List Of Tables

List of figures

Problem Statement

The data contains the details for the Uber rides across various boroughs (subdivisions) of New York City at an hourly level and attributes associated with weather conditions at that time.

Importing the Important libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

Loading the Dataset

In [2]:
```
df = pd.read_csv("D:/dataset.csv")
```

1- Display first five rows of teh dataset

In [3]:
```
df.head()
```

Out[3]:

	pickup_dt	borough	pickups	spd	vsb	temp	dewp	slp	pcp01	pcp06	pcp24
0	01-01-2015 01:00	Bronx	152.0	5.0	10.0	30.0	7.0	1023.5	0.0	0.0	0.0
1	01-01-2015 01:00	Brooklyn	1519.0	5.0	10.0	NaN	7.0	1023.5	0.0	0.0	0.0
2	01-01-2015 01:00	EWR	0.0	5.0	10.0	30.0	7.0	1023.5	0.0	0.0	0.0
3	01-01-2015 01:00	Manhattan	5258.0	5.0	10.0	30.0	7.0	1023.5	0.0	0.0	0.0
4	01-01-2015 01:00	Queens	405.0	5.0	10.0	30.0	7.0	1023.5	0.0	0.0	0.0

	pickup_dt	borough	pickups	spd	vsb	temp	dewp	slp	pcp01	pcp06	pcp24	sd	hday
0	1/1/2015 1:00	Bronx	152.0	5.0	10.0	30.0	7.0	1023.5	0.0	0.0	0.0	0.0	Y
1	1/1/2015 1:00	Brooklyn	1519.0	5.0	10.0	NaN	7.0	1023.5	0.0	0.0	0.0	0.0	?
2	1/1/2015 1:00	EWR	0.0	5.0	10.0	30.0	7.0	1023.5	0.0	0.0	0.0	0.0	Y
3	1/1/2015 1:00	Manhattan	5258.0	5.0	10.0	30.0	7.0	1023.5	0.0	0.0	0.0	0.0	Y
4	1/1/2015 1:00	Queens	405.0	5.0	10.0	30.0	7.0	1023.5	0.0	0.0	0.0	0.0	Y

Observations:

- First five rows of the dataset
- In first five rows we can see a "?" in the hday values.

2- Display last five rows of the dataset

In [4]:
```
df.tail()
```

Out[4]:

	pickup_dt	borough	pickups	spd	vsb	temp	dewp	slp	pcp01	pcp06	p
29096	30-06-2015 23:00	EWR	0.0	7.0	10.0	75.0	65.0	1011.8	0.0	0.0	
29097	30-06-2015 23:00	Manhattan	3828.0	7.0	10.0	75.0	65.0	1011.8	0.0	0.0	
29098	30-06-2015 23:00	Queens	580.0	7.0	10.0	75.0	65.0	1011.8	0.0	0.0	
29099	30-06-2015 23:00	Staten Island	0.0	7.0	10.0	75.0	65.0	1011.8	0.0	0.0	
29100	30-06-2015 23:00	NaN	3.0	7.0	10.0	75.0	65.0	1011.8	0.0	0.0	

	pickup_dt	borough	pickups	spd	vsb	temp	dewp	slp	pcp01	pcp06	pcp24	sd	hday
29096	30-06-2015 23:00	EWR	0.0	7.0	10.0	75.0	65.0	1011.8	0.0	0.0	0.0	0.0	N
29097	30-06-2015 23:00	Manhattan	3828.0	7.0	10.0	75.0	65.0	1011.8	0.0	0.0	0.0	0.0	N
29098	30-06-2015 23:00	Queens	580.0	7.0	10.0	75.0	65.0	1011.8	0.0	0.0	0.0	0.0	N
29099	30-06-2015 23:00	Staten Island	0.0	7.0	10.0	75.0	65.0	1011.8	0.0	0.0	0.0	0.0	N
29100	30-06-2015 23:00	NaN	3.0	7.0	10.0	75.0	65.0	1011.8	0.0	0.0	0.0	0.0	N

3- Check for shape of the dataset

In [5]:
```
df.shape
```

Out[5]: (29101, 13)

(29101, 13)

Observations:

- There are 29101 number of rows in our dataset and 13 columns

4- Check the datatypes of each feature.

In [6]:
```
df.dtypes
```

Out[6]:
```
pickup_dt     object
borough       object
pickups      float64
spd          float64
vsb          float64
temp         float64
dewp         float64
slp          float64
pcp01        float64
pcp06        float64
pcp24        float64
sd           float64
hday          object
dtype: object
```


```
pickup_dt     object
borough       object
pickups      float64
spd          float64
vsb          float64
temp         float64
dewp         float64
slp          float64
pcp01        float64
pcp06        float64
pcp24        float64
sd           float64
hday          object
dtype: object
```


5- Check the Statistical summary

In [7]:
```
df.describe()
```

Out[7]:

	pickups	spd	vsb	temp	dewp	
count	29099.000000	29101.000000	29101.000000	28742.000000	29101.000000	2.910100e
mean	490.236022	5.984924	8.818125	47.900262	30.823065	1.052633e
std	995.680628	3.699007	2.442897	19.800541	21.283444	5.945147e
min	0.000000	0.000000	0.000000	0.000000	-16.000000	1.000000e
25%	1.000000	3.000000	9.100000	32.000000	14.000000	1.012500e
50%	54.000000	6.000000	10.000000	46.500000	30.000000	1.018200e
75%	449.000000	8.000000	10.000000	65.000000	50.000000	1.022900e
max	7883.000000	21.000000	10.000000	89.000000	73.000000	1.015200e

	pickups	spd	vsb	temp	dewp	slp	pcp01	pcp06	pcp24	sd
count	29099.000000	29101.000000	29101.000000	28742.000000	29101.000000	2.910100e+04	29101.000000	29101.000000	29101.000000	29101.000000
mean	490.236022	5.984924	8.818125	47.900262	30.823065	1.052633e+03	0.003830	0.026129	0.090464	2.529169
std	995.680628	3.699007	2.442897	19.800541	21.283444	5.945147e+03	0.018933	0.093125	0.219402	4.520325
min	0.000000	0.000000	0.000000	0.000000	-16.000000	1.000000e+00	0.000000	0.000000	0.000000	0.000000
25%	1.000000	3.000000	9.100000	32.000000	14.000000	1.012500e+03	0.000000	0.000000	0.000000	0.000000
50%	54.000000	6.000000	10.000000	46.500000	30.000000	1.018200e+03	0.000000	0.000000	0.000000	0.000000
75%	449.000000	8.000000	10.000000	65.000000	50.000000	1.022900e+03	0.000000	0.000000	0.050000	2.958333
max	7883.000000	21.000000	10.000000	89.000000	73.000000	1.015200e+06	0.280000	1.240000	2.100000	19.000000

6- Check the null values

In [8]:
```
df.isnull().sum()
```

Out[8]:
```
pickup_dt       0
borough      3043
pickups         2
spd             0
vsb             0
temp          359
dewp            0
slp             0
pcp01           0
pcp06           0
pcp24           0
sd              0
hday            0
dtype: int64
```


```
pickup_dt       0
borough      3043
pickups         2
spd             0
vsb             0
temp          359
dewp            0
slp             0
pcp01           0
pcp06           0
pcp24           0
sd              0
hday            0
dtype: int64
```


Observations:

- There are 3043 null values in our dataset in borough column.
- There are 2 null values in pickup column and 359 null values in the temp column of the dataset.

