PUBLIC TRANSPORTATION ANALYSIS

PHASE 5: PROJECT DOCUMENTATION AND SUBMISSION

PROJECT OBJECTIVE:

Public transportation systems play a pivotal role in urban areas, ensuring the seamless movement of people. It is an efficient mode of travel due to its ability to carry a large number of passengers at once. By utilizing dedicated lanes or routes, it can bypass traffic congestion, ensuring a more reliable and timely journey. Moreover, advancements in technology have enabled real-time tracking and scheduling systems, further enhancing the efficiency of public transit.

However, various challenges affect the efficiency and quality of these services. Timeliness, passenger satisfaction, and operational effectiveness are crucial aspects that demand continuous evaluation and improvement. Delays, overcrowding, and passenger dissatisfaction can lead to decreased ridership and affect the overall urban mobility experience. This project aims to address these challenges by analyzing public transportation data comprehensively. By focusing on on-time performance, passenger feedback, and service efficiency, we intend to identify key bottlenecks, assess customer experience, and propose data driven strategies. Through this analysis, our goal is to enhance the overall quality of public transportation, making it more reliable, convenient, and passenger-friendly.

DESIGN THINKING PROCESS:

ANALYSIS OBJECTIVES:

1.On-Time Performance

Define specific objectives for analyzing public transportation data such as assessing on-time performance. One of the primary objectives is to evaluate the on-time performance of public transportation services. We will measure and report the percentage of services that adhere to their schedules.

2. Efficiency:

Identify objectives for analyzing the efficiency of public transportation services. To determine the efficiency of public transportation services, we will assess factors such as route optimization, vehicle utilization, and punctuality.

3. Passenger Satisfaction:

Assess passenger satisfaction through data analysis. Another key objective is to gauge passenger satisfaction. This will involve the collection and analysis of passenger feedback through surveys or other available data sources

DATA COLLECTION PROCESS:

In order to analyze public transportation data, we need to identify trustworthy sources and methods for collecting transportation data. These sources could include schedules, real-time updates, and passenger feedback.

1.Schedules Data:

We will collect schedules data from the provided dataset. This data will include information about planned departure and arrival times, routes, and stops.

2.Real-time Updates:

Real-time data will be gathered to track actual departure and arrival times, allowing us to measure on-time performance accurately.

3.Passenger Feedback:

Passenger feedback will be collected through surveys or online platforms, if available. This data will provide insights into passenger satisfaction and areas for improvement.

4.Weather Data:

Weather data may also be considered to understand its impact on service efficiency and delays.

DATA VISUALISATION:

To effectively communicate insights from our analysis, we need a plan for visualizing the data. IBM Cognos is an excellent tool for creating informative dashboards and reports.

1.IBM Cognos Dashboards:

We will use IBM Cognos to design informative dashboards and reports. These dashboards will include visualizations such as line charts for tracking on-time performance trends, bar charts for comparing passenger satisfaction across different routes, and geographic maps to visualize service efficiency based on location.

2.Interactive Reports:

Interactive reports will allow stakeholders to drill down into specific details, making it easier to identify areas that require improvement.

3.Key Performance Indicators (KPIs):

We will present KPIs like on time percentage, passenger satisfaction scores, and service efficiency indices prominently on the dashboards.

CODE INTEGRATION:

1.Data Cleaning:

Code will be used to clean and preprocess the raw transportation data. This may include handling missing values, standardizing data formats, and removing outliers. Clean the data to ensure accurate, unbiased analysis results.

2.Data Transformation:

Code will be employed to transform data into a format suitable for analysis, including merging data from different sources and creating derived variables for deeper insights. Transform the data into a more useful format for further analysis.

3.Statistical Analysis:

Advanced statistical analysis, if necessary, will be conducted using code to identify correlations, trends, and potential areas for optimization. Use code to perform statistical analysis and discover meaningful insights.

INNOVATION:

DESIGN AND INNOVATION STRATEGIES:

Implementing "Gender-Responsive Transportation" could be a creative way to improve public transportation effectiveness while addressing gender-related issues. According to this idea, transportation services would be planned and designed to take differing travel preferences and safety issues for men and women into account. This can entail offering distinct but equal services at particular times to cater to the needs of both genders, ensuring that all passengers travel safely and comfortably. Such a strategy might aid in boosting the number of passengers as well as the general public's opinion of the safety and inclusivity of public transportation networks.

Data Collection and Feature Engineering

Innovation: Comprehensive Data Gathering

Implement advanced web scraping techniques and leverage real estate APIs to collect diverse datasets encompassing property features, location data, market trends, and historical price data. Apply innovative feature engineering techniques, such as text summarization for property descriptions, to extract meaningful information from both structured and unstructured data.

Collect and analyze passenger feedback and sentiment data from sources like social media, surveys, and customer support interactions

Data Pre-processing

Innovation: Natural Language Processing (NLP) for Sentiment Analysis

Utilize Natural Language Processing (NLP) techniques to pre-process textual data, including passenger feedback and comments. Develop a custom NLP pipeline that includes tokenization, lemmatization, sentiment analysis, and topic modelling to extract valuable insights from passenger comments. Handle missing data with innovative methods, such as imputation based on historical patterns and feedback from similar situations.

Model Selection and Training

Innovation: Machine Learning and Deep Learning Integration

Employ a combination of machine learning algorithms, such as Random Forests, Support Vector Machines, and XGBoost, for service disruption prediction. Incorporate deep learning models, such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs), to analyze temporal patterns and passenger sentiment in textual data. Develop an ensemble model that combines the strengths of machine learning and deep learning approaches for more accurate predictions.

Model Interpretability and Visualization

Innovation: Explainable AI (XAI):

Incorporate Explainable AI techniques such as SHAP values and LIME to provide transparent explanations for model predictions. This helps stakeholders understand the rationale behind efficiency assessments and recommendations. Develop an interactive dashboard with visualizations that showcase key performance indicators, route efficiency scores, and passenger sentiment trends. This user-friendly interface ensures that stakeholders can easily access and interpret the analysis results.

Data Intergration with IBM cognos

Use IBM Cognos' data integration capabilities to combine and merge data from different sources into a unified dataset. This often requires using ETL (Extract, Transform, Load) processes.

Public Transporatation efficiency reports and dashboards

The development of simple-to-understand visual representations of critical data is required for creating reports and dashboards for public transportation efficiency. These tools offer quick, high-level insights into things like riding patterns, punctuality, maintenance requirements, and fuel usage. They enable transportation authorities to evaluate the system's condition swiftly, pinpoint areas that require repair, and make data-driven choices. Reports and dashboards enable stakeholders to improve service quality, optimize routes, cut costs, and guarantee a more effective and dependable public transportation system for commuters by making data easily understandable and accessible.

