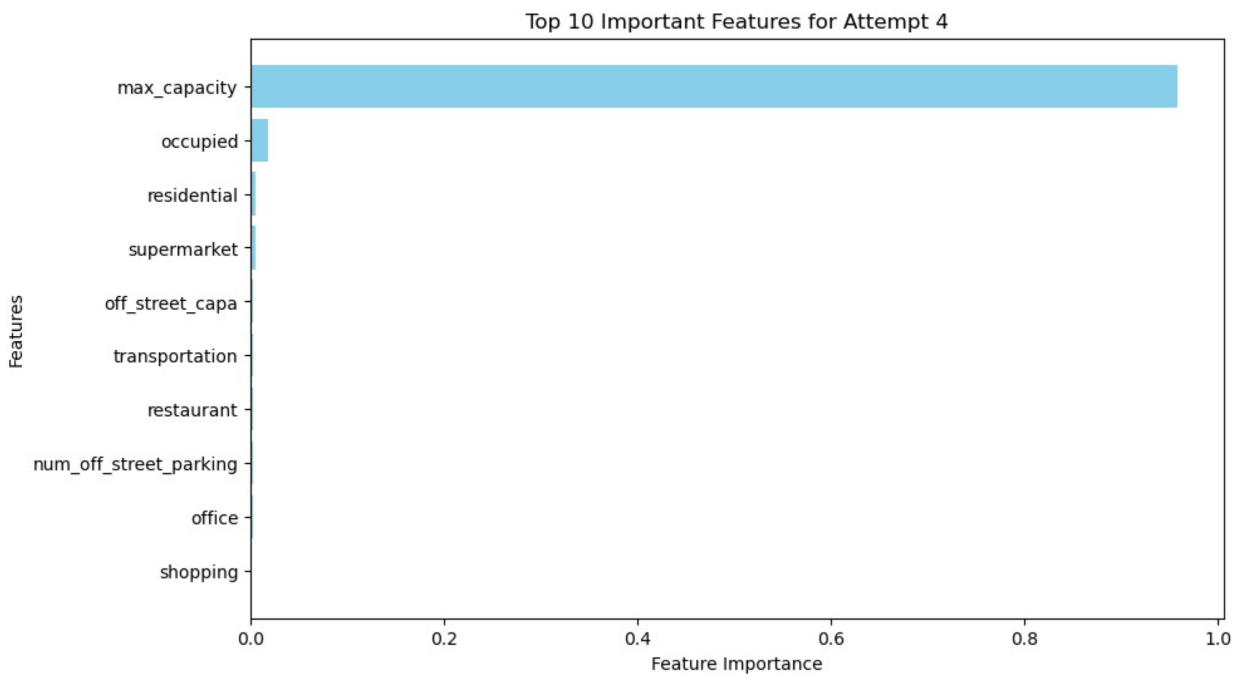
```
Attempt: Attempt 3
Mean Absolute Error: 1.1459261655961397
Root Mean Squared Error: 2.2659800618889285
R-squared: 0.9001604362218294
```




```
# Attempt 4 - More feature engineering (lag and rolling features :
occupied)
df['occupied_lag_1'] = df['occupied'].shift(1)
df['occupied_lag_3'] = df['occupied'].shift(3)
df['occupied_lag_6'] = df['occupied'].shift(6)
df['occupied_rolling_mean_3'] =
df['occupied'].rolling(window=3).mean()
df['occupied_rolling_mean_6'] =
df['occupied'].rolling(window=6).mean()
df['occupied_rolling_mean_12'] =
df['occupied'].rolling(window=12).mean()
df.fillna(0, inplace=True)
```

```
attempt4 = ['max_capacity', 'occupied', 'occupied_lag_1',
'occupied_lag_3', 'occupied_rolling_mean_3',
                      'occupied_rolling_mean_6', 'tempC',
'windspeedKmph', 'precipMM', 'commercial',
                      'residential', 'transportation', 'schools',
'eventsites', 'restaurant',
                      'shopping', 'office', 'supermarket',
'num_off_street_parking', 'off_street_capa',
                      'day_of_week', 'is_weekend', 'hour']
run_experiment(df, attempt4, 'available', "Attempt 4")
```

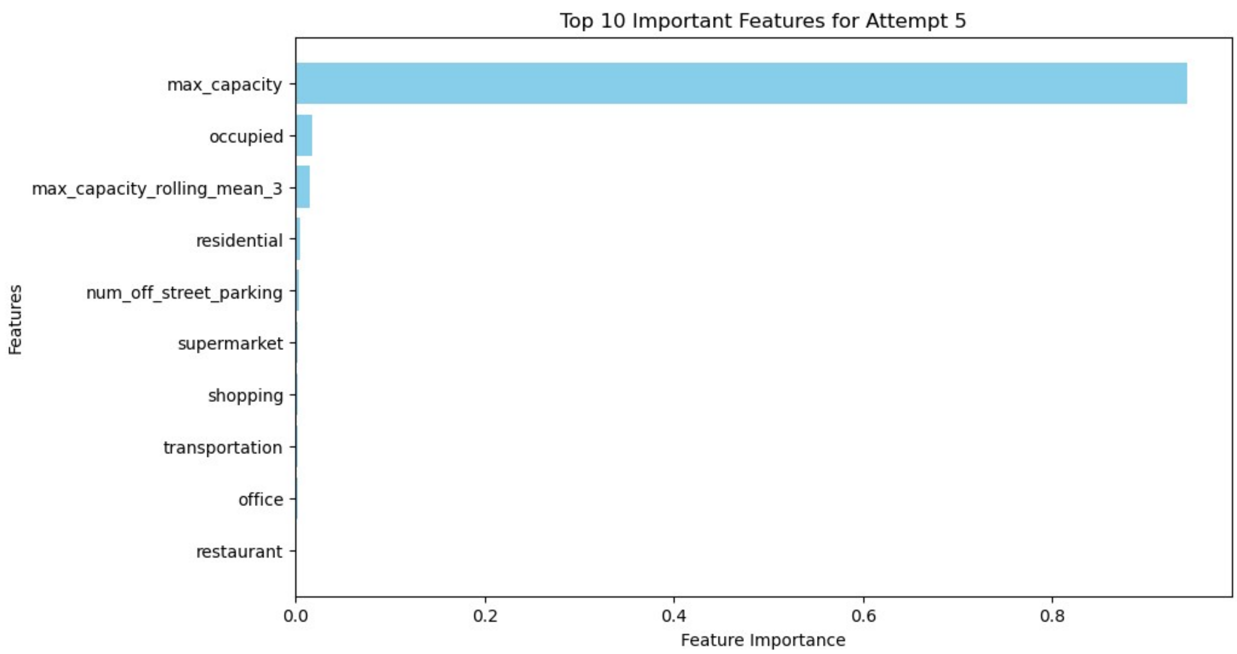
```
Attempt: Attempt 4
Mean Absolute Error: 1.1653860288243378
Root Mean Squared Error: 2.299110173079787
R-squared: 0.8972196546641568
```




```
# Attempt 5 - More feature engineering (lag and rolling features :
occupied, max_capacity)