7- Check the duplicate values

In [9]:
```
duplicates = df.duplicated().sum()
print(f"Number of duplicate rows: {duplicates}")
```

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

Number of duplicate rows: 0

8- Check for outliers and their authenticity

In [10]:
```
numerical_columns = df.select_dtypes(include=['float64']).columns
# Calculate IQR to identify outliers
Q1 = df[numerical_columns].quantile(0.25)
Q3 = df[numerical_columns].quantile(0.75)
IQR = Q3 - Q1

# Identify outliers
outliers = (df[numerical_columns] < (Q1 - 1.5 * IQR)) | (df[numerical_c

# Display outliers summary
outliers_summary = outliers.sum()
print("Number of outliers in each column:")
print(outliers_summary)
```

```
Number of outliers in each column:
pickups    3498
spd         451
vsb        5322
temp          0
dewp          0
slp         281
pcp01      2633
pcp06      5641
pcp24      5016
sd         6060
dtype: int64
```

Number of outliers in each column:
pickups   3498
spd   451
vsb   5322
temp   0
dewp   0
slp   281
pcp01   2633
pcp06   5641
pcp24   5016
sd   6060
dtype: int64

In [11]:

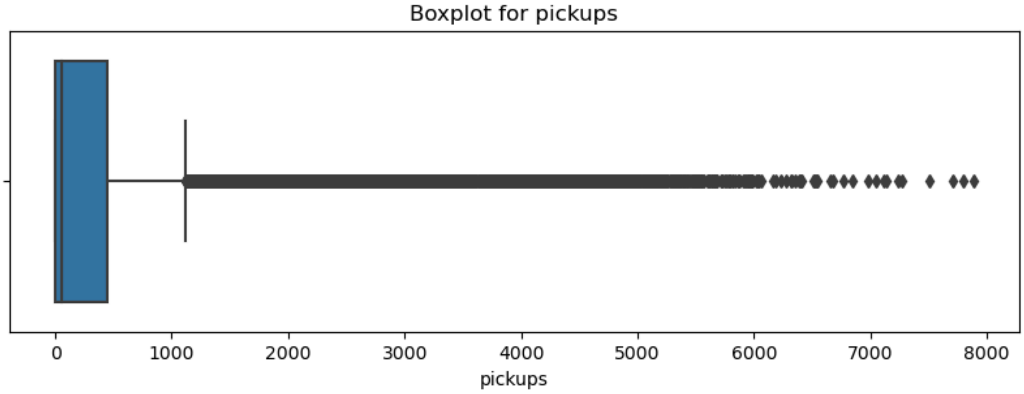
```
outlier_counts = outliers.sum()
total_counts = df.shape[0]
outlier_percentage = (outlier_counts / total_counts) * 100

# Display the percentage of outliers
print("Percentage of outliers in each column:")
print(outlier_percentage)
```

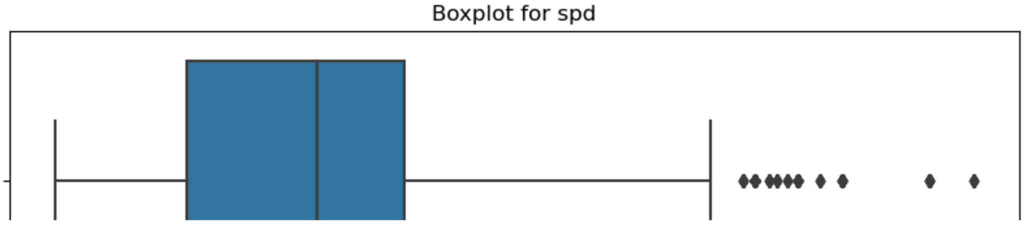
```
Percentage of outliers in each column:
pickups    12.020205
spd         1.549775
vsb        18.288031
temp        0.000000
dewp        0.000000
slp         0.965603
pcp01       9.047799
pcp06      19.384214
pcp24      17.236521
sd         20.824027
dtype: float64
```

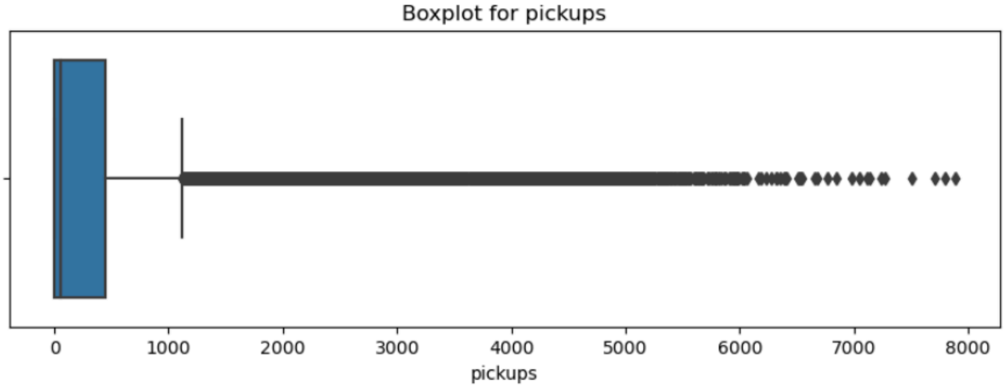

```
Percentage of outliers in each column:
pickups    12.020205
spd         1.549775
vsb        18.288031
temp        0.000000
dewp        0.000000
slp         0.965603
pcp01       9.047799
pcp06      19.384214
pcp24      17.236521
sd         20.824027
dtype: float64
```

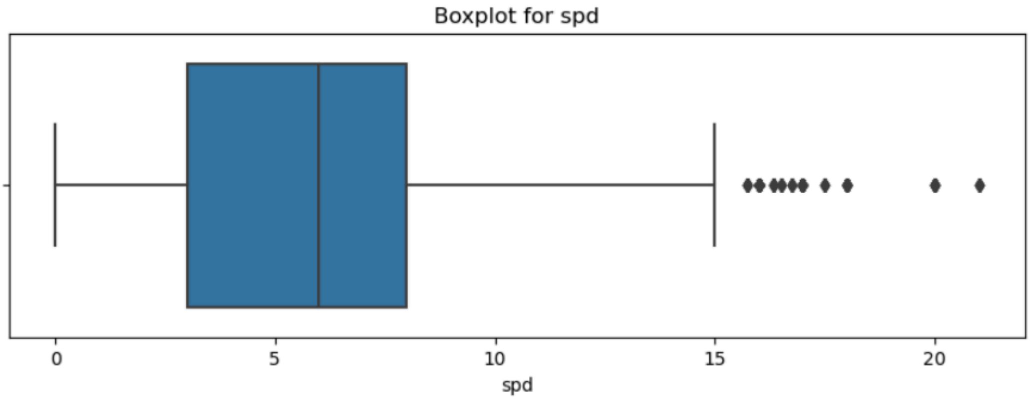
In [12]:

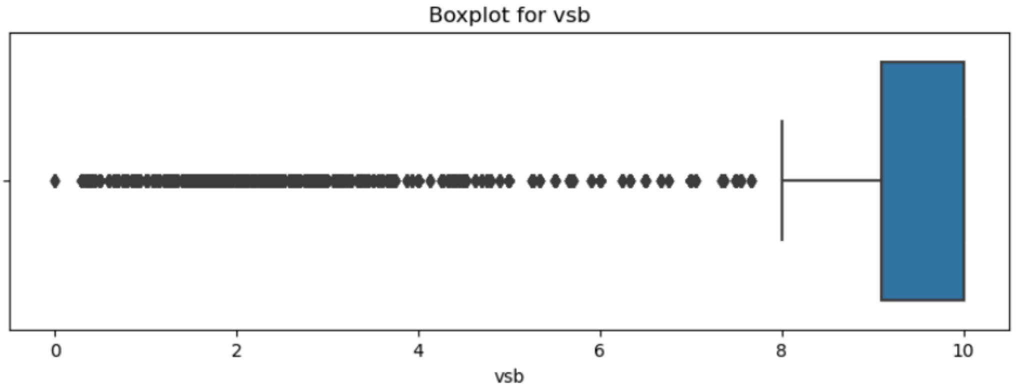
```
numerical_columns = df.select_dtypes(include=['float64']).columns

for column in numerical_columns:
    plt.figure(figsize=(10, 3))
    sns.boxplot(x=df[column])
    plt.title(f'Boxplot for {column}')
    plt.show()
```

