PUBLIC TRANSPORT OPTIMIZATION

TEAM MEMBER

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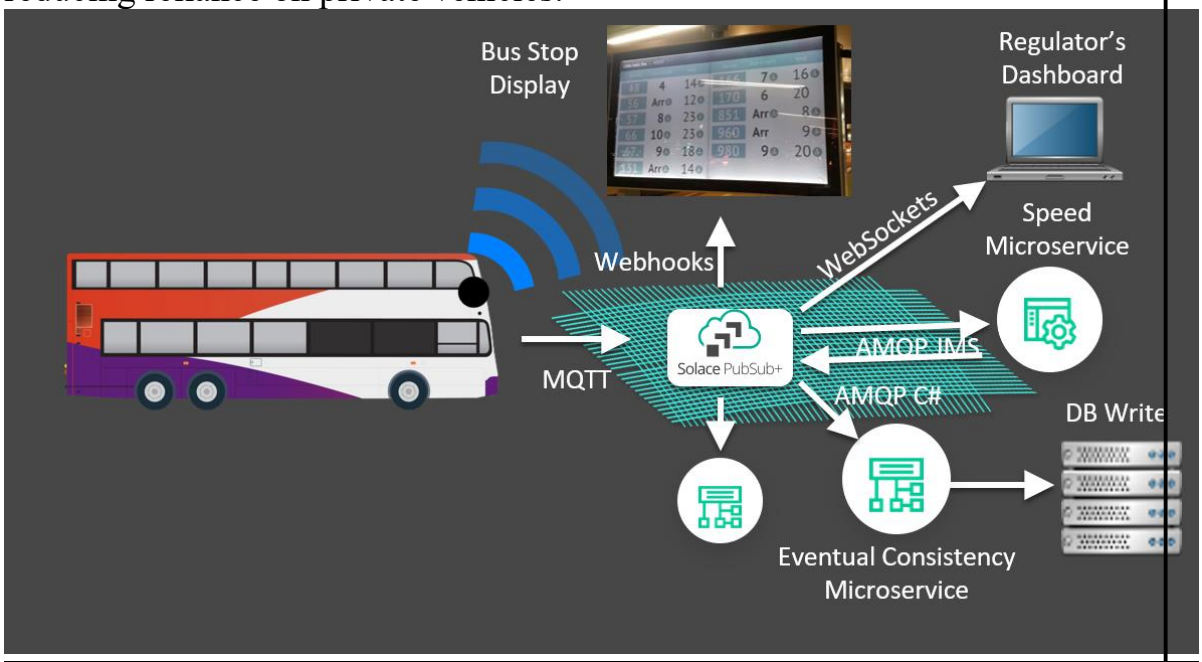
Phase 2 Submission Document

Project: Public Transport Optimization

Introduction:

- Public transport optimization refers to the process of improving the efficiency, accessibility, and sustainability of public transportation systems.
- It involves employing various strategies and technologies to enhance the overall performance of buses, trains, trams, and other modes of public transit.
- This can include route planning, scheduling, fare structures, and the integration of emerging technologies like real-time tracking and data analytics.
- The goal is to make public transport more convenient, cost-effective, and environmentally friendly, ultimately encouraging its use and reducing reliance on private vehicles.



Content for Project Phase 2 :

Consider incorporating machine learning algorithms to improve arrival time prediction accuracy based on historical data and traffic conditions.

Data Source

A good data source for public transport optimization using machine learning should be

Accurate, Complete, Covering the geographic area of interest, Accessible

Dataset Link: (https://www.kaggle.com/datasets/asjad99/rome-taxi-data-subset)

