```
#Downloading the dataset and storing it
!wget https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/551/original/delhivery_data.csv
--2023-03-18 14:38:16-- https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/551/original/delhivery_data.csv
```

Resolving d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)... 18.65.40.200, 18.65.40.33, 18.65.40.189, ...

Connecting to d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)|18.65.40.200|:443... connected.

HTTP request sent, awaiting response... 200 OK

Length: 55617130 (53M) [text/plain]

Saving to: 'delhivery\_data.csv.15'

2023-03-18 14:38:17 (121 MB/s) - 'delhivery\_data.csv.15' saved [55617130/55617130]

#Importing all the required packages
import pandas as pd
import numpy as np
import seaborn as sns
from scipy.stats import ttest\_ind, pearsonr
from matplotlib import pyplot as plt
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.preprocessing import LabelEncoder
import re
import warnings

#to ignore the warnings
warnings.filterwarnings("ignore")

#Store the dataset in the dataframe

df = pd.read\_csv("delhivery\_data.csv")

#View first 5 records using the head command

df.head()

data tri	ip_creation_time	route_schedule_uuid ro	oute_type	trip_uuid	source_center	source_name	destination_center	destination_name	od_start_time	cutoff_timestamp	actual_distance_to_destination	actual_time os:	rm_time osrn
<b>0</b> training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3	Carting	trip- 153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	2018-09-20 03:21:32.418600	2018-09-20 04:27:55	10.435660	14.0	11.0
1 training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3	Carting	trip- 153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	2018-09-20 03:21:32.418600	2018-09-20 04:17:55	18.936842	24.0	20.0
2 training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3	Carting	trip- 153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	2018-09-20 03:21:32.418600	2018-09-20 04:01:19.505586	27.637279	40.0	28.0
3 training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3	Carting	trip- 153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	2018-09-20 03:21:32.418600	2018-09-20 03:39:57	36.118028	62.0	40.0
4 training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3	Carting	trip- 153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	2018-09-20 03:21:32.418600	2018-09-20 03:33:55	39.386040	68.0	44.0

5 rows × 24 columns



# Provided Columns and thier description

- 1. data tells whether the data is testing or training data
- 2. trip\_creation\_time Timestamp of trip creation3. route\_schedule\_uuid Unique ld for a particular route schedule
- 4. route\_type Transportation type
- 5. FTL Full Truck Load: FTL shipments get to the destination sooner, as the truck is making no other pickups or drop-offs along the way
- 6. Carting: Handling system consisting of small vehicles (carts)
- 7. trip\_uuid Unique ID given to a particular trip (A trip may include . different source and destination centers)
- 8. source\_center Source ID of trip origin
- 9. source\_name Source Name of trip origin
- 10. destination\_cente Destination ID
- 11. destination\_name Destination Name
- 12. od\_start\_time Trip start time
- 13. od\_end\_time Trip end time
- 14. start\_scan\_to\_end\_scan Time taken to deliver from source to destination
- 15. is\_cutoff Unknown field
- 16. cutoff\_factor Unknown field
- 17. cutoff\_timestamp Unknown field
- 18. actual\_distance\_to\_destination Distance in Kms between source and destination warehouse
- 19. actual\_time Actual time taken to complete the delivery (Cumulative)
- 20. osrm\_time An open-source routing engine time calculator which computes the shortest path between points in a given map (Includes usual traffic, distance through major and minor roads) and gives the time (Cumulative)
- 21. osrm\_distance An open-source routing engine which computes the shortest path between points in a given map (Includes usual traffic,
- distance through major and minor roads) (Cumulative)
- 22. factor Unknown field
- 23. segment\_actual\_time This is a segment time. Time taken by the subset of the package delivery
- 24. segment\_osrm\_time This is the OSRM segment time. Time taken by the subset of the package delivery
- 25. segment\_osrm\_distance This is the OSRM distance. Distance covered by subset of the package delivery
- 26. segment\_factor Unknown field

#Drop the columns which are not clear and which are unknown
df.drop(["is\_cutoff","cutoff\_factor","cutoff\_timestamp","factor","segment\_factor"], axis=1, inplace=True)

df.columns

 $https://colab.research.google.com/drive/1wXxN4WW\_813D4xSwl6ehIZnDCnLReGQR\#scrollTo=QHhSBewAvHdJ\&printMode=trueAvHdJ\&printMod$ 

```
18/03/2023, 20:43
               'destination_name', 'od_start_time', 'od_end_time',
               'start_scan_to_end_scan', 'actual_distance_to_destination',
               'actual_time', 'osrm_time', 'osrm_distance', 'segment_actual_time',
               'segment osrm time', 'segment osrm distance'],
              dtype='object')
       (144867, 19)
```

#After droping the unwanted columns, the dataframe consists of 19 columns and 144867 rows df.shape

df.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 144867 entries, 0 to 144866 Data columns (total 19 columns): Non-Null Count Dtype # Column --------144867 non-null object 0 data 1 trip\_creation\_time 144867 non-null object 2 route\_schedule\_uuid 144867 non-null object route\_type 144867 non-null object 144867 non-null object 4 trip\_uuid source\_center 144867 non-null object source\_name 144574 non-null object 144867 non-null object 7 destination\_center 8 destination\_name 144606 non-null object 9 od\_start\_time 144867 non-null object 144867 non-null object 10 od\_end\_time 144867 non-null float64 11 start\_scan\_to\_end\_scan 12 actual\_distance\_to\_destination 144867 non-null float64 13 actual\_time 144867 non-null float64 14 osrm\_time 144867 non-null float64 15 osrm\_distance 144867 non-null float64 144867 non-null float64 16 segment\_actual\_time 17 segment\_osrm\_time 144867 non-null float64 18 segment\_osrm\_distance 144867 non-null float64 dtypes: float64(8), object(11)

#Checking for the null values using the isna() function

df.isna().sum()

memory usage: 21.0+ MB

trip\_creation\_time route\_schedule\_uuid route\_type trip\_uuid source\_center 293 source\_name destination\_center 261 destination\_name od\_start\_time od\_end\_time start\_scan\_to\_end\_scan actual\_distance\_to\_destination actual\_time osrm\_time osrm\_distance segment\_actual\_time segment\_osrm\_time segment\_osrm\_distance dtype: int64

293 null values found in source\_name column and 261 null values found in destination\_name columns

#Droping the null values df.dropna(inplace=True)

There are 144867 rows and out of which 554 rows contains null values, which is 0.3%, hence we can delete those entires

df.isna().sum()

trip\_creation\_time route\_schedule\_uuid route\_type trip\_uuid source\_center source\_name destination\_center destination\_name od\_start\_time od\_end\_time start\_scan\_to\_end\_scan actual\_distance\_to\_destination  $actual\_time$ osrm\_time osrm\_distance segment\_actual\_time segment\_osrm\_time segment\_osrm\_distance dtype: int64

df.shape

(144316, 19)

#Checking for any duplicate entires df.duplicated().any()

False

There are no duplicate entires found

#The describe function used to show the Mean, Median, percentile, min and max values of all numerical columns df.describe()

	start_scan_to_end_scan	actual_distance_to_destination	actual_time	osrm_time	osrm_distance	segment_actual_time	segment_osrm_time	segment_osrm_distance
count	144316.000000	144316.000000	144316.000000	144316.000000	144316.000000	144316.000000	144316.000000	144316.000000
mean	963.697698	234.708498	417.996237	214.437055	285.549785	36.175379	18.495697	22.818993
std	1038.082976	345.480571	598.940065	308.448543	421.717826	53.524298	14.774008	17.866367
min	20.000000	9.000045	9.000000	6.000000	9.008200	-244.000000	0.000000	0.000000
25%	161.000000	23.352027	51.000000	27.000000	29.896250	20.000000	11.000000	12.053975
50%	451 000000	66 135322	132 000000	64 000000	78 624400	28 000000	17 000000	23 508300

#The describe function with include="object", shows the count, unique and freq of the columns whose type is object.