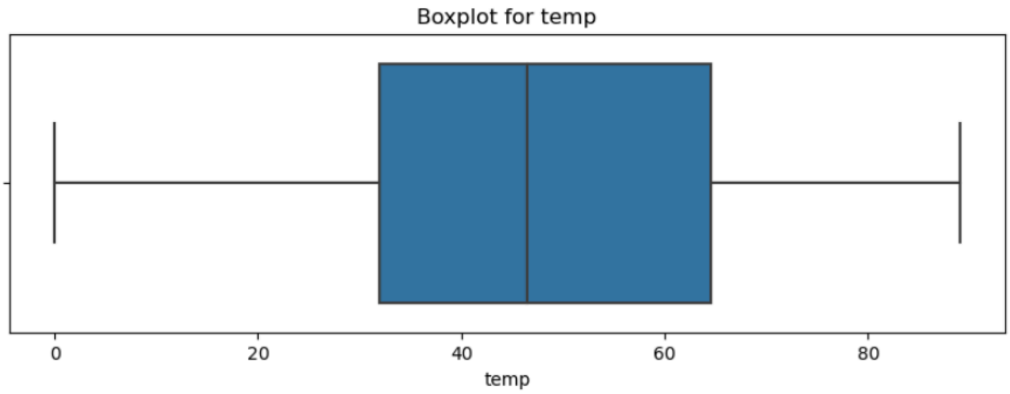


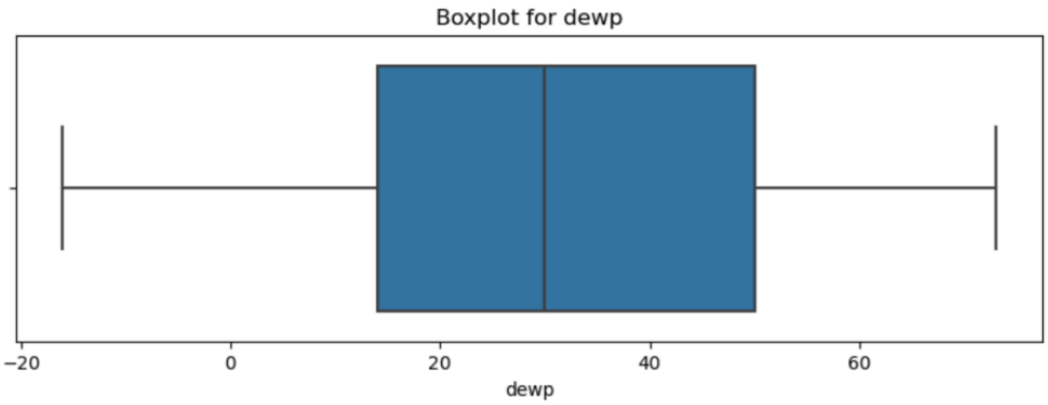


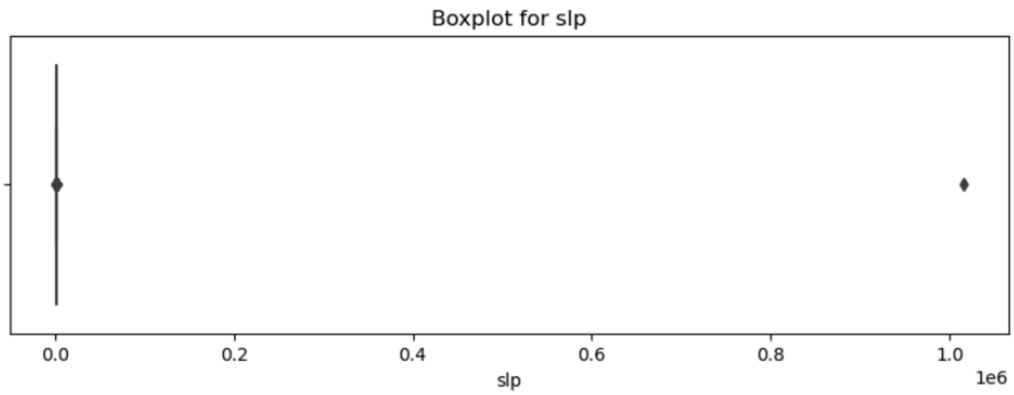


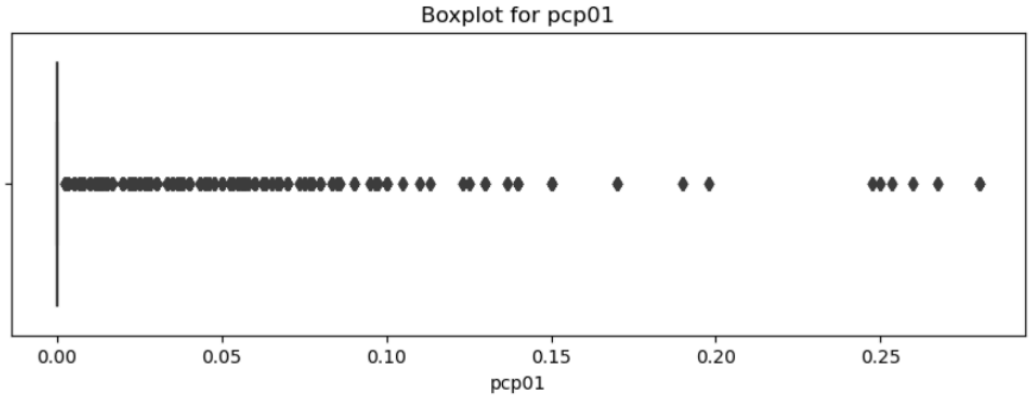


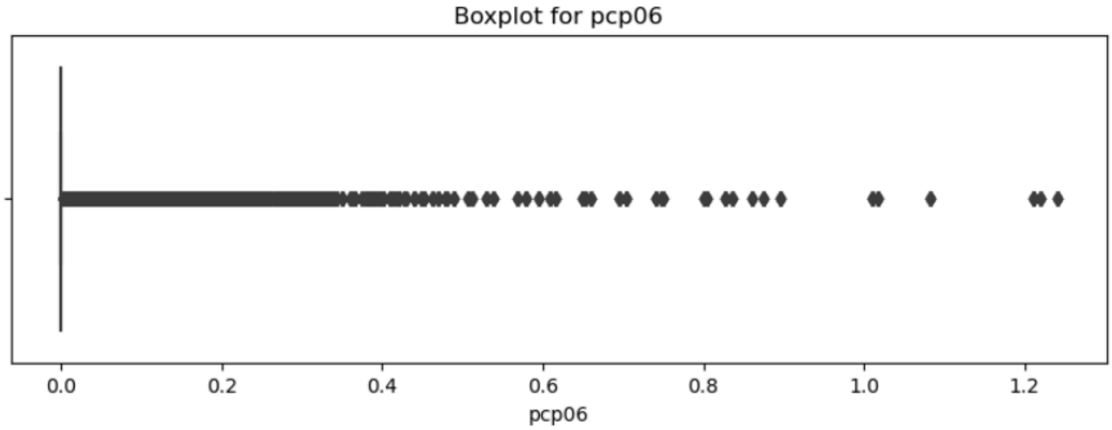

Boxplot for vsb
0
2
4
6
8
10
vsb

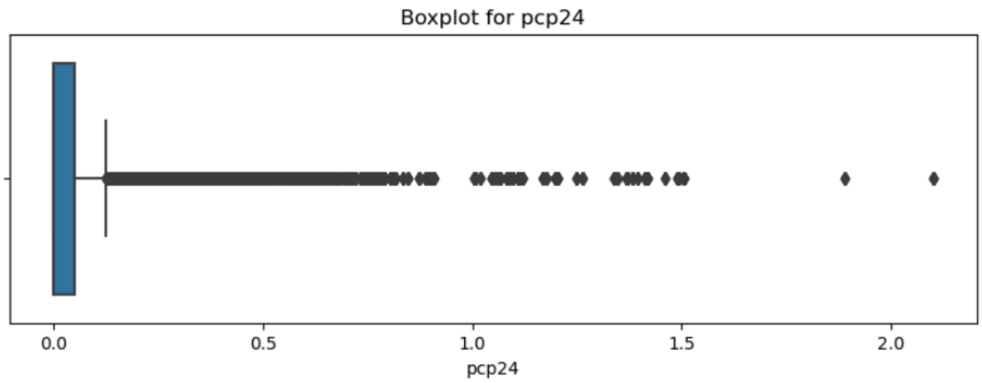

Boxplot for temp
0
20
40
60
80
temp

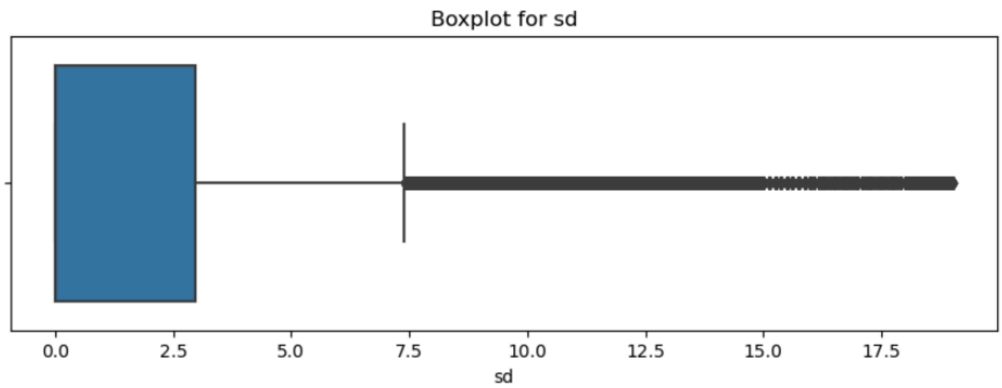

Boxplot for dewp
−20
0
20
40
60
dewp


Boxplot for slp
0.0
0.2
0.4
0.6
0.8
1.0
1e6
slp









9- Check for Anomalies:

In [13]:
```
columns_with_question_mark = {}
for column in df.columns:
    count = (df[column] == '?').sum()
    if count > 0:
        columns_with_question_mark[column] = count

print("Columns with '?' and their counts:")
for column, count in columns_with_question_mark.items():
    print(f"{column}: {count}")
```

```
Columns with '?' and their counts:
hday: 2
```


```
Columns with '?' and their counts:
hday: 2
```


In [14]:
```
# Filter rows where 'hday' column has '?'
rows_with_question_mark= df[df['hday'] == '?']

print("Rows with '?' in 'hday' column:")
print(rows_with_question_mark)
```

```
Rows with '?' in 'hday' column:
               pickup_dt   borough  pickups  spd   vsb  temp  dewp     sl
p  \
1    01-01-2015 01:00  Brooklyn   1519.0  5.0  10.0   NaN   7.0  1023.
5
123  01-01-2015 19:00    Queens    238.0  7.0  10.0  37.0   7.0  1016.
2

     pcp01  pcp06  pcp24   sd hday
1      0.0    0.0    0.0  0.0    ?
123    0.0    0.0    0.0  0.0    ?
```

```
Rows with '?' in 'hday' column:
            pickup_dt   borough  pickups  spd   vsb  temp  dewp     slp  pcp01  \
1     1/1/2015 1:00  Brooklyn   1519.0  5.0  10.0   NaN   7.0  1023.5    0.0
123  1/1/2015 19:00    Queens    238.0  7.0  10.0  37.0   7.0  1016.2    0.0

     pcp06  pcp24   sd hday
1      0.0    0.0  0.0    ?
123    0.0    0.0  0.0    ?
```

Observations:

- We have got dtypes of date as object that should be date and time.
- There are two rows which have "?" as the value in their hday value.
- The number of outliers is much more in our dataset percentage ranging from 12-20%.

10- Necessary cleaning needed

In [15]:
```
df.replace('?', np.nan, inplace=True)
```

In [16]:
```
rows_with_question_mark= df[df['hday'] == '?']

print("Rows with '?' in 'hday' column:")
print(rows_with_question_mark)
```

```
Rows with '?' in 'hday' column:
Empty DataFrame
Columns: [pickup_dt, borough, pickups, spd, vsb, temp, dewp, slp, pcp0
1, pcp06, pcp24, sd, hday]
Index: []
```


```
Rows with '?' in 'hday' column:
Empty DataFrame
Columns: [pickup_dt, borough, pickups, spd, vsb, temp, dewp, slp, pcp01, pcp06, pcp24, sd, hday]
Index: []
```


Removing null values using mean,median and mode

In [17]:
```
# Filling missing values in pickups coloumn with the median of the colu
df['pickups'].replace(np.nan,df['pickups'].median(),inplace=True)
```

In [18]:
```
# Filling null values in borough column with the mode of the column
df['borough'].replace(np.nan,df['borough'].mode().values[0],inplace=Tru
```

In [19]:
```
# Filling missing values in temp columns with the median of the column
df['temp'].replace(np.nan,df['temp'].median(),inplace=True)
```

In [20]:
```
# Filling null values in hday column with the mode of the column
df['hday'].replace(np.nan,df['hday'].mode().values[0],inplace=True)
```

In [21]:
```
df.isnull().sum()
```

Out[21]:
```
pickup_dt    0
borough      0
pickups      0
spd          0
vsb          0
temp         0
dewp         0
slp          0
pcp01        0
pcp06        0
pcp24        0
sd           0
hday         0
dtype: int64
```


```
pickup_dt    0
borough      0
pickups      0
spd          0
vsb          0
temp         0
dewp         0
slp          0
pcp01        0
pcp06        0
pcp24        0
sd           0
hday         0
dtype: int64
```


Removing Outliers from the dataset as data cleaning process

In [22]:
```
#Function to remove the Outliers

def remove_outlier(col):
    sorted(col)
    Q1,Q3=col.quantile([0.25,0.75])
    IQR=Q3-Q1
    lower_range= Q1-(1.5 * IQR)
    upper_range= Q3+(1.5 * IQR)
    return lower_range, upper_range

for i in df.columns:
    if df[i].dtype !='object':
        lr,ur=remove_outlier(df[i])
        df[i]=np.where(df[i]>ur,ur,df[i])
        df[i]=np.where(df[i]<lr,lr,df[i])
```

In [23]:
```python
# Calculate IQR to identify outliers
Q1 = df[numerical_columns].quantile(0.25)
Q3 = df[numerical_columns].quantile(0.75)
IQR = Q3 - Q1

# Identify outliers
outliers = (df[numerical_columns] < (Q1 - 1.5 * IQR)) | (df[numerical_c

# Display outliers summary
outliers_summary = outliers.sum()
print("Number of outliers in each column:")
print(outliers_summary)
```

```
Number of outliers in each column:
pickups    0
spd        0
vsb        0
temp       0
dewp       0
slp        0
pcp01      0
pcp06      0
pcp24      0
sd         0
dtype: int64
```


```
Number of outliers in each column:
pickups    0
spd        0
vsb        0
temp       0
dewp       0
slp        0
pcp01      0
pcp06      0
pcp24      0
sd         0
dtype: int64
```


Observations:

- No null values in the dataset.
- Now there is no outliers in our data.
- Since we have done most of the necessary cleaning of our data, now we will perform EDA on it.

In [24]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29101 entries, 0 to 29100
Data columns (total 13 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   pickup_dt  29101 non-null  object 
 1   borough    29101 non-null  object 
 2   pickups    29101 non-null  float64
 3   spd        29101 non-null  float64
 4   vsb        29101 non-null  float64
 5   temp       29101 non-null  float64
 6   dewp       29101 non-null  float64
 7   slp        29101 non-null  float64
 8   pcp01      29101 non-null  float64
 9   pcp06      29101 non-null  float64
 10  pcp24      29101 non-null  float64
 11  sd         29101 non-null  float64
 12  hday       29101 non-null  object 
dtypes: float64(10), object(3)
memory usage: 2.9+ MB
```