Deploying and monitoring the model

Deploying and monitoring a Public Transportation Efficiency model involves implementing it within the transit system's infrastructure. This includes integrating data sources, setting up real-time monitoring, and establishing alerts for anomalies. Regularly assessing the model's performance ensures it continues to provide accurate insights for route optimization, cost reduction, and improved service quality. Effective deployment and ongoing monitoring are essential to sustain and enhance public transportation efficiency, benefiting both commuters and the transportation authorities

Continuous Improvement and Feedback Loops

Innovation: Feedback Mechanisms:

Establish mechanisms for continuous feedback from passengers, transit staff, and city officials. This feedback loop will allow for ongoing adjustments and improvements to the public transport system. By incorporating these design and innovation strategies, Public Transport Efficiency Analysis can become a dynamic and data-driven process that leads to more effective, user-centric, and sustainable public transportation systems.

Innovation: Model Maintenance and Improvement

Establish a continuous learning framework that adapts to changing conditions and passenger preferences. Regularly retrain the models using new data to improve prediction accuracy and sentiment analysis. Implement automated data pipelines for seamless data ingestion, model retraining, and feedback incorporation.

DEVELOPMENT PHASES:

Data Exploration and Understanding

- Load the dataset using Pandas.
- Our focus will be on understanding the dataset's structure, consisting of 6 columns: TripID, RouteID, StopID, StopName, WeekBeginning, and NumberOfBoardings and understand the column meanings, and potential relationships between variables.
- Identify data quality issues, missing values, and outliers.

Data Preprocessing

- Select relevant columns for analysis (e.g., TripID, RouteID, StopName).
- Handle missing data, duplicates, and irrelevant entries.
- Convert data types if needed

Predicting Service Disruptions

- Innovation: Define how service disruption is determined from given features
- Select a set of features and Service Disruption as target feature
- Create DecisionTreeClassifier and train on 80% of dataset
- Test the classifier on remaining 20% of dataset

Sentiment Analysis for Passenger Feedback

A. Data Preprocessing

- For sentiment analysis, we need to extract and clean the text data containing passenger feedback.
- Load the dataset using Pandas.
- Select relevant columns for sentiment analysis (e.g., TripID, StopName).
- Remove duplicates and any irrelevant entries.
- Handle missing data, if any.

B. Text Preprocessing

- The text data may contain noise and irrelevant information. Text preprocessing is essential to ensure the accuracy of sentiment analysis.
- Tokenization: Split text into words.
- Lowercasing: Convert all text to lowercase.
- Removing special characters and punctuation.
- Stopword Removal: Eliminate common words (e.g., "the," "and") that do not carry sentiment.
- Lemmatization or stemming to reduce words to their base form.

C. Model Selection VADER Model for Sentiment Analysis:

- VADER is a specialized NLP model for sentiment analysis.
- It provides polarity and intensity scores.
- Suitable for real-time analysis and informal text.
- Ideal for public transportation feedback analysis.

D. Feature Engineering

- Create additional features or transformations that could enhance the analysis, such as time-based aggregations, seasonality, or weather data.
- Machine Learning Model Development
- Random Forest is an ensemble learning method that can be used for public transportation analysis as it can handle complex, multifaceted data.
- It combines multiple decision trees for enhanced accuracy and robustness.
- The Random Forest model has high accuracy, can handle large datasets, reduces overfitting, is robust to outliers and handles non-linearity.

E. Model Training and Validation

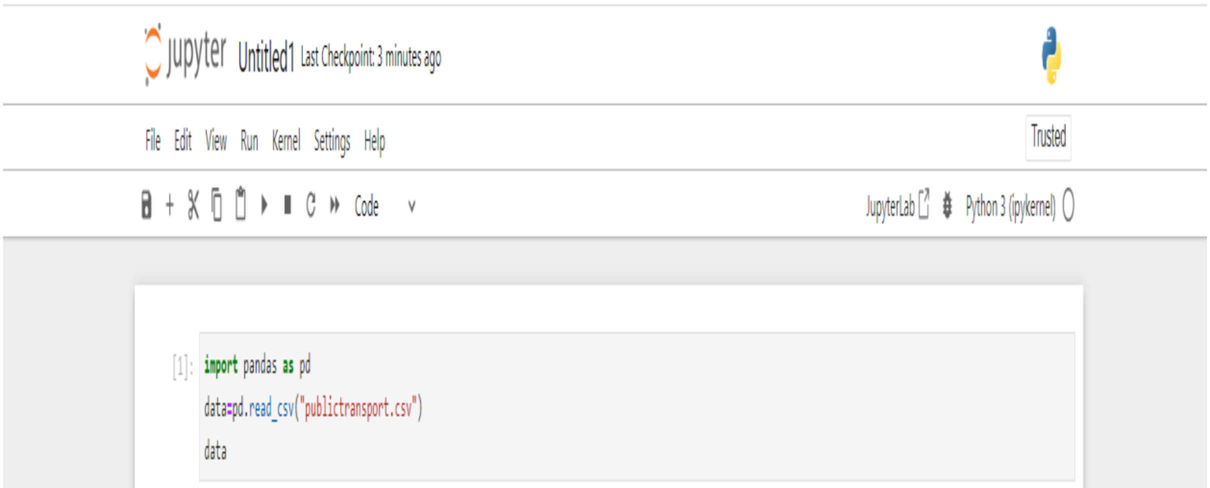
- Split the dataset into training and testing sets.
- Train the models for both service disruption prediction and overall analysis.
- Evaluate the model's performance using relevant metrics.
- Fine-tune the models if necessary.

F. Integration with IBM Cognos

- Integrate the machine learning and sentiment analysis results into IBM Cognos for streamlined data analytics and reporting.

G. Data Visualization and Reporting

- Create dashboards and reports in IBM Cognos to display insights from the analysis.
- Utilize charts, graphs, and maps to make the results easily interpretable for decision-makers.



