DEVELOPMENT PHASE PART 2

PUBLIC TRANSPORT EFFICIENCY ANALYSIS

Date	31-10-2023
Project Name	Public Transport Efficiency Analysis

Table of Content:

1.Introduction

In the phase of this project, we continue our exploration of data analysis, diving deeper into the realm of public transport efficiency, In this phase, we shift our focus to public transport efficiency analysis, employing visualization techniques and predictive modeling to extract meaningful information and make data-driven decisions.

2.Data Preprocessing

Just as in the previous phase, data preprocessing remains a critical and essential step in our journey towards understanding and optimizing public transport efficiency. Data preprocessing can be described as "the collection and manipulation of data components to produce meaningful information." In this phase, we are dedicated to refining and enhancing the quality of our data, paving the way for more accurate predictions and insights

3. Data cleaning and preprocessing:

```python
import pandas as pd

# Load your dataset
data = pd.read_csv(' Indrajithdataset.CSV')
```

```python
# Data cleaning and preprocessing steps (e.g., handling missing values, data type conversions, etc.)
# Example: Convert 'WeekBeginning' column to datetime
data['WeekBeginning'] = pd.to_datetime(data['WeekBeginning'], format='%d-%m%Y %H:%M')

# More data cleaning and preprocessing steps can be added here

data.head(25)
```

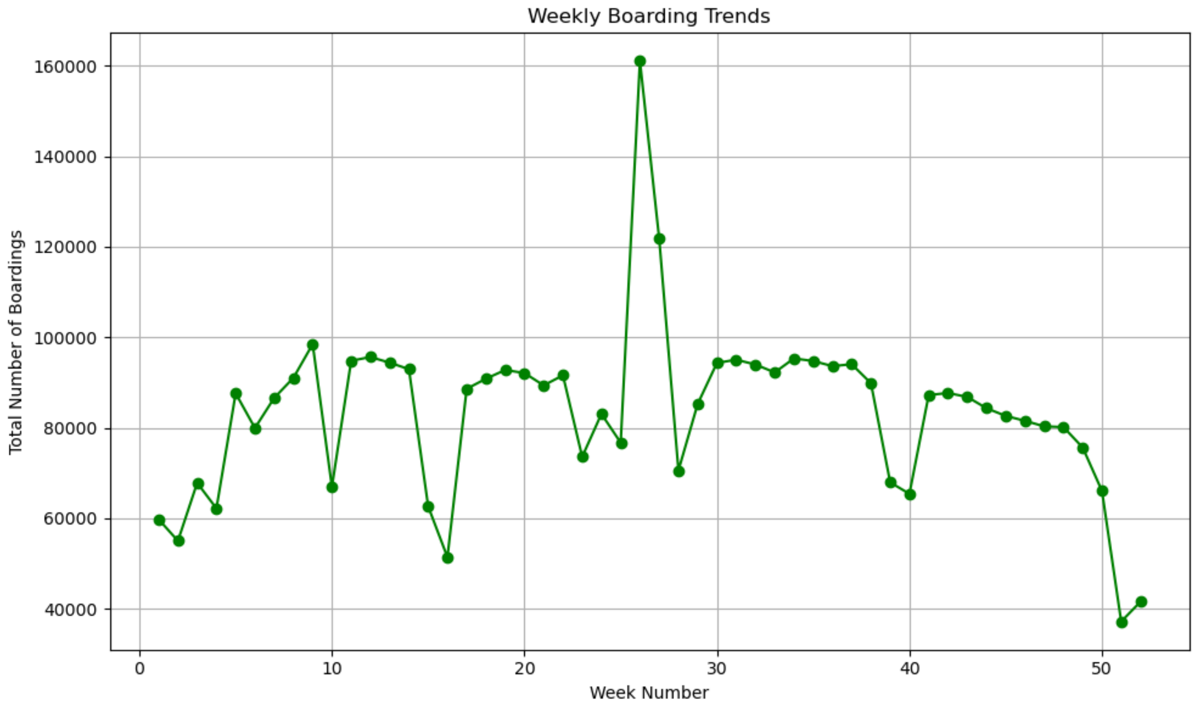
	TripID	RouteID	StopID	StopName	WeekBeginning	No.Of.Boardings
1	23631	100	14144	177 Cross Rd	2013-06-30	1
2	23632	100	14132	175 Cross Rd	2013-06-30	1
3	23633	100	12266	Zone A Arndale Interchange	2013-06-30	2
4	23633	100	14147	178 Cross Rd	2013-06-30	1
5	23634	100	13907	9A Marion Rd	2013-06-30	1
6	23634	100	14132	175 Cross Rd	2013-06-30	1
7	23634	100	13335	9A Holbrooks Rd	2013-06-30	1
8	23634	100	13875	9 Marion Rd	2013-06-30	1
9	23634	100	13045	206 Holbrooks Rd	2013-06-30	1
10	23635	100	13335	9A Holbrooks Rd	2013-06-30	1
11	23635	100	13383	8A Marion Rd	2013-06-30	1
12	23635	100	13586	8D Marion Rd	2013-06-30	2
13	23635	100	12726	23 Findon Rd	2013-06-30	1
14	23635	100	13813	8K Marion Rd	2013-06-30	1
15	23635	100	14062	20 Cross Rd	2013-06-30	1
16	23636	100	12780	22A Crittenden Rd	2013-06-30	1
17	23636	100	13383	8A Marion Rd	2013-06-30	1
18	23636	100	14154	180 Cross Rd	2013-06-30	2
19	23636	100	13524	8C Marion Rd	2013-06-30	3
20	23636	100	14122	173 Cross Rd	2013-06-30	1
21	23636	100	13813	8K Marion Rd	2013-06-30	1
22	23637	100	14156	181 Cross Rd	2013-06-30	1
23	23637	100	14154	180 Cross Rd	2013-06-30	1
24	23637	100	13335	9A Holbrooks Rd	2013-06-30	3