```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29101 entries, 0 to 29100
Data columns (total 13 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   pickup_dt  29101 non-null  object 
 1   borough    29101 non-null  object 
 2   pickups    29101 non-null  float64
 3   spd        29101 non-null  float64
 4   vsb        29101 non-null  float64
 5   temp       29101 non-null  float64
 6   dewp       29101 non-null  float64
 7   slp        29101 non-null  float64
 8   pcp01      29101 non-null  float64
 9   pcp06      29101 non-null  float64
 10  pcp24      29101 non-null  float64
 11  sd         29101 non-null  float64
 12  hday       29101 non-null  object 
dtypes: float64(10), object(3)
memory usage: 2.9+ MB
```

In [25]:
```
#Statistical summary
df.describe()
```

Out[25]:

	pickups	spd	vsb	temp	dewp	
count	29101.000000	29101.000000	29101.000000	29101.000000	29101.000000	29101.00(
mean	282.045256	5.961970	9.487576	47.882988	30.823065	1017.81(
std	386.660889	3.631521	0.906658	19.678631	21.283444	7.70
min	0.000000	0.000000	7.750000	0.000000	-16.000000	996.90(
25%	1.000000	3.000000	9.100000	32.000000	14.000000	1012.50(
50%	54.000000	6.000000	10.000000	46.500000	30.000000	1018.20(
75%	449.000000	8.000000	10.000000	64.500000	50.000000	1022.90(
max	1121.000000	15.500000	10.000000	89.000000	73.000000	1038.50(

	pickups	spd	vsb	temp	dewp	slp	pcp01	pcp06	pcp24	sd
count	29101.000000	29101.000000	29101.000000	29101.000000	29101.000000	29101.000000	29101.0	29101.0	29101.000000	29101.000000
mean	282.045256	5.961970	9.487576	47.882988	30.823065	1017.810618	0.0	0.0	0.030223	1.861165
std	386.660889	3.631521	0.906658	19.678631	21.283444	7.701187	0.0	0.0	0.049091	3.104397
min	0.000000	0.000000	7.750000	0.000000	-16.000000	996.900000	0.0	0.0	0.000000	0.000000
25%	1.000000	3.000000	9.100000	32.000000	14.000000	1012.500000	0.0	0.0	0.000000	0.000000
50%	54.000000	6.000000	10.000000	46.500000	30.000000	1018.200000	0.0	0.0	0.000000	0.000000
75%	449.000000	8.000000	10.000000	64.500000	50.000000	1022.900000	0.0	0.0	0.050000	2.958333
max	1121.000000	15.500000	10.000000	89.000000	73.000000	1038.500000	0.0	0.0	0.125000	7.395833

1- Pickup Analysis

In [26]:
```
# 1. Total number of Uber pickups across all boroughs
total_pickups = df['pickups'].sum()
total_pickups
```

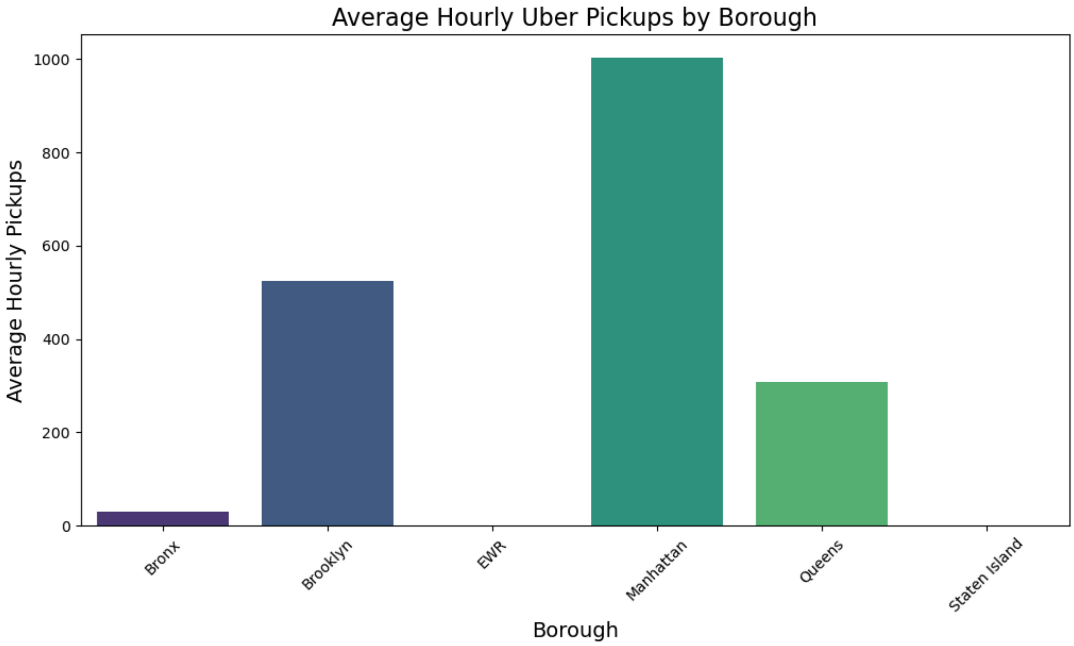
Out[26]: 8207799.0

8207799.0

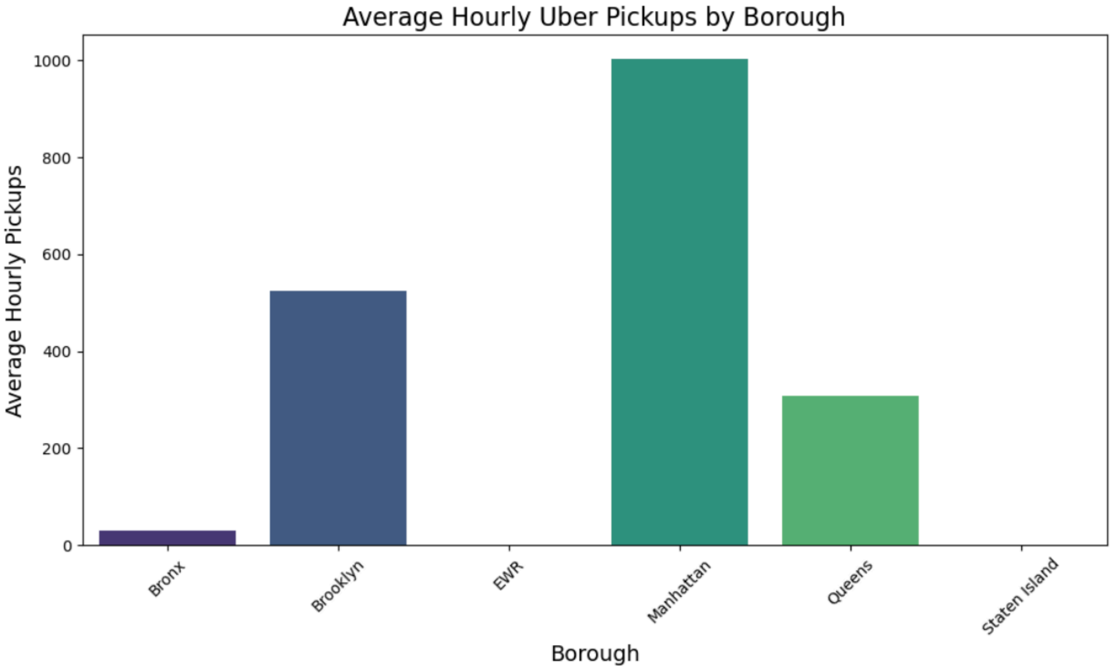
In [27]:

```
avg_hourly_pickups = df.groupby('borough')['pickups'].mean()
highest_avg_borough = avg_hourly_pickups.idxmax()
highest_avg_pickups = avg_hourly_pickups.max()


print(f"Borough with highest average hourly pickups: {highest_avg_borou

# Plotting the data
plt.figure(figsize=(12, 6))
sns.barplot(x=avg_hourly_pickups.index, y=avg_hourly_pickups.values, pa


plt.title('Average Hourly Uber Pickups by Borough', fontsize=16)
plt.xlabel('Borough', fontsize=14)
plt.ylabel('Average Hourly Pickups', fontsize=14)
plt.xticks(rotation=45)

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

```
Borough with highest average hourly pickups: Manhattan (1002.285056412
618 pickups/hour)
```



```
Borough with highest average hourly pickups: Manhattan (1002.285056412618 pickups/hour)
```



In [28]:

```
# Converting pickup_dt to datetime
df['pickup_dt'] = pd.to_datetime(df['pickup_dt'])

# Adding a column for the hour of the day
df['hour'] = df['pickup_dt'].dt.hour

# Adding a column for the day of the week
df['day_of_week'] = df['pickup_dt'].dt.day_name()

# Number of pickups by hour of the day
hourly_pickups = df.groupby('hour')['pickups'].mean().reset_index()

print(f"Number of pickups by hour of the day:\n{hourly_pickups}")
```

```
Number of pickups by hour of the day:
    hour     pickups
0      0  333.861411
1      1  276.578638
2      2  205.149573
3      3  153.505181
4      4  138.691581
5      5  148.648718
6      6  192.377500
7      7  237.443994
8      8  275.824247
9      9  292.635922
10    10  292.722449
11    11  291.485950
12    12  287.656250
13    13  284.920816
14    14  292.911184
15    15  304.999182
16    16  310.843393
17    17  315.169381
18    18  336.570728
19    19  346.274128
20    20  351.917275
21    21  353.895935
22    22  359.273242
23    23  359.614064
```

```
Number of pickups by hour of the day:
    hour     pickups
0      0  333.861411
1      1  276.578638
2      2  205.149573
3      3  153.505181
4      4  138.691581
5      5  148.648718
6      6  192.377500
7      7  237.443994
8      8  275.824247
9      9  292.635922
10    10  292.722449
11    11  291.485950
12    12  287.656250
13    13  284.920816
14    14  292.911184
15    15  304.999182
16    16  310.843393
17    17  315.169381
18    18  336.570728
19    19  346.274128
20    20  351.917275
21    21  353.895935
22    22  359.273242
23    23  359.614064
```

In [29]:

```
# Day of the week with the highest number of pickups
day_of_week_pickups = df.groupby('day_of_week')['pickups'].mean().reset
day_with_highest_pickups = day_of_week_pickups.loc[day_of_week_pickups[

print(f"Day of the week with the highest number of pickups:\n{day_with_
```

```
Day of the week with the highest number of pickups:
day_of_week      Saturday
pickups        313.247615
Name: 2, dtype: object
```


```
Day of the week with the highest number of pickups:
day_of_week      Saturday
pickups        313.247615
Name: 2, dtype: object
```


2- Weather Impact

In [30]:

```
#Correlation between temperature and the number of pickups
temp_pickup_corr = df['temp'].corr(df['pickups'])

print(f"The correlation between temperature and the number of pickups:\
```

```
The correlation between temperature and the number of pickups:
0.06813480303893318
```

```
The correlation between temperature and the number of pickups:
0.0681348030389327
```

In [31]:

```python
# Correlation between visibility and the number of pickups
vsb_pickup_corr = df['vsb'].corr(df['pickups'])

print(f"The Correlation between visibility and the number of pickups:\n
```

```
The Correlation between visibility and the number of pickups:
-0.0028513311640650245
```

```
The Correlation between visibility and the number of pickups:
-0.002851331164065039
```