df['max_capacity_lag_1'] = df['max_capacity'].shift(1)
df['max_capacity_lag_3'] = df['max_capacity'].shift(3)
df['max_capacity_lag_6'] = df['max_capacity'].shift(6)
df['max_capacity_rolling_mean_3'] =
df['max_capacity'].rolling(window=3).mean()
df['max_capacity_rolling_mean_6'] =
df['max_capacity'].rolling(window=6).mean()
df['max_capacity_rolling_mean_12'] =
df['max_capacity'].rolling(window=12).mean()
```

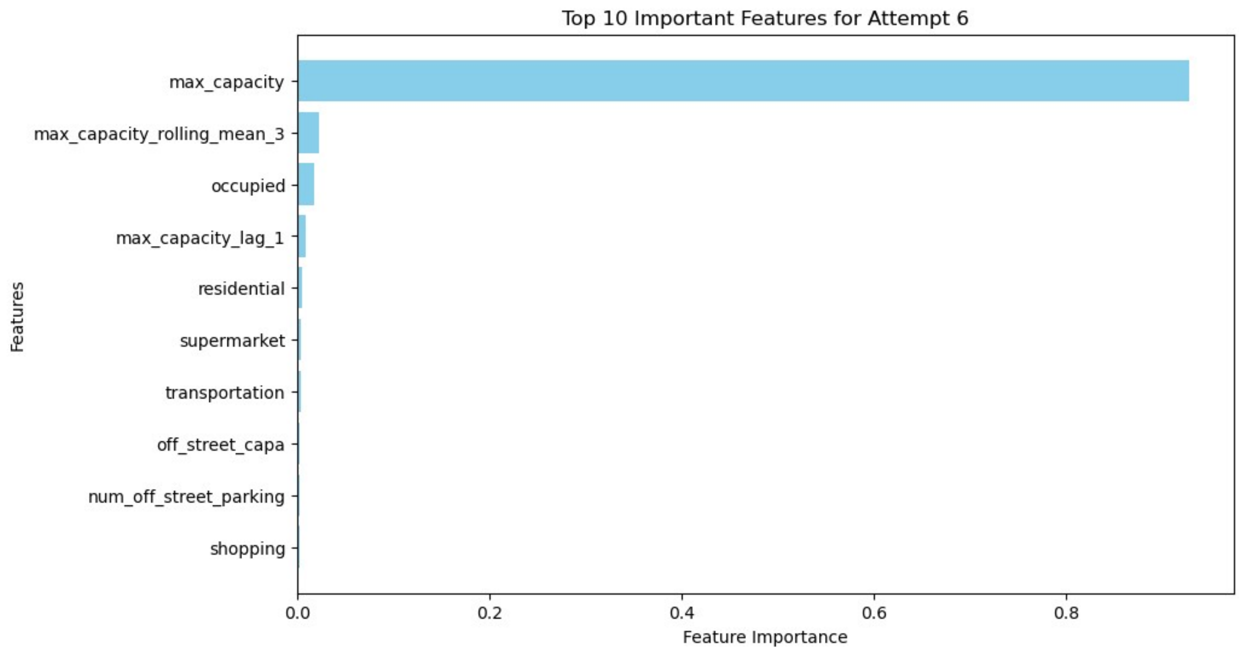
```
df.fillna(0, inplace=True)

attempt5 = ['max_capacity', 'occupied', 'occupied_lag_1',
'occupied_lag_3', 'occupied_rolling_mean_3',
                      'occupied_rolling_mean_6', 'max_capacity_lag_1',
'max_capacity_lag_3', 'max_capacity_rolling_mean_3',
                      'max_capacity_rolling_mean_6',  'tempC',
'windspeedKmph', 'precipMM', 'commercial',
                      'residential', 'transportation', 'schools',
'eventsites', 'restaurant',
                      'shopping', 'office', 'supermarket',
'num_off_street_parking', 'off_street_capa',
                      'day_of_week', 'is_weekend', 'hour']
run_experiment(df, attempt5, 'available', "Attempt 5")
```

```
Attempt: Attempt 5
Mean Absolute Error: 1.014532722973189
Root Mean Squared Error: 2.0527633303156416
R-squared: 0.9180652244334556
```




```
# Attempt 6 - More feature engineering (lag and rolling features:
occupied, max_capacity) and treating outliers