 # Convert WeekBeginning to datetime and extract week number

3.Visualization

Line Chart - Weekly Boarding Trends

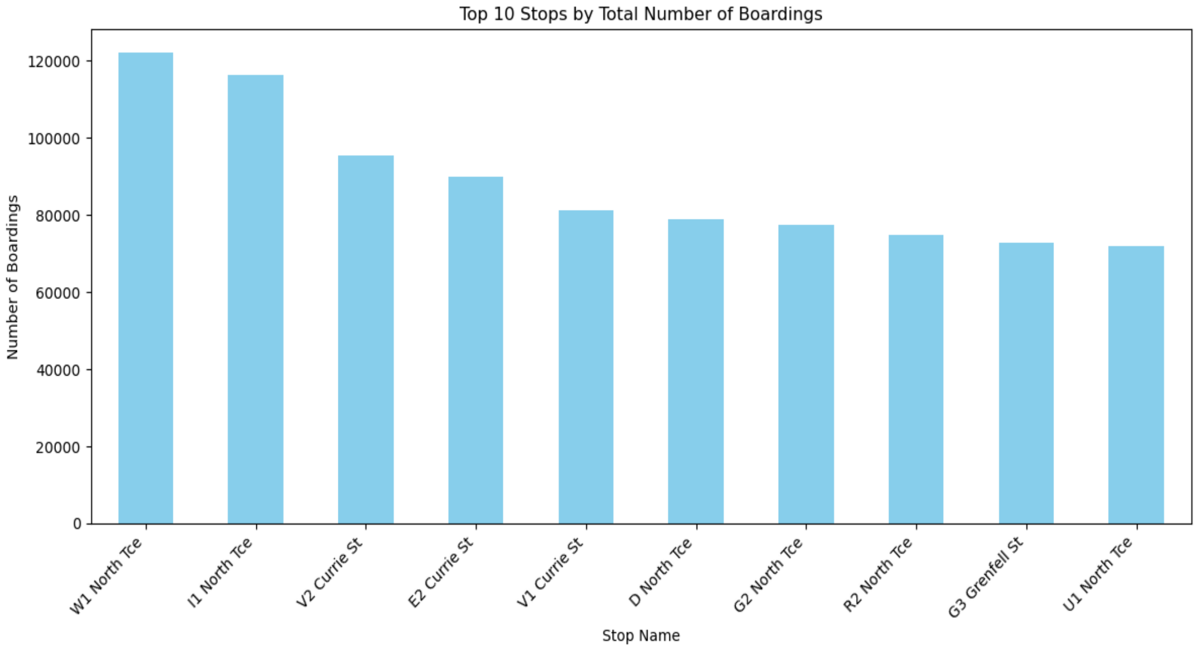
```
# Convert WeekBeginning to datetime and extract week number
data['WeekBeginning']=pd.to_datetime(data['WeekBeginning'])
data['WeekNumber'] = data['WeekBeginning'].dt. isocalendar().week

# Group data by WeekNumber and sum the NumberOfBoardings weekly_boardings
= data.groupby('WeekNumber')['NumberOfBoardings'].sum()

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

plt.plot(weekly_boardings.index, weekly_boardings.values, marker='o', color='green')

plt.title('Weekly Boarding Trends')
plt.xlabel('Week Number') plt.ylabel('Total
Number of Boardings') plt.grid(True)
plt.tight_layout() plt.show()
```