DriveNo		Date and Time	Longitude	Latitude
1	156	2014-02-01 00:00:00.739166+01	41.88367183	12.48777756
2	187	2014-02-01 00:00:01.148457+01	41.92854333	12.46903667
3	297	2014-02-01 00:00:01.220066+01	41.89106861	12.49270456
4	89	2014-02-01 00:00:01.470854+01	41.79317669	12.43212196
5	79	2014-02-01 00:00:01.631136+01	41.90027472	12.46274618
6	191	2014-02-01 00:00:02.048546+01	41.85230476	12.57740658
7	343	2014-02-01 00:00:02.647839+01	41.89217183	12.46969962
8	341	2014-02-01 00:00:02.709888+01	41.91021256	12.47700043
9	260	2014-02-01 00:00:03.458195+01	41.86582086	12.46552211
10	59	2014-02-01 00:00:03.707117+01	41.89678316	12.4821987
11	122	2014-02-01 00:00:04.232912+01	41.92308749	12.50220354
12	311	2014-02-01 00:00:04.436445+01	41.90681379	12.4902084
13	351	2014-02-01 00:00:04.487352+01	41.91005082	12.49660921
14	58	2014-02-01 00:00:05.182068+01	41.91755922	12.51327352
15	196	2014-02-01 00:00:05.429831+01	41.89222982	12.46977921
16	105	2014-02-01 00:00:06.06672+0141.89714356	12.47295309	
17	331	2014-02-01 00:00:06.362172+01	41.90550407	12.44506426
18	362	2014-02-01 00:00:06.508353+01	41.91019934	12.47700165
19	188	2014-02-01 00:00:06.830676+01	41.92193188	12.49078989
20	172	2014-02-01 00:00:07.028304+01	41.91988508	12.50271848
21	352	2014-02-01 00:00:07.040664+01	41.89783253	12.46939475
22	188	2014-02-01 00:00:07.122411+01	41.92266639	12.48712614
23	361	2014-02-01 00:00:07.311678+01	41.9224726	12.48736664
24	321	2014-02-01 00:00:07.629026+01	41.89724661	12.47285113
25	318	2014-02-01 00:00:07.774661+01	41.88323171	12.46921012
26	188	2014-02-01 00:00:07.820636+01	41.92193188	12.49078989
27	317	2014-02-01 00:00:08.452163+01	41.90041222	12.47283687
28	368	2014-02-01 00:00:08.646102+01	41.89045333	12.47419667
29	295	2014-02-01 00:00:09.135615+01	41.89578956	12.47192042
30	197	2014-02-01 00:00:09.207596+01	41.88486123	12.47064281
31	298	2014-02-01 00:00:09.534952+01	41.89379748	12.47038004
32	232	2014-02-01 00:00:09.889075+01	41.90382928	12.48445171
33	315	2014-02-01 00:00:10.098237+01	41.90006536	12.45728872
34	2	2014-02-01 00:00:10.168741+01	41.9081301	12.5043669
35	135	2014-02-01 00:00:10.198107+01	41.93318995	12.51178471
36	248	2014-02-01 00:00:10.709166+01	41.89590199	12.47688189
37	132	2014-02-01 00:00:10.733119+01	41.85528839	12.47714136
38	104	2014-02-01 00:00:10.855133+01	41.79153962	12.2502862
39	234	2014-02-01 00:00:11.214262+01	41.89778328	12.46933121
40	357	2014-02-01 00:00:11.336365+01	41.83459338	12.47166415

41	281	2014-02-01 00:00:11.8629+01	41.89590769	12.48275946
42	341	2014-02-01 00:00:12.098922+01	41.91090884	12.47728158
43	53	2014-02-01 00:00:12.23614+0141.89120201		12.50254796
44	257	2014-02-01 00:00:12.341827+01	41.92463612	12.4862287
45	37	2014-02-01 00:00:12.578331+01	41.89784189	12.46842041
46	224	2014-02-01 00:00:12.880149+01	41.96531436	12.45640665
47	178	2014-02-01 00:00:12.926514+01	41.92176792	12.48506951
48	174	2014-02-01 00:00:13.311114+01	41.88981282	12.47450704
49	61	2014-02-01 00:00:13.400034+01	41.90031167	12.47273833
50	291	2014-02-01 00:00:13.406692+01	41.85738267	12.49118118

Data Collection and Preprocessing:

- Optimizing public transport involves gathering data on various aspects like passenger demand, traffic patterns, and operational efficiency.
- This data is collected through methods like GPS tracking, passenger surveys, and traffic monitoring.
- Once collected, it's processed to generate insights and inform decision-making.
- Techniques such as data analytics, machine learning, and simulation models can be used to analyze and optimize routes, schedules, and resource allocation for better efficiency and service quality.