df.describe(include="object")

	data	trip_creation_time	route_schedule_uuid r	coute_type	trip_uuid	source_center	source_name	destination_center	destination_name	od_start_time	od_end_time
count	144316	144316	144316	144316	144316	144316	144316	144316	144316	144316	144316
unique	2	14787	1497	2	14787	1496	1496	1466	1466	26223	26223
top	training 2	2018-10-01 05:04:55.268931 t	hanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f	FTL	trip-153837029526866991	IND00000ACB	Gurgaon_Bilaspur_HB (Haryana)	IND00000ACB	Gurgaon_Bilaspur_HB (Haryana)	2018-09-21 18:37:09.322207	2018-09-24 09:59:15.691618
freq	104632	101	1812	99132	101	23267	23267	15192	15192	81	81



#Converting the datatype from object to datetime

df['od\_start\_time'] = pd.to\_datetime(df['od\_start\_time'])

df['od\_end\_time'] = pd.to\_datetime(df['od\_end\_time']) df['trip\_creation\_time'] = pd.to\_datetime(df['trip\_creation\_time'])

#### df.info()

<class 'pandas.core.frame.DataFrame'> Int64Index: 144316 entries, 0 to 144866 Data columns (total 19 columns): # Column

Non-Null Count Dtype --------144316 non-null object 0 data 144316 non-null datetime64[ns] 1 trip\_creation\_time 2 route\_schedule\_uuid 144316 non-null object 3 route\_type 144316 non-null object 4 trip\_uuid 144316 non-null object source\_center 144316 non-null object 6 source\_name 144316 non-null object 7 destination\_center 144316 non-null object 8 destination\_name 144316 non-null object 9 od\_start\_time 144316 non-null datetime64[ns] 10 od\_end\_time 144316 non-null datetime64[ns] 11 start\_scan\_to\_end\_scan 144316 non-null float64 12 actual\_distance\_to\_destination 144316 non-null float64 13 actual\_time 144316 non-null float64 14 osrm\_time 144316 non-null float64 15 osrm\_distance 144316 non-null float64 16 segment\_actual\_time 144316 non-null float64 17 segment\_osrm\_time 144316 non-null float64 18 segment\_osrm\_distance 144316 non-null float64 dtypes: datetime64[ns](3), float64(8), object(8) memory usage: 22.0+ MB

#Calculating the time taken between strat time and the end time and storing it as od\_total\_time df["od\_total\_time"] = (df.od\_end\_time-df.od\_start\_time).astype('timedelta64[m]')

df.head()

data	trip_creation_time	route_schedule_uuid r	route_type trip_uuid	source_center	source_name	destination_center	destination_name	od_start_time	od_end_time	start_scan_to_end_scan ad	ctual_distance_to_destination a	actual_time
0 training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3	Carting trip- 153741093647649320	IND388121AAA <sup>Ar</sup>	nand_VUNagar_DC (Gujarat)	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	2018-09-20 03:21:32.418600	2018-09-20 04:47:45.236797	86.0	10.435660	14.0
1 training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3	Carting trip- 153741093647649320	IND388121AAA <sup>Ar</sup>	nand_VUNagar_DC (Gujarat)	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	2018-09-20 03:21:32.418600	2018-09-20 04:47:45.236797	86.0	18.936842	24.0
2 training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3	Carting trip- 153741093647649320	IND388121AAA <sup>Ar</sup>	nand_VUNagar_DC (Gujarat)	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	2018-09-20 03:21:32.418600	2018-09-20 04:47:45.236797	86.0	27.637279	40.0
3 training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3	Carting trip- 153741093647649320	IND388121AAA <sup>Ar</sup>	nand_VUNagar_DC (Gujarat)	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	2018-09-20 03:21:32.418600	2018-09-20 04:47:45.236797	86.0	36.118028	62.0
4 training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3	Carting trip- 153741093647649320	IND388121AAA Ar	nand_VUNagar_DC (Gujarat)	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	2018-09-20 03:21:32.418600	2018-09-20 04:47:45.236797	86.0	39.386040	68.0



#Performing one hot encoding for the categorical column route\_type

print(df["route\_type"].value\_counts())

label\_encoder = LabelEncoder()

df["route\_type"] = label\_encoder.fit\_transform(df["route\_type"]) print(df["route\_type"].value\_counts())

FTL99132 Carting 45184

Name: route\_type, dtype: int64 1 99132

0 45184

Name: route\_type, dtype: int64

After one hot encoding, FTL is marked as 1 and Carting is marked as 0

sns.countplot(x = 'route\_type', data = df, color='cornflowerblue')

```
<Axes: xlabel='route_type', ylabel='count'>

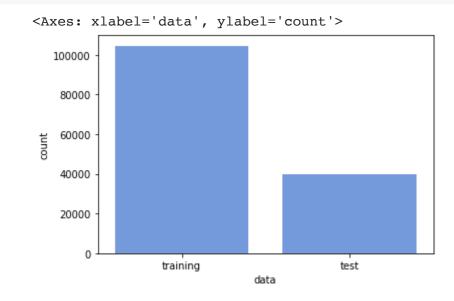
100000 -
80000 -
40000 -
```

There are total of 99132 FTL(Full Truck Load) and 45184 Carting

print(df["data"].value\_counts())

training 104632 test 39684 Name: data, dtype: int64

sns.countplot(x = 'data', data = df, color='cornflowerblue')



There are total of 104632 Training data and 39684 Testing data

```
df[["temp_source", "Soruce_State"]]=df['source_name'].str.split('(',expand=True))
df['Soruce_State'] = df['Soruce_State'].str.replace(")","")
df[["Source_City", "Soruce_Place", "Soruce_Code"]] = df['temp_source'].str.split('_',expand=True).drop(columns=[3])
df[["temp_destination", "Destination_State"]]=df['destination_name'].str.split('(',expand=True))
df['Destination_State'] = df['Destination_State'].str.replace(")","")
df[["Destination_City", "Destination_Place", "Destination_Code"]] = df['temp_destination'].str.split('_',expand=True).drop(columns=[3])
df.drop(["temp_destination", "temp_source"], axis=1, inplace=True)
```

- Splitting the source\_name to Soruce\_State, Source\_City, Source\_Place, Soruce\_Code and storing it in each columns
- Splitting the destination\_name to Destination\_State, Destination\_City, Destination\_Place, Destination\_Code and storing it in each columns

df['trip\_year'] = df['trip\_creation\_time'].dt.year
df['trip\_month'] = df['trip\_creation\_time'].dt.month
df['trip\_day'] = df['trip\_creation\_time'].dt.day

Splitting the trip\_creation\_time to trip\_year, trip\_month, trip\_day and storing it in each columns

df["source\_to\_destination\_state"] = df['Soruce\_State']+" to "+df ['Destination\_State']
df["source\_to\_destination\_city"] = df['Source\_City']+" to "+df ['Destination\_City']
df["source\_to\_destination\_place"] = df['Soruce\_Place']+" to "+df ['Destination\_Place']

Merging each Source and Destination State, City and Place and sotring it in each columns

df.head()

data tı	rip_creation_time	route_schedule_uuid r	coute_type trip_uuid	source_center	source_name	destination_center	destination_name	od_start_time	Destin	ation_State	Destination_City	Destination_Place	Destination_Code trip
<b>0</b> training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3	0 trip- 153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	2018-09-20 03:21:32.418600		Gujarat	Khambhat	MotvdDPP	D
<b>1</b> training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3	0 trip- 153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	2018-09-20 03:21:32.418600		Gujarat	Khambhat	MotvdDPP	D
2 training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3	0 trip- 153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	2018-09-20 03:21:32.418600		Gujarat	Khambhat	MotvdDPP	D
<b>3</b> training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3	0 trip- 153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	2018-09-20 03:21:32.418600		Gujarat	Khambhat	MotvdDPP	D
4 training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3	0 trip- 153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	2018-09-20 03:21:32.418600		Gujarat	Khambhat	MotvdDPP	D

5 rows × 34 columns

\*\*

df[["Source\_City", "Soruce\_Place", "Soruce\_Code", "Soruce\_State", "Destination\_City", "Destination\_State", "source\_to\_destination\_state", "source\_to\_destination\_city", "source\_to\_destination\_place"]].describe()

	Source_City S	Soruce_Place	Soruce_Code	Soruce_State	Destination_City	Destination_Place	Destination_Code	Destination_State	source_to_destination_state	source_to_destination_city	source_to_destination_place
count	144316	142218	129688	144316	144316	141884	128883	144316	144316	144316	139818
unique	1260	1153	24	31	1256	1130	27	32	155	2355	2377
top	Gurgaon	Bilaspur	НВ	Haryana	Gurgaon	Bilaspur	Н	Karnataka	Maharashtra to Maharashtra	Gurgaon to Bangalore	Bilaspur to Nelmngla
freq	23585	23384	41097	27408	15393	15363	34572	21049	11876	4976	4976