In [32]:

```python
# Correlation between wind speed and the number of pickups
spd_pickup_corr = df['spd'].corr(df['pickups'])

print(f"The Correlation between wind speed and the number of pickups:\n
```

```
The Correlation between wind speed and the number of pickups:
-0.005233034976392448
```

```
The Correlation between wind speed and the number of pickups:
-0.005233034976392543
```

In [33]:

```python
# Correlation between 1-hour precipitation and the number of pickups
pcp01_pickup_corr = df['pcp01'].corr(df['pickups'])

# Correlation between 6-hour precipitation and the number of pickups
pcp06_pickup_corr = df['pcp06'].corr(df['pickups'])

# Correlation between 24-hour precipitation and the number of pickups
pcp24_pickup_corr = df['pcp24'].corr(df['pickups'])

print(f"The Correlation between 1-hour precipitation and the number of
print(f"The Correlation between 6-hour precipitation and the number of
print(f"The Correlation between 24-hour precipitation and the number of
```

```
The Correlation between 1-hour precipitation and the number of pickup
s:
nan

The Correlation between 6-hour precipitation and the number of pickup
s:
nan

The Correlation between 24-hour precipitation and the number of pickup
s:
-0.016615510422116304
```

```
The Correlation between 1-hour precipitation and the number of pickups:
nan

The Correlation between 6-hour precipitation and the number of pickups:
nan

The Correlation between 24-hour precipitation and the number of pickups:
-0.01661551042211662
```

3- Seasonal Trends

In [34]:

```
# Convert pickup_dt to datetime
df['pickup_dt'] = pd.to_datetime(df['pickup_dt'])

# Adding a column for the season
def get_season(date):
    if date.month in [12, 1, 2]:
        return 'Winter'
    elif date.month in [3, 4, 5]:
        return 'Spring'
    elif date.month in [6, 7, 8]:
        return 'Summer'
    else:
        return 'Fall'

df['season'] = df['pickup_dt'].apply(get_season)

# Column for the hour of the day
df['hour'] = df['pickup_dt'].dt.hour
```

In [35]:

```
# Number of pickups by season
season_pickups = df.groupby('season')['pickups'].mean()

print(f"Number of pickups by season:\n{season_pickups}")
```

```
Number of pickups by season:
season
Fall      274.790931
Spring    286.412525
Summer    299.506847
Winter    266.311539
Name: pickups, dtype: float64
```


```
Number of pickups by season:
season
Fall      274.790931
Spring    286.412525
Summer    299.506847
Winter    266.311539
Name: pickups, dtype: float64
```

In [36]:

```
# Average number of pickups during holidays vs non-holidays
df['is_holiday'] = df['hday'] == 'Y'
holiday_pickups = df.groupby('is_holiday')['pickups'].mean()

print(f"Average number of pickups during holidays vs non-holidays:\n{ho
```

```
Average number of pickups during holidays vs non-holidays:
is_holiday
False    282.180652
True     278.659517
Name: pickups, dtype: float64
```


```
Average number of pickups during holidays vs non-holidays:
is_holiday
False    282.180652
True     278.659517
Name: pickups, dtype: float64
```


In [37]:

```
# Correlation between snow depth and number of pickups
snow_depth_corr = df['sd'].corr(df['pickups'])

print(f"The correlation between snow depth and number of pickups:\n{sno
```

```
The correlation between snow depth and number of pickups:
-0.025359545201926337
```

```
The correlation between snow depth and number of pickups:
-0.025359545201925526
```

4- Hourly Trends

In [38]:

```
# Peak hours for Uber pickups in each borough
peak_hours_borough = df.groupby(['borough', 'hour'])['pickups'].mean().
peak_hours_borough = peak_hours_borough.loc[peak_hours_borough.groupby(

print(f"Peak hours for Uber pickups in each borough:\n{peak_hours_borou
```

```
Peak hours for Uber pickups in each borough:
           borough  hour      pickups
18           Bronx    18    40.496855
46        Brooklyn    22   785.226519
63             EWR    15     0.066298
89       Manhattan    17  1121.000000
118         Queens    22   477.403315
138  Staten Island    18     2.403315
```

```
Peak hours for Uber pickups in each borough:
           borough  hour      pickups
18           Bronx    18    40.496855
46        Brooklyn    22   785.226519
63             EWR    15     0.066298
89       Manhattan    17  1121.000000
118         Queens    22   477.403315
138  Staten Island    18     2.403315
```

In [39]:

```
# Number of pickups during rush hours (7-9 AM, 5-7 PM)
df['is_rush_hour'] = df['hour'].isin([7, 8, 9, 17, 18, 19])
rush_hour_pickups = df.groupby('is_rush_hour')['pickups'].mean()

print(f"Number of pickups during rush hours (7-9 AM, 5-7 PM):\n{rush_ho
```

```
Number of pickups during rush hours (7-9 AM, 5-7 PM):
is_rush_hour
False    275.735359
True     300.613332
Name: pickups, dtype: float64
```


```
Number of pickups during rush hours (7-9 AM, 5-7 PM):
is_rush_hour
False    275.735359
True     300.613332
Name: pickups, dtype: float64
```


In [40]:

```
# Average number of pickups during late-night hours (12 AM - 4 AM)
df['is_late_night'] = df['hour'].isin([0, 1, 2, 3, 4])
late_night_pickups = df.groupby('is_late_night')['pickups'].mean()
print(f"Average number of pickups during late-night hours (12 AM - 4 AM
```

```
Average number of pickups during late-night hours (12 AM - 4 AM):
is_late_night
False    297.110618
True     222.625892
Name: pickups, dtype: float64
```


```
Average number of pickups during late-night hours (12 AM - 4 AM):
is_late_night
False    297.110618
True     222.625892
Name: pickups, dtype: float64
```


5- Borough Comparison

In [41]:

```
# Adding a column for weekends
df['is_weekend'] = df['pickup_dt'].dt.dayofweek >= 5
```

In [42]:

```python
# Borough comparison during different weather conditions
weather_conditions = ['temp', 'vsb', 'spd', 'pcp01', 'pcp06', 'pcp24',
borough_weather_pickups = df.groupby(['borough'] + weather_conditions)[

print(f"Borough comparison during different weather conditions:\n{borou
```

```
Borough comparison during different weather conditions:
             borough  temp    vsb   spd  pcp01  pcp06  pcp24        sd  
\
0              Bronx   2.0  10.00   7.0    0.0    0.0  0.090  7.395833   
1              Bronx   2.0  10.00   8.0    0.0    0.0  0.090  7.395833   
2              Bronx   2.0  10.00  13.0    0.0    0.0  0.090  7.395833   
3              Bronx   3.0  10.00  11.0    0.0    0.0  0.090  7.395833   
4              Bronx   3.0  10.00  14.0    0.0    0.0  0.090  7.395833   
...              ...   ...    ...   ...    ...    ...    ...       ...   
17783  Staten Island  88.0   9.10   8.0    0.0    0.0  0.000  0.000000   
17784  Staten Island  88.0  10.00   7.0    0.0    0.0  0.000  0.000000   
17785  Staten Island  89.0   7.75   3.0    0.0    0.0  0.125  0.000000   
17786  Staten Island  89.0   7.75   5.0    0.0    0.0  0.125  0.000000   
17787  Staten Island  89.0   9.10   7.0    0.0    0.0  0.000  0.000000   

       pickups  
0         22.0  
1         20.5  
2         51.0  
3         24.0  
4         36.0  
...        ...  
17783      1.0  
17784      2.0  
17785      3.0  
17786      2.0  
17787      3.0  

[17788 rows x 9 columns]
```


```
Borough comparison during different weather conditions:
             borough  temp    vsb   spd  pcp01  pcp06  pcp24        sd  \
0              Bronx   2.0  10.00   7.0    0.0    0.0  0.090  7.395833   
1              Bronx   2.0  10.00   8.0    0.0    0.0  0.090  7.395833   
2              Bronx   2.0  10.00  13.0    0.0    0.0  0.090  7.395833   
3              Bronx   3.0  10.00  11.0    0.0    0.0  0.090  7.395833   
4              Bronx   3.0  10.00  14.0    0.0    0.0  0.090  7.395833   
...              ...   ...    ...   ...    ...    ...    ...       ...   
17783  Staten Island  88.0   9.10   8.0    0.0    0.0  0.000  0.000000   
17784  Staten Island  88.0  10.00   7.0    0.0    0.0  0.000  0.000000   
17785  Staten Island  89.0   7.75   3.0    0.0    0.0  0.125  0.000000   
17786  Staten Island  89.0   7.75   5.0    0.0    0.0  0.125  0.000000   
17787  Staten Island  89.0   9.10   7.0    0.0    0.0  0.000  0.000000   

       pickups  
0         22.0  
1         20.5  
2         51.0  
3         24.0  
4         36.0  
...        ...  
17783      1.0  
17784      2.0  
17785      3.0  
17786      2.0  
17787      3.0  

[17788 rows x 9 columns]
```