Out[4]:

	TripID	RouteID	StopID	StopName	WeekBeginning	NumberOfBoardings
0	23631	100	14156	181 Cross Rd	2013-06-30 00:00:00	1
1	23631	100	14144	177 Cross Rd	2013-06-30 00:00:00	1
2	23632	100	14132	175 Cross Rd	2013-06-30 00:00:00	1
3	23633	100	12266	Zone A Arndale Interchange	2013-06-30 00:00:00	2
4	23633	100	14147	178 Cross Rd	2013-06-30 00:00:00	1
...	...	...	...	...	...	...
10857229	13346	W91C	14629	21 Cashel St	2014-07-06 00:00:00	1
10857230	13346	W91C	14708	22 Cashel St	2014-07-06 00:00:00	3
10857231	13346	W91C	13709	2 Greenhill Rd	2014-07-06 00:00:00	1
10857232	13346	W91C	14029	10 East Av	2014-07-06 00:00:00	1
10857233	13346	W91C	13824	6 Leader St	2014-07-06 00:00:00	1

10857234 rows × 6 columns

In [10]:
```
data.head(10)
```

Out[10]:

	TripID	RouteID	StopID	StopName	WeekBeginning	NumberOfBoardings
0	23631	100	14156	181 Cross Rd	2013-06-30 00:00:00	1
1	23631	100	14144	177 Cross Rd	2013-06-30 00:00:00	1
2	23632	100	14132	175 Cross Rd	2013-06-30 00:00:00	1
3	23633	100	12266	Zone A Arndale Interchange	2013-06-30 00:00:00	2
4	23633	100	14147	178 Cross Rd	2013-06-30 00:00:00	1
5	23634	100	13907	9A Marion Rd	2013-06-30 00:00:00	1
6	23634	100	14132	175 Cross Rd	2013-06-30 00:00:00	1
7	23634	100	13335	9A Holbrooks Rd	2013-06-30 00:00:00	1
8	23634	100	13875	9 Marion Rd	2013-06-30 00:00:00	1
9	23634	100	13045	206 Holbrooks Rd	2013-06-30 00:00:00	1

In [7]:
```
data.shape
```

Out[7]:
```
(10857234, 6)
```

In [8]:
```
data.columns
```

Out[8]:
```
Index(['TripID', 'RouteID', 'StopID', 'StopName', 'WeekBeginning',
       'NumberOfBoardings'],
      dtype='object')
```

In [9]:
```
data.isnull().sum()
```

Out[9]:
```
TripID               0
RouteID              0
StopID               0
StopName             0
WeekBeginning        0
NumberOfBoardings    0
dtype: int64
```

In [11]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10857234 entries, 0 to 10857233
Data columns (total 6 columns):
 #   Column             Dtype 
---  ------             ----- 
 0   TripID             int64 
 1   RouteID            object
 2   StopID             int64 
 3   StopName           object
 4   WeekBeginning      object
 5   NumberOfBoardings  int64 
dtypes: int64(3), object(3)
memory usage: 497.0+ MB
```

In [16]:
```
df=data
```

In [19]:
```
a=df.TripID.value_counts()
a
```

Out[19]:
```
57020    2819
57018    2741
27478    2733
57041    2718
57029    2691
         ...
59297       1
3061        1
3414        1
3415        1
61163       1
Name: TripID, Length: 39282, dtype: int64
```

In [20]:
```
b=df.RouteID.value_counts()
b
```

Out[20]:
```
G10     358005
B10     332694
M44     331442
H30     326004
300     228373
         ...
FX1          1
FX10         1
FX8          1
FX3          1
FX2          1
Name: RouteID, Length: 619, dtype: int64
```

In [21]:
```
c=df.StopID.value_counts()
c
```

Out[21]:
```
13354    44089
13277    43339
13364    43265
13330    36992
13279    33800
         ...
17107        1
15420        1
15243        1
17805        1
17807        1
Name: StopID, Length: 7397, dtype: int64
```

In [22]:
```
d=df.WeekBeginning.value_counts()
d
```

```
Out[22]: 2014-03-02 00:00:00    217162
         2014-05-18 00:00:00    215932
         2014-05-11 00:00:00    214947
         2014-06-01 00:00:00    213789
         2014-05-04 00:00:00    212681
         2014-03-23 00:00:00    212552
         2014-03-16 00:00:00    212188
         2014-02-23 00:00:00    212103
         2013-09-08 00:00:00    211914
         2014-04-27 00:00:00    211782
         2014-05-25 00:00:00    211534
         2014-03-30 00:00:00    211460
         2013-09-01 00:00:00    210968
         2014-04-06 00:00:00    210557
         2013-08-25 00:00:00    209497
         2013-11-17 00:00:00    209341
         2013-11-24 00:00:00    208881
         2013-10-20 00:00:00    208655
         2013-12-01 00:00:00    208470
         2014-06-15 00:00:00    208457
         2014-06-08 00:00:00    208417
         2013-09-15 00:00:00    208241
         2014-02-16 00:00:00    208178
         2013-10-27 00:00:00    207971
         2013-09-22 00:00:00    207769
         2013-12-08 00:00:00    207353
         2013-10-13 00:00:00    207351
         2013-08-04 00:00:00    207082
         2013-11-03 00:00:00    206863
         2013-11-10 00:00:00    206853
         2014-06-29 00:00:00    206138
         2013-07-28 00:00:00    205492
         2013-08-11 00:00:00    205385
         2013-08-18 00:00:00    203852
         2013-07-21 00:00:00    201257
         2014-06-22 00:00:00    200950
         2014-02-09 00:00:00    197978
         2014-01-19 00:00:00    196344
```

```
         2013-10-06 00:00:00    195830
         2014-03-09 00:00:00    195200
         2013-12-15 00:00:00    194102
         2014-02-02 00:00:00    192507
         2013-09-29 00:00:00    192023
         2013-07-07 00:00:00    190543
         2014-04-13 00:00:00    190060
         2013-07-14 00:00:00    187192
         2014-01-05 00:00:00    186105
         2014-04-20 00:00:00    185080
         2013-06-30 00:00:00    182229
         2014-01-26 00:00:00    180259
         2014-01-12 00:00:00    178456
         2013-12-29 00:00:00    168771
         2013-12-22 00:00:00    163331
         2014-07-06 00:00:00    149202
         Name: WeekBeginning, dtype: int64
```

In [24]:

```
e=df.NumberOfBoardings.value_counts()
e
```

Out[24]:

```
1      4270812
2      2057245
3      1128820
4       731537
5       502763
        ...
547          1
539          1
443          1
474          1
342          1
Name: NumberOfBoardings, Length: 400, dtype: int64
```

In [29]:

```
data['WeekBeginning'] = pd.to_datetime(data['WeekBeginning']).dt.date
data['WeekBeginning'][1]
```

Out[29]:

```
datetime.date(2013, 6, 30)
```

In [38]:

```
grouped = data.groupby(['StopName','WeekBeginning',]).agg({'NumberOfBoardings': ['sum', 'count','max']})
grouped
```

Out[38]:

		NumberOfBoardings		
		sum	count	max
StopName	WeekBeginning			
1 Anzac Hwy	2013-06-30	1003	378	51
	2013-07-07	783	360	28
	2013-07-14	843	343	45
	2013-07-21	710	356	28
	2013-07-28	898	379	41
...	...	...	...	...
Zone I Salisbury Interchange	2014-06-08	822	117	44
	2014-06-15	965	113	39
	2014-06-22	896	111	58
	2014-06-29	1052	113	39
	2014-07-06	534	90	21

207864 rows × 3 columns

In [40]:

```
st_week_grp = pd.DataFrame(grouped).reset_index()
st_week_grp1 = pd.DataFrame(st_week_grp.groupby('StopName')["WeekBeginning"].count()).reset_index()
st_week_grp1.head()
```

Out[40]:

	StopName	WeekBeginning
0	1 Anzac Hwy	54
1	1 Bartels Rd	54
2	1 Botanic Rd	54
3	1 Frome Rd	54
4	1 Fullarton Rd	54

In [49]:

```
stopListName = list(st_week_grp1[st_week_grp1['WeekBeginning'] == 54]['StopName'])
stopListName[1:30]
```

Out[49]:
```
['1 Bartels Rd',
 '1 Botanic Rd',
 '1 Frome Rd',
 '1 Fullarton Rd',
 '1 George St',
 '1 Glen Osmond Rd',
 '1 Goodwood Rd',
 '1 Henley Beach Rd',
 '1 Kensington Rd',
 '1 King William Rd',
 '1 Port Rd',
 '1 Sir Donald Bradman Dr',
 '1 Sir Edwin Smith Av',
 '1 Unley Rd',
 '10  Holbrooks Rd',
 '10  Marion Rd',
 '10  Portrush Rd',
 '10 Airport Rd',
 '10 Anzac Hwy',
 '10 Ashley St',
 '10 Belair Rd',
 '10 Churchill Rd',
 '10 East Av',
 '10 Fullarton Rd',
 '10 Garden Tce',
 '10 Glen Osmond Rd',
 '10 Goodwood Rd',
 '10 Greenhill Rd',
 '10 Harrow Tce']
```

In [59]:
```
stopageName_with_boarding = data.groupby(['StopName']).agg({'NumberOfBoardings': ['sum']}).reset_index()
```

Out[60]:

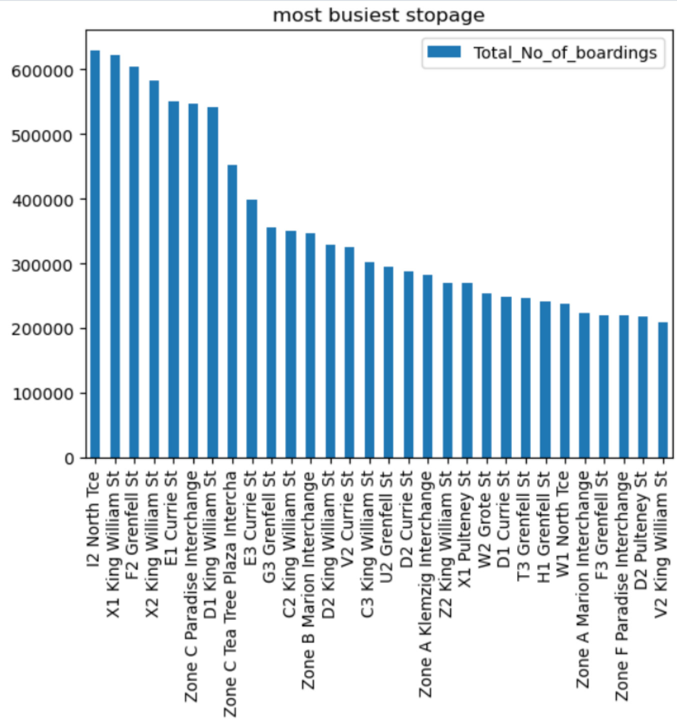
	stopName	Total_No_of_boardings
0	1 Anzac Hwy	39429
1	1 Bartels Rd	8412
2	1 Botanic Rd	14868
3	1 Frome Rd	67458
4	1 Fullarton Rd	585

In [63]:
```
stopageName_with_boarding = stopageName_with_boarding.sort_values("Total_No_of_boardings", ascending = False)
#stopage with most no of boarding
stopageName_with_boarding.head(10)
```

Out[63]:

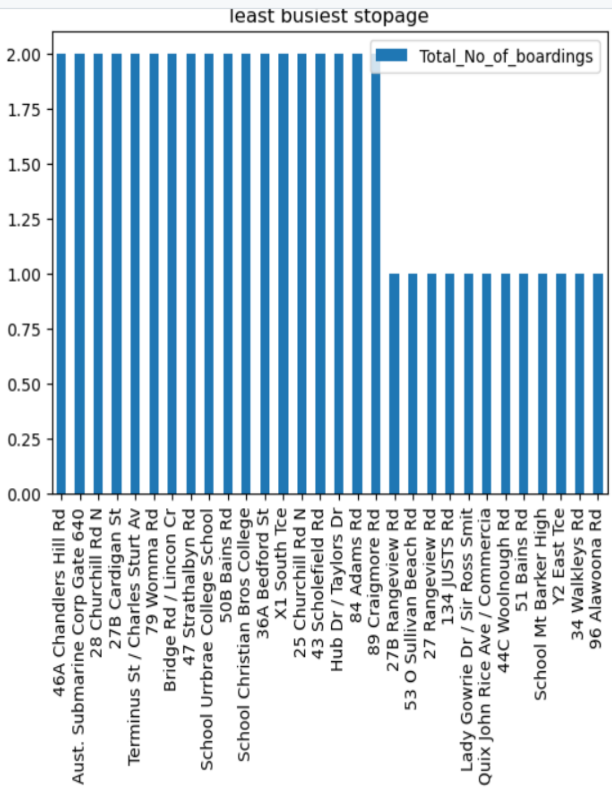
	stopName	Total_No_of_boardings
3841	I2 North Tce	628859
4023	X1 King William St	622099
3807	F2 Grenfell St	604149
4029	X2 King William St	583227
3791	E1 Currie St	550396
4120	Zone C Paradise Interchange	547709
3784	D1 King William St	541046
4124	Zone C Tea Tree Plaza Intercha	451960
3796	E3 Currie St	399351
3819	G3 Grenfell St	356518

In [76]:
```
busiestStop = stopageName_with_boarding.head(30).plot.bar(x="stopName", y="Total_No_of_boardings", rot=90)
plt.title("most busiest stopage")
plt.legend()
```



In [75]:

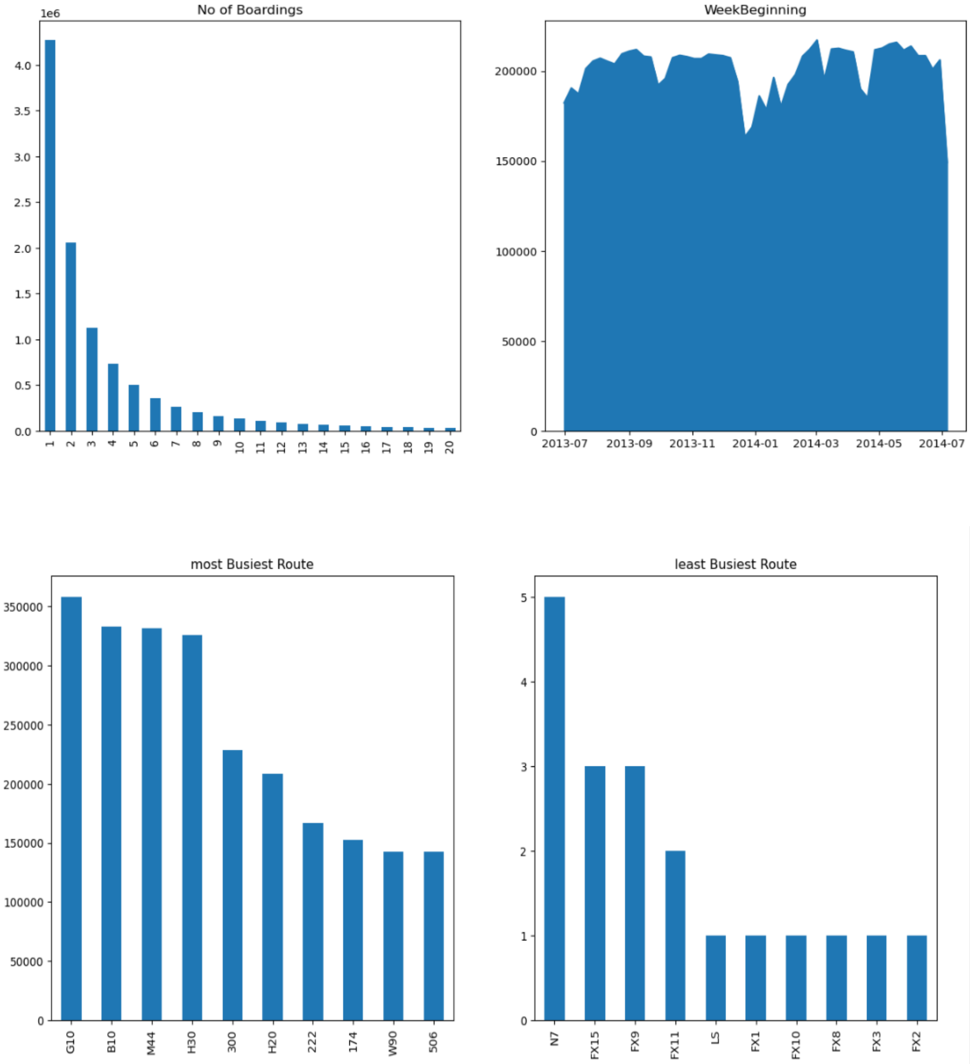
```
leastBusiestStop = stopageName_with_boarding.tail(30).plot.bar(x='stopName', y='Total_No_of_boardings', rot=90)
plt.title("least busiest stopage")
plt.legend()
```



In [30]:

```
import matplotlib.pyplot as plt
fig,axrr=plt.subplots(2,2,figsize=(15,15))

ax=axrr[0][0]
ax.set_title("No of Boardings")
data['NumberOfBoardings'].value_counts().sort_index().head(20).plot.bar(ax=axrr[0][0])

ax=axrr[0][1]
ax.set_title("WeekBeginning")
data['WeekBeginning'].value_counts().plot.area(ax=axrr[0][1])

ax=axrr[1][0]
ax.set_title("most Busiest Route")
data['RouteID'].value_counts().head(10).plot.bar(ax=axrr[1][0])

ax=axrr[1][1]
ax.set_title("least Busiest Route")
data['RouteID'].value_counts().tail(10).plot.bar(ax=axrr[1][1])
```

Out[30]: <Axes: title={'center': 'least Busiest Route'}>



Analysis Objectives:

The primary objectives of this project are to assess and improve public transportation efficiency. This involves evaluating factors such as ridership trends, route optimization, on-time performance, and environmental impact. We seek to leverage IBM Cognos for data visualization to gain actionable insights, enhance decision-making for transportation authorities, and contribute to more sustainable and effective urban mobility systems.

At present we tried visualisations that show how NumberOfBoardings is distributed across routes, stops and a week.

Data Cleaning and Preprocessing

In [1]:

```
import numpy as np
import pandas as pd

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

```
/kaggle/input/unisys/Public Transport Boarding Summary by Route, Trip, Stop and Week of Year.doc
/kaggle/input/unisys/20140711.CSV
/kaggle/input/unisys/ptsboardingsummary/Public Transport Boarding Summary by Route, Trip, Stop and Week of Year.doc
/kaggle/input/unisys/ptsboardingsummary/20140711.CSV
```

The data fields in the given file are

- **TripID** Unique identity of trip
- **RouteID** Value representing public transport route
- **StopID** Unique identity of stop
- **StopName** Name of given stop
- **WeekBeginning** Date representing first day of any week
- **NumberOfBoarding** Count of all boarding's occurred at this stop for the named trip over the previous week

In [2]:

```python
# Step 1: Load the dataset
print("Load the dataset")
import pandas as pd
data = pd.read_csv('/kaggle/input/unisys/20140711.CSV', low_memory=False)
data.shape
data.head(10)
```

Load the dataset

Out[2]:

	TripID	RouteID	StopID	StopName	WeekBeginning	NumberOfBoardings
0	23631	100	14156	181 Cross Rd	2013-06-30 00:00:00	1
1	23631	100	14144	177 Cross Rd	2013-06-30 00:00:00	1
2	23632	100	14132	175 Cross Rd	2013-06-30 00:00:00	1
3	23633	100	12266	Zone A Arndale Interchange	2013-06-30 00:00:00	2
4	23633	100	14147	178 Cross Rd	2013-06-30 00:00:00	1
5	23634	100	13907	9A Marion Rd	2013-06-30 00:00:00	1
6	23634	100	14132	175 Cross Rd	2013-06-30 00:00:00	1
7	23634	100	13335	9A Holbrooks Rd	2013-06-30 00:00:00	1
8	23634	100	13875	9 Marion Rd	2013-06-30 00:00:00	1
9	23634	100	13045	206 Holbrooks Rd	2013-06-30 00:00:00	1