• There are 31 unique Source State

18/03/2023, 20:43

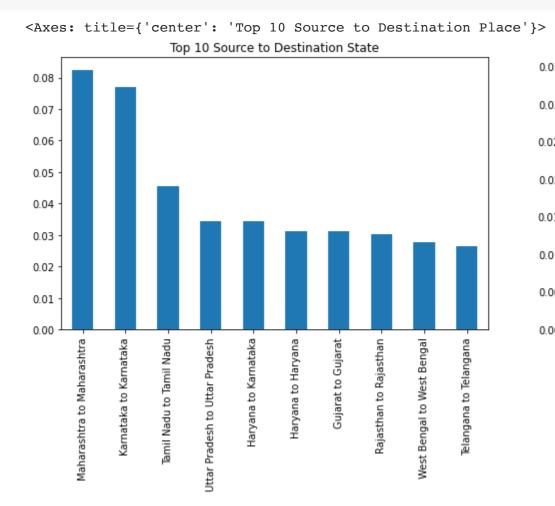
- There are 32 unique Destination State
- There are 155 unique source\_to\_destination\_state
- There are 2355 unique source\_to\_destination\_state
- There are 2377 unique source\_to\_destination\_state

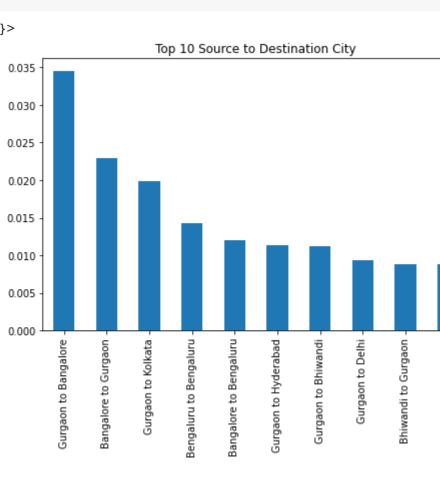
#### df[["trip\_year","trip\_month","trip\_day"]].describe()

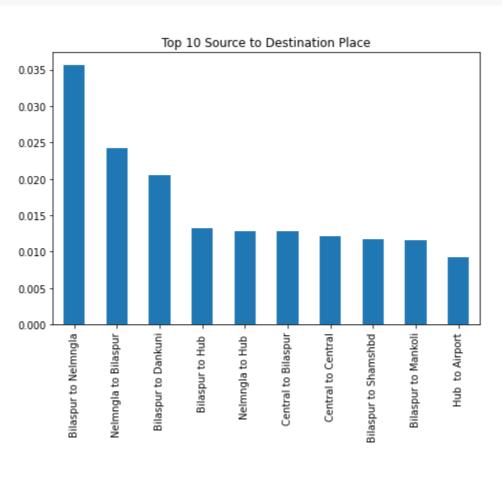
	trip_year	trip_month	trip_day
count	144316.0	144316.000000	144316.000000
mean	2018.0	9.120458	18.383111
std	0.0	0.325497	7.865996
min	2018.0	9.000000	1.000000
25%	2018.0	9.000000	14.000000
50%	2018.0	9.000000	19.000000
75%	2018.0	9.000000	25.000000
max	2018.0	10.000000	30.000000

#### The given dataset is for the year 2018 for the month 9 and 10

```
plt.figure(figsize=(26,5))
plt.subplot(131)
plt.title("Top 10 Source to Destination State")
df['source_to_destination_state'].value_counts(1)[:10].plot(kind='bar')
plt.subplot(132)
plt.title("Top 10 Source to Destination City")
df['source_to_destination_city'].value_counts(1)[:10].plot(kind='bar')
plt.subplot(133)
plt.title("Top 10 Source to Destination Place")
df['source_to_destination_place'].value_counts(1)[:10].plot(kind='bar')
```

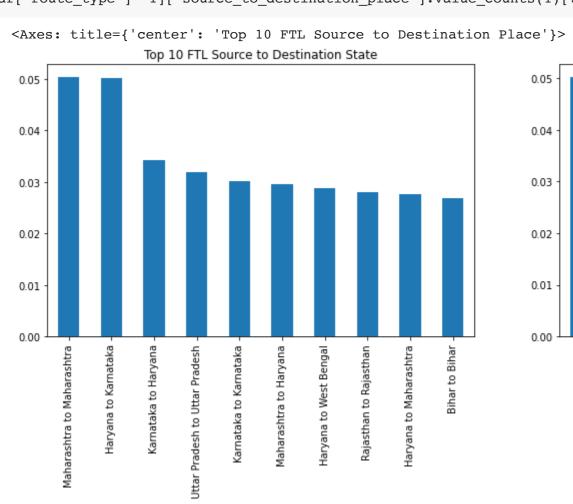


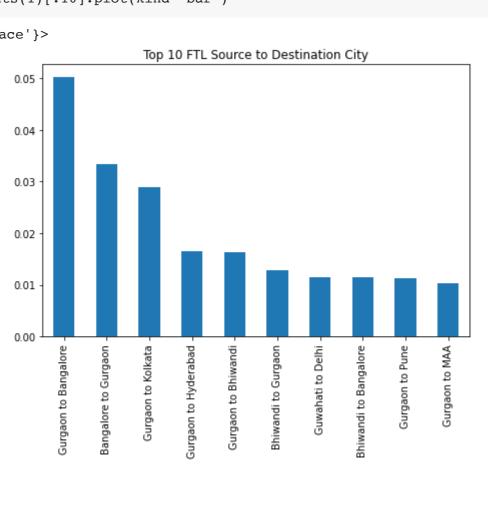


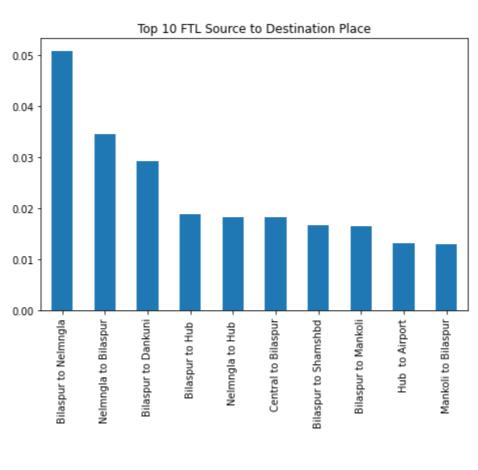


## In the above graph we can see the TOP 10 Source to Destination State, City and Place

```
plt.figure(figsize=(26,5))
plt.subplot(131)
plt.title("Top 10 FTL Source to Destination State")
df[df["route_type"]==1]['source_to_destination_state'].value_counts(1)[:10].plot(kind='bar')
plt.subplot(132)
plt.title("Top 10 FTL Source to Destination City")
df[df["route_type"]==1]['source_to_destination_city'].value_counts(1)[:10].plot(kind='bar')
plt.subplot(133)
plt.title("Top 10 FTL Source to Destination Place")
df[df["route_type"]==1]['source_to_destination_place'].value_counts(1)[:10].plot(kind='bar')
```







# In the above graph we can see the TOP 10 FTL Source to Destination State, City and Place

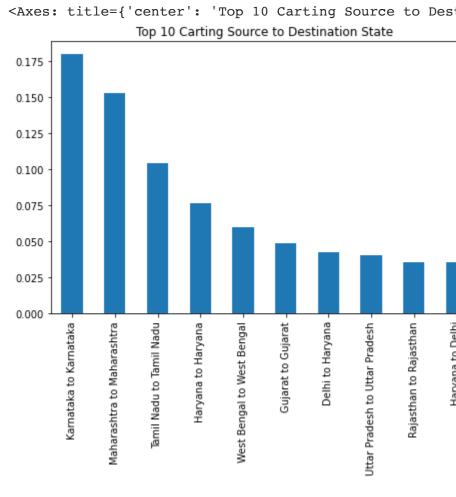
plt.figure(figsize=(26,5))
plt.subplot(131)