Bar Chart - Number of Boardings per StopName

```
import matplotlib.pyplot as plt

# Group data by StopName and sum the NumberOfBoardings
boarding_counts = data.groupby('StopName')['NumberOfBoardings'].sum()

# Plotting
plt.figure(figsize=(12, 6))
```

```
boarding_counts.sort_values(ascending=False).head(10).plot(kind='bar', color='skyblue')
plt.title('Top 10 Stops by Total Number of Boardings')
 plt.xlabel('Stop Name')
 plt.ylabel('Number of Boardings')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```



3.1.Advanced data analysis

Aggregating Boarding Counts by RouteID

```
import pandas as pd

# Group by RouteID and sum the NumberOfBoardings
boarding_by_route = data.groupby('RouteID')['NumberOfBoardings'].sum()

# Display the result print(boarding_by_route)
```

```
RouteID
117      312470
118      319790
140       83064
141      331118
142       79091
147      169540
148        5190
150      318672
168      296199
169       13397
```

```
170      143076
171       91911
100      328740
100B       8250
100C      11828
100K       6364
100N       6419
100P      13277
100S        260
101       39114
115       15460
117       67637
142      287270
144      183253
144G      15814
147      136496
150      105953
150B      55517
150P       8147
155       98191
157      307301
157X      81745
162       92171
167      237238
167C      32195
168       30858
Name: NumberOfBoardings, dtype: int64
```

```
# Group by StopID and calculate the average number of boardings
avg_boardings_per_stop = data.groupby('StopID')['NumberOfBoardings'].mean()

# Display the result

print(avg_boardings_per_stop)
```

```
StopID

10817      2.776013
10818      2.333333
10843      2.257143

10877      2.326316

10879      1.400000
...

18408      1.875000
18409      2.714286
18410      1.500000
18411      1.156250
18493    9.122678

Name: NumberOfBoardings, Length: 969, dtype: float64
```

Finding Stops with Highest Weekly Boarding Counts

```python
# Convert WeekBeginning to datetime and extract week number
data['WeekBeginning']=pd.to_datetime(data['WeekBeginning'])
data['WeekNumber'] = data['WeekBeginning'].dt.isocalendar().week

# Group by StopName and WeekNumber, then sum the NumberOfBoardings
weekly_boarding_counts = data.groupby(['StopName', 'WeekNumber'])['NumberOfBoardings'].sum()

# Find stops with the highest weekly boarding counts
stops_with_highest_boardings = weekly_boarding_counts.groupby('StopName').idxmax()