In [43]:
```
# Borough with the highest increase in pickups during holidays
df['is_holiday'] = df['hday'] == 'Y'
holiday_increase_borough = df.groupby(['borough', 'is_holiday'])['picku
holiday_increase_borough = holiday_increase_borough.loc[holiday_increas

print(f"Borough with the highest increase in pickups during holidays:\n
```

```
Borough with the highest increase in pickups during holidays:
          borough  is_holiday      pickups
0           Bronx       False    30.709296
2        Brooklyn       False   525.110127
5             EWR        True     0.041916
6       Manhattan       False  1002.765565
9          Queens        True   319.945783
10  Staten Island       False     1.606082
```


```
Borough with the highest increase in pickups during holidays:
          borough  is_holiday      pickups
0           Bronx       False    30.709296
2        Brooklyn       False   525.110127
5             EWR        True     0.041916
6       Manhattan       False  1002.765565
9          Queens        True   319.945783
10  Staten Island       False     1.606082
```


In [44]:
```
# Number of pickups on weekdays vs weekends for each borough
weekday_weekend_pickups = df.groupby(['borough', 'is_weekend'])['pickup

print(f"Number of pickups on weekdays vs weekends for each borough:\n{w
```

```
Number of pickups on weekdays vs weekends for each borough:
          borough  is_weekend      pickups
0           Bronx       False    28.792893
1           Bronx        True    35.098048
2        Brooklyn       False   477.847173
3        Brooklyn        True   640.487179
4             EWR       False     0.025525
5             EWR        True     0.020833
6       Manhattan       False   993.933441
7       Manhattan        True  1022.996795
8          Queens       False   302.674637
9          Queens        True   325.750801
10  Staten Island       False     1.520517
11  Staten Island        True     1.803686
```

```
Number of pickups on weekdays vs weekends for each borough:
          borough  is_weekend     pickups
0           Bronx       False   28.792893
1           Bronx        True   35.098048
2        Brooklyn       False  477.847173
3        Brooklyn        True  640.487179
4             EWR       False    0.025525
5             EWR        True    0.020833
6       Manhattan       False  993.933441
7       Manhattan        True 1022.996795
8          Queens       False  302.674637
9          Queens        True  325.750801
10  Staten Island       False    1.520517
11  Staten Island        True    1.803686
```

6- Weather Extremes

In [45]:

```
# Extreme weather conditions effect on pickups
extreme_weather = df[(df['temp'] > 90) | (df['temp'] < 20) | (df['pcp01
extreme_weather_pickups = extreme_weather.groupby(['temp', 'pcp01', 'sd

print(f"Extreme weather conditions effect on pickups:\n{extreme_weather
```

```
Extreme weather conditions effect on pickups:
temp  pcp01  sd
0.0   0.0    0.000000      0.000000
2.0   0.0    7.395833    272.300000
3.0   0.0    7.395833    301.000000
4.0   0.0    7.395833    253.788235
5.0   0.0    7.395833    262.515152
                           ...
55.0  0.0    7.041667    310.500000
56.0  0.0    7.395833    352.833333
57.0  0.0    7.250000    292.428571
58.0  0.0    7.395833    353.000000
59.0  0.0    7.395833    307.285714
Name: pickups, Length: 353, dtype: float64
```


```
Extreme weather conditions effect on pickups:
temp  pcp01  sd
0.0   0.0    0.000000      0.000000
2.0   0.0    7.395833    272.300000
3.0   0.0    7.395833    301.000000
4.0   0.0    7.395833    253.788235
5.0   0.0    7.395833    262.515152
                           ...
55.0  0.0    7.041667    310.500000
56.0  0.0    7.395833    352.833333
57.0  0.0    7.250000    292.428571
58.0  0.0    7.395833    353.000000
59.0  0.0    7.395833    307.285714
Name: pickups, Length: 353, dtype: float64
```

In [46]:

```
# Impact of visibility less than 1 mile on pickups
low_visibility = df[df['vsb'] < 1]
low_visibility_pickups = low_visibility['pickups'].mean()
normal_visibility_pickups = df[df['vsb'] >= 1]['pickups'].mean()

print(f"Low Visibility Pickups:\n{low_visibility_pickups}\n")
print(f"Normal Visibility Pickups:\n{normal_visibility_pickups}\n")
```

```
Low Visibility Pickups:
nan

Normal Visibility Pickups:
282.0452561767637
```


```
Low Visibility Pickups:
nan

Normal Visibility Pickups:
282.0452561767637
```


7- Data Correlations

In [47]:

```
# Correlation between sea level pressure and number of pickups
slp_pickup_corr = df['slp'].corr(df['pickups'])

print(f"The Correlation between sea level pressure and number of pickup
```

```
The Correlation between sea level pressure and number of pickups:
-0.011690175691148488
```

```
The Correlation between sea level pressure and number of pickups:
-0.011690175691148415
```

In [48]:

```
# Impact of different weather variables on pickups (correlation matrix)
weather_vars = df[['temp', 'dewp', 'spd', 'vsb', 'pickups']]
weather_corr_matrix = weather_vars.corr()
print(f"Impact of different weather variables on pickups (correlation m
```

```
Impact of different weather variables on pickups (correlation matrix):
             temp      dewp       spd       vsb   pickups
temp     1.000000  0.890263 -0.291404 -0.050096  0.068135
dewp     0.890263  1.000000 -0.320986 -0.316896  0.047266
spd     -0.291404 -0.320986  1.000000  0.122279 -0.005233
vsb     -0.050096 -0.316896  0.122279  1.000000 -0.002851
pickups  0.068135  0.047266 -0.005233 -0.002851  1.000000
```

```
Impact of different weather variables on pickups (correlation matrix):
             temp      dewp       spd       vsb   pickups
temp     1.000000  0.890263 -0.291404 -0.050096  0.068135
dewp     0.890263  1.000000 -0.320986 -0.316896  0.047266
spd     -0.291404 -0.320986  1.000000  0.122279 -0.005233
vsb     -0.050096 -0.316896  0.122279  1.000000 -0.002851
pickups  0.068135  0.047266 -0.005233 -0.002851  1.000000
```

In [49]:

```python
# Define weather conditions of interest
weather_conditions = ['temp', 'vsb', 'spd', 'pcp01', 'pcp06', 'pcp24',

# Group by holiday status and weather conditions to find the average nu
holiday_weather_pickups = df.groupby([df['hday']=='Y'] + weather_condit

print(f"Average number of pickups on the basis of holiday status and we
```