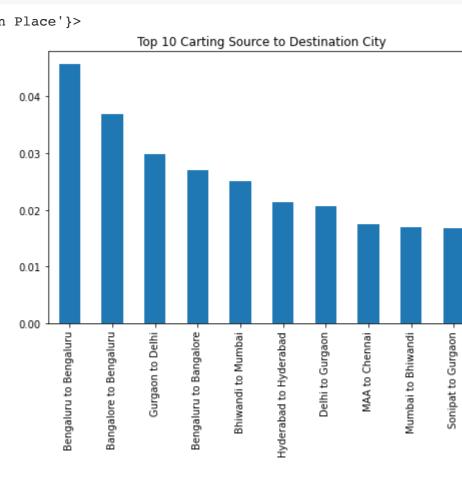
 $https://colab.research.google.com/drive/1wXxN4WW\_813D4xSwl6ehIZnDCnLReGQR\#scrollTo=QHhSBewAvHdJ\&printMode=truewardspaces and the contraction of the contraction of$ 

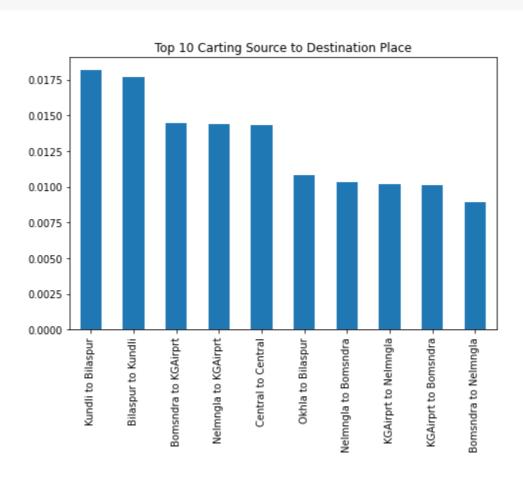
18/03/2023, 20:43 plt.title("Top 10 Carting Source to Destination State") df[df["route\_type"]==0]['source\_to\_destination\_state'].value\_counts(1)[:10].plot(kind='bar') plt.subplot(132) plt.title("Top 10 Carting Source to Destination City") df[df["route\_type"]==0]['source\_to\_destination\_city'].value\_counts(1)[:10].plot(kind='bar') plt.subplot(133) plt.title("Top 10 Carting Source to Destination Place")

df[df["route\_type"]==0]['source\_to\_destination\_place'].value\_counts(1)[:10].plot(kind='bar')

<Axes: title={'center': 'Top 10 Carting Source to Destination Place'}>

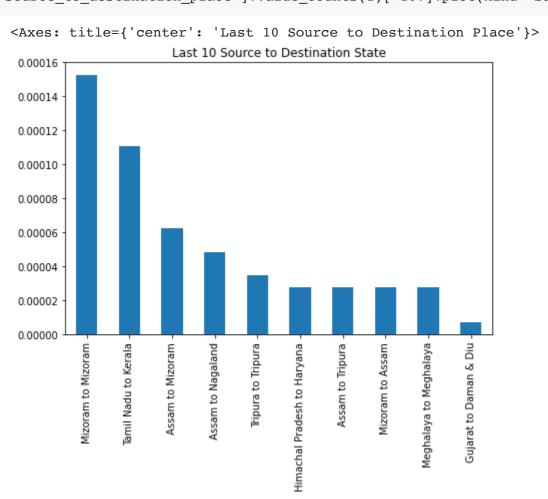


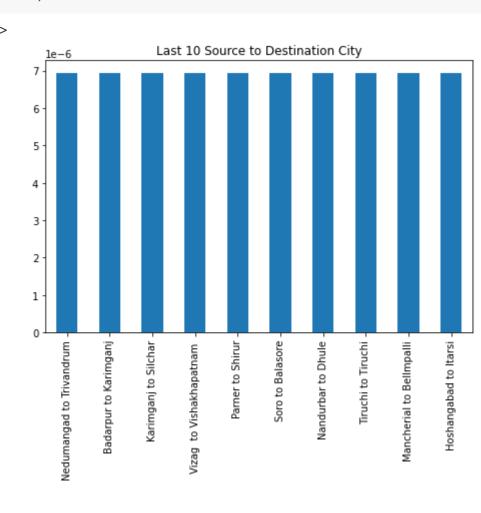


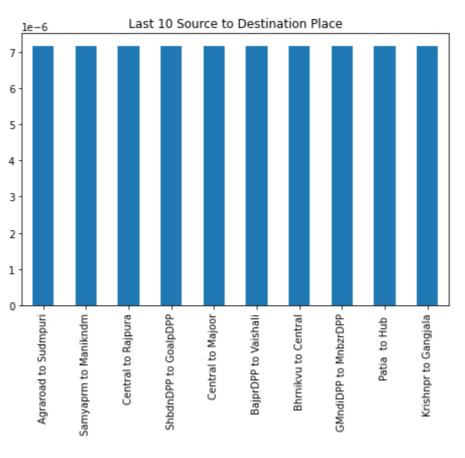


#### In the above graph we can see the TOP 10 Carting Source to Destination State, City and Place

plt.figure(figsize=(26,5)) plt.subplot(131) plt.title("Last 10 Source to Destination State") df['source\_to\_destination\_state'].value\_counts(1)[-10:].plot(kind='bar') plt.subplot(132) plt.title("Last 10 Source to Destination City") df['source\_to\_destination\_city'].value\_counts(1)[-10:].plot(kind='bar') plt.subplot(133) plt.title("Last 10 Source to Destination Place") df['source\_to\_destination\_place'].value\_counts(1)[-10:].plot(kind='bar')

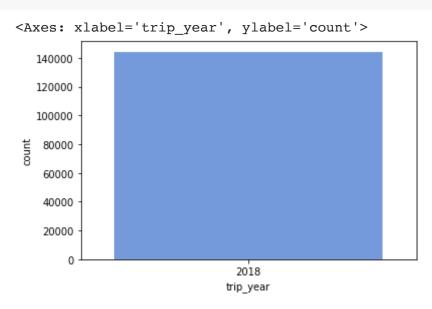






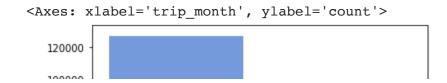
### In the above graph we can see the Least 10 Source to Destination State, City and Place

# sns.countplot(x = 'trip\_year', data = df, color='cornflowerblue')



# In the given data set, the data is given for the year 2018

sns.countplot(x = 'trip\_month', data = df, color='cornflowerblue')

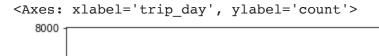


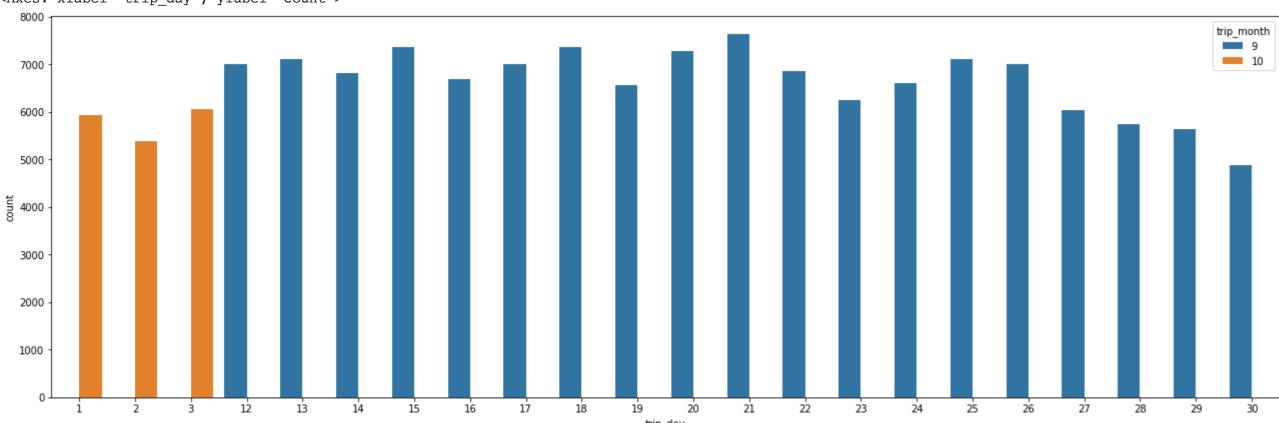
In the given data set, the data is given for the month 9 and 10

plt.figure(figsize=(22, 7))