Exploratory Data Analysis (EDA):

- Gather data on passenger demand, routes, schedules, vehicle locations, and any other relevant variables.
- Handle missing values: Identify and appropriately deal with missing data points.
- Outlier detection: Address any anomalies that could skew the analysis.
- Calculate mean, median, mode, variance, etc., for key variables.

Feature Engineering:

- Stops and Stations: Distance between stops, location-based demand, connectivity to other transportation modes.
- Time of Day: Different demand patterns during peak hours, off-peak hours, and weekend
- Transfer Efficiency: Ease and efficiency of transferring between different modes of transport.
- Passenger Load Data: Number of passengers on board at any given time.

Advanced Regression Techniques:

- Time Series Regression :Utilize historical data to model the relationship between time-dependent variables (e.g., passenger demand) and other factors such as time of day, day of week, and seasonality.
- Gradient Boosting Regression:Techniques like XGBoost, LightGBM, and CatBoost can handle complex interactions between features and provide accurate predictions.

Model Evaluation and Selection:

- Regression Models: If you're predicting continuous variables like travel time or cost, regression models like linear regression or decision trees could be considered.
- Classification Models: If the problem involves categorical outcomes, such as route selection or mode choice, classification models like Random Forest or Logistic Regression might be appropriate.
- Time Series Models: For forecasting tasks (e.g., predicting demand over time), models like ARIMA or LSTM can be effective.

Model Interpretability:

- Feature Importance Analysis:

Identify which features have the most influence on the model's predictions. Techniques like permutation importance or SHAP (SHapley Additive exPlanations) values can be used.

- *LIME (Local Interpretable Model-agnostic Explanations)*:

- LIME creates locally faithful explanations for a specific prediction by training an interpretable surrogate model in the vicinity of that prediction.

- User Feedback and Expert Input:
  - Incorporate feedback from stakeholders, domain experts, and end-users to validate and refine the model's interpretations.

Deployment and Prediction:

Problem Definition:

- Clearly define the optimization problem. Are you focusing on route planning, scheduling, fare optimization, or a combination?

Data Collection:

- Gather relevant data like passenger demand, traffic patterns, schedules, vehicle capacities, and any other factors that influence public transport operations.

. *Data Preprocessing and Cleaning*:

- Prepare the data for modeling by handling missing values, outliers, and ensuring data quality.

Loading the Data

```
#load data install.packages("data.table")
library(data.table)
taxi_data = fread(file.choose(), header = T, sep =
','data.table=FALSE)
```

PROGRAM

Exploring the data:

After loading the dataset, we perform a general exploratory analysis of this dataset to understand the data at hand.

head(dataset, 10)

The dataset contains 4 attributes:

ID of a taxi driver. This is a unique numeric ID.

Date and time in the format Y:m:d H:m:s.msec+tz, where msec is micro-seconds, and tz is a time-zone adjustment.

Longitude, Latitude: These provide explicit trajectory information and if analysed properly contains rich spatiotemporal information.

Since they are a a series of chronologically ordered points, they represent taxi movement traces. i.e spatial trajectory generated by moving taxis in Rome.

In exploratory phase, a good way to start is to get a high level overview of the data using the summary method, which shows the relevant stats such as the total number of samples, possible missing values and the data type for each column. Let's get compute some quick stats(minimum, maximum, and mean location values)

summary(taxi_data)

Visualisation:

Visualisation is an effective way to understand the data at hand and get a sense of common routes taken by the taxi drivers. Since we are plotting 27 million rows of data, the basic plot will get us nothing but a splash of circles on the screen. We experimeted with ggplot and its size parameter to obtain a sensible. (this also saves compute time).