# Capping outliers at the 99th percentile for precipMM and
transportation
precip_cap = df['precipMM'].quantile(0.99)
trans_cap = df['transportation'].quantile(0.99)

df['precipMM'] = np.where(df['precipMM'] > precip_cap, precip_cap,
df['precipMM'])
```

```
df['transportation'] = np.where(df['transportation'] > trans_cap,
trans_cap, df['transportation'])

attempt6 = ['max_capacity', 'occupied', 'occupied_lag_1',
'occupied_lag_3', 'occupied_rolling_mean_3',
                      'occupied_rolling_mean_6', 'max_capacity_lag_1',
'max_capacity_lag_3', 'max_capacity_rolling_mean_3',
                      'max_capacity_rolling_mean_6',  'tempC',
'windspeedKmph', 'precipMM', 'commercial',
                      'residential', 'transportation', 'schools',
'eventsites', 'restaurant',
                      'shopping', 'office', 'supermarket',
'num_off_street_parking', 'off_street_capa',
                      'day_of_week', 'is_weekend', 'hour']
run_experiment(df, attempt6, 'available', "Attempt 6")

Attempt: Attempt 6
Mean Absolute Error: 1.0984482152558084
Root Mean Squared Error: 2.2488428796709456
R-squared: 0.9016648615763506
```



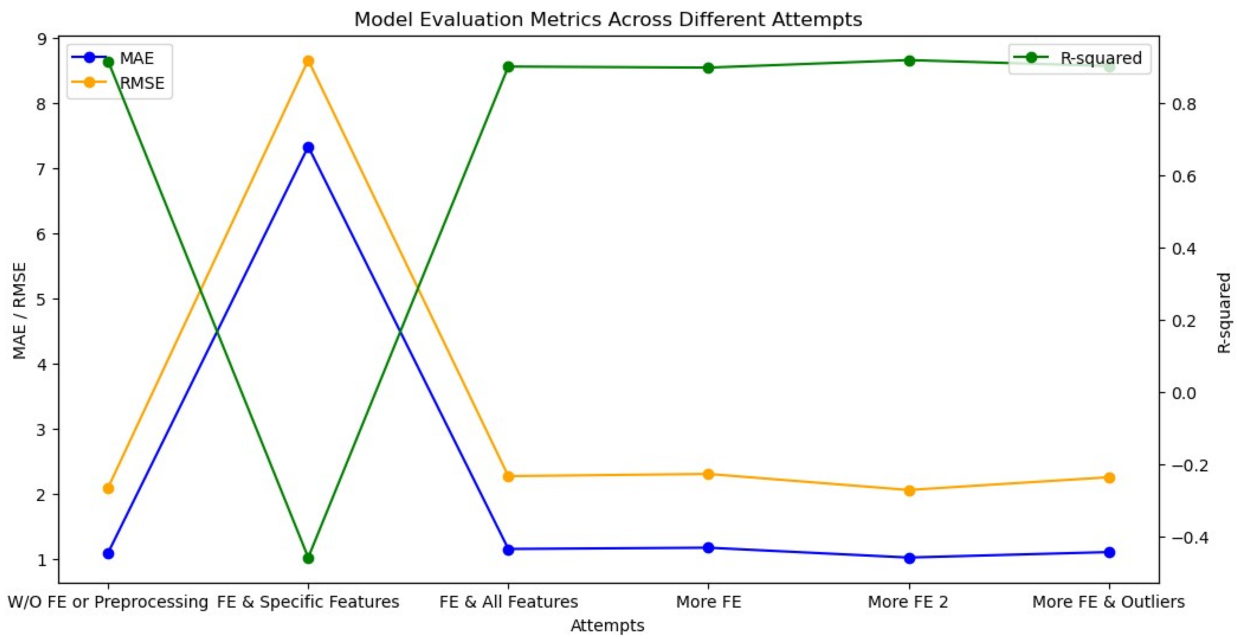
6. Results Summary and Visualization

```
# Convert results to DataFrame
results_df = pd.DataFrame(results)

# Mapping old attempt names to new names
attempt_names = {
```

```python
    'Attempt 1': 'W/O FE or Preprocessing',