# Display the result

print(stops_with_highest_boardings)
```

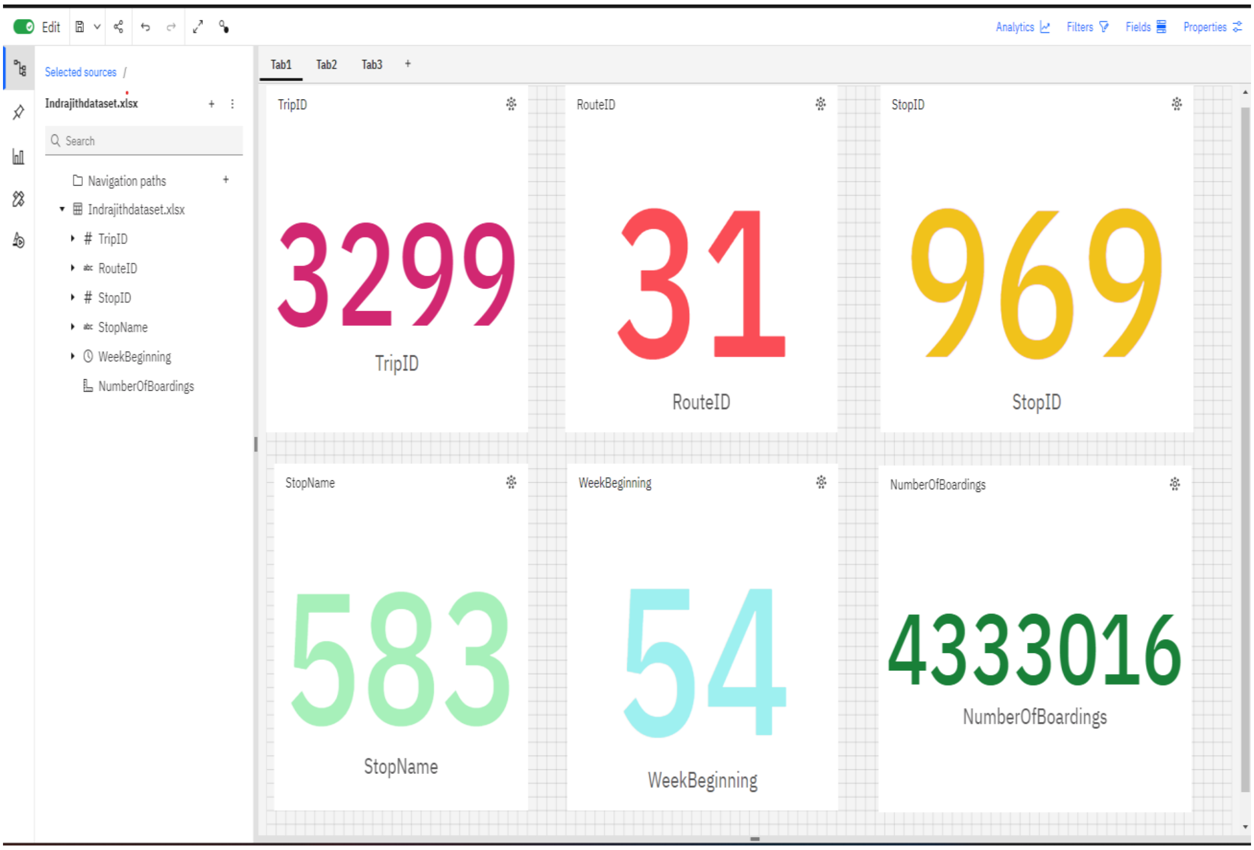
```
StopName
1 Anzac Hwy                       (1 Anzac Hwy, 26)
1 Fullarton Rd                    (1 Fullarton Rd, 8)
1 George St                       (1 George St, 27)
1 Glen Osmond Rd                  (1 Glen Osmond Rd, 33)
1 Henley Beach Rd                 (1 Henley Beach Rd, 26)                    ...
Zone B Registry Rd Flinders Un    (Zone B Registry Rd Flinders Un, 11)
Zone B West Lakes Interchange     (Zone B West Lakes Interchange, 26)
Zone C Moseley St                 (Zone C Moseley St, 26)