#Plot the location points (2D plot)

#create a dataframe

taxi_pickup_data <- data.frame(taxi_data[,.(Longitude)], taxi_data[,.(Latitude)])

taxi_pickup_data <- data.frame(taxi_data[,.(DriveNo)], taxi_data[,.(DateandTime)])

#basic plot gives a big blob (uncomment if needed)

#plot(taxi_pickup_data)

install.packages("ggplot2")

library(ggplot2)

ggplot(taxi_data, aes(x= Longitude, y= Latitude)) + geom_point(size=0.02)

This result doesn't make a lot of sense but we can clearly see some points are not part of the trips(outliers). Let's proceed to pre-processing and come back to improving the plot later.

Pre-Processing:

In this step we identify missing values, erroneous entries and remove a few outliers(noise or data that is not relevant to our analysis)

remove duplicates:

```
taxi_data_subset = taxi_data_subset[!duplicated(taxi_data_subset[1:3]), ]
```

Detecting outliers:

Easiest way to remove outliers is to simply plot the longitude and latitude and visually define the area of Rome on which we want to focus our analysis.

A bounding box was created(as shown in Figure 1) with the below values. The bounding box is based on rome city coordinates from google maps.

Any point outside this bounding box was considered an outlier as it was too far from the heart of the city.

Min_lat= 41.793710

Max_lat = 41.991390

Min_lon = 12.372598

Max_lon = 12.622537

we will create a Tranformation Function for preprocessing and applying Tranformation to raw data.

```
nw <- list(lat = 40.5, lon = 13)
se <- list(lat = 43, lon = 11)


trans <- function(x) {
   # set coordinates outside of NYC bounding box to NA
  ind <- which(x$Longitude < nw$lon & x$Longitude > se$lon)
  x$dropoff_longitude[ind] <- NA
  ind <- which(x$Longitude < nw$lon & x$Longitude > se$lon)
  x$Longitude[ind] <- NA

 }

#Apply the Tranformation
taxi_data_subset = trans(taxi_data_subset)
```

The result of applying the bounding box was that 1,563,893 points were removed as outliers.

Now with the relatively clean dataset, we can give visualisation and EDA another shot. For dataset to make more sense, we can visualize the dataset on top of the rome's actual map. We can confirm from the figure below that city centre are the frequently visited regions of rome. We can also see how timings effect the routes as many of the trips early in the day and late afternoon could be part of the daily commute for taxi customers.

Analysis of Travel Behaviour:

We can Obtain the most active, least active, and average activity of the taxi drivers (most time driven, least time driven, and mean time driven)

Identify the most Active drivers:

Most active drivers earn the most revenue and chances are they will be following the most optimal routes instead of engaging in fraudulent behaviour. Let's calculate taxi activity is to compute total time driven by each taxi driver

In [ ]:

```
compute_timedriven_2 <- function(DriverID,mytaxi_data) {
print("calculating total_time for driver no.")
print(DriverID)


#create a dataframe containing only the rows of that taxi driver and selecting DriveNo and Data and Time Columns only
```

```
temp_dataf <- mytaxi_data[mytaxi_data$DriveNo == DriverID,2]
print(summary(temp_dataf))

if(length(temp_dataf) == 0){ return(0)
}

#iterate over the rows total_time <- as.numeric(1.0000)
len = length(temp_dataf) -1 for(i in 1:len){

total_time = total_time + as.numeric(difftime(strptime(temp_dataf[i+1],"%Y-%m-%d
%H:%M:%OS"),strptime(temp_dataf[i],"%Y-%m-%d %H:%M:%OS"),units="min"))
}

print(total_time) #return(as.numeric(total_time), digits=15)
}
total_time_driven <- 0.0000 time_driven_list <- list()

for (i in 1:320){
time_driven_list[i] <- compute_timedriven_2(as.double(i),taxi_data_subset) total_time_driven
<- total_time_driven + as.numeric(time_driven_list[i])
}
print(which.max(time_driven_list)) print(which.min(time_driven_list))
#average time driven print(as.numeric(total_time_driven/320),digits = 5)
```

we can repurpose this to compute to the time for any given driver.