    'Attempt 2': 'FE & Specific Features',
    'Attempt 3': 'FE & All Features',
    'Attempt 4': 'More FE',
    'Attempt 5': 'More FE 2',
    'Attempt 6': 'More FE & Outliers',
}

# Rename attempts
results_df['Attempt'] = results_df['Attempt'].map(attempt_names)
results_df
```

	Attempt	MAE	RMSE	R2
0	W/O FE or Preprocessing	1.09	2.09	0.92
1	FE & Specific Features	7.33	8.66	-0.46
2	FE & All Features	1.15	2.27	0.90
3	More FE	1.17	2.30	0.90
4	More FE 2	1.01	2.05	0.92
5	More FE & Outliers	1.10	2.25	0.90

```python
# Plotting the results
fig, ax1 = plt.subplots(figsize=(12, 6))

# Plot MAE, RMSE, and R-squared on the same plot
ax1.plot(results_df['Attempt'], results_df['MAE'], marker='o',
label='MAE', color='blue')
ax1.plot(results_df['Attempt'], results_df['RMSE'], marker='o',
label='RMSE', color='orange')
ax2 = ax1.twinx()
ax2.plot(results_df['Attempt'], results_df['R2'], marker='o',
label='R-squared', color='green')

# Labeling the plots
ax1.set_xlabel("Attempts")
ax1.set_ylabel("MAE / RMSE")
ax2.set_ylabel("R-squared")
ax1.legend(loc="upper left")
ax2.legend(loc="upper right")
plt.title("Model Evaluation Metrics Across Different Attempts")
plt.savefig("evaluation_metrics.png")
plt.show()
```



Model Evaluation Metrics Across Different Attempts
MAE
RMSE
R-squared
MAE / RMSE
R-squared
W/O FE or Preprocessing
FE & Specific Features
FE & All Features
More FE
More FE 2
More FE & Outliers
Attempts