Zone D Arndale Interchange        (Zone D Arndale Interchange, 38)
Zone D Port Adelaide Interchan    (Zone D Port Adelaide Interchan, 26)
Name: NumberOfBoardings, Length: 583, dtype: object
```

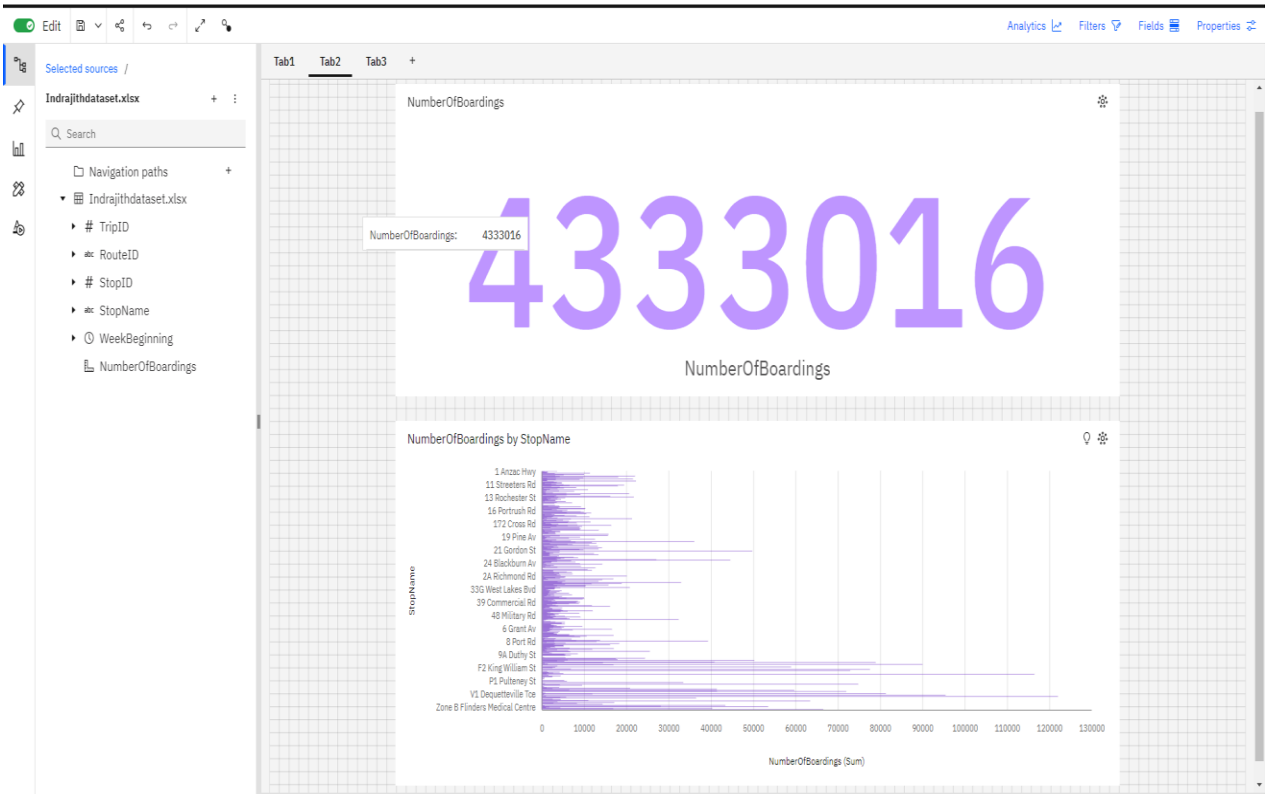
Analyzing Trends Over Time (Weekly/Monthly)

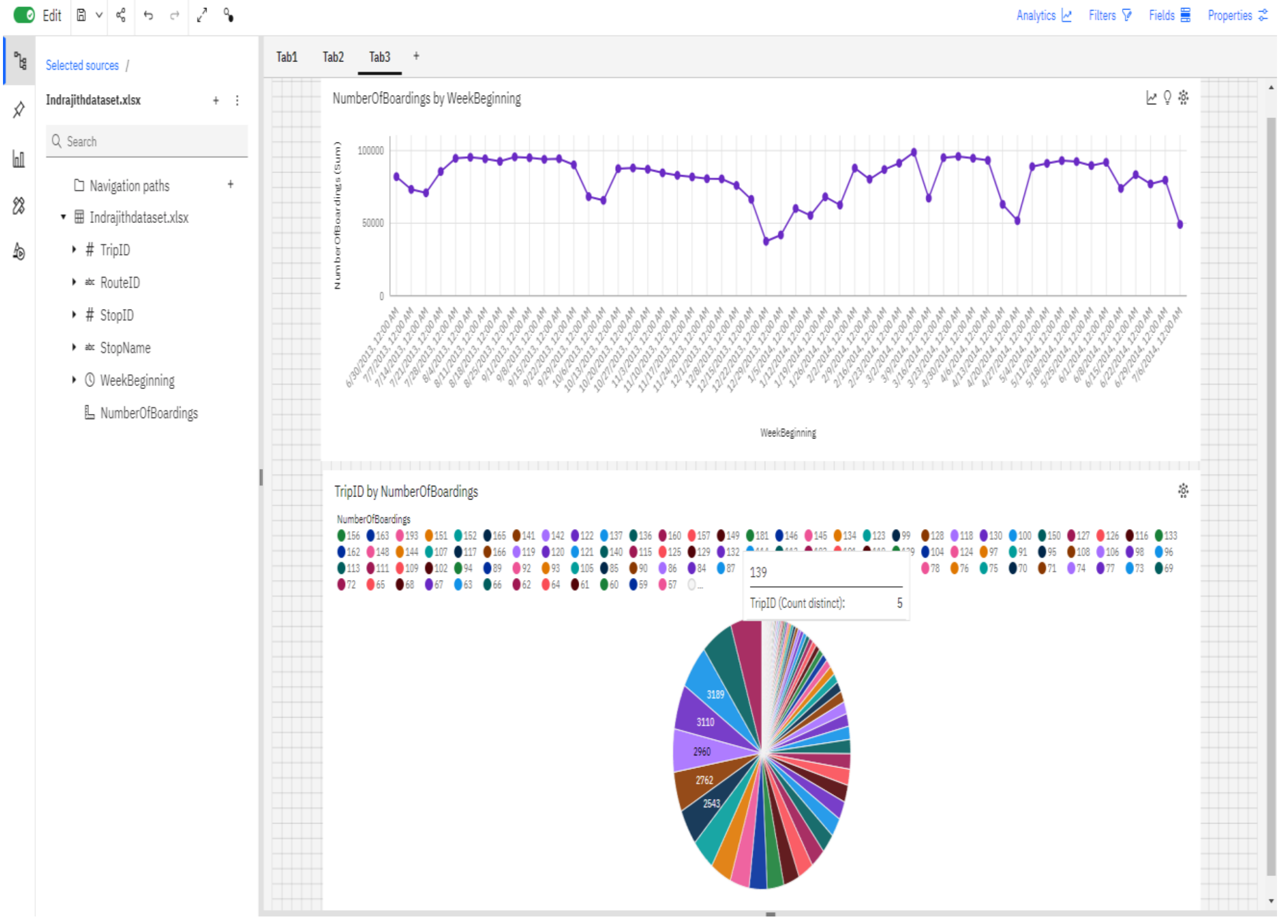
```python
# Convert WeekBeginning to datetime and extract week and
month
data['WeekBeginning'] = pd.to_datetime(data['WeekBeginning'])
data['WeekNumber'] = data['WeekBeginning'].dt.week
 data['Month'] = data['WeekBeginning'].dt.month