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sns.countplot(data=df, x="trip\_day", hue="trip\_month")





From the above graph we can see that, the maximum trips is happening in the 9th month on 15, 18 and 21

trip\_state\_time\_distance = df.groupby(["source\_to\_destination\_state"]).agg({'start\_scan\_to\_end\_scan':'mean','actual\_distance\_to\_destination':'mean'}).reset\_index() trip\_state\_time\_distance.sort\_values('start\_scan\_to\_end\_scan',ascending = False).head(10)

	source_to_destination_state	start_scan_to_end_scan	actual_distance_to_destination
117	Punjab to Karnataka	3802.000000	1050.751668
22	Delhi to Assam	3702.000000	759.661163
152	West Bengal to Maharashtra	3630.310160	837.091932
80	Karnataka to West Bengal	3595.000000	804.067604
9	Assam to Delhi	3573.291117	748.599138
53	Haryana to Tamil Nadu	3355.808867	876.628008
118	Punjab to Maharashtra	3297.000000	660.579031
101	Maharashtra to West Bengal	3167.635682	831.090075
71	Karnataka to Haryana	3125.825869	869.096298
47	Haryana to Karnataka	3097.507637	859.827666

From the above table we can see that, the top 10 most time taking trip from the source to destination state

trip\_state\_time\_distance.sort\_values('actual\_distance\_to\_destination',ascending = False).head(10)

	source_to_destination_state	start_scan_to_end_scan	actual_distance_to_destination
117	Punjab to Karnataka	3802.000000	1050.751668
53	Haryana to Tamil Nadu	3355.808867	876.628008
71	Karnataka to Haryana	3125.825869	869.096298
47	Haryana to Karnataka	3097.507637	859.827666
152	West Bengal to Maharashtra	3630.310160	837.091932
101	Maharashtra to West Bengal	3167.635682	831.090075
80	Karnataka to West Bengal	3595.000000	804.067604
77	Karnataka to Rajasthan	3076.875256	781.405522
22	Delhi to Assam	3702.000000	759.661163
9	Assam to Delhi	3573.291117	748.599138

From the above table we can see that, the top 10 most long distance trip from the source to destination state

trip\_city\_time\_distance = df.groupby(["source\_to\_destination\_city"]).agg({'start\_scan\_to\_end\_scan':'mean','actual\_distance\_to\_destination':'mean'}).reset\_index() trip\_city\_time\_distance.sort\_values('start\_scan\_to\_end\_scan',ascending = False).head(10)

	source_to_destination_city	start_scan_to_end_scan	actual_distance_to_destination
449	Chandigarh to Bangalore	3802.000000	1050.751668
582	Delhi to Guwahati	3702.000000	759.661163
1265	Kolkata to Bhiwandi	3630.310160	837.091932
207	Bangalore to Kolkata	3595.000000	804.067604
851	Guwahati to Delhi	3573.291117	748.599138
834	Gurgaon to MAA	3355.808867	876.628008
452	Chandigarh to Bhiwandi	3297.000000	660.579031
336	Bhiwandi to Kolkata	3167.635682	831.090075
271	Bengaluru to Gurgaon	3140.000000	870.118858
198	Bangalore to Gurgaon	3125.492461	869.072245

trip\_city\_time\_distance.sort\_values('actual\_distance\_to\_destination',ascending = False).head(10)

	source_to_destination_city	start_scan_to_end_scan	actual_distance_to_destination
449	Chandigarh to Bangalore	3802.000000	1050.751668
834	Gurgaon to MAA	3355.808867	876.628008
271	Bengaluru to Gurgaon	3140.000000	870.118858
198	Bangalore to Gurgaon	3125.492461	869.072245
810	Gurgaon to Bangalore	3097.507637	859.827666
1265	Kolkata to Bhiwandi	3630.310160	837.091932
336	Bhiwandi to Kolkata	3167.635682	831.090075
207	Bangalore to Kolkata	3595.000000	804.067604
204	Bangalore to Jaipur	3076.875256	781.405522
582	Delhi to Guwahati	3702.000000	759.661163

From the above table we can see that, the top 10 most long distance trip from the source to destination city

```
df.drop(["od_end_time","od_start_time"], axis=1, inplace=True)
```

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```
#Defining the alpha value to 0.05
alpha = 0.05
#Function to plot the graph
def analysis_plot(new_df,col_a,col_b):
 plt.figure(figsize=(25,5))
 plt.subplot(131)
 plt.title(col_a+" vs "+col_b)
 sns.scatterplot(data=new_df, x=new_df[col_a], y=new_df[col_b])
 plt.subplot(132)
 plt.title(col_a)
 sns.histplot(new_df[col_a],kde=True)
 plt.subplot(133)
 plt.title(col_b)
 sns.histplot(new_df[col_b],kde=True)
#Function to perform the hypothesis testing
def feature_analysis(new_df,col_a,col_b):
 H0 = col_a + " and "+col_b + " are Equal"
 Ha = col_a+" and "+col_b+" are Not Equal"
 print("Given H0 --> "+ H0)
 print("Given Ha --> "+ Ha)
 stat, pvalue = ttest_ind(new_df[col_a], new_df[col_b])
 print("Statistics --> "+str(stat))
 print("Pvalue --> "+str(pvalue))
  if(pvalue<alpha):
   print("H0 is Rejected, Therefore "+Ha)
   print("H0 is Accepted, Therefore "+H0)
#Function to plot the box plot
def box_plot(new_df,col_a,col_b,col_c):
 plt.figure(figsize=(25,5))
 plt.subplot(131)
 sns.boxplot(y=col_a,data=new_df)
 print("\n"+"*"*20+" "+col_a+" "+"*"*20)
 outlier_detection(new_df,col_a)
 plt.subplot(132)
 sns.boxplot(y=col_b,data=new_df)
 print("\n"+"*"*20+" "+col_b+" "+"*"*20)
 outlier_detection(new_df,col_b)
 plt.subplot(133)
 sns.boxplot(y=col_c,data=new_df)
 print("\n"+"*"*20+" "+col_c+" "+"*"*20)
 outlier_detection(new_df,col_c)
#Function to detect the outliers and count number of outliers
def outlier_detection(new_df,col_name):
 p_25 = np.percentile(new_df[col_name], 25)
 p_50 = np.percentile(new_df[col_name], 50)
 p_75 = np.percentile(new_df[col_name], 75)
 print("First Quartile: ", p_25) # p = 25%
 print("Second Quartile: ", p_50)# p = 50%
 print("Third Quartile: ", p_75) # p = 75%
 print("IQR: ", p_75 - p_25)
 left_whis = max(p_25 - 1.5 * (p_75 - p_25), 0)
 right_whis = p_75 + 1.5 * (p_75 - p_25)
 print("Left: ", left_whis)
 print("Right: ", right_whis)
 num_outliers = len(new_df[new_df[col_name] > right_whis])
 print(col_name+" outliers: ", num_outliers)
 print(col_name+" std: ", new_df[col_name].std())
trip_time_distance = df.groupby(["trip_uuid"]).agg({'actual_time':'max','od_total_time':'max','start_scan_to_end_scan':'max','segment_actual_time':'sum',
```

'osrm\_distance':'max','segment\_osrm\_distance':'sum','segment\_osrm\_time':'sum','actual\_distance\_to\_destination':'max'}).reset\_index()

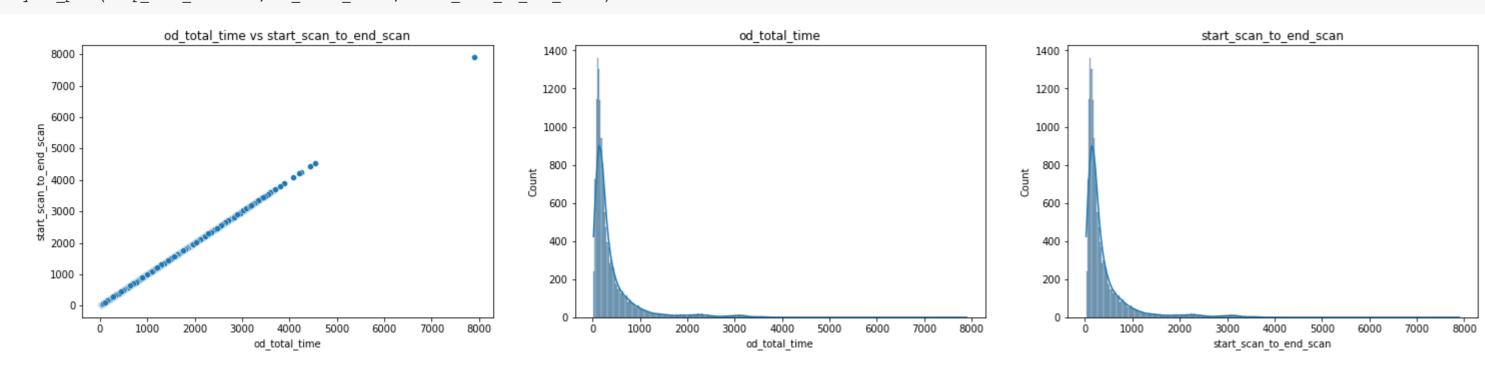
Grouping by the trip\_uuid and calculating the Aggregated actual\_time, osrm\_time, od\_total\_time, start\_scan\_to\_end\_scan, segment\_actual\_time, osrm\_distance, segment\_osrm\_distance, segment\_osrm\_time, actual\_distance\_to\_destination

trip\_time\_distance

	trip_uuid	actual_time	osrm_time	od_total_time	start_scan_to_end_scan	segment_actual_time	osrm_distance	segment_osrm_distance	segment_osrm_time	actual_distance_to_destination	7
0	trip-153671041653548748	830.0	394.0	1260.0	1260.0	1548.0	544.8027	1320.4733	1008.0	440.973689	
1	trip-153671042288605164	96.0	42.0	122.0	122.0	141.0	56.9116	84.1894	65.0	48.542890	
2	trip-153671043369099517	2736.0	1529.0	3099.0	3099.0	3308.0	2090.8743	2545.2678	1941.0	1689.964663	
3	trip-153671046011330457	59.0	15.0	100.0	100.0	59.0	19.6800	19.8766	16.0	17.175274	
4	trip-153671052974046625	147.0	46.0	485.0	485.0	340.0	63.6461	146.7919	115.0	59.530350	
14782	trip-153861095625827784	49.0	34.0	152.0	152.0	82.0	44.5639	64.8551	62.0	31.261599	
14783	trip-153861104386292051	21.0	12.0	60.0	60.0	21.0	16.0882	16.0883	11.0	15.513784	
14784	trip-153861106442901555	190.0	29.0	248.0	248.0	281.0	32.2277	104.8866	88.0	19.349008	
14785	trip-153861115439069069	90.0	50.0	105.0	105.0	258.0	52.8070	223.5324	221.0	37.387664	
14786	trip-153861118270144424	233.0	42.0	287.0	287.0	274.0	52.5303	80.5787	67.0	40.546740	

14787 rows × 10 columns

#### analysis\_plot(trip\_time\_distance,"od\_total\_time","start\_scan\_to\_end\_scan")



feature\_analysis(trip\_time\_distance, "od\_total\_time", "start\_scan\_to\_end\_scan")

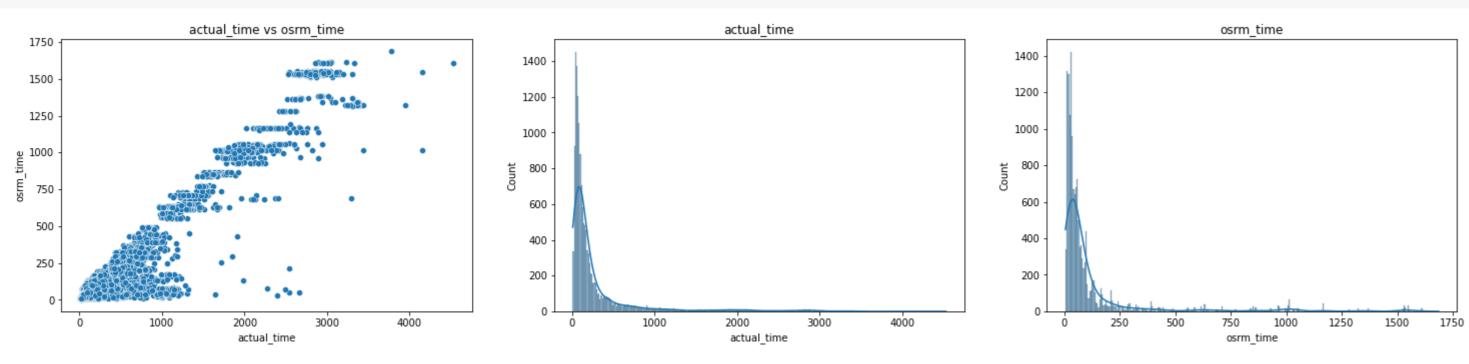
Given H0 --> od\_total\_time and start\_scan\_to\_end\_scan are Equal

Given Ha --> od\_total\_time and start\_scan\_to\_end\_scan are Not Equal

Statistics --> 0.0
Pvalue --> 1.0

HO is Accepted, Therefore od\_total\_time and start\_scan\_to\_end\_scan are Equal

#### analysis\_plot(trip\_time\_distance,"actual\_time","osrm\_time")



feature\_analysis(trip\_time\_distance,"actual\_time","osrm\_time")

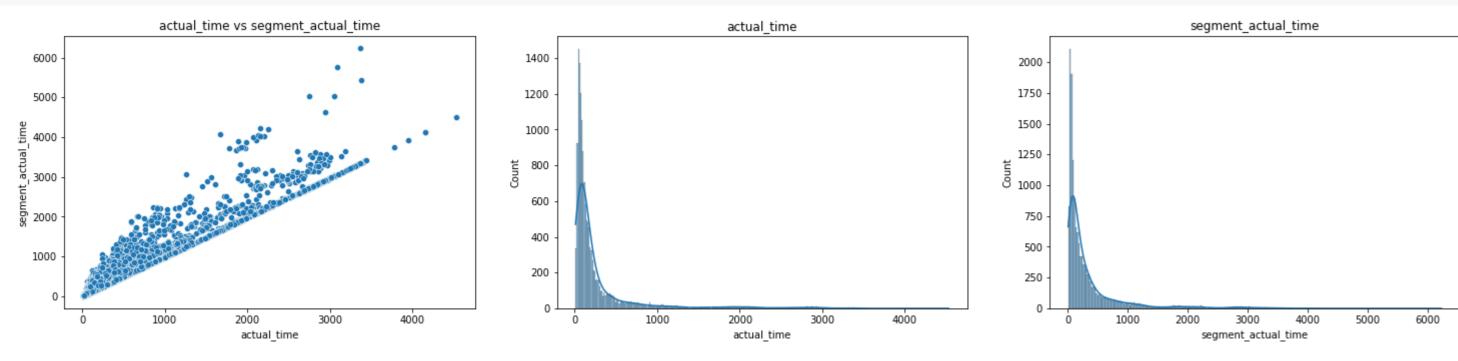
Given H0 --> actual\_time and osrm\_time are Equal
Given Ha --> actual\_time and osrm\_time are Not Equal

Statistics --> 35.08988288617061

Pvalue --> 2.5609809806142685e-264

HO is Rejected, Therefore actual\_time and osrm\_time are Not Equal

### analysis\_plot(trip\_time\_distance,"actual\_time","segment\_actual\_time")



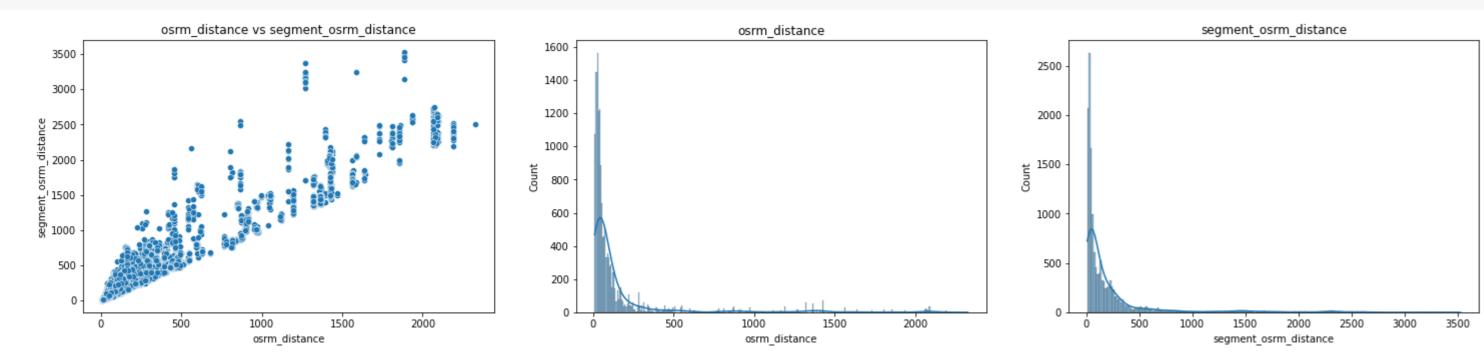
feature\_analysis(trip\_time\_distance, "segment\_actual\_time", "actual\_time")

Given H0 --> segment\_actual\_time and actual\_time are Equal

Statistics --> 12.366405130681308

Pvalue --> 4.849541124158181e-35
H0 is Rejected, Therefore segment\_actual\_time and actual\_time are Not Equal

#### analysis\_plot(trip\_time\_distance,"osrm\_distance","segment\_osrm\_distance")

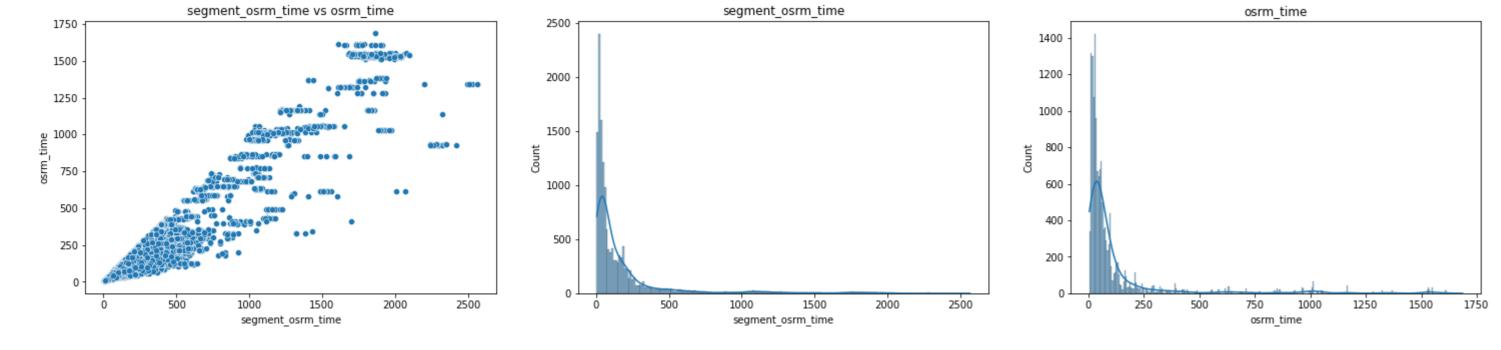


### feature\_analysis(trip\_time\_distance, "segment\_osrm\_distance", "osrm\_distance")

Given H0 --> segment\_osrm\_distance and osrm\_distance are Equal Given Ha --> segment\_osrm\_distance and osrm\_distance are Not Equal Statistics --> 15.373808827249137 Pvalue --> 3.9396914792427207e-53

HO is Rejected, Therefore segment\_osrm\_distance and osrm\_distance are Not Equal

#### analysis\_plot(trip\_time\_distance, "segment\_osrm\_time", "osrm\_time")

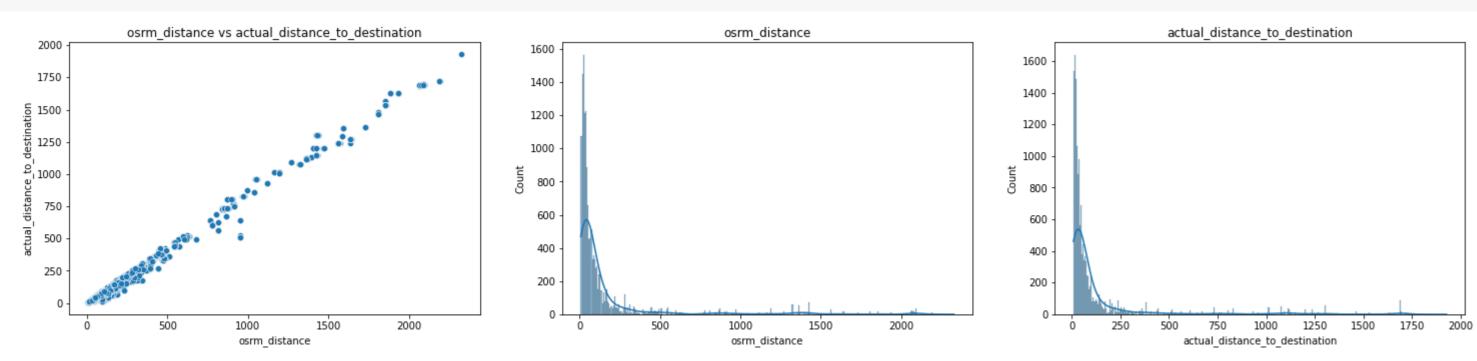


#### feature\_analysis(trip\_time\_distance, "segment\_osrm\_time", "osrm\_time")

Given H0 --> segment\_osrm\_time and osrm\_time are Equal Given Ha --> segment\_osrm\_time and osrm\_time are Not Equal Statistics --> 18.108706618672148

Pvalue --> 6.745046176314656e-73
H0 is Rejected, Therefore segment\_osrm\_time and osrm\_time are Not Equal

# analysis\_plot(trip\_time\_distance,"osrm\_distance","actual\_distance\_to\_destination")



# feature\_analysis(trip\_time\_distance, "osrm\_distance", "actual\_distance\_to\_destination")

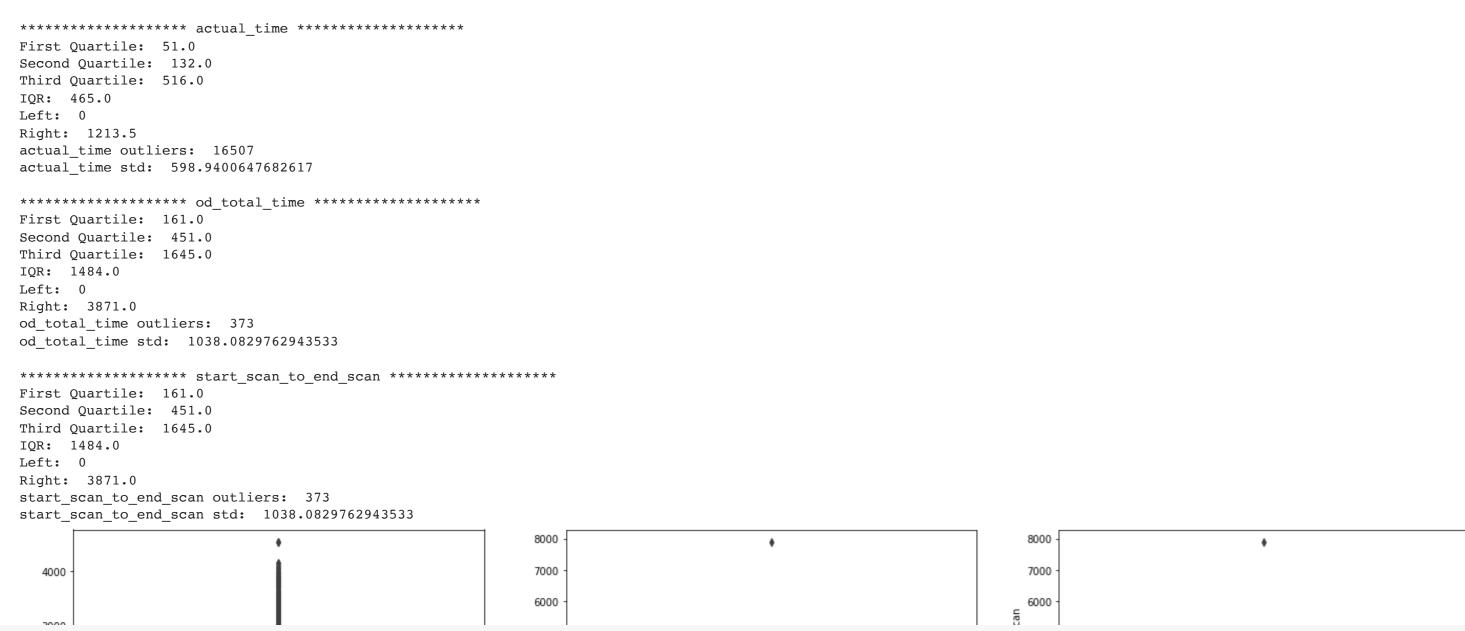
Given H0 --> osrm\_distance and actual\_distance\_to\_destination are Equal Given Ha --> osrm\_distance and actual\_distance\_to\_destination are Not Equal Statistics --> 8.84614890355335

Pvalue --> 9.552148425013404e-19

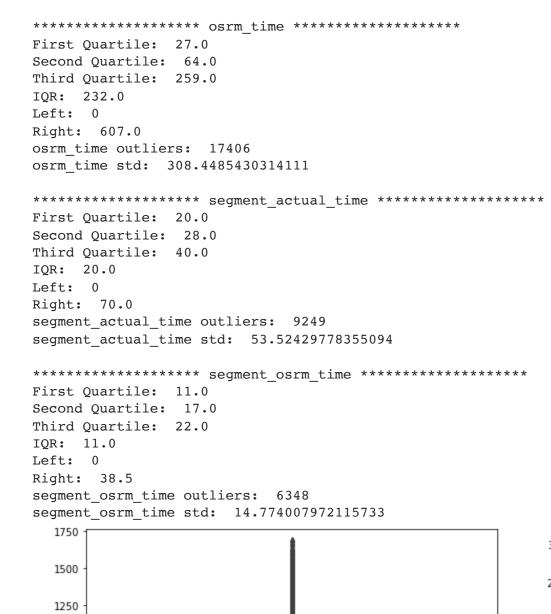
HO is Rejected, Therefore osrm\_distance and actual\_distance\_to\_destination are Not Equal

### trip\_time\_distance.columns

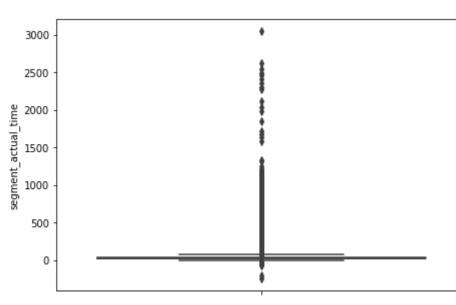
box\_plot(df,"actual\_time","od\_total\_time","start\_scan\_to\_end\_scan")

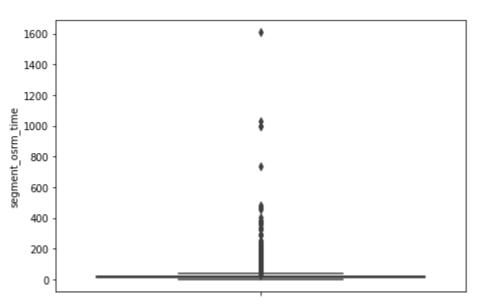


box\_plot(df,"osrm\_time","segment\_actual\_time","segment\_osrm\_time")



<u>u</u> 1000 ⋅





box\_plot(df,"osrm\_distance","segment\_osrm\_distance","actual\_distance\_to\_destination")

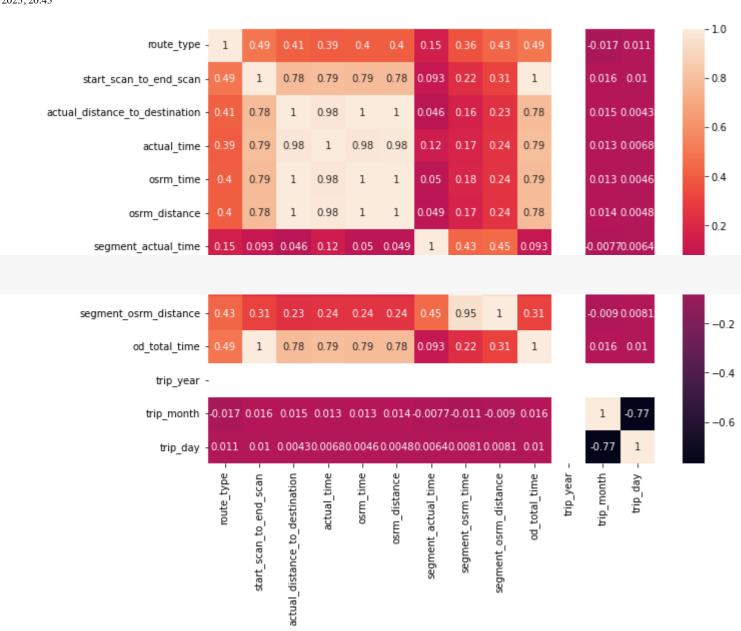
```
***************** osrm distance *************
    First Quartile: 29.89625
    Second Quartile: 78.6244
    Third Quartile: 346.3054
    IQR: 316.40915
    Left: 0
    Right: 820.9191250000001
    osrm_distance outliers: 17547
    osrm_distance std: 421.7178256506773
    ************ segment osrm distance ***********
    First Quartile: 12.053975000000001
    Second Quartile: 23.5083
trip_time_distance.drop(["trip_uuid"], axis=1, inplace=True)
    Left: 0
trip_time_distance_normal = MinMaxScaler().fit_transform(trip_time_distance)
trip_time_distance_normal
    array([[0.18151669, 0.23095238, 0.15707937, ..., 0.37313365, 0.39171228,
           [0.01923502, 0.02142857, 0.01257143, ..., 0.02137295, 0.02306489,
           0.02061066],
           [0.60291842, 0.90654762, 0.39060317, ..., 0.72162526, 0.75645035,
           0.87621067],
           [0.04001769, 0.01369048, 0.02857143, ..., 0.02726194, 0.03205629,
           0.00539319],
           [0.01790847, 0.02619048, 0.0104127, ..., 0.06102031, 0.08405004,
           0.01479594],
           [0.04952465, 0.02142857, 0.03352381, ..., 0.02034559, 0.02384676,
           0.01644263]])
                                                                                                                [ VVC1 B: |
  • Normalizing the numerical values using fit_transform and MinMaxScaler
  • The below Graph shows the Normalized Scatter Graph for the numerical values
                                                                                                                | ₩ 750 -
plt.figure(figsize=(25,5))
plt.subplot(131)
sns.scatterplot(x=trip_time_distance_normal[:,2], y=trip_time_distance_normal[:,3])
plt.subplot(132)
sns.scatterplot(x=trip_time_distance_normal[:,0], y=trip_time_distance_normal[:,1])
plt.subplot(133)
sns.scatterplot(x=trip_time_distance_normal[:,0], y=trip_time_distance_normal[:,4])
    <Axes: >
                        0.4
                                                                                                                                                0.6
                                                                                                                                                         0.8
                0.2
                                 0.6
                                          0.8
                                                                        0.2
                                                                                 0.4
                                                                                                 0.8
                                                                                                                               0.2 0.4
plt.figure(figsize=(25,5))
plt.subplot(131)
sns.scatterplot(x=trip_time_distance_normal[:,5], y=trip_time_distance_normal[:,6])
plt.subplot(132)
sns.scatterplot(x=trip_time_distance_normal[:,1], y=trip_time_distance_normal[:,7])
plt.subplot(133)
sns.scatterplot(x=trip_time_distance_normal[:,5], y=trip_time_distance_normal[:,8])
    <Axes: >
```

0.8

plt.figure(figsize=(10, 8))
sns.heatmap(df.corr(), annot=True);

https://colab.research.google.com/drive/1wXxN4WW\_813D4xSwl6ehIZnDCnLReGQR#scrollTo=QHhSBewAvHdJ&printMode=true

Delhivery\_Case\_Study.ipynb - Colaboratory



✓ 2s completed at 8:43 PM • X