In [3]:

```
# Step 2:  Drop duplicates and Check data types of columns
data = data.drop_duplicates()
import seaborn as sns
print(data.dtypes)
```

```
TripID               int64
RouteID             object
StopID               int64
StopName            object
WeekBeginning       object
NumberOfBoardings    int64
dtype: object
```

In [4]:

```
# Step 2: Check data types of columns
print("\nCheck data types of columns")
print(data.dtypes)
```

```
Check data types of columns
TripID               int64
RouteID             object
StopID               int64
StopName            object
WeekBeginning       object
NumberOfBoardings    int64
dtype: object
```

In [5]:

```
# Step 3: Handle mixed data types
#'RouteID' column has mixed types, convert it to numeric
data['RouteID'] = pd.to_numeric(data['RouteID'], errors='coerce')
print("Handle mixed data types")
print(data.shape)
```

```
Handle mixed data types
(10857234, 6)
```

In [6]:

```
# Step 4: Handle missing values
# Drop rows with missing values or fill them based on your project requirements
data = data.dropna()
print("\nHandle missing values")
print(data.shape)
```

```
Handle missing values
(6414906, 6)
```

In [7]:

```
# Step 5: Convert 'WeekBeginning' column to datetime format
data['WeekBeginning'] = pd.to_datetime(data['WeekBeginning'], errors='coerce')
print("\nConvert 'WeekBeginning' column to datetime format")
print(data['WeekBeginning'].head())
```

```
Convert 'WeekBeginning' column to datetime format
0   2013-06-30
1   2013-06-30
2   2013-06-30
3   2013-06-30
4   2013-06-30
Name: WeekBeginning, dtype: datetime64[ns]
```

In [8]:

```
# Step 6: Clean 'StopName' column
# Remove leading and trailing whitespaces
data['StopName'] = data['StopName'].str.strip()
print("\nClean 'StopName' column")
print(data['StopName'].head())
```

```
Clean 'StopName' column
0                  181 Cross Rd
1                  177 Cross Rd
2                  175 Cross Rd
3     Zone A Arndale Interchange
4                  178 Cross Rd
Name: StopName, dtype: object
```

In [9]:

```
data.head()
```

Out[9]:

	TripID	RouteID	StopID	StopName	WeekBeginning	NumberOfBoardings
0	23631	100.0	14156	181 Cross Rd	2013-06-30	1
1	23631	100.0	14144	177 Cross Rd	2013-06-30	1
2	23632	100.0	14132	175 Cross Rd	2013-06-30	1
3	23633	100.0	12266	Zone A Arndale Interchange	2013-06-30	2
4	23633	100.0	14147	178 Cross Rd	2013-06-30	1

In [10]:

```
#Step 8 : Unique values for each column in the DataFrame
print(data.nunique())
```

```
TripID               23926
RouteID                323
StopID                6718
StopName              3840
WeekBeginning           54
NumberOfBoardings      381
dtype: int64
```

In [11]:

```
data.shape
data.columns
data.head(3)
```

Out[11]:

	TripID	RouteID	StopID	StopName	WeekBeginning	NumberOfBoardings
0	23631	100.0	14156	181 Cross Rd	2013-06-30	1
1	23631	100.0	14144	177 Cross Rd	2013-06-30	1
2	23632	100.0	14132	175 Cross Rd	2013-06-30	1

In [12]:

```
#Count the number of missing value in each coloumn
data.isnull().sum()
```

Out[12]:

```
TripID               0
RouteID              0
StopID               0
StopName             0
WeekBeginning        0
NumberOfBoardings    0
dtype: int64
```


In [12]:

```
#Count the number of missing value in each coloumn
data.isnull().sum()
```

Out[12]:

```
TripID               0
RouteID              0
StopID               0
StopName             0
WeekBeginning        0
NumberOfBoardings    0
dtype: int64
```


In [13]:

```
#different type of Unique Data in the dataset
data['WeekBeginning'].unique()
```

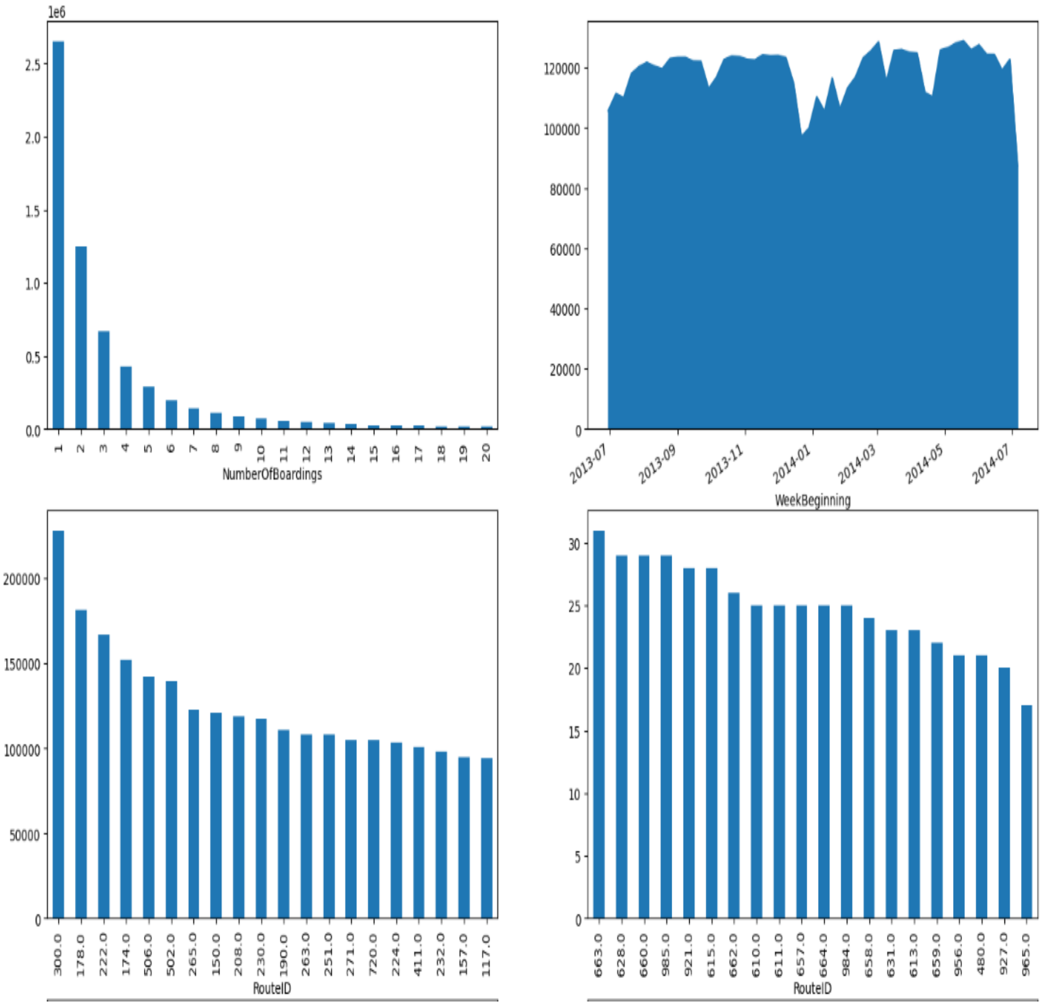
Out[13]:

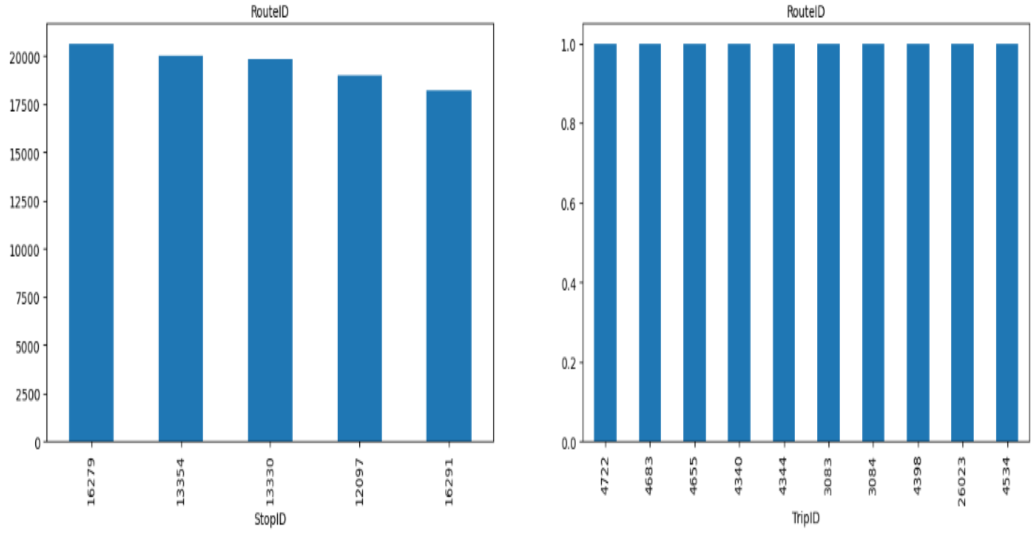
```
<DatetimeArray>
['2013-06-30 00:00:00', '2013-07-07 00:00:00', '2013-07-14 00:00:00',
 '2013-07-21 00:00:00', '2013-07-28 00:00:00', '2013-08-04 00:00:00',
 '2013-08-11 00:00:00', '2013-08-18 00:00:00', '2013-08-25 00:00:00',
 '2013-09-01 00:00:00', '2013-09-08 00:00:00', '2013-09-15 00:00:00',
 '2013-09-22 00:00:00', '2013-09-29 00:00:00', '2013-10-06 00:00:00',
 '2013-10-13 00:00:00', '2013-10-20 00:00:00', '2013-10-27 00:00:00',
 '2013-11-03 00:00:00', '2013-11-10 00:00:00', '2013-11-17 00:00:00',
 '2013-11-24 00:00:00', '2013-12-01 00:00:00', '2013-12-08 00:00:00',
 '2013-12-15 00:00:00', '2013-12-22 00:00:00', '2013-12-29 00:00:00',
 '2014-01-05 00:00:00', '2014-01-12 00:00:00', '2014-01-19 00:00:00',
 '2014-01-26 00:00:00', '2014-02-02 00:00:00', '2014-02-09 00:00:00',
 '2014-02-16 00:00:00', '2014-02-23 00:00:00', '2014-03-02 00:00:00',
 '2014-03-09 00:00:00', '2014-03-16 00:00:00', '2014-03-23 00:00:00',
 '2014-03-30 00:00:00', '2014-04-06 00:00:00', '2014-04-13 00:00:00',
 '2014-04-20 00:00:00', '2014-04-27 00:00:00', '2014-05-04 00:00:00',
 '2014-05-11 00:00:00', '2014-05-18 00:00:00', '2014-05-25 00:00:00',
 '2014-06-01 00:00:00', '2014-06-08 00:00:00', '2014-06-15 00:00:00',
 '2014-06-22 00:00:00', '2014-06-29 00:00:00', '2014-07-06 00:00:00']
Length: 54, dtype: datetime64[ns]
```

In [14]:

```python
import matplotlib.pyplot as plt
fig,axrr=plt.subplots(3,2,figsize=(18,18))
data['NumberOfBoardings'].value_counts().sort_index().head(20).plot.bar(ax=axrr[0][0])
data['WeekBeginning'].value_counts().plot.area(ax=axrr[0][1])
data['RouteID'].value_counts().head(20).plot.bar(ax=axrr[1][0])
data['RouteID'].value_counts().tail(20).plot.bar(ax=axrr[1][1])
data['StopID'].value_counts().head(5).plot.bar(ax=axrr[2][0])
data['TripID'].value_counts().tail(10).plot.bar(ax=axrr[2][1])
```

```
Out[14]: <Axes: xlabel='TripID'>
```