In [ ]:

```
compute_timedriven_2 <- function(DriverID,mytaxi_data) {
print("calculating total_time for driver no.")
print(DriverID)

#create a dataframe containing only the rows of that taxi driver and selecting DriveNo and
Data and Time Columns only

temp_dataf <- mytaxi_data[mytaxi_data$DriveNo == DriverID,2]
print(summary(temp_dataf))

if(length(temp_dataf) == 0){ return(0)

}
#iterate over the rows total_time <- as.numeric(1.0000)
len = length(temp_dataf) -1 for(i in 1:len){
```

```
total_time = total_time + as.numeric(difftime(strptime(temp_dataf[i+1],"%Y-%m-%d
%H:%M:%OS"),strptime(temp_dataf[i],"%Y-%m-%d %H:%M:%OS"),units="min"))
}
print(total_time) }
compute_timedriven_2(211,taxi_data)
```

Similarly, we can write another function that lets us compute the total distance travelled by a particular diver:

In [ ]:

linkcode

```
compute_distance_travelled <- function(DriverID,taxi_data) {
#create a dataframe containing only the rows of that taxi driver temp_dataf <-
taxi_data[taxi_data$DriveNo == DriverID,3:4]
print(temp_dataf)
#radius of earth
R=6371000
distance = 0
total_distance = 0 #print(summary(temp_dataf))
len = length(temp_dataf) -1 for(i in 1:len) {
lon1<- temp_dataf[i,1] lon2 <- temp_dataf[i+1,1]
lat1<- temp_dataf[i,2] lat2 <- temp_dataf[i+1,2]
dlon = lon2 - lon1 dlat = lat2 - lat1
print(dlon) print(dlat)
a = (sin(dlat/2))^2 + cos(lat1) * cos(lat2) * (sin(dlon/2))^2 c = 2 * atan2( sqrt(a), sqrt(1-a))
distance = R * c
total_distance = total_distance + distance

} return(total_distance)
} compute_distance_travelled(122,taxi_data_subset)
```

OUTPUT:

In the plot above we compare Vfractal values of three different routes taken by three different drivers(extracted in the previous step). The higher values(closer to 2.0) indicate a more torturous path, which means the driver didn't take the most direct route even though it existed. We repeated the process for several other extracted paths and noticed a similar pattern. The results of our analysis show that taxi drivers may not always take the most optimal route. Moreover, we noticed that Taxi drivers tend to exhibit different behaviour on longer trips, as the incentives change. In particular we noticed that for a longer trip even the most top drivers(with respect to distance travelled) tend to take longer routes.

In this Notebooks we used the rome taxi dataset to analyse pattern movement of taxi drivers. Analysis of this sort can yield various insights for planning bureaus, city planners and transportation analysis etc. After initial exploration and cleaning of data we extracted various routes and then Fractal analysis was employed to quantify tortuosity of movement paths in order to explore how top and ordinary drivers operate on different spatial scales at different times, where the primary focus is to reveal top driver mobility intelligence. Based on our results we can conclude that taxi drivers indeed sometimes try to maximize their income using unethical ways. Moreover, its interesting to see how taxi' drivers intelligence can be learned from a large number of historical data.

Future work: One of the improvements that can made to this work is registering the extracted paths with the underlying road network to get more accurate comparison of paths. We also aim to perform the same analysis based on varying trip length.

CONCLUSION:

Optimizing public transport holds significant potential for enhancing urban mobility, reducing congestion, and mitigating environmental impacts. By employing advanced technologies, implementing efficient routes, and promoting sustainable practices, cities can create a more accessible, reliable, and eco-friendly transportation system. This leads to improved quality of life for residents and fosters economic growth. Continued investment and innovation in public transport optimization are crucial steps towards creating smarter, more livable cities for the future.

FUTURE WORK:

- Embrace advances in automation, artificial intelligence, and data analytics to enhance real-time monitoring, predictive maintenance, and adaptive scheduling.
- Develop seamless connections between different modes of transport, including buses, trains, trams, bicycles, and ride-sharing services, to create a comprehensive, user-friendly transportation network.
- Utilize data-driven insights to tailor services to individual passenger needs, such as customized routes, real-time updates, and fare options.