# Group by WeekNumber and Month, then sum the NumberOfBoardings
weekly_boarding_trends = data.groupby(['WeekNumber', 'Month'])['NumberOfBoardings'].sum()

# Display the result

print(weekly_boarding_trends)
```

```
WeekNumber  Month
1           1          59791
2           1          55026
3           1          67844
4           1          62204
5           2          87621
6           2          79964
7           2          86610
8           2          91046
9           3          98500
10          3          66953
11          3          94828
12          3          95643
13          3          94406
14          4          92959
15          4          62636
16          4          51434
17          4          88624
18          5          90852
19          5          92782
20          5          92112
21          5          89378
22          6          91608
23          6          73602
24          6          83086
25          6          76725
26          6         161049
27          7         121795
28          7          70588
29          7          85288
30          7          94344
31          8          95061
32          8          93992
33          8          92247
34          8          95341
35          9          94762
36          9          93643
37          9          94053
38          9          89866
39          9          67959
40          10         65428
41          10         87246
42          10         87703
43          10         86839
44          11         84346
45          11         82642
46          11         81556
47          11         80333
48          12         80176
49          12         75652
50          12         66079
51          12         37207
52          12         41587
Name: NumberOfBoardings, dtype: int64
```

VISUALIZATION USING IBM COGNOS







4.Conclusion:

In this project, we have continued our journey in the pursuit of comprehensive data analysis by creating visualizations and constructing a predictive model. Leveraging the capabilities of visualization libraries such as Matplotlib and Seaborn, we have unveiled insights through histograms, scatter plots, and correlation matrices. Additionally, we have delved into the realm of predictive modeling, where we have applied data-driven techniques to gain a better understanding of public transport efficiency Analysis.