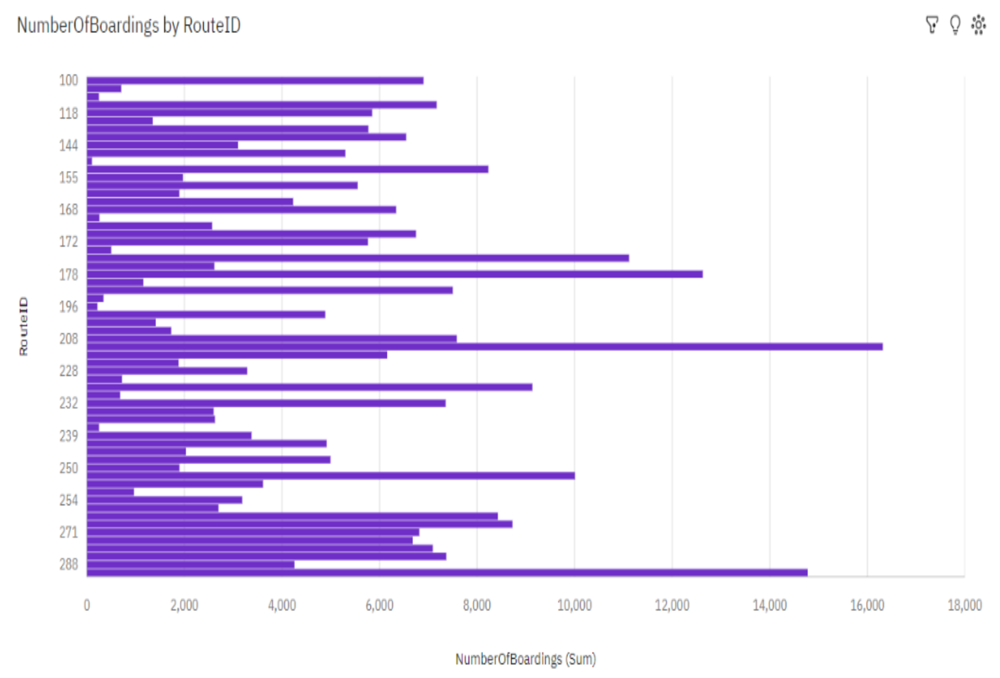
In [15]:

```python
# Save the cleaned dataset to a new CSV file
data.to_csv('cleaned_data.csv', index=False)
print("\nSave the cleaned dataset to a new CSV file")
print("Cleaned dataset saved successfully.")
```

```
Save the cleaned dataset to a new CSV file
Cleaned dataset saved successfully.
```

Visualisation in IBM Cognos

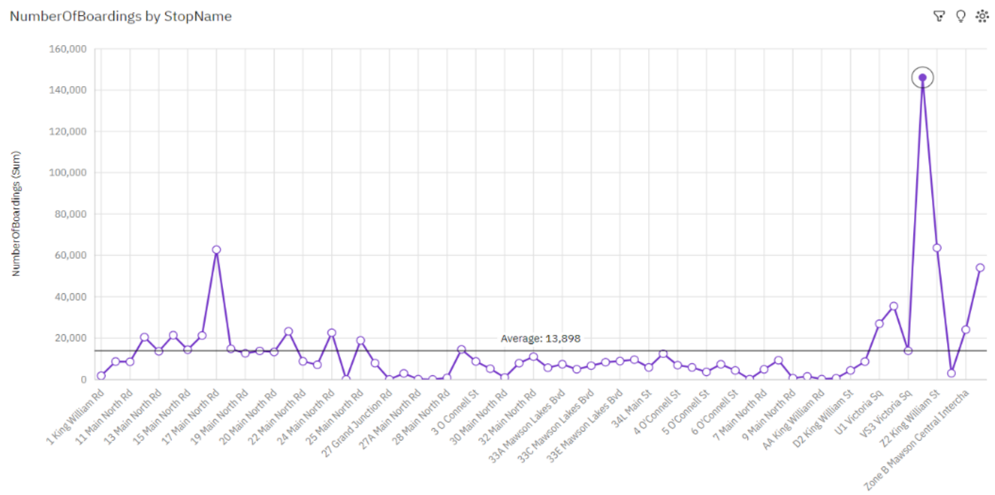
A bar chart visualizing the **noOfBoardings** for each route for **RouteID** ranging from **100 to 288**



Insights:

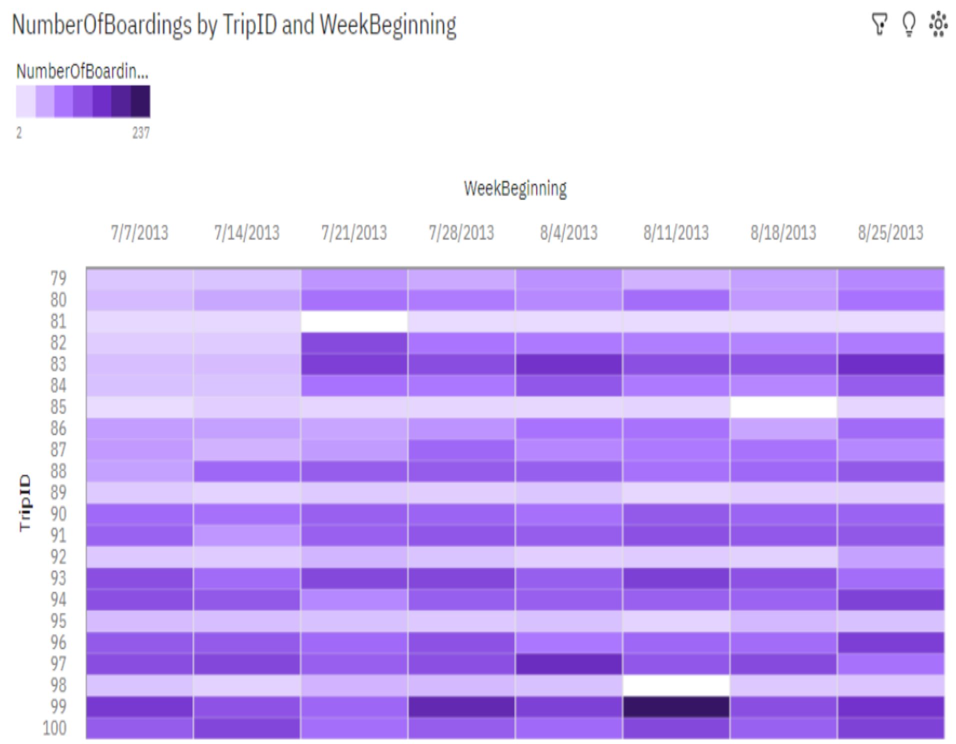
RouteID 222.0 has the **highest total NumberOfBoardings** due to WeekBeginning 2013-07-21. **NumberOfBoardings** is unusually high when **RouteID is 222 and 300**.

Visualizing **NoOfBoardings** by **StopName**



Insight: NumberOfBoardings is unusually high when **StopName** is **X1 King William St.**

A heat map representing **NoOfBoardings** by **TripID** for the **WeekBeginning from 7/7/2013 to 8/25/2013**



CONCLUSION:

This document outlines the project's objectives, design thinking process, data collection process, data visualisation, analysis objectives, innovation, development phases and the role of code in analyzing public transportation data to improve service efficiency. The defined timeline provides a structured approach to project execution.

Through the analysis of public transportation data, we have identified areas that require improvement and support transport improvement initiatives. Effective data visualization strategies and code integration will simplify complex transportation data analysis and provide actionable insights for public transportation improvement.

In conclusion, the use of IBM Cognos for visualization in the public transportation efficiency analysis project has brought about positive changes, leading to more efficient and user-friendly services, better decision-making, and improved sustainability