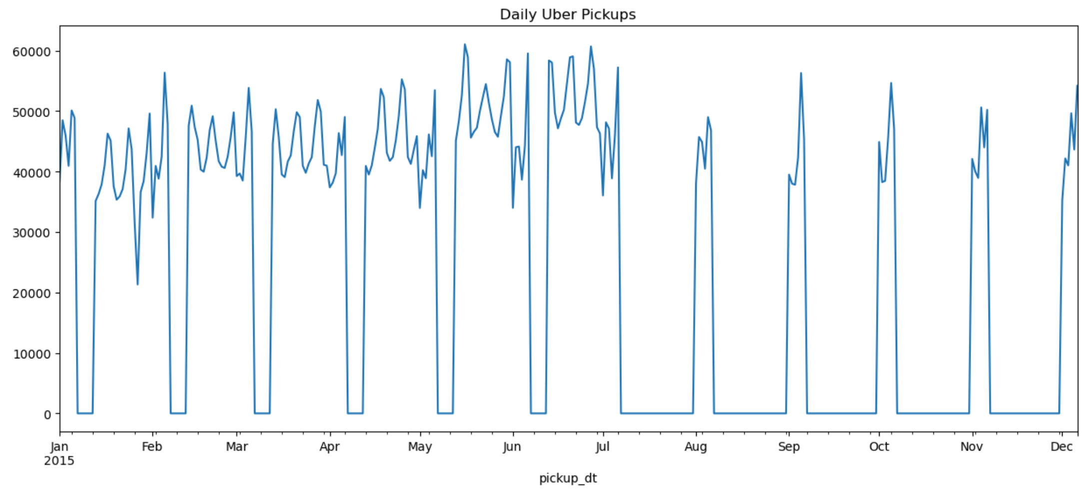
```
Average number of pickups on the basis of holiday status and weather c
onditions:

hday   temp  vsb   spd        pcp01  pcp06  pcp24  sd
False  2.0   10.0  7.000000   0.0    0.0    0.090  7.395833    256.285
714
                   8.000000   0.0    0.0    0.090  7.395833    267.714
286
                   13.000000  0.0    0.0    0.090  7.395833    296.333
333
       3.0   10.0  11.000000  0.0    0.0    0.090  7.395833    289.428
571
                   14.000000  0.0    0.0    0.090  7.395833    312.571
429
                                                                  ...
True   83.0  10.0  5.500000   0.0    0.0    0.000  0.000000    386.714
286
       84.0  10.0  4.333333   0.0    0.0    0.125  0.000000    365.857
143
                   6.000000   0.0    0.0    0.125  0.000000    389.428
571
                   10.000000  0.0    0.0    0.125  0.000000    392.571
429
       85.0  10.0  3.666667   0.0    0.0    0.125  0.000000    377.857
143
Name: pickups, Length: 3259, dtype: float64
```

```
Average number of pickups on the basis of holiday status and weather conditions:

      is_holiday  temp   vsb        spd  pcp01  pcp06  pcp24        sd  \
0          False   2.0  10.0   7.000000    0.0    0.0  0.090  7.395833
1          False   2.0  10.0   8.000000    0.0    0.0  0.090  7.395833
2          False   2.0  10.0  13.000000    0.0    0.0  0.090  7.395833
3          False   3.0  10.0  11.000000    0.0    0.0  0.090  7.395833
4          False   3.0  10.0  14.000000    0.0    0.0  0.090  7.395833
...          ...   ...   ...        ...    ...    ...    ...       ...
3254        True  83.0  10.0   5.500000    0.0    0.0  0.000  0.000000
3255        True  84.0  10.0   4.333333    0.0    0.0  0.125  0.000000
3256        True  84.0  10.0   6.000000    0.0    0.0  0.125  0.000000
3257        True  84.0  10.0  10.000000    0.0    0.0  0.125  0.000000
3258        True  85.0  10.0   3.666667    0.0    0.0  0.125  0.000000

         pickups
0     256.285714
1     267.714286
2     296.333333
3     289.428571
4     312.571429
...          ...
3254  386.714286
3255  365.857143
3256  389.428571
3257  392.571429
3258  377.857143

[3259 rows x 9 columns]
```

Other than given questions I have tried many things in the EDA to do.

In [50]:

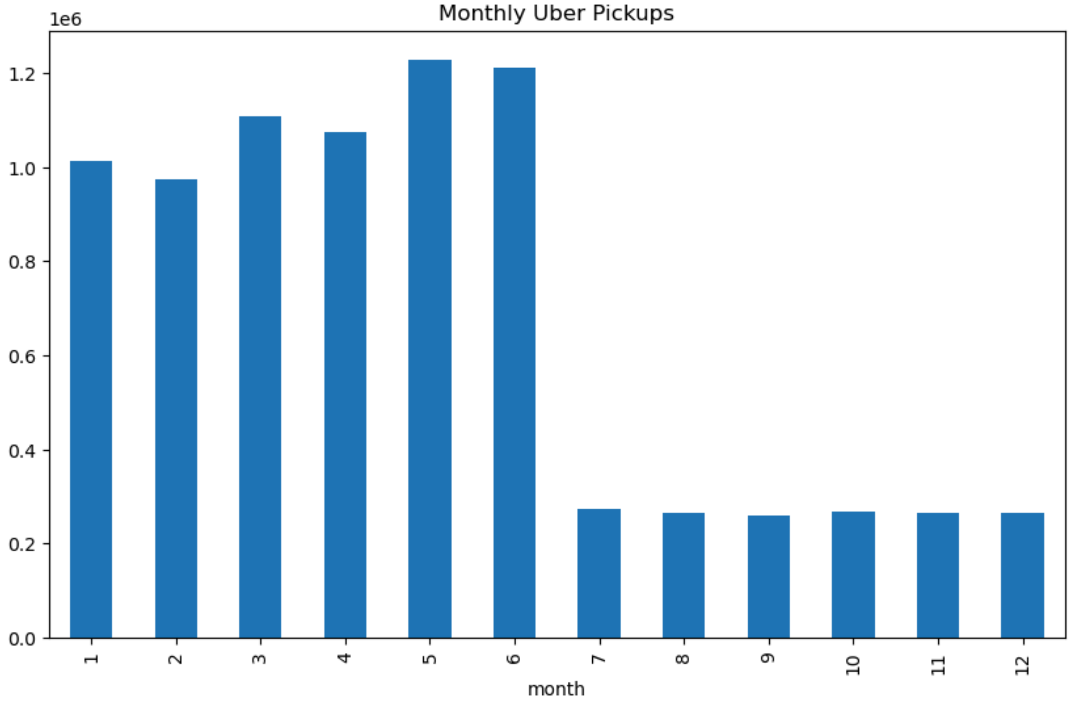
```
df.set_index('pickup_dt', inplace=True)
df['pickups'].resample('D').sum().plot(figsize=(15, 6))
plt.title('Daily Uber Pickups')
plt.show()
```

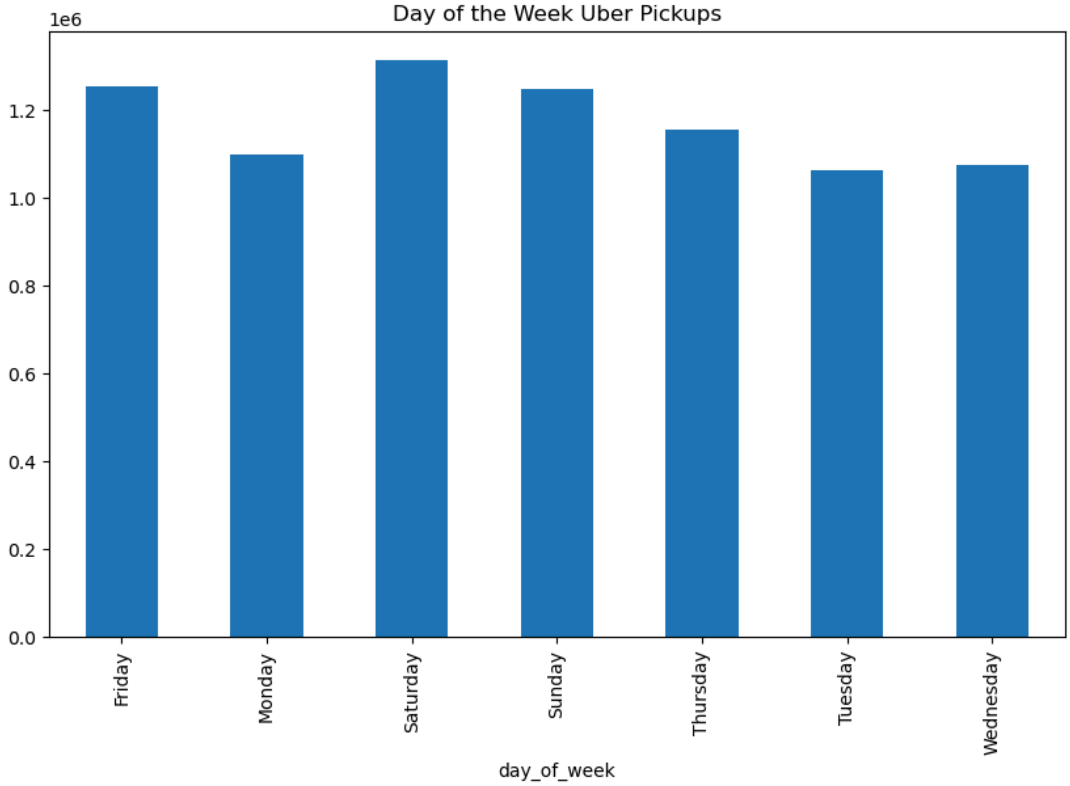


- Time series analysis by which we can see that how the number of pickups are changing across the months

In [51]:

```
df['month'] = df.index.month
df['day_of_week'] = df.index.day_name()

seasonal_pickups = df.groupby('month')['pickups'].sum()
day_of_week_pickups = df.groupby('day_of_week')['pickups'].sum()

seasonal_pickups.plot(kind='bar', figsize=(10, 6))
plt.title('Monthly Uber Pickups')
plt.show()

day_of_week_pickups.plot(kind='bar', figsize=(10, 6))
plt.title('Day of the Week Uber Pickups')
plt.show()
```




Day of the Week Uber Pickups
1e6
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Friday
Monday
Saturday
Sunday
Thursday
Tuesday
Wednesday
day_of_week

In [ ]: