Problem Statement:

- Delhivery is the largest and fastest-growing fully integrated player in India by revenue in Fiscal 2021.
    1. The company wants to understand and process the data coming out of data engineering pipelines:
    2. Clean, sanitize and manipulate data to get useful features out of raw fields 3.Make sense out of the raw data and help the data science team to build forecasting models on it

In [118…

```
# downloading data to working directory
!wget https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/551/original/delhivery_data.csv?1642751181
```

```
--2023-04-23 10:22:46--  https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/551/original/delhivery_data.csv?1642
751181
Resolving d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)... 108.157.172.176, 108.157.172.173, 108.157.172.10, ...
Connecting to d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)|108.157.172.176|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 55617130 (53M) [text/plain]
Saving to: ‘delhivery_data.csv?1642751181.1’

delhivery_data.csv? 100%[===================>]  53.04M  40.3MB/s    in 1.3s

2023-04-23 10:22:47 (40.3 MB/s) - ‘delhivery_data.csv?1642751181.1’ saved [55617130/55617130]
```

In [119…

```
#importing libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.special import comb
from scipy.stats import binom
import seaborn as sns
from statsmodels.distributions.empirical_distribution import ECDF # empirical CDF\n",
from scipy.stats import norm,poisson,expon ## norm --> 'Normal' or \"Gaussian' "
from scipy.stats import ttest_ind,ttest_ind_from_stats,ttest_1samp,levene,shapiro,t,f_oneway,f,chi2_contingency,chi2,ttest_rel,kı
from datetime import datetime, timedelta
import statsmodels.api as sm
import warnings
warnings.filterwarnings('ignore')
```

In [120…
```
# assigning data to object
df=pd.read_csv("/content/delhivery_data.csv?1642751181")
```

In [121…
```
#Exploring first five rows of data set
df.head()
```

Out[121]:

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_center	desti
0	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_
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_
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_
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_
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_

5 rows × 24 columns

In [122…
```
#Exploring last five rows of data set
df.tail()
```

Out[122]:

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_center	desti
144862	training	2018-09-20 16:24:28.436231	thanos::sroute:f0569d2f-4e20-4c31-8542-67b86d5...	Carting	trip-153746066843555182	IND131028AAB	Sonipat_Kundli_H (Haryana)	IND000000ACB	Gurgaoı
144863	training	2018-09-20 16:24:28.436231	thanos::sroute:f0569d2f-4e20-4c31-8542-67b86d5...	Carting	trip-153746066843555182	IND131028AAB	Sonipat_Kundli_H (Haryana)	IND000000ACB	Gurgaoı
144864	training	2018-09-20 16:24:28.436231	thanos::sroute:f0569d2f-4e20-4c31-8542-67b86d5...	Carting	trip-153746066843555182	IND131028AAB	Sonipat_Kundli_H (Haryana)	IND000000ACB	Gurgaoı
144865	training	2018-09-20 16:24:28.436231	thanos::sroute:f0569d2f-4e20-4c31-8542-67b86d5...	Carting	trip-153746066843555182	IND131028AAB	Sonipat_Kundli_H (Haryana)	IND000000ACB	Gurgaoı
144866	training	2018-09-20 16:24:28.436231	thanos::sroute:f0569d2f-4e20-4c31-8542-67b86d5...	Carting	trip-153746066843555182	IND131028AAB	Sonipat_Kundli_H (Haryana)	IND000000ACB	Gurgaoı

5 rows × 24 columns

EDA

In [123…

```
# Checking dataset shape
df.shape
```

Out[123]:

```
(144867, 24)
```

In [124…

```
# Length of dataset
len(df)
```

Out[124]:

```
144867
```

In [125…

```
# Checking dataset datatypes
df.dtypes
```

Out[125]:
```
data                               object
trip_creation_time                 object
route_schedule_uuid                object
route_type                         object
trip_uuid                          object
source_center                      object
source_name                        object
destination_center                 object
destination_name                   object
od_start_time                      object
od_end_time                        object
start_scan_to_end_scan            float64
is_cutoff                            bool
cutoff_factor                       int64
cutoff_timestamp                   object
actual_distance_to_destination    float64
actual_time                       float64
osrm_time                         float64
osrm_distance                     float64
factor                            float64
segment_actual_time               float64
segment_osrm_time                 float64
segment_osrm_distance             float64
segment_factor                    float64
dtype: object
```

In [126…
```
#converting datetime column to datetime format
df['trip_creation_time'] = pd.to_datetime(df['trip_creation_time'])
df['od_start_time'] = pd.to_datetime(df['od_start_time'])
df['od_end_time'] = pd.to_datetime(df['od_end_time'])
df['cutoff_timestamp'] = pd.to_datetime(df['cutoff_timestamp'])
```

In [127…
```
# Checking dataset datatypes
df.dtypes
```

Out[127]:
```
data                                      object
trip_creation_time                datetime64[ns]
route_schedule_uuid                       object
route_type                                object
trip_uuid                                 object
source_center                             object
source_name                               object
destination_center                        object
destination_name                          object
od_start_time                     datetime64[ns]
od_end_time                       datetime64[ns]
start_scan_to_end_scan                   float64
is_cutoff                                   bool
cutoff_factor                              int64
cutoff_timestamp                  datetime64[ns]
actual_distance_to_destination           float64
actual_time                              float64
osrm_time                                float64
osrm_distance                            float64
factor                                   float64
segment_actual_time                      float64
segment_osrm_time                        float64
segment_osrm_distance                    float64
segment_factor                           float64
dtype: object
```

In [128…
```
# information about the data
# column names, datatypes, non-null values, memory usage
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144867 entries, 0 to 144866
Data columns (total 24 columns):
 #   Column                          Non-Null Count   Dtype
---  ------                          --------------   -----
 0   data                            144867 non-null  object
 1   trip_creation_time              144867 non-null  datetime64[ns]
 2   route_schedule_uuid             144867 non-null  object
 3   route_type                      144867 non-null  object
 4   trip_uuid                       144867 non-null  object
 5   source_center                   144867 non-null  object
 6   source_name                     144574 non-null  object
 7   destination_center              144867 non-null  object
 8   destination_name                144606 non-null  object
 9   od_start_time                   144867 non-null  datetime64[ns]
 10  od_end_time                     144867 non-null  datetime64[ns]
 11  start_scan_to_end_scan          144867 non-null  float64
 12  is_cutoff                       144867 non-null  bool
 13  cutoff_factor                   144867 non-null  int64
 14  cutoff_timestamp                144867 non-null  datetime64[ns]
 15  actual_distance_to_destination  144867 non-null  float64
 16  actual_time                     144867 non-null  float64
 17  osrm_time                       144867 non-null  float64
 18  osrm_distance                   144867 non-null  float64
 19  factor                          144867 non-null  float64
 20  segment_actual_time             144867 non-null  float64
 21  segment_osrm_time               144867 non-null  float64
 22  segment_osrm_distance           144867 non-null  float64
 23  segment_factor                  144867 non-null  float64
dtypes: bool(1), datetime64[ns](4), float64(10), int64(1), object(8)
memory usage: 25.6+ MB
```

In [129…

```
df.isna().sum()
```

Out[129]:

```
data                              0
trip_creation_time                0
route_schedule_uuid               0
route_type                        0
trip_uuid                         0
source_center                     0
source_name                     293
destination_center                0
destination_name                261
od_start_time                     0
od_end_time                       0
start_scan_to_end_scan            0
is_cutoff                         0
cutoff_factor                     0
cutoff_timestamp                  0
actual_distance_to_destination    0
actual_time                       0
osrm_time                         0
osrm_distance                     0
factor                            0
segment_actual_time               0
segment_osrm_time                 0
segment_osrm_distance             0
segment_factor                    0
dtype: int64
```

In [130…

```
df.nunique()
```

Out[130]:
```
data                               2
trip_creation_time             14817
route_schedule_uuid             1504
route_type                         2
trip_uuid                      14817
source_center                   1508
source_name                     1498
destination_center              1481
destination_name                1468
od_start_time                  26369
od_end_time                    26369
start_scan_to_end_scan          1915
is_cutoff                          2
cutoff_factor                    501
cutoff_timestamp               93180
actual_distance_to_destination    144515
actual_time                     3182
osrm_time                       1531
osrm_distance                 138046
factor                         45641
segment_actual_time              747
segment_osrm_time                214
segment_osrm_distance         113799
segment_factor                  5675
dtype: int64
```

Observations:

- Delhivery Business case study having 144867 rows and 24 columns.
- Data set are containing four 'segment_factor','factor','cutoff_timestamp','cutoff_factor','is_cutoff' unknow fields.
- Out of total 19 known fields trip_creation_time, od_start_time,od_end_time are datetimestamp columns.
- Columns name data and route type are belongs to categorical type data.
- In this data set null values has been observed in columns source name and destination name.

In [131…
```
# droping unknown data field
df = df.drop( columns=['segment_factor','factor','cutoff_timestamp','cutoff_factor','is_cutoff'])
```

In [132…
```
# checking again shape of dataset
df.shape
```

Out[132]:
```
(144867, 19)
```

Comments:

- Unknown fields has been dropped from data set, Now data set having only 19 columns and 144867 rows

Data Transformation:

In [133…
```
# Performing Aggregation on data_set:
df_lv_1=df.groupby(['trip_uuid','source_center','destination_center']).agg({'data':'first',
                                                                            'trip_creation_time':'first',
                                                                            'route_type':'first',
                                                                            'source_name':'first',
                                                                              'destination_name':'last',
                                                                              'od_start_time':'first',
                                                                              'od_end_time':'first',
                                                                              'start_scan_to_end_scan':'first',
                                                                              'actual_distance_to_destination':'last',
                                                                              'actual_time':'last',
                                                                              'osrm_time':'last',
                                                                              'osrm_distance':'last',
                                                                              'segment_actual_time':'sum',
                                                                              'segment_osrm_time':'sum',
                                                                              'segment_osrm_distance':'sum'}).reset_index()
df_lv_1.sort_values(by = ['trip_uuid','od_start_time'],inplace = True, ignore_index = True)
df_lv_1
```

Out[133]:

	trip_uuid	source_center	destination_center	data	trip_creation_time	route_type	source_name	destination_name
0	trip-153671041653548748	IND462022AAA	IND209304AAA	training	2018-09-12 00:00:16.535741	FTL	Bhopal_Trnsport_H (Madhya Pradesh)	Kanpur_Central_H_6 (Uttar Pradesh)
1	trip-153671041653548748	IND209304AAA	IND000000ACB	training	2018-09-12 00:00:16.535741	FTL	Kanpur_Central_H_6 (Uttar Pradesh)	Gurgaon_Bilaspur_HB (Haryana)
2	trip-153671042288605164	IND572101AAA	IND561203AAB	training	2018-09-12 00:00:22.886430	Carting	Tumkur_Veersagr_I (Karnataka)	Doddablpur_ChikaDPP_D (Karnataka)
3	trip-153671042288605164	IND561203AAB	IND562101AAA	training	2018-09-12 00:00:22.886430	Carting	Doddablpur_ChikaDPP_D (Karnataka)	Chikblapur_ShntiSgr_D (Karnataka)
4	trip-153671043369099517	IND562132AAA	IND000000ACB	training	2018-09-12 00:00:33.691250	FTL	Bangalore_Nelmngla_H (Karnataka)	Gurgaon_Bilaspur_HB (Haryana)
...	...	...	...	...	...	...	...	...
26363	trip-153861115439069069	IND628204AAA	IND627657AAA	test	2018-10-03 23:59:14.390954	Carting	Tirchchndr_Shnmgprm_D (Tamil Nadu)	Thisayanvilai_UdnkdiRD_D (Tamil Nadu)
26364	trip-153861115439069069	IND627657AAA	IND628613AAA	test	2018-10-03 23:59:14.390954	Carting	Thisayanvilai_UdnkdiRD_D (Tamil Nadu)	Peikulam_SriVnktpm_D (Tamil Nadu)
26365	trip-153861115439069069	IND628613AAA	IND627005AAA	test	2018-10-03 23:59:14.390954	Carting	Peikulam_SriVnktpm_D (Tamil Nadu)	Tirunelveli_VdkkuSrt_I (Tamil Nadu)
26366	trip-153861118270144424	IND583201AAA	IND583119AAA	test	2018-10-03 23:59:42.701692	FTL	Hospet (Karnataka)	Sandur_WrdN1DPP_D (Karnataka)
26367	trip-153861118270144424	IND583119AAA	IND583101AAA	test	2018-10-03 23:59:42.701692	FTL	Sandur_WrdN1DPP_D (Karnataka)	Bellary_Dc (Karnataka)

26368 rows × 18 columns

In [134…

```
df_final=df_lv_1.groupby(['trip_uuid']).agg({'data':'first','source_center':'first','destination_center':'last',
                                              'trip_creation_time':'first',
                                              'route_type':'first',
                                              'source_name':'first',
                                                'destination_name':'last',
                                                'od_start_time':'first',
                                                'od_end_time':'last',
```

```
                                              'start_scan_to_end_scan':'sum',
                                              'actual_distance_to_destination':'sum',
                                              'actual_time':'sum',
                                              'osrm_time':'sum',
                                              'osrm_distance':'sum',
                                              'segment_actual_time':'sum',
                                              'segment_osrm_time':'sum',
                                              'segment_osrm_distance':'sum'}).reset_index()

df_final
```

Out[134]:

	trip_uuid	data	source_center	destination_center	trip_creation_time	route_type	source_name	destination_name
0	trip-153671041653548748	training	IND462022AAA	IND000000ACB	2018-09-12 00:00:16.535741	FTL	Bhopal_Trnsport_H (Madhya Pradesh)	Gurgaon_Bilaspur_HB (Haryana)
1	trip-153671042288605164	training	IND572101AAA	IND562101AAA	2018-09-12 00:00:22.886430	Carting	Tumkur_Veersagr_I (Karnataka)	Chikblapur_ShntiSgr_D (Karnataka)
2	trip-153671043369099517	training	IND562132AAA	IND160002AAC	2018-09-12 00:00:33.691250	FTL	Bangalore_Nelmngla_H (Karnataka)	Chandigarh_Mehmdpur_H (Punjab)
3	trip-153671046011330457	training	IND400072AAB	IND401104AAA	2018-09-12 00:01:00.113710	Carting	Mumbai Hub (Maharashtra)	Mumbai_MiraRd_IP (Maharashtra)
4	trip-153671052974046625	training	IND583101AAA	IND583101AAA	2018-09-12 00:02:09.740725	FTL	Bellary_Dc (Karnataka)	Bellary_Dc (Karnataka)
...	...	...	...	...	...	...	...	...
14812	trip-153861095625827784	test	IND160002AAC	IND160002AAC	2018-10-03 23:55:56.258533	Carting	Chandigarh_Mehmdpur_H (Punjab)	Chandigarh_Mehmdpur_H (Punjab)
14813	trip-153861104386292051	test	IND121004AAB	IND121004AAA	2018-10-03 23:57:23.863155	Carting	FBD_Balabhgarh_DPC (Haryana)	Faridabad_Blbgarh_DC (Haryana)
14814	trip-153861106442901555	test	IND209304AAA	IND209304AAA	2018-10-03 23:57:44.429324	Carting	Kanpur_Central_H_6 (Uttar Pradesh)	Kanpur_Central_H_6 (Uttar Pradesh)
14815	trip-153861115439069069	test	IND627005AAA	IND627005AAA	2018-10-03 23:59:14.390954	Carting	Tirunelveli_VdkkuSrt_I (Tamil Nadu)	Tirunelveli_VdkkuSrt_I (Tamil Nadu)
14816	trip-153861118270144424	test	IND583201AAA	IND583101AAA	2018-10-03 23:59:42.701692	FTL	Hospet (Karnataka)	Bellary_Dc (Karnataka)

14817 rows × 18 columns

In [135…

```
df_final.isna().sum()
```

Out[135]:
```
trip_uuid                          0
data                               0
source_center                      0
destination_center                 0
trip_creation_time                 0
route_type                         0
source_name                       10
destination_name                   8
od_start_time                      0
od_end_time                        0
start_scan_to_end_scan             0
actual_distance_to_destination     0
actual_time                        0
osrm_time                          0
osrm_distance                      0
segment_actual_time                0
segment_osrm_time                  0
segment_osrm_distance              0
dtype: int64
```

In [136…
```
df_final.nunique()
```

Out[136]:
```
trip_uuid                         14817
data                                  2
source_center                       868
destination_center                  956
trip_creation_time                14817
route_type                            2
source_name                         867
destination_name                    950
od_start_time                     14817
od_end_time                       14817
start_scan_to_end_scan             2208
actual_distance_to_destination    14801
actual_time                        1853
osrm_time                           817
osrm_distance                     14734
segment_actual_time                1890
segment_osrm_time                  1242
segment_osrm_distance             14754
dtype: int64
```

Observations:

- After performing aggregation on dataset,14817 unique trip id has been found.
- In this data set, total 868 unique source centre has been detected.
- Total Unique destination centre are 956.

In [137…

```
# Creating feature name of 'diff' which is difference between od_end_time and od_start_time
df_final['diff'] = (df_final['od_end_time'] - df_final['od_start_time'])/np.timedelta64(1,'m')
```

In [138…

```
df_final.shape
```

Out[138]:

```
(14817, 19)
```

In [139…

```
df_final.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14817 entries, 0 to 14816
Data columns (total 19 columns):
 #   Column                          Non-Null Count  Dtype         
---  ------                          --------------  -----         
 0   trip_uuid                       14817 non-null  object        
 1   data                            14817 non-null  object        
 2   source_center                   14817 non-null  object        
 3   destination_center              14817 non-null  object        
 4   trip_creation_time              14817 non-null  datetime64[ns]
 5   route_type                      14817 non-null  object        
 6   source_name                     14807 non-null  object        
 7   destination_name                14809 non-null  object        
 8   od_start_time                   14817 non-null  datetime64[ns]
 9   od_end_time                     14817 non-null  datetime64[ns]
 10  start_scan_to_end_scan          14817 non-null  float64       
 11  actual_distance_to_destination  14817 non-null  float64       
 12  actual_time                     14817 non-null  float64       
 13  osrm_time                       14817 non-null  float64       
 14  osrm_distance                   14817 non-null  float64       
 15  segment_actual_time             14817 non-null  float64       
 16  segment_osrm_time               14817 non-null  float64       
 17  segment_osrm_distance           14817 non-null  float64       
 18  diff                            14817 non-null  float64       
dtypes: datetime64[ns](3), float64(9), object(7)
memory usage: 2.1+ MB
```

In [140…

```
df_final.isna().sum()
```

Out[140]:
```
trip_uuid                          0
data                               0
source_center                      0
destination_center                 0
trip_creation_time                 0
route_type                         0
source_name                       10
destination_name                   8
od_start_time                      0
od_end_time                        0
start_scan_to_end_scan             0
actual_distance_to_destination     0
actual_time                        0
osrm_time                          0
osrm_distance                      0
segment_actual_time                0
segment_osrm_time                  0
segment_osrm_distance              0
diff                               0
dtype: int64
```

In [141…
```
#  just checking Rows, which are having null values.
df_final[df_final['source_name'].isna()]
```

Out[141]:

	trip_uuid	data	source_center	destination_center	trip_creation_time	route_type	source_name	destination_name	od_start_time
8762	trip-153776806236494354	training	IND282002AAD	IND205001AAB	2018-09-24 05:47:42.365186	FTL	None	Mainpuri_Agraroad_I (Uttar Pradesh)	2018-09-24 13:50:39.828453
9835	trip-153791004076950775	training	IND577116AAA	IND577101AAA	2018-09-25 21:14:00.769759	FTL	None	Chikmagalur_DC (Karnataka)	2018-09-26 02:05:06.856776
10562	trip-153800051661903546	training	IND331022A1B	IND331001A1C	2018-09-26 22:21:56.619259	FTL	None	None	2018-09-27 03:19:14.797080
11468	trip-153811367563100850	test	IND282002AAD	IND205001AAB	2018-09-28 05:47:55.631256	FTL	None	Mainpuri_Agraroad_I (Uttar Pradesh)	2018-09-28 14:57:13.276811
12097	trip-153820032399976293	test	IND282002AAD	IND205001AAB	2018-09-29 05:52:04.000013	FTL	None	Mainpuri_Agraroad_I (Uttar Pradesh)	2018-09-29 14:25:12.074915
13104	trip-153835867702133730	test	IND282002AAD	IND281004AAA	2018-10-01 01:51:17.021624	FTL	None	Mathura_DC (Uttar Pradesh)	2018-10-01 01:51:17.021624
13168	trip-153836697913613926	test	IND282002AAD	IND205001AAB	2018-10-01 04:09:39.136394	FTL	None	Mainpuri_Agraroad_I (Uttar Pradesh)	2018-10-01 14:14:21.656658
13644	trip-153843937115921268	test	IND282002AAD	IND281004AAA	2018-10-02 00:16:11.159597	FTL	None	Mathura_DC (Uttar Pradesh)	2018-10-02 00:16:11.159597
13793	trip-153846056503320607	test	IND282002AAD	IND205001AAB	2018-10-02 06:09:25.033504	FTL	None	Mainpuri_Agraroad_I (Uttar Pradesh)	2018-10-02 15:01:17.497129
14199	trip-153852612674280168	test	IND282002AAD	IND281004AAA	2018-10-03 00:22:06.743062	FTL	None	Mathura_DC (Uttar Pradesh)	2018-10-03 00:22:06.743062

In [142…

```
# just checking Rows, which are having null values.
df_final[df_final['destination_name'].isna()]
```

Out[142]:

	trip_uuid	data	source_center	destination_center	trip_creation_time	route_type	source_name	destination_name	od_sta
5289	trip-153733592611290696	training	IND000000ACB	IND122015AAC	2018-09-19 05:45:26.113345	Carting	Gurgaon_Bilaspur_HB (Haryana)	None	201 05:45:26.
5778	trip-153739792417979729	training	IND504215AAA	IND505326AAB	2018-09-19 22:58:44.180028	FTL	Luxettipet_ShivaDPP_D (Telangana)	None	201 06:17:36.
5961	trip-153741501937042684	training	IND000000ACB	IND122015AAC	2018-09-20 03:43:39.370661	Carting	Gurgaon_Bilaspur_HB (Haryana)	None	201 03:43:39.
8796	trip-153777348608709328	training	IND202001AAB	IND282002AAD	2018-09-24 07:18:06.087341	FTL	Aligarh_KhirByps_I (Uttar Pradesh)	None	201 15:02:13.
10562	trip-153800051661903546	training	IND331022A1B	IND331001A1C	2018-09-26 22:21:56.619259	FTL	None	None	201 03:19:14.
13313	trip-153839879406683648	test	IND131028AAB	IND250002AAC	2018-10-01 12:59:54.067059	FTL	Sonipat_Kundli_H (Haryana)	None	201 12:59:54.
13408	trip-153841850974526339	test	IND110037AAM	IND250002AAC	2018-10-01 18:28:29.745506	FTL	Delhi_Airport_H (Delhi)	None	201 18:28:29.
14453	trip-153857174991144707	test	IND110037AAM	IND250002AAC	2018-10-03 13:02:29.911693	FTL	Delhi_Airport_H (Delhi)	None	201 13:02:29.

In [143…

```
# As the nulls values entry is very less compare to the size of dataset.
d_f=df_final.dropna(axis=0,subset=["source_name","destination_name"])
```

In [144…

```
d_f
```

Out[144]:

	trip_uuid	data	source_center	destination_center	trip_creation_time	route_type	source_name	destination_name
0	trip-153671041653548748	training	IND462022AAA	IND000000ACB	2018-09-12 00:00:16.535741	FTL	Bhopal_Trnsport_H (Madhya Pradesh)	Gurgaon_Bilaspur_HB (Haryana)
1	trip-153671042288605164	training	IND572101AAA	IND562101AAA	2018-09-12 00:00:22.886430	Carting	Tumkur_Veersagr_I (Karnataka)	Chikblapur_ShntiSgr_D (Karnataka)
2	trip-153671043369099517	training	IND562132AAA	IND160002AAC	2018-09-12 00:00:33.691250	FTL	Bangalore_Nelmngla_H (Karnataka)	Chandigarh_Mehmdpur_H (Punjab)
3	trip-153671046011330457	training	IND400072AAB	IND401104AAA	2018-09-12 00:01:00.113710	Carting	Mumbai Hub (Maharashtra)	Mumbai_MiraRd_IP (Maharashtra)
4	trip-153671052974046625	training	IND583101AAA	IND583101AAA	2018-09-12 00:02:09.740725	FTL	Bellary_Dc (Karnataka)	Bellary_Dc (Karnataka)
...	...	...	...	...	...	...	...	...
14812	trip-153861095625827784	test	IND160002AAC	IND160002AAC	2018-10-03 23:55:56.258533	Carting	Chandigarh_Mehmdpur_H (Punjab)	Chandigarh_Mehmdpur_H (Punjab)
14813	trip-153861104386292051	test	IND121004AAB	IND121004AAA	2018-10-03 23:57:23.863155	Carting	FBD_Balabhgarh_DPC (Haryana)	Faridabad_Blbgarh_DC (Haryana)
14814	trip-153861106442901555	test	IND209304AAA	IND209304AAA	2018-10-03 23:57:44.429324	Carting	Kanpur_Central_H_6 (Uttar Pradesh)	Kanpur_Central_H_6 (Uttar Pradesh)
14815	trip-153861115439069069	test	IND627005AAA	IND627005AAA	2018-10-03 23:59:14.390954	Carting	Tirunelveli_VdkkuSrt_I (Tamil Nadu)	Tirunelveli_VdkkuSrt_I (Tamil Nadu)
14816	trip-153861118270144424	test	IND583201AAA	IND583101AAA	2018-10-03 23:59:42.701692	FTL	Hospet (Karnataka)	Bellary_Dc (Karnataka)

14800 rows × 19 columns

In [144…

Feature Engineering:

In [145…

```
# Adding three more columns while extracting date and time from trip_creation_time column.
d_f['date'] = pd.to_datetime(d_f['trip_creation_time']).dt.date
d_f["day"] = pd.to_datetime(d_f["date"]).dt.day
d_f["month"] = pd.to_datetime(d_f["date"]).dt.month
d_f["year"] = pd.to_datetime(d_f["date"]).dt.year
```

In [146…

```
# created features from time
d_f.iloc[:,-4:].head(5)
```

Out[146]:

	date	day	month	year
0	2018-09-12	12	9	2018
1	2018-09-12	12	9	2018
2	2018-09-12	12	9	2018
3	2018-09-12	12	9	2018
4	2018-09-12	12	9	2018

In [147…

```
# Adding four more feature with source state,city, destination state and city name.
d_f['source_city'] = d_f['source_name'].str.replace("_"," ").str.split().str.get(0)
d_f['source_state'] = d_f['source_name'].str.extract('.*\((.*)\).*')
d_f['destination_city'] = d_f['destination_name'].str.replace("_"," ").str.split().str.get(0)
d_f['destination_state'] = d_f['destination_name'].str.extract('.*\((.*)\).*')
```

In [148…

```
# created features from source and destination centers
d_f.iloc[:,-4:].head(5)
```

Out[148]:

	source_city	source_state	destination_city	destination_state
0	Bhopal	Madhya Pradesh	Gurgaon	Haryana
1	Tumkur	Karnataka	Chikblapur	Karnataka
2	Bangalore	Karnataka	Chandigarh	Punjab
3	Mumbai	Maharashtra	Mumbai	Maharashtra
4	Bellary	Karnataka	Bellary	Karnataka

In [149…
```
d_f.describe(include=["int","float"])
```

Out[149]:

	start_scan_to_end_scan	actual_distance_to_destination	actual_time	osrm_time	osrm_distance	segment_actual_time	segment_osrm_time	segm
count	14800.000000	14800.000000	14800.000000	14800.000000	14800.000000	14800.000000	14800.000000	
mean	530.956824	164.583349	357.282905	161.478851	204.472239	354.028919	181.056284	
std	658.712230	305.543364	561.595093	271.498419	370.584337	556.443324	314.703250	
min	23.000000	9.002461	9.000000	6.000000	9.072900	9.000000	6.000000	
25%	149.000000	22.786366	67.000000	29.000000	30.775025	66.000000	30.000000	
50%	280.000000	48.463337	149.000000	60.000000	65.591250	147.000000	65.000000	
75%	638.000000	164.705551	370.000000	168.250000	208.632775	367.000000	185.000000	
max	7898.000000	2186.531787	6265.000000	2032.000000	2840.081000	6230.000000	2564.000000	

In [150…
```
d_f.describe(include=["object"])
```

Out[150]:

	trip_uuid	data	source_center	destination_center	route_type	source_name	destination_name	date	source_city	source
count	14800	14800	14800	14800	14800	14800	14800	14800	14800	
unique	14800	2	865	951	2	866	949	22	666	
top	trip-153671041653548748	training	IND000000ACB	IND000000ACB	Carting	Gurgaon_Bilaspur_HB (Haryana)	Gurgaon_Bilaspur_HB (Haryana)	2018-09-18	Gurgaon	Maha
freq	1	10647	946	813	8906	946	813	791	1022	

Observations:

- As per statistical summary highest order of source city is Gurgaon.
- Highest order delivered by state, that is Maharashtra.
- Highest order received by Mumbai city.

- Highest order received by state-wise is Maharashtra.
- Most preferred route type is carting.
- Most of the data entries belongs to the training category.

In [151…

```
# checking data under unique trip uuid
d_f.groupby('data')['trip_uuid'].nunique().to_frame().T
```

Out[151]:

data	test	training
trip_uuid	4153	10647

In [152…

```
# checking route type under unique trip uuid
d_f.groupby('route_type')['trip_uuid'].nunique().to_frame().T
```

Out[152]:

route_type	Carting	FTL
trip_uuid	8906	5894

In [153…

```
# checking day under unique trip uuid
d_f.groupby('day')['trip_uuid'].nunique().sort_values(ascending=False)
```

Out[153]:
```
day
18    791
15    783
13    750
12    747
22    740
21    740
17    722
14    712
20    703
25    696
26    684
19    674
24    658
27    652
23    631
3     629
16    616
28    607
29    606
1     601
2     550
30    508
Name: trip_uuid, dtype: int64
```

In [154…
```
# checking month under unique trip uuid
d_f.groupby('month')['trip_uuid'].nunique().to_frame().T
```

Out[154]:

month	9	10
trip_uuid	13020	1780

Observations:

- In this data set, 60% of the order delivered through carting and for rest of the Full truck load (FTL) is preferred.
- Order frequency is independent from days as we can see it is more or less same across the whole month.
- Data set entries belongs to two months only that is September and October.

In [155…
```
# checking source_state under unique trip uuid
d_f.groupby('source_state')['trip_uuid'].nunique().sort_values(ascending=False)
```

Out[155]:
```
source_state
Maharashtra               2682
Karnataka                 2229
Haryana                   1681
Tamil Nadu                1085
Delhi                      791
Telangana                  779
Gujarat                    746
Uttar Pradesh              720
West Bengal                677
Punjab                     630
Rajasthan                  493
Andhra Pradesh             407
Bihar                      358
Madhya Pradesh             332
Kerala                     289
Assam                      273
Jharkhand                  160
Uttarakhand                114
Orissa                     107
Goa                         65
Chandigarh                  48
Chhattisgarh                43
Himachal Pradesh            34
Jammu & Kashmir             17
Dadra and Nagar Haveli      15
Pondicherry                 12
Nagaland                     5
Mizoram                      4
Arunachal Pradesh            4
Name: trip_uuid, dtype: int64
```

In [156…
```python
# checking source_city under unique trip uuid
d_f.groupby('source_city')['trip_uuid'].nunique().sort_values(ascending=False).to_frame().head(20)
```

Out[156]:

source_city	trip_uuid
Gurgaon	1022
Bengaluru	1015
Mumbai	893
Bhiwandi	811
Bangalore	755
Delhi	618
Hyderabad	562
Pune	445
Chandigarh	418
Kolkata	339
Chennai	316
MAA	300
Ahmedabad	298
Sonipat	288
Jaipur	247
Del	172
FBD	169
Muzaffrpur	159
Kanpur	144
Noida	143

In [157…

```
# checking destination_state under unique trip uuid
d_f.groupby('destination_state')['trip_uuid'].nunique().sort_values(ascending=False)
```

Out[157]:
```
destination_state
Maharashtra               2591
Karnataka                 2275
Haryana                   1667
Tamil Nadu                1072
Telangana                  838
Gujarat                    746
Uttar Pradesh              732
West Bengal                708
Punjab                     693
Delhi                      675
Rajasthan                  523
Andhra Pradesh             414
Bihar                      363
Madhya Pradesh             337
Kerala                     273
Assam                      234
Jharkhand                  168
Orissa                     119
Uttarakhand                113
Goa                         65
Chhattisgarh                43
Himachal Pradesh            40
Chandigarh                  29
Arunachal Pradesh           23
Dadra and Nagar Haveli      17
Jammu & Kashmir             15
Pondicherry                 10
Meghalaya                    8
Mizoram                      6
Daman & Diu                  1
Nagaland                     1
Tripura                      1
Name: trip_uuid, dtype: int64
```

In [158…
```
# checking destination_city under unique trip uuid
d_f.groupby('destination_city')['trip_uuid'].nunique().sort_values(ascending=False).to_frame().head(20)
```

Out[158]:

	trip_uuid
destination_city	
Mumbai	1127
Bengaluru	1056
Gurgaon	869
Bangalore	646
Hyderabad	630
Bhiwandi	604
Delhi	576
Chandigarh	463
Chennai	388
Sonipat	375
Pune	347
Kolkata	320
Ahmedabad	257
MAA	241
Jaipur	235
FBD	145
Muzaffrpur	139
Noida	135
HBR	133
Bhopal	131

Observations:

- Top 5 source states are Maharashtra,Karnataka,Haryana TamilNadu and Delhi.
- Source States with less than 10 orders are Nagaland, Mizoram, and Arunachal Pradesh.
- Top 5 source cities are Gurgaon, Bengaluru ,Mumbai, Bhiwandi and Bangalore
- Top 5 destination states are Maharashtra, Karnataka, Haryana, Tamil Nadu, and Telangana.
- Destination states with less than 10 orders are Meghalaya, Mizoram Daman & Diu, Nagaland, and Tripura
- Top 5 destination cities are Mumbai, Bengaluru, Gurgaon, Bangalore and Hyderabad.

In [159…

```
# just where most orders are coming from which corridor,avg distance between them, avg time taken
d_f.groupby(['source_city','destination_city']).agg({'trip_uuid':'count','actual_distance_to_destination':'mean','actual_time':'r
```

Out[159]:

		trip_uuid	actual_distance_to_destination	actual_time
source_city	**destination_city**			
Mumbai	**Mumbai**	600	15.988461	62.815000
Bengaluru	**Bengaluru**	549	32.252836	88.089253
Bangalore	**Bengaluru**	455	27.056047	77.720879
Bhiwandi	**Mumbai**	437	22.610231	74.281465
Hyderabad	**Hyderabad**	398	85.867238	200.856784
...	**...**	...	...	...
Bhubaneshwar	**Kendrpara**	1	112.858220	625.000000
	Jaleswar	1	216.531310	287.000000
Bhopal	**Shujalpur**	1	207.425934	386.000000
Ludhiana	**Raikot**	1	58.520829	97.000000
Jhajjar	**Gurgaon**	1	169.384937	415.000000

1620 rows × 3 columns

In [160…

```
# just where most orders are coming from which corridor,avg distance between them, avg time taken
d_f.groupby(['source_city','destination_city']).agg({'trip_uuid':'count','actual_distance_to_destination':'mean','actual_time':'r
```

Out[160]:

source_city	destination_city	trip_uuid	actual_distance_to_destination	actual_time
Guwahati	Bhiwandi	5	2139.367518	5457.000000
Bhiwandi	Guwahati	1	2061.156970	5067.000000
Chandigarh	Bangalore	20	1927.400257	3331.750000
Bangalore	Chandigarh	17	1927.089877	3372.470588
	Delhi	14	1765.193320	3039.571429
...	...	...	...	...
Vapi	Daman	1	9.376028	43.000000
Bhubaneswar	Bhubaneshwar	6	9.306479	35.333333
Hyderabad	Hyd	2	9.126716	26.500000
Manikchak	Paranpur	1	9.100748	52.000000
Delhi	North	1	9.045083	27.000000

1620 rows × 3 columns

In [161…

```
# just where most orders are coming from which corridor,avg distance between them, avg time taken
d_f.groupby(['source_state','destination_state']).agg({'trip_uuid':'count','actual_distance_to_destination':'mean','actual_time'
```

Out[161]:

source_state	destination_state	trip_uuid	actual_distance_to_destination	actual_time
Maharashtra	**Maharashtra**	2406	60.110614	164.041563
Karnataka	**Karnataka**	2015	55.185319	137.804963
Tamil Nadu	**Tamil Nadu**	1016	70.125746	153.220472
Haryana	**Haryana**	871	122.749575	277.407577
Telangana	**Telangana**	655	96.038032	217.586260
...	**...**	...	...	...
Gujarat	**Daman & Diu**	1	9.376028	43.000000
Haryana	**Andhra Pradesh**	1	1366.581459	2462.000000
Andhra Pradesh	**West Bengal**	1	769.326535	1018.000000
Tamil Nadu	**Andhra Pradesh**	1	152.380543	234.000000
Assam	**Nagaland**	1	58.732392	306.000000

156 rows × 3 columns

In [162…

```
# just where most orders are coming from which corridor,avg distance between them, avg time taken
d_f.groupby(['source_state','destination_state']).agg({'trip_uuid':'count','actual_distance_to_destination':'mean','actual_time'
```

Out[162]:

source_state	destination_state	trip_uuid	actual_distance_to_destination	actual_time
Assam	Maharashtra	5	2139.367518	5457.000000
Maharashtra	Assam	1	2061.156970	5067.000000
Punjab	Karnataka	20	1927.400257	3331.750000
Karnataka	Punjab	17	1927.089877	3372.470588
	Delhi	14	1765.193320	3039.571429
...	...	...	...	...
Punjab	Chandigarh	28	32.324005	68.464286
Gujarat	Dadra and Nagar Haveli	17	14.408057	34.647059
Dadra and Nagar Haveli	Gujarat	15	14.349976	48.333333
Chandigarh	Chandigarh	1	10.991515	22.000000
Gujarat	Daman & Diu	1	9.376028	43.000000

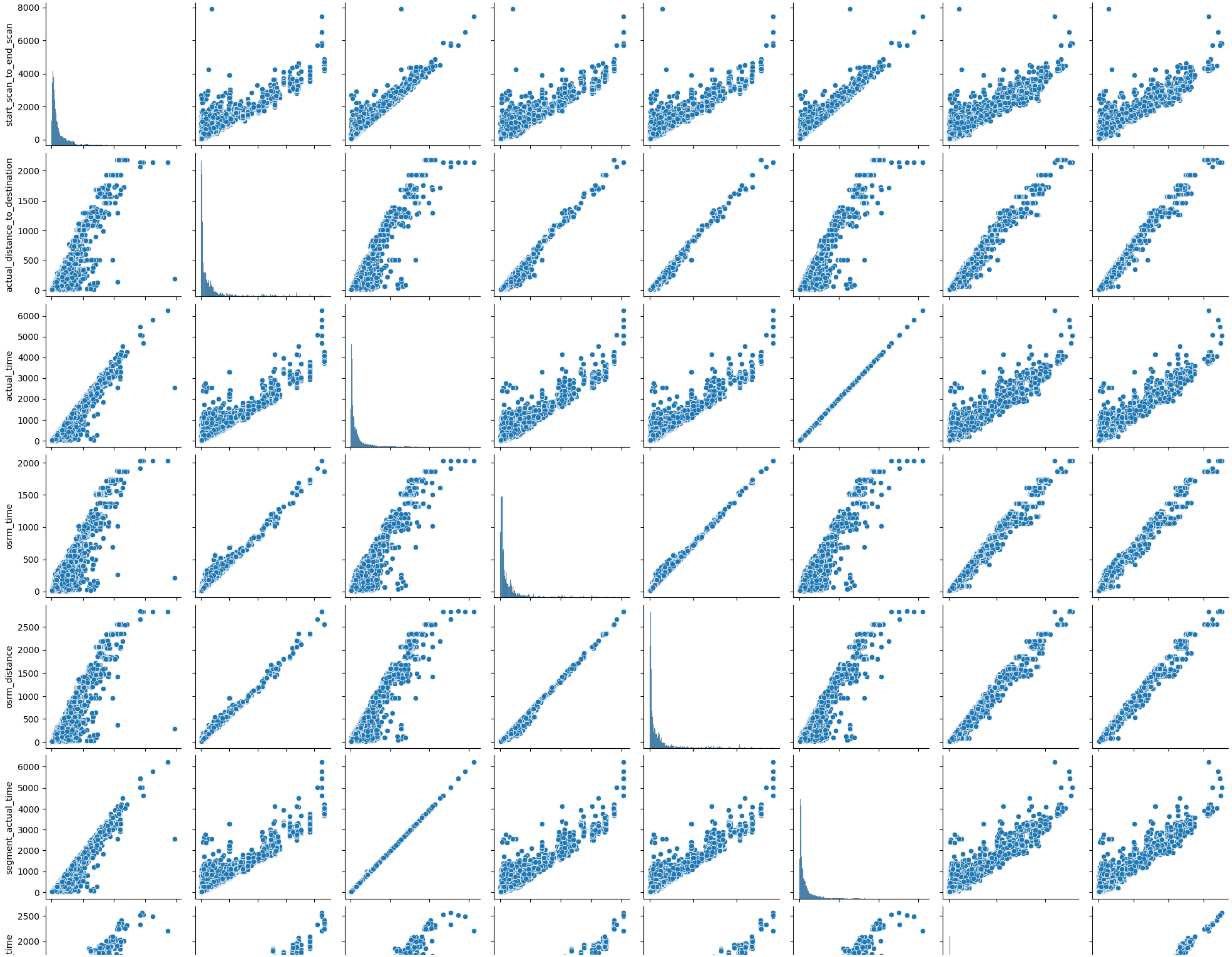
156 rows × 3 columns

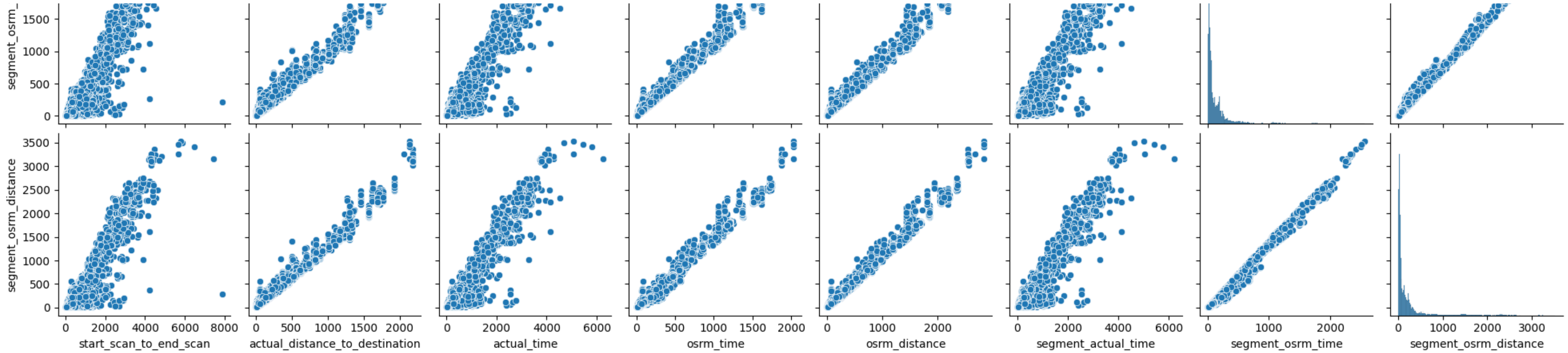
Observations:

- Busiest corridors are Mumbai to Mumbai having average distance is 16Km taking approximately 63 minutes.
- Longest Corridor between cities is Guwahati to Bhiwandi having distance of 2140 Km.
- Longest Corridor between states is Assam to Maharashtra having distance of 2140 Km and taking average time around 5457 minutes to delivered order.

In [163…

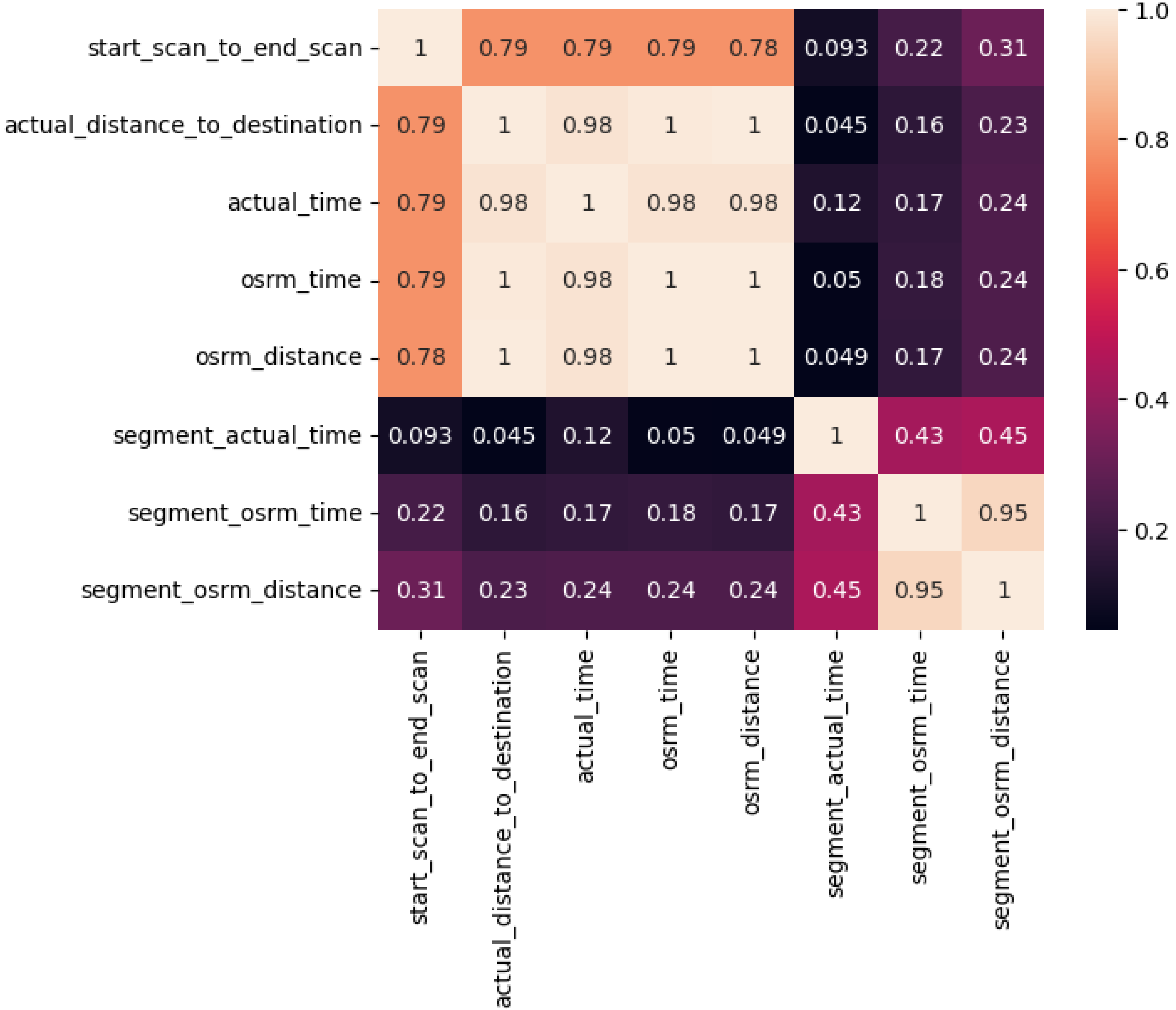
```
sns.pairplot(d_f[['start_scan_to_end_scan','actual_distance_to_destination', 'actual_time', 'osrm_time',
                  'osrm_distance', 'segment_actual_time', 'segment_osrm_time',
                  'segment_osrm_distance']])
plt.show()
```


start_scan_to_end_scan
actual_distance_to_destination
actual_time
osrm_time
osrm_distance
segment_actual_time
time



In [164…

```
heat_map=sns.heatmap(df[['start_scan_to_end_scan','actual_distance_to_destination', 'actual_time', 'osrm_time',
                      'osrm_distance', 'segment_actual_time', 'segment_osrm_time',
                      'segment_osrm_distance']].corr(), annot=True)
```



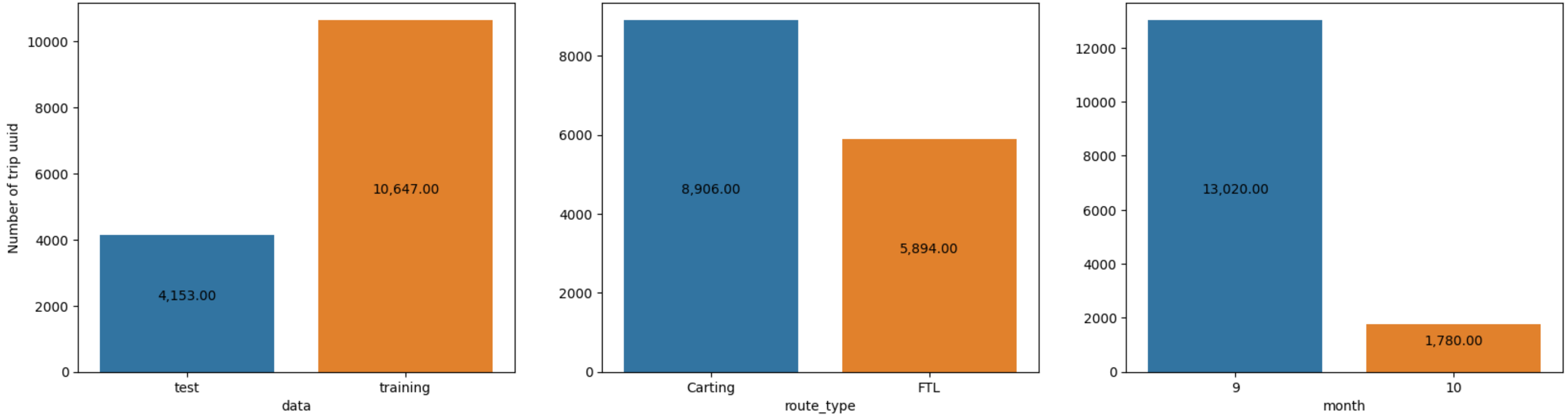
Observations:

- As we can see OSRM time highly correlated with OSRM distance.

- Positively Correleted varaibles are following.
    1. actual_time - actual_distance_to_destination (0.98)
    2. start_scan_to_end_scan-actual_distance_to_destination (0.98)
    3. start_scan_to_end_scan-actual_time(0.79)
    4. start_scan_to_end_scan-osrm_time(0.78)
    5. segment_osrm_time'-'segment_osrm_distance'(0.95)
    6. actual_time-'osrm_distance'(0.98)

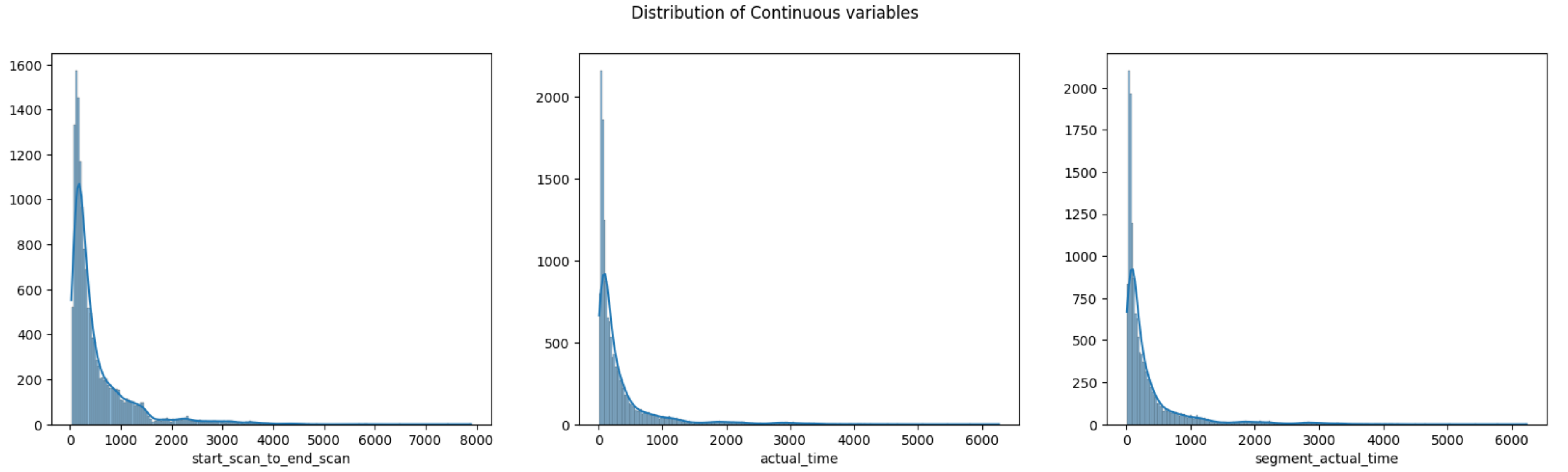
In [165…

```
## Distribution of categorical variables
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 3, 1)
ax = sns.barplot(data=d_f.groupby('data')['trip_uuid'].nunique().reset_index(),y='trip_uuid',x='data')
for p in ax.patches:
  ax.annotate("{:,.2f}".format(p.get_height()),
 (p.get_x() + p.get_width()/2, p.get_height()/2),ha = 'center', va = 'bottom')
plt.xlabel('data')
plt.ylabel('Number of trip uuid')
plt.subplot(1,3, 2)
ax = sns.barplot(data=d_f.groupby('route_type')['trip_uuid'].nunique().reset_index(),y='trip_uuid',x='route_type')
for p in ax.patches:
  ax.annotate("{:,.2f}".format(p.get_height()),
 (p.get_x() + p.get_width()/2, p.get_height()/2),ha = 'center', va = 'bottom')
plt.xlabel('route_type')
plt.ylabel('')
plt.subplot(1,3, 3)
ax = sns.barplot(data=d_f.groupby('month')['trip_uuid'].nunique().reset_index(),y='trip_uuid',x='month')
for p in ax.patches:
  ax.annotate("{:,.2f}".format(p.get_height()),
 (p.get_x() + p.get_width()/2, p.get_height()/2),ha = 'center', va = 'bottom')
plt.xlabel('month')
plt.ylabel('')
plt.show()
```



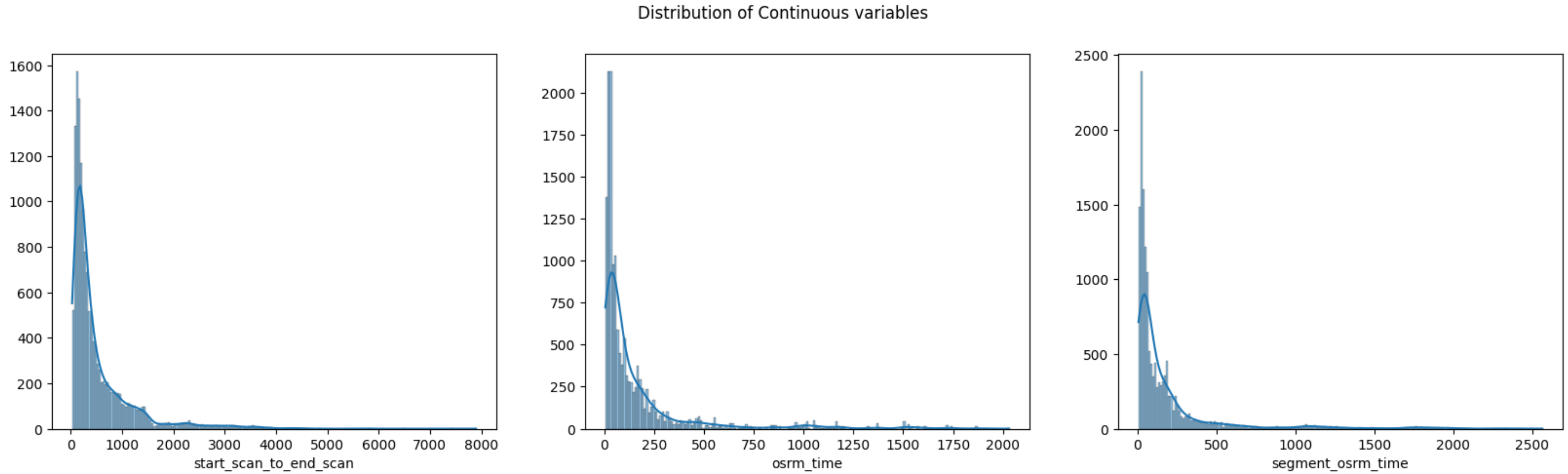
In [166…

```
# Distribution of Actual time
fig = plt.figure(figsize=(20,5))
# Distribution of start_scan_to_end_scan
plt.subplot(1, 3, 1)
ax = sns.histplot(d_f,x='start_scan_to_end_scan',kde=True)
plt.xlabel('start_scan_to_end_scan')
plt.ylabel('')
# Distribution of actual_time
plt.subplot(1,3,2)
ax = sns.histplot(d_f,x='actual_time',kde=True)
plt.xlabel('actual_time')
plt.ylabel("")
# Distribution of segment_actual_time
plt.subplot(1,3,3)
sns.histplot(d_f,x='segment_actual_time',kde=True)
plt.xlabel('segment_actual_time')
plt.ylabel("")
plt.suptitle("Distribution of Continuous variables")
plt.show()
```



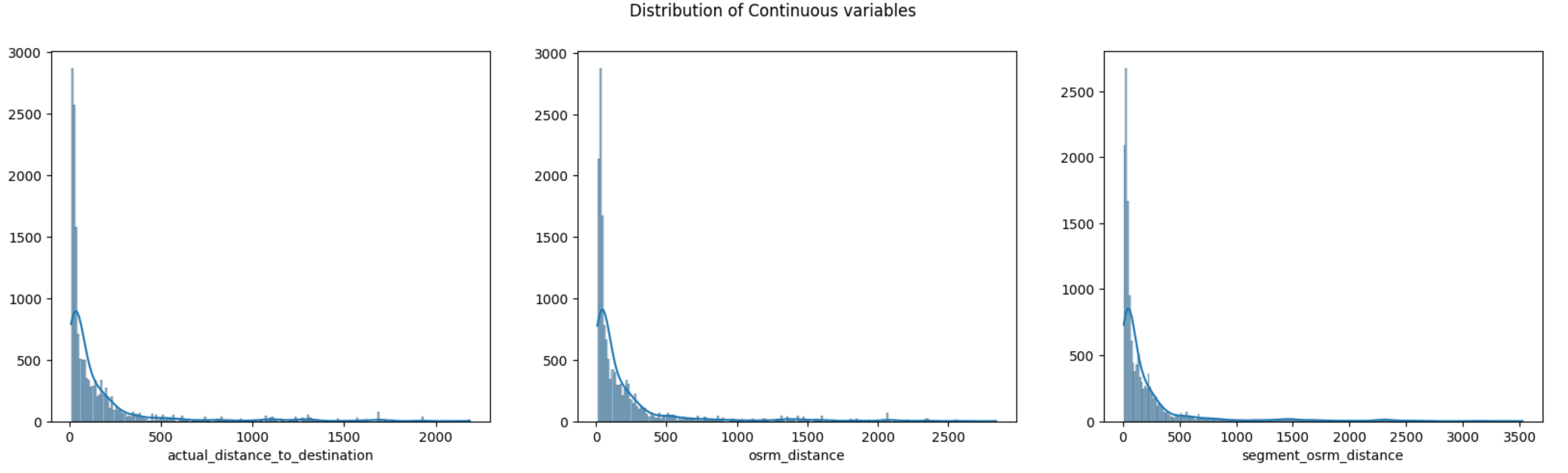
In [167…

```
# Distribution of osrm time
fig = plt.figure(figsize=(20,5))
# Distribution of start_scan_to_end_scan
plt.subplot(1, 3, 1)
ax = sns.histplot(d_f,x='start_scan_to_end_scan',kde=True)
plt.xlabel('start_scan_to_end_scan')
plt.ylabel('')
# Distribution of actual_time
plt.subplot(1,3,2)
ax = sns.histplot(d_f,x='osrm_time',kde=True)
plt.xlabel('osrm_time')
plt.ylabel("")
# Distribution of segment_actual_time
plt.subplot(1,3,3)
sns.histplot(d_f,x='segment_osrm_time',kde=True)
plt.xlabel('segment_osrm_time')
plt.ylabel("")
plt.suptitle("Distribution of Continuous variables")
plt.show()
```



In [168…

```
# Distribution of distance
fig = plt.figure(figsize=(20,5))
# Distribution of actual_distance_to_destination
plt.subplot(1, 3, 1)
ax = sns.histplot(d_f,x='actual_distance_to_destination',kde=True)
plt.xlabel('actual_distance_to_destination')
plt.ylabel('')
# Distribution of osrm_distance
plt.subplot(1,3,2)
ax = sns.histplot(d_f,x='osrm_distance',kde=True)
plt.xlabel('osrm_distance')
plt.ylabel("")
# Distribution of segment_osrm_distance
plt.subplot(1,3,3)
sns.histplot(d_f,x='segment_osrm_distance',kde=True)
plt.xlabel('segment_osrm_distance')
plt.ylabel("")
plt.suptitle("Distribution of Continuous variables")
plt.show()
```



Observations:

- It is clear from histplot, most of the numerical data are rightly skewed.

In [169…

```
# Just droping few of the columns which are not usefull for hypothesis testing.
d__f=d_f.drop(axis=1,columns=['source_name','destination_name', 'od_start_time', 'od_end_time','trip_creation_time'])
```

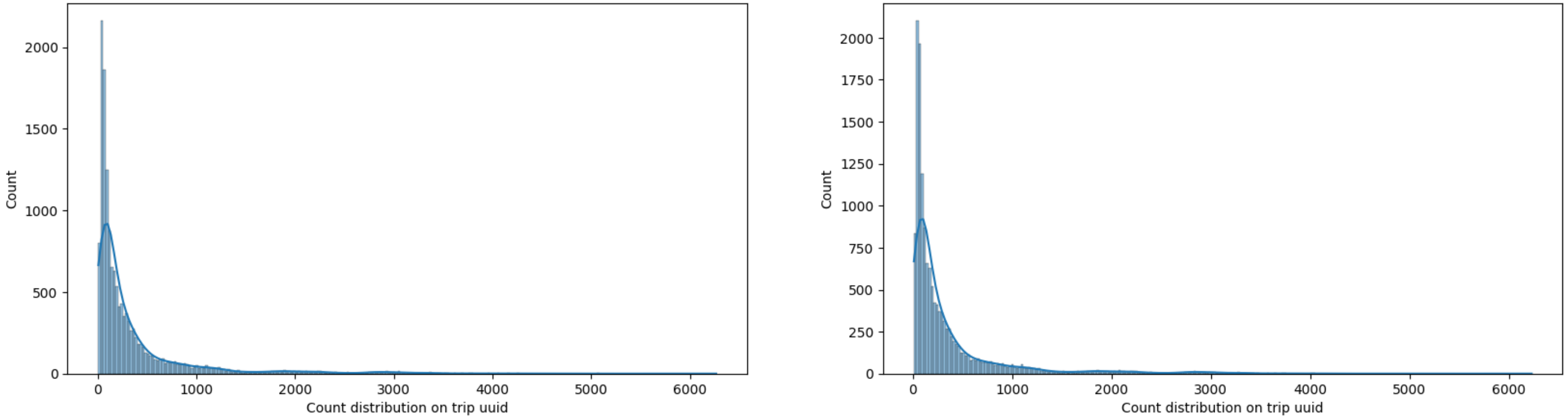
Hypothesis Testing

CASE1: hypothesis testing/ visual analysis between actual_time aggregated value and OSRM time aggregated value:

In [170…

```
# visual representation for normality test
d__f_at=d__f["actual_time"].reset_index(drop=True)
d__f_sat=d__f["segment_actual_time"].reset_index(drop=True)
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
sns.histplot(d__f_at,kde = True)
plt.xlabel('Count distribution on trip uuid',fontsize=10)
plt.subplot(1, 2, 2)
```

```
sns.histplot(d__f_sat,kde = True)
plt.xlabel('Count distribution on trip uuid',fontsize=10)
plt.show()
```



Assumptions under Student's t-test:

- Observations in each sample are independent and identically distributed (iid).
- Observations in each sample are normally distributed.
- Observations in each sample have the same variance.

Validation of assumptions:

In [171…

```
# Validation of Assumption 1 by performing Spearman's Rank Correlation:
# H0: The two samples are independent.
# H1: There is a dependency between the samples.
d__f_at=d__f["actual_time"].sample(14800)
d__f_sat=d__f["segment_actual_time"].sample(14800)
print("sample size d__f_at :",len(d__f_at))
print("sample size d__f_sat:",len(d__f_sat))
alpha=0.05
statistic,p_value=spearmanr(d__f_at, d__f_sat)
print("alpha:",0.05)
print("p_value:",p_value)
print("stat:",statistic)
```

```
if p_value<alpha:
  print("Reject Null Hypothesis: There is a dependency between the samples")
else:
  print('Accept Null Hypothesis: The two samples are independent')
```

```
sample size d__f_at : 14800
sample size d__f_sat: 14800
alpha: 0.05
p_value: 0.1409598423786
stat: -0.012102202720226517
Accept Null Hypothesis: The two samples are independent
```

In [172…

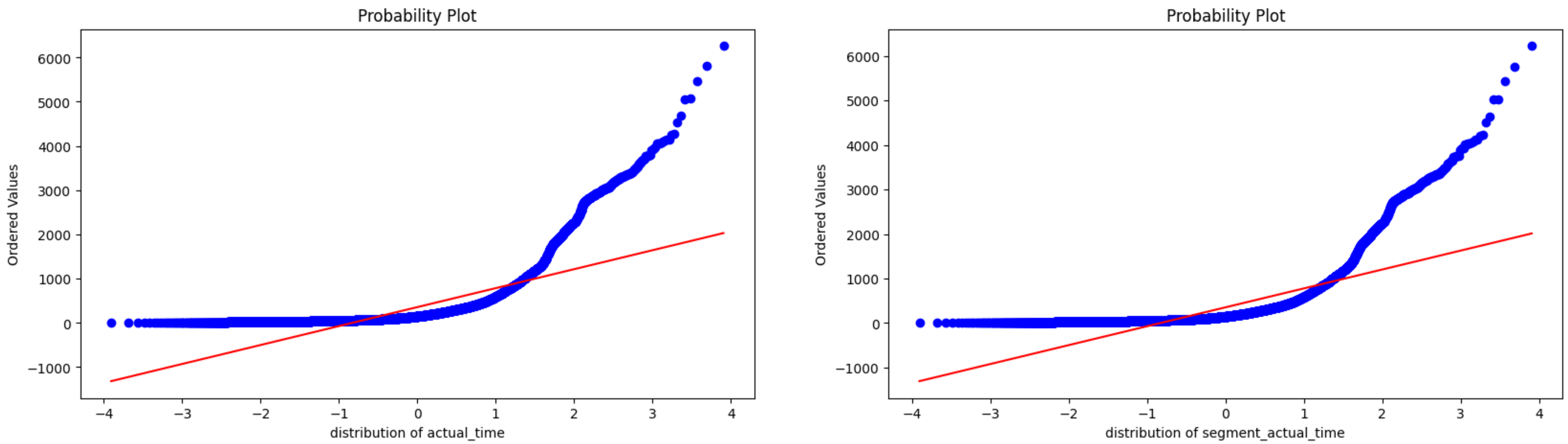
```
#  Validation of Assumption 1 by performing Kruskal-Wallis H Test:
# H0: The distributions of all samples are equal.
# H1: The distributions of one or more samples are not equal.
d__f_at=d__f["actual_time"].sample(14800)
d__f_sat=d__f["segment_actual_time"].sample(14800)
print("sample size d__f_at :",len(d__f_at))
print("sample size d__f_sat:",len(d__f_sat))
alpha=0.05
statistic,p_value=kruskal(d__f_at, d__f_sat)
print("alpha:",0.05)
print("p_value:",p_value)
print("stat:",statistic)
if p_value<alpha:
  print("Reject Null Hypothesis: The distributions of one or more samples are not equal")
else:
  print('Accept Null Hypothesis: The distributions of all samples are equal')
```

```
sample size d__f_at : 14800
sample size d__f_sat: 14800
alpha: 0.05
p_value: 0.416662704607331
stat: 0.6597089756568684
Accept Null Hypothesis: The distributions of all samples are equal
```

In [173…

```
# Validation of Assumption 2 by performing Quantile-Quantile Plot Test:
# H0: The sample has a Gaussian distribution.
# H1: The sample does not have a Gaussian distribution.
d__f_at=d__f["actual_time"].sample(14800)
d__f_sat=d__f["segment_actual_time"].sample(14800)
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
probplot(d__f_at,dist="norm",plot=plt)
```

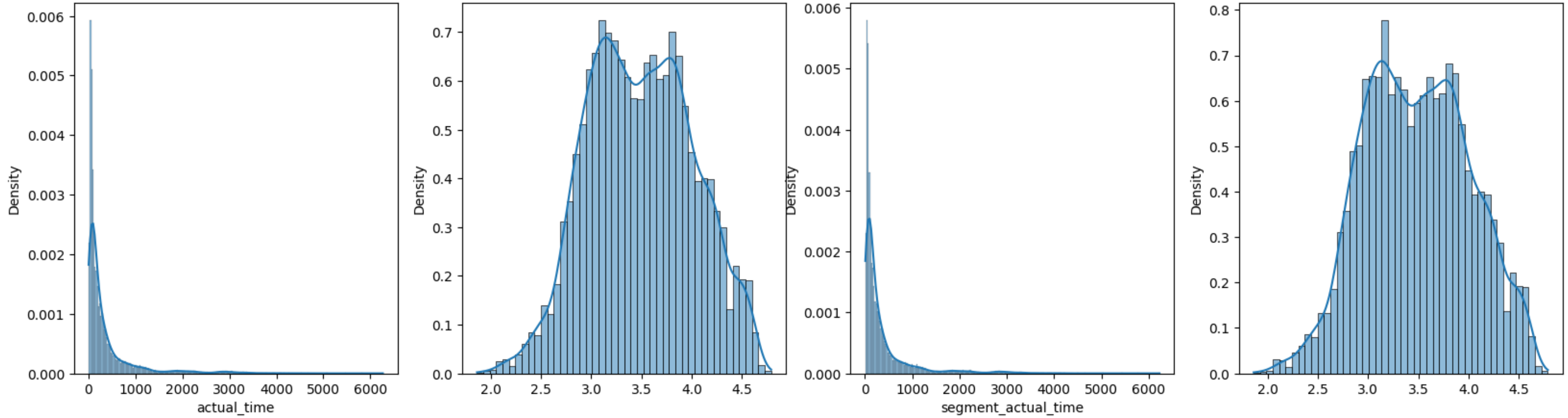
```
plt.xlabel('distribution of actual_time',fontsize=10)
plt.subplot(1, 2, 2)
probplot(d__f_sat,dist="norm",plot=plt)
plt.xlabel('distribution of segment_actual_time',fontsize=10)
plt.show()
```



In [174...

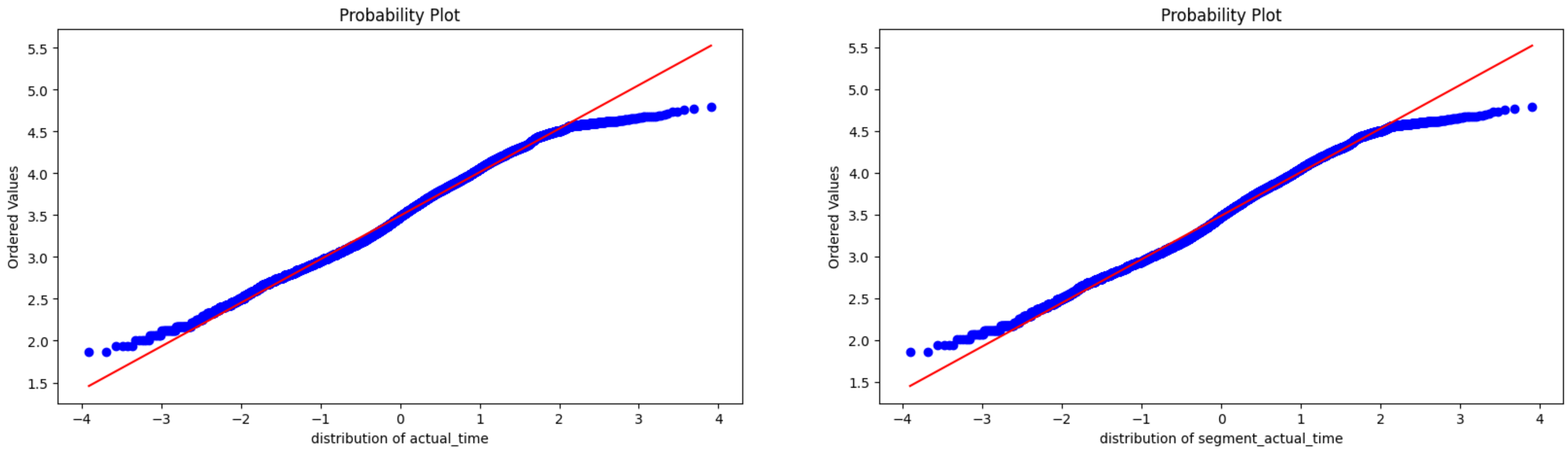
```
# Transforming data by using boxcox transformation:
original_data1=d__f_at
fitted_data1, fitted_lambda1 = boxcox(d__f_at)
original_data2=d__f_sat
fitted_data2, fitted_lambda2 = boxcox(d__f_sat)
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 4, 1)
sns.histplot(original_data1, kde=True, stat="density")
plt.subplot(1, 4, 2)
sns.histplot(fitted_data1, kde=True, stat="density")
print(f"Lambda value used for Transformation of actual time data: {fitted_lambda1}")
plt.subplot(1, 4, 3)
sns.histplot(original_data2, kde=True, stat="density")
plt.subplot(1, 4, 4)
sns.histplot(fitted_data2, kde=True, stat="density")
print(f"Lambda value used for Transformation of segment actual time data : {fitted_lambda2}")
plt.show()
```

```
Lambda value used for Transformation of actual time data: -0.1547546728203356
Lambda value used for Transformation of segment actual time data : -0.15491026962058227
```



In [175…

```
# Quantile-Quantile Plot after data transformation:
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
probplot(fitted_data1,dist="norm",plot=plt)
plt.xlabel('distribution of actual_time',fontsize=10)
plt.subplot(1, 2, 2)
probplot(fitted_data2,dist="norm",plot=plt)
plt.xlabel('distribution of segment_actual_time',fontsize=10)
plt.show()
```



In [176…

```
#  Validation of Assumption 3:
# H0:variance of the sample is same.
# Ha:variances of the sample is not same.
alpha=0.05
levene_stat,p_value=levene(d__f_at,d__f_sat)
print("alpha:",0.05)
print("p_value:",p_value)
if p_value<alpha:
  print("Reject Null Hypothesis: Variance of the input datasets is not same")
else:
  print('Accept Null Hypothesis: Variance of the input datasets is Same/Close')
```

```
alpha: 0.05
p_value: 0.6954490990469593
Accept Null Hypothesis: Variance of the input datasets is Same/Close
```

Observations:

- As per result of Spearman’s Rank Correlation test, both the samples data are independent.
- It is clear from Kruskal-Wallis H Test, samples are identically distributed.
- Both sample data are not following normally distributed it is clear from Q-Q plot.
- After boxcox transformation, it is clear from Q-Q plot, approximately 95% (+-2 sigma) of data points are following normally distribution.
- It is clear from levene test,Variance of the samples are same.

Student’s t-test:

- Tests whether the means of two independent samples are significantly different. ### **Interpretation:**
- H0: the means of the samples are equal.

- H1: the means of the samples are unequal.

In [177…

```
print(d__f["actual_time"].mean())
print(d__f["segment_actual_time"].mean())
```

```
357.2829054054054
354.0289189189189
```

In [178…

```
# 2- Sample T-Test
d__f_at=d__f["actual_time"].sample(14800)
d__f_sat=d__f["segment_actual_time"].sample(14800)
print("sample size d__f_at :",len(d__f_at))
print("sample size d__f_sat:",len(d__f_sat))
def t_test(CL):
  alpha=1-(CL/100) # significance level(alpha)
  t_stat,p_value=ttest_ind(d__f_at,d__f_sat)
  print("Alpha:",alpha)
  print("p value:",p_value)
  print("t statistics:",t_stat)
  if p_value<alpha:
    print("Reject Null Hypothesis: The means of the samples are unequal")
  else:
    print('Accept Null Hypothesis: The means of the samples are equal')
t_test(95)
```

```
sample size d__f_at : 14800
sample size d__f_sat: 14800
Alpha: 0.050000000000000044
p value: 0.6165675968933484
t statistics: 0.5007261390408064
Accept Null Hypothesis: The means of the samples are equal
```

Observations:

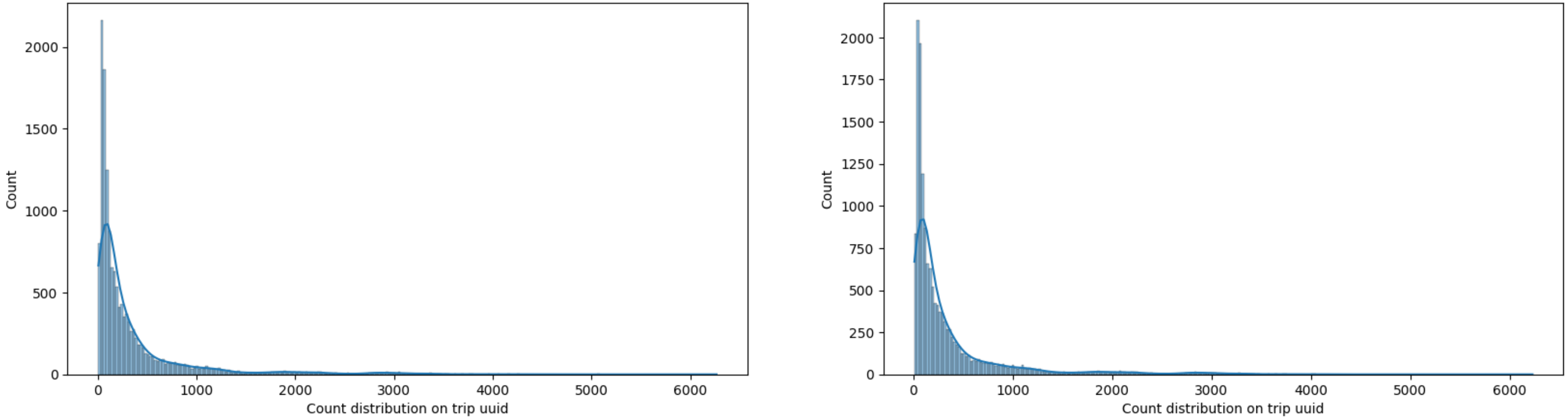
- The calculated p-value : 0.6159
- which is greater than the significance level.
- Null Hypothesis is accepted.
- The means of the actual time and segment actual times are equal.

CASE 2: hypothesis testing/ visual analysis between time difference between od_start_time and od_end_time & start_scan_to_end_scan:

In [179…

```
# visual representation for normality test
d__f_d=d__f["diff"].reset_index()
d__f_sses=d__f["start_scan_to_end_scan"].reset_index()
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
```

```
sns.histplot(d__f_at,kde = True)
plt.xlabel('Count distribution on trip uuid',fontsize=10)
plt.subplot(1, 2, 2)
sns.histplot(d__f_sat,kde = True)
plt.xlabel('Count distribution on trip uuid',fontsize=10)
plt.show()
```



Assumptions under Student's t-test:

- Observations in each sample are independent and identically distributed (iid).
- Observations in each sample are normally distributed.
- Observations in each sample have the same variance.

Validation of assumptions:

In [180…

```
# Validation of Assumption 1 by performing Spearman's Rank Correlation:
# H0: the two samples are independent.
# H1: there is a dependency between the samples.
d__f_d=d__f["diff"].sample(14800)
d__f_sses=d__f["start_scan_to_end_scan"].sample(14800)
print("sample size d__f_at :",len(d__f_d))
print("sample size d__f_sat:",len(d__f_sses))
```

```
alpha=0.05
statistic,p_value=spearmanr(d__f_d, d__f_sses)
print("alpha:",0.05)
print("p_value:",p_value)
print("stat:",statistic)
if p_value<alpha:
  print("Reject Null Hypothesis: There is a dependency between the samples")
else:
  print('Accept Null Hypothesis: The two samples are independent')
```

```
sample size d__f_at : 14800
sample size d__f_sat: 14800
alpha: 0.05
p_value: 0.14082983166130156
stat: 0.012106162827176612
Accept Null Hypothesis: The two samples are independent
```

In [181…

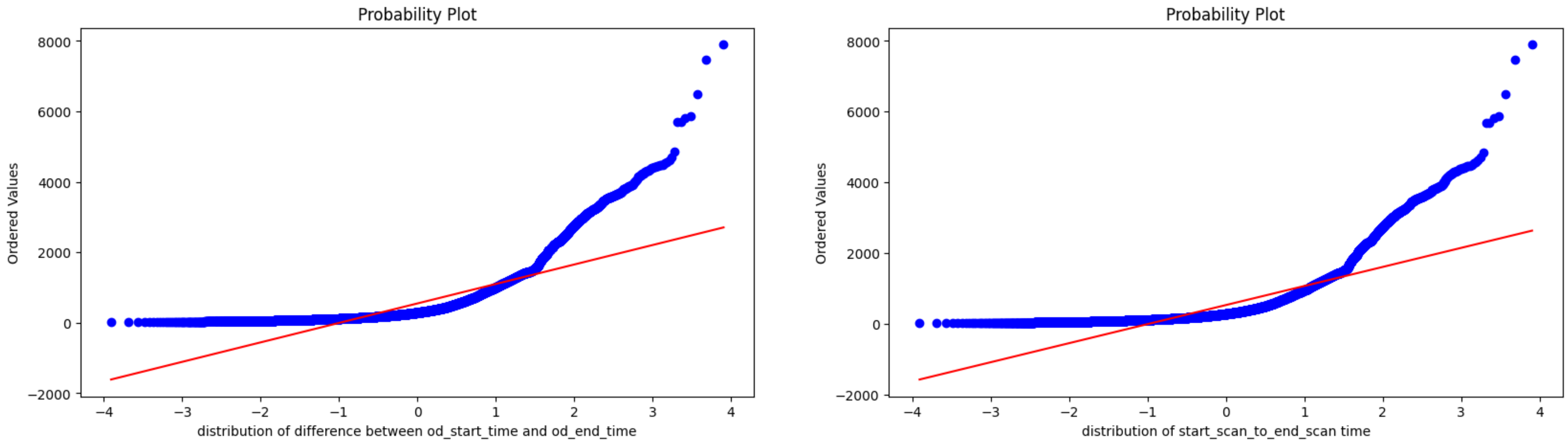
```
#  Validation of Assumption 1 by performing Kruskal-Wallis H Test:
# H0: The distributions of all samples are equal.
# H1: The distributions of one or more samples are not equal.
d__f_d=d__f["diff"].sample(14800)
d__f_sses=d__f["start_scan_to_end_scan"].sample(14800)
print("sample size d__f_at :",len(d__f_d))
print("sample size d__f_sat:",len(d__f_sses))
alpha=0.05
statistic,p_value=kruskal(d__f_d, d__f_sses)
print("alpha:",0.05)
print("p_value:",p_value)
print("stat:",statistic)
if p_value<alpha:
  print("Reject Null Hypothesis: The distributions of one or more samples are not equal")
else:
  print('Accept Null Hypothesis: The distributions of all samples are equal')
```

```
sample size d__f_at : 14800
sample size d__f_sat: 14800
alpha: 0.05
p_value: 0.021603510774351797
stat: 5.277438274400661
Reject Null Hypothesis: The distributions of one or more samples are not equal
```

In [182…

```
# Validation of Assumption 2 by performing Quantile-Quantile Plot Test:
# H0: The sample has a Gaussian distribution.
# H1: The sample does not have a Gaussian distribution.
```

```
d__f_d=d__f["diff"].sample(14800)
d__f_sses=d__f["start_scan_to_end_scan"].sample(14800)
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
probplot(d__f_d,dist="norm",plot=plt)
plt.xlabel('distribution of difference between od_start_time and od_end_time',fontsize=10)
plt.subplot(1, 2, 2)
probplot(d__f_sses,dist="norm",plot=plt)
plt.xlabel('distribution of start_scan_to_end_scan time',fontsize=10)
plt.show()
```

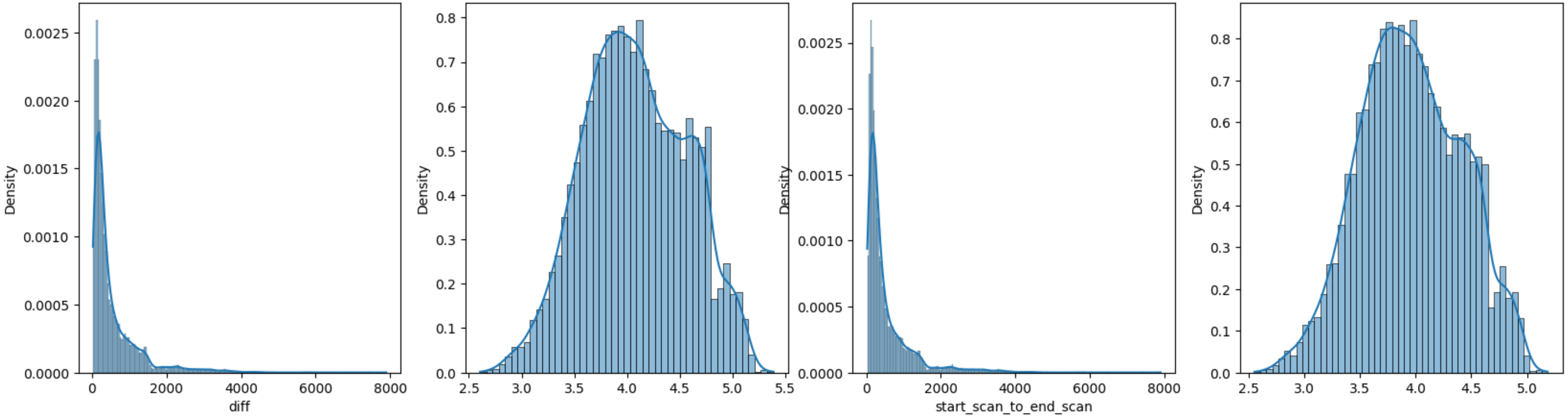


In [183…

```
# Transforming data by using boxcox transformation:
original_data1=d__f_d
fitted_data1, fitted_lambda1 = boxcox(d__f_d)
original_data2=d__f_sses
fitted_data2, fitted_lambda2 = boxcox(d__f_sses)
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 4, 1)
sns.histplot(original_data1, kde=True, stat="density")
plt.subplot(1, 4, 2)
sns.histplot(fitted_data1, kde=True, stat="density")
print(f"Lambda value used for Transformation of actual time data: {fitted_lambda1}")
plt.subplot(1, 4, 3)
sns.histplot(original_data2, kde=True, stat="density")
plt.subplot(1, 4, 4)
sns.histplot(fitted_data2, kde=True, stat="density")
```

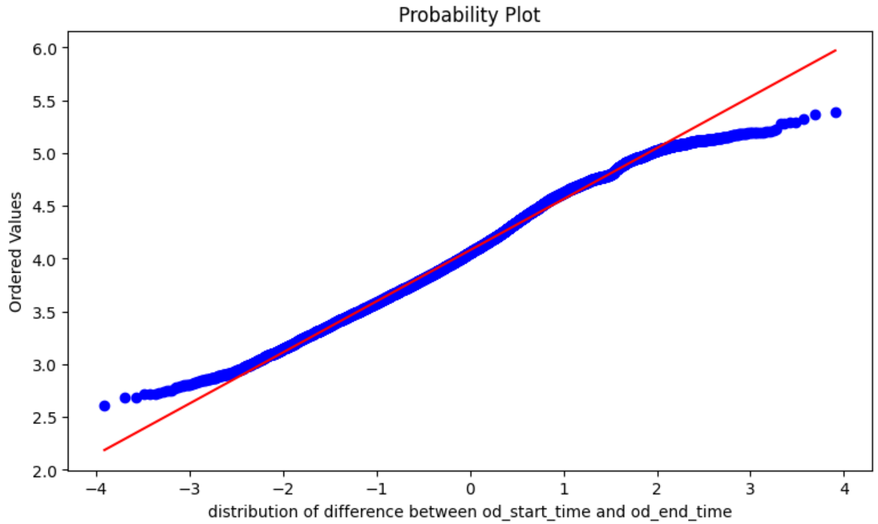
```
print(f"Lambda value used for Transformation of segment actual time data : {fitted_lambda2}")
plt.show()
```

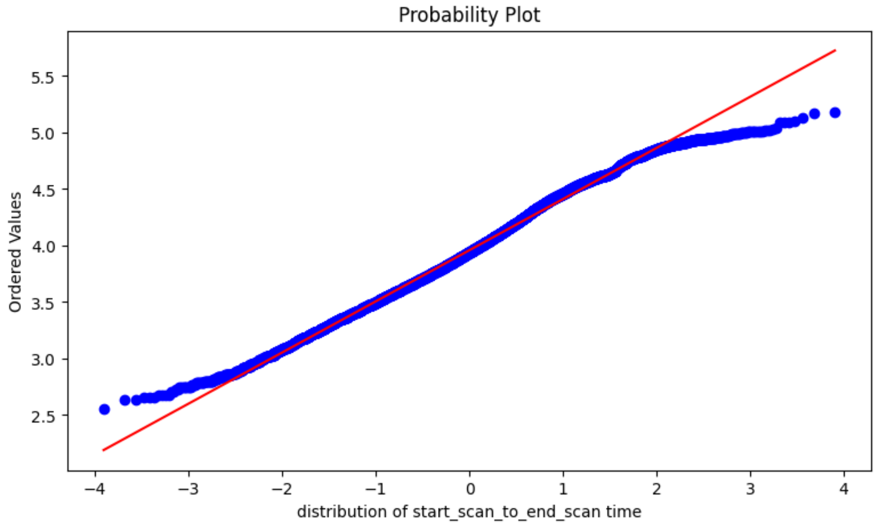
```
Lambda value used for Transformation of actual time data: -0.12530413647612393
Lambda value used for Transformation of segment actual time data : -0.1358531063601212
```



In [184…

```
# Quantile-Quantile Plot after data transformation:
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
probplot(fitted_data1,dist="norm",plot=plt)
plt.xlabel('distribution of difference between od_start_time and od_end_time',fontsize=10)
plt.subplot(1, 2, 2)
probplot(fitted_data2,dist="norm",plot=plt)
plt.xlabel('distribution of start_scan_to_end_scan time',fontsize=10)
plt.show()
```





In [185…

```
#  Validation of Assumption 3:
# H0:variance of the sample is same.
# Ha:variances of the sample is not same.
alpha=0.05
levene_stat,p_value=levene(d__f_d,d__f_sses)
print("alpha:",0.05)
print("p_value:",p_value)
if p_value<alpha:
  print("Reject Null Hypothesis: Variance of the input datasets is not same")
else:
  print('Accept Null Hypothesis: Variance of the input datasets is Same/Close')
```

```
alpha: 0.05
p_value: 0.045220025213086545
Reject Null Hypothesis: Variance of the input datasets is not same
```

Observations:

- As per result of Spearman’s Rank Correlation test, both the samples data are independent.
- It is clear from Kruskal-Wallis H Test, samples are not identically distributed.
- Both sample data are not following normally distributed it is clear from Q-Q plot.
- After boxcox transformation, it is clear from Q-Q plot, approximately 95% (+-2 sigma) of data points are following normally distribution.
- It is clear from levene test, Variance of the samples are not same.

Student's t-test:

- Tests whether the means of two samples are significantly different. ### **Interpretation:**
- H0: The means of the samples are equal.
- H1: The means of the samples are unequal.

In [186…

```
print(d__f["diff"].mean())
print(d__f["start_scan_to_end_scan"].mean())
```

```
547.628388248428
530.9568243243243
```

In [187…

```
# Student's t-test
d__f_d=d__f["diff"].sample(14800)
d__f_sses=d__f["start_scan_to_end_scan"].sample(14800)
print("sample size d__f_at :",len(d__f_d))
print("sample size d__f_sat:",len(d__f_sses))
def t_test(CL):
  alpha=1-(CL/100) # significance level(alpha)
  t_stat,p_value=ttest_ind(d__f_d,d__f_sses,alternative='greater')
  print("Alpha:",alpha)
  print("p value:",p_value)
  print("t statistics:",t_stat)
  if p_value<alpha:
    print("Reject Null Hypothesis: The means of the samples are unequal")
  else:
    print('Accept Null Hypothesis: The means of the samples are equal')
t_test(95)
```

```
sample size d__f_at : 14800
sample size d__f_sat: 14800
Alpha: 0.050000000000000044
p value: 0.015359490228817607
t statistics: 2.160797513574266
Reject Null Hypothesis: The means of the samples are unequal
```

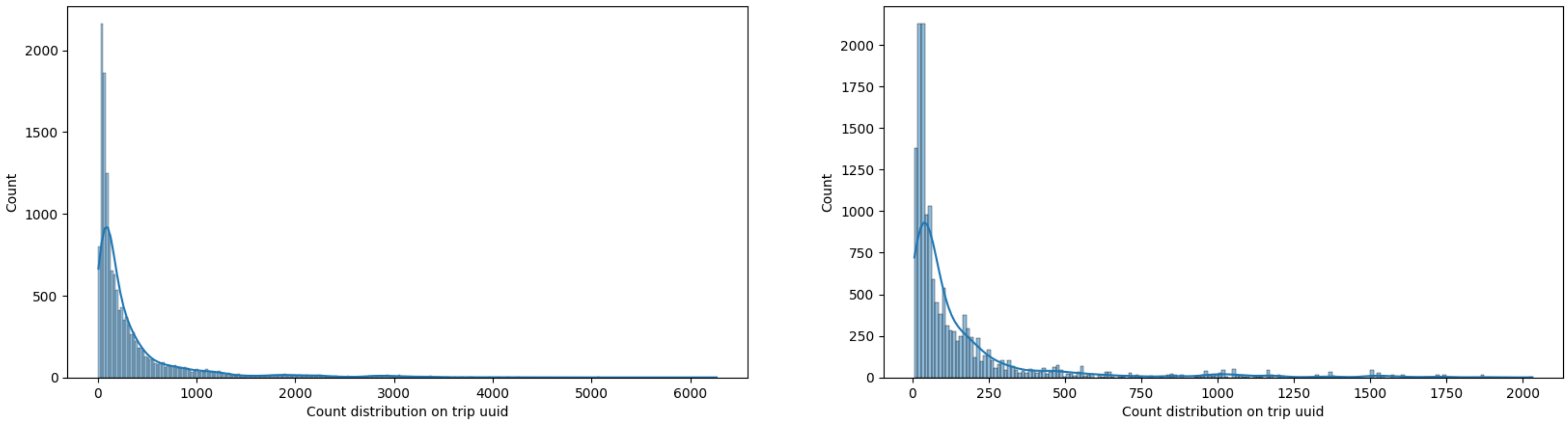
Observations:

- The calculated p-value : 0.01535
- Which is lessar than the significance level.
- Null Hypothesis is Rejected.
- The mean of the difference between order start time to order end time & start scan to end scan are higher.

CASE 3: hypothesis testing/ visual analysis between actual_time and OSRM time:

In [188…

```
# visual representation for normality test
d__f_at=d__f["actual_time"].reset_index(drop=True)
d__f_ot=d__f["osrm_time"].reset_index(drop=True)
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
sns.histplot(d__f_at,kde = True)
plt.xlabel('Count distribution on trip uuid',fontsize=10)
plt.subplot(1, 2, 2)
sns.histplot(d__f_ot,kde = True)
plt.xlabel('Count distribution on trip uuid',fontsize=10)
plt.show()
```



Assumptions under Student's t-test:

- Observations in each sample are independent and identically distributed (iid).
- Observations in each sample are normally distributed.
- Observations in each sample have the same variance.

Validation of assumptions:

In [189…

```
# Validation of Assumption 1 by performing Spearman’s Rank Correlation:
# H0: the two samples are independent.
# H1: there is a dependency between the samples.
d__f_at=d__f["actual_time"].sample(14800)
d__f_ot=d__f["osrm_time"].sample(14800)
print("sample size d__f_at :",len(d__f_at))
print("sample size d__f_sat:",len(d__f_ot))
alpha=0.05
statistic,p_value=spearmanr(d__f_at, d__f_ot)
print("alpha:",0.05)
print("p_value:",p_value)
print("stat:",statistic)
if p_value<alpha:
  print("Reject Null Hypothesis: There is a dependency between the samples")
else:
  print('Accept Null Hypothesis: The two samples are independent')
```

```
sample size d__f_at : 14800
sample size d__f_sat: 14800
alpha: 0.05
p_value: 0.9878611122734979
stat: 0.0001250723793130502
Accept Null Hypothesis: The two samples are independent
```

In [221…

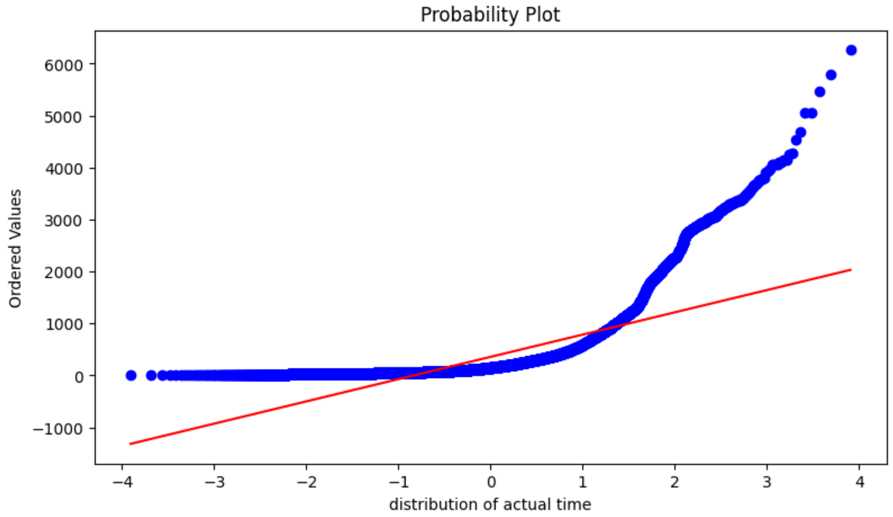
```
#  Validation of Assumption 1 by performing Kruskal-Wallis H Test:
# H0: The distributions of all samples are equal.
# H1: The distributions of one or more samples are not equal.
d__f_at=d__f["actual_time"].sample(14800)
d__f_ot=d__f["osrm_time"].sample(14800)
print("sample size d__f_at :",len(d__f_at))
print("sample size d__f_sat:",len(d__f_ot))
alpha=0.05
statistic,p_value=kruskal(d__f_at, d__f_ot)
```

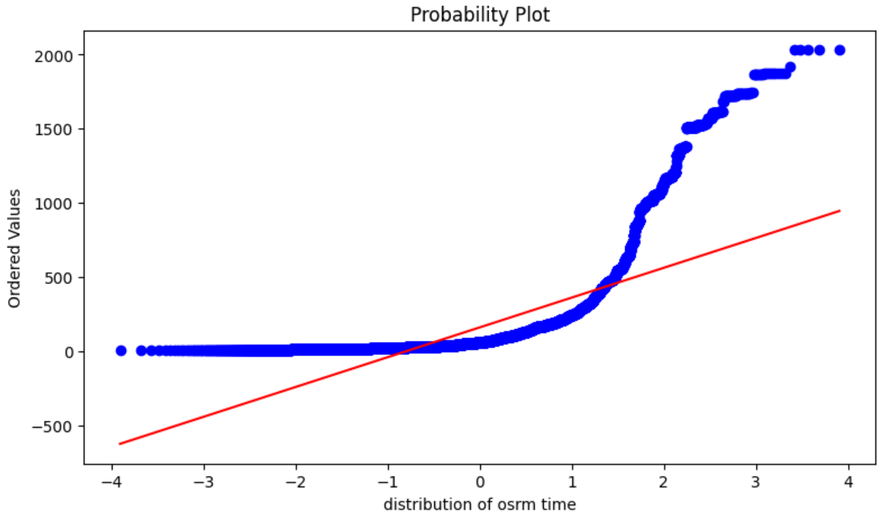
```
print("alpha:",0.05)
print("p_value:",p_value)
print("stat:",statistic)
if p_value<alpha:
  print("Reject Null Hypothesis: The distributions of one or more samples are not equal")
else:
  print('Accept Null Hypothesis: The distributions of all samples are equal')
```

```
sample size d__f_at : 14800
sample size d__f_sat: 14800
alpha: 0.05
p_value: 0.0
stat: 3400.115860061145
Reject Null Hypothesis: The distributions of one or more samples are not equal
```

In [191…

```
# Validation of Assumption 2 by performing Quantile-Quantile Plot Test:
# H0: The sample has a Gaussian distribution.
# H1: The sample does not have a Gaussian distribution.
d__f_at=d__f["actual_time"].sample(14800)
d__f_ot=d__f["osrm_time"].sample(14800)
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
probplot(d__f_at,dist="norm",plot=plt)
plt.xlabel('distribution of actual time',fontsize=10)
plt.subplot(1, 2, 2)
probplot(d__f_ot,dist="norm",plot=plt)
plt.xlabel('distribution of osrm time',fontsize=10)
plt.show()
```

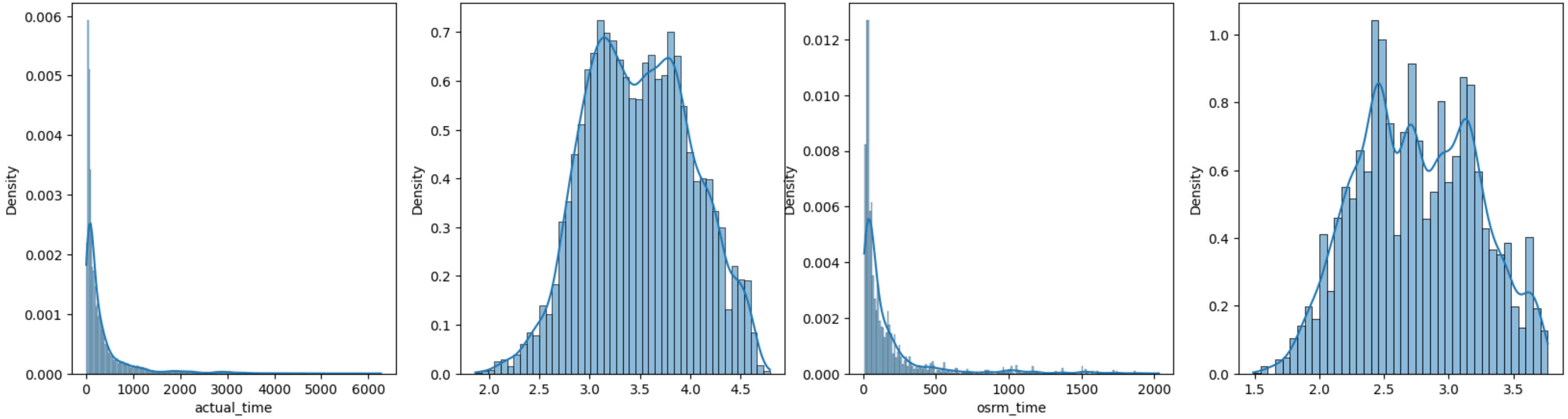




In [192…

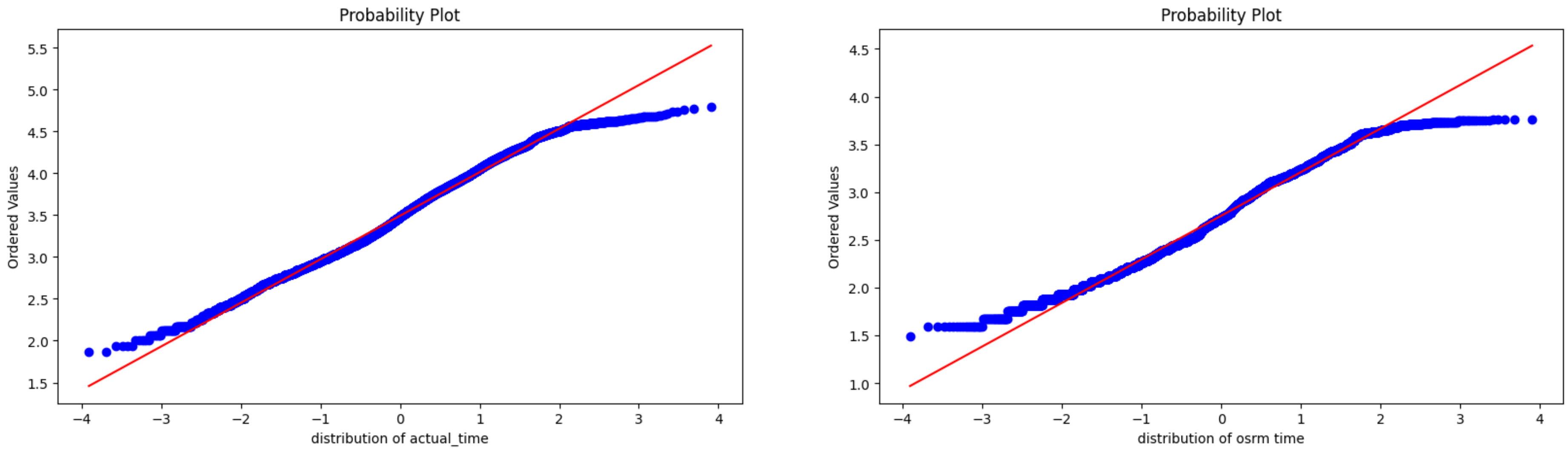
```
# Transforming data by using boxcox transformation:
original_data1=d__f_at
fitted_data1, fitted_lambda1 = boxcox(d__f_at)
original_data2=d__f_ot
fitted_data2, fitted_lambda2 = boxcox(d__f_ot)
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 4, 1)
sns.histplot(original_data1, kde=True, stat="density")
plt.subplot(1, 4, 2)
sns.histplot(fitted_data1, kde=True, stat="density")
print(f"Lambda value used for Transformation of actual time data: {fitted_lambda1}")
plt.subplot(1, 4, 3)
sns.histplot(original_data2, kde=True, stat="density")
plt.subplot(1, 4, 4)
sns.histplot(fitted_data2, kde=True, stat="density")
print(f"Lambda value used for Transformation of segment actual time data : {fitted_lambda2}")
plt.show()
```

```
Lambda value used for Transformation of actual time data: -0.15475467353456
Lambda value used for Transformation of segment actual time data : -0.21319196584205294
```



In [193…

```
# Quantile-Quantile Plot after data transformation:
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
probplot(fitted_data1,dist="norm",plot=plt)
plt.xlabel('distribution of actual_time',fontsize=10)
plt.subplot(1, 2, 2)
probplot(fitted_data2,dist="norm",plot=plt)
plt.xlabel('distribution of osrm time',fontsize=10)
plt.show()
```



In [194…

```
#  Validation of Assumption 3:
# H0:variance of the sample is same.
# Ha:variances of the sample is not same.
alpha=0.05
levene_stat,p_value=levene(d__f_at,d__f_ot)
print("alpha:",0.05)
print("p_value:",p_value)
if p_value<alpha:
  print("Reject Null Hypothesis: Variance of the input datasets is not same")
else:
  print('Accept Null Hypothesis: Variance of the input datasets is Same/Close')
```

```
alpha: 0.05
p_value: 3.470800813899771e-220
Reject Null Hypothesis: Variance of the input datasets is not same
```

Observations:

- As per result of Spearman’s Rank Correlation test, both the samples data are independent.
- It is clear from Kruskal-Wallis H Test, samples are not identically distributed.
- Both sample data are not following normal distribution,it is clear from Q-Q plot.
- After boxcox transformation, it is clear from Q-Q plot, approximately 95% (+-2 sigma) of data points are following normally distribution.
- From levene test it is clear that,Variance of the samples are not same.

Student’s t-test:

- Tests whether the means of two samples are significantly different. ### **Interpretation:**

- H0: The means of the samples are equal.

- H1: The means of the samples are unequal.

In [195…

```
print(d__f["actual_time"].mean())
print(d__f["osrm_time"].mean())
```

```
357.2829054054054
161.47885135135135
```

In [196…

```
# Student’s t-test
d__f_at=d__f["actual_time"]
d__f_ot=d__f["osrm_time"]
print("sample size d__f_at :",len(d__f_at))
print("sample size d__f_sat:",len(d__f_ot))
def t_test(CL):
  alpha=1-(CL/100) # significance level(alpha)
  t_stat,p_value=ttest_ind(d__f_at,d__f_ot,alternative='greater')
  print("Alpha:",alpha)
  print("p value:",p_value)
  print("t statistics:",t_stat)
  if p_value<alpha:
    print("Reject Null Hypothesis: The means of the samples are unequal")
  else:
    print('Accept Null Hypothesis: The means of the samples are equal')
t_test(95)
```

```
sample size d__f_at : 14800
sample size d__f_sat: 14800
Alpha: 0.050000000000000044
p value: 0.0
t statistics: 38.18753943384186
Reject Null Hypothesis: The means of the samples are unequal
```

Observations:

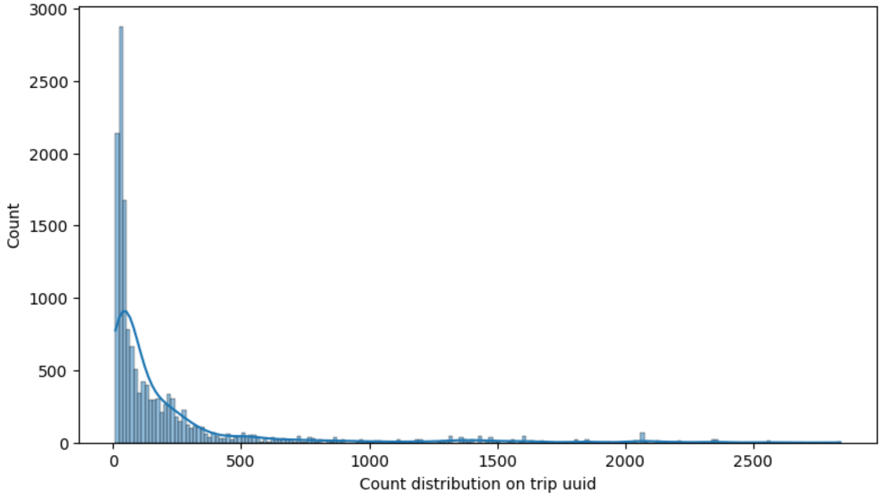
- The calculated p-value : 0.0
- Which is lessar than the significance level.
- Null Hypothesis is Rejected.
- The means of the actual time is significantly greater than osrm time.

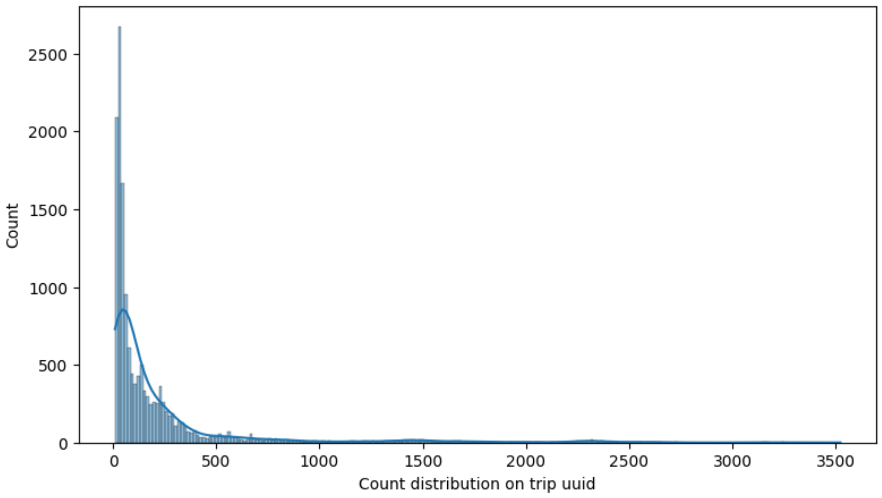
CASE 4: hypothesis testing/ visual analysis between osrm distance aggregated value and segment osrm distance aggregated value

In [197…

```
# visual representation for normality test
d__f_od=d__f["osrm_distance"].reset_index(drop=True)
d__f_sod=d__f["segment_osrm_distance"].reset_index(drop=True)
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
```

```
sns.histplot(d__f_od,kde = True)
plt.xlabel('Count distribution on trip uuid',fontsize=10)
plt.subplot(1, 2, 2)
sns.histplot(d__f_sod,kde = True)
plt.xlabel('Count distribution on trip uuid',fontsize=10)
plt.show()
```





Assumptions under Student's t-test:

- Observations in each sample are independent and identically distributed (iid).
- Observations in each sample are normally distributed.
- Observations in each sample have the same variance.

Validation of assumptions:

In [198…

```
# Validation of Assumption 1 by performing Spearman's Rank Correlation:
# H0: the two samples are independent.
# H1: there is a dependency between the samples.
d__f_od=d__f["osrm_distance"].sample(14800)
d__f_sod=d__f["segment_osrm_distance"].sample(14800)
print("sample size d__f_at :",len(d__f_od))
print("sample size d__f_sat:",len(d__f_sod))
```

```
alpha=0.05
statistic,p_value=spearmanr(d__f_od, d__f_sod)
print("alpha:",0.05)
print("p_value:",p_value)
print("stat:",statistic)
if p_value<alpha:
  print("Reject Null Hypothesis: There is a dependency between the samples")
else:
  print('Accept Null Hypothesis: The two samples are independent')
```

```
sample size d__f_at : 14800
sample size d__f_sat: 14800
alpha: 0.05
p_value: 0.9482026037271275
stat: -0.0005340464768059765
Accept Null Hypothesis: The two samples are independent
```

In [199…

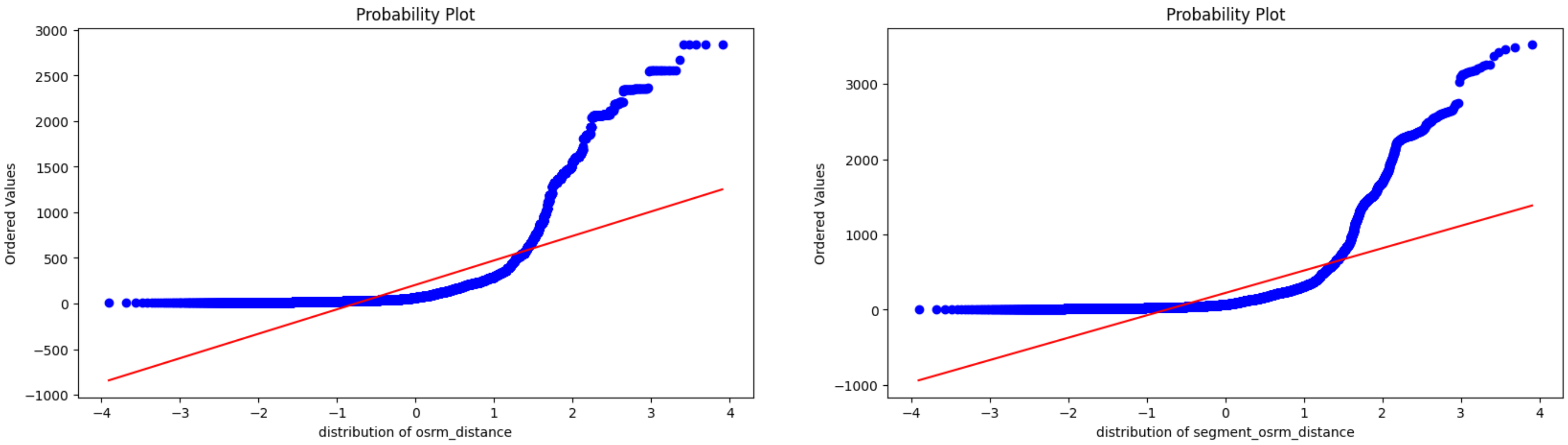
```
#  Validation of Assumption 1 by performing Kruskal-Wallis H Test:
# H0: The distributions of all samples are equal.
# H1: The distributions of one or more samples are not equal.
d__f_od=d__f["osrm_distance"].sample(14800)
d__f_sod=d__f["segment_osrm_distance"].sample(14800)
print("sample size d__f_at :",len(d__f_od))
print("sample size d__f_sat:",len(d__f_sod))
alpha=0.05
statistic,p_value=kruskal(d__f_od, d__f_sod)
print("alpha:",0.05)
print("p_value:",p_value)
print("stat:",statistic)
if p_value<alpha:
  print("Reject Null Hypothesis: The distributions of one or more samples are not equal")
else:
  print('Accept Null Hypothesis: The distributions of all samples are equal')
```

```
sample size d__f_at : 14800
sample size d__f_sat: 14800
alpha: 0.05
p_value: 9.74541771905497e-07
stat: 23.977775085670274
Reject Null Hypothesis: The distributions of one or more samples are not equal
```

In [200…

```
# Validation of Assumption 2 by performing Quantile-Quantile Plot Test:
# H0: The sample has a Gaussian distribution.
# H1: The sample does not have a Gaussian distribution.
```

```
d__f_od=d__f["osrm_distance"].sample(14800)
d__f_sod=d__f["segment_osrm_distance"].sample(14800)
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
probplot(d__f_od,dist="norm",plot=plt)
plt.xlabel('distribution of osrm_distance',fontsize=10)
plt.subplot(1, 2, 2)
probplot(d__f_sod,dist="norm",plot=plt)
plt.xlabel('distribution of segment_osrm_distance',fontsize=10)
plt.show()
```

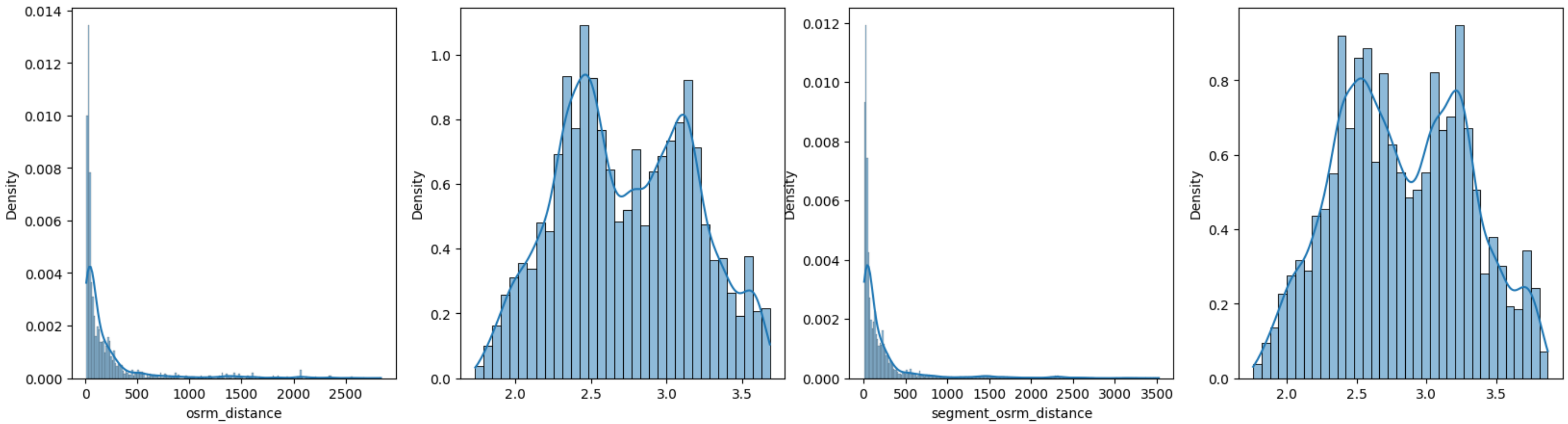


In [201…

```
# Transforming data by using boxcox transformation:
original_data1=d__f_od
fitted_data1, fitted_lambda1 = boxcox(d__f_od)
original_data2=d__f_sod
fitted_data2, fitted_lambda2 = boxcox(d__f_sod)
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 4, 1)
sns.histplot(original_data1, kde=True, stat="density")
plt.subplot(1, 4, 2)
sns.histplot(fitted_data1, kde=True, stat="density")
print(f"Lambda value used for Transformation of actual time data: {fitted_lambda1}")
plt.subplot(1, 4, 3)
sns.histplot(original_data2, kde=True, stat="density")
plt.subplot(1, 4, 4)
sns.histplot(fitted_data2, kde=True, stat="density")
```

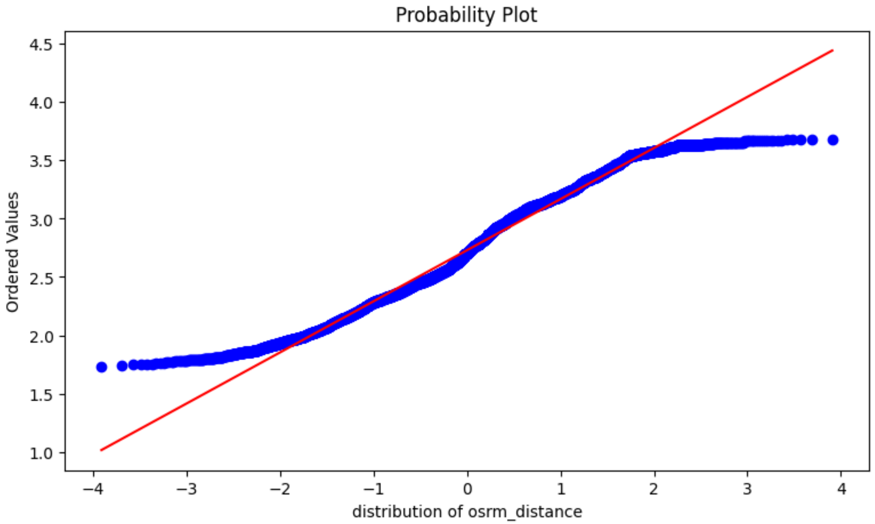
```
print(f"Lambda value used for Transformation of segment actual time data : {fitted_lambda2}")
plt.show()
```

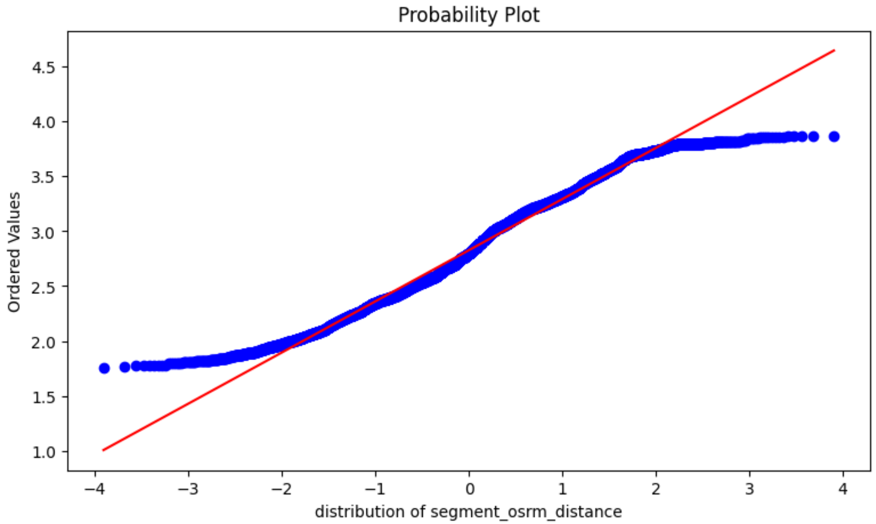
```
Lambda value used for Transformation of actual time data: -0.22688048897680974
Lambda value used for Transformation of segment actual time data : -0.2131924334750331
```



In [202…

```
# Quantile-Quantile Plot after data transformation:
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
probplot(fitted_data1,dist="norm",plot=plt)
plt.xlabel('distribution of osrm_distance',fontsize=10)
plt.subplot(1, 2, 2)
probplot(fitted_data2,dist="norm",plot=plt)
plt.xlabel('distribution of segment_osrm_distance',fontsize=10)
plt.show()
```





In [203…

```
#  Validation of Assumption 3:
# H0:variance of the sample is same.
# Ha:variances of the sample is not same.
alpha=0.05
levene_stat,p_value=levene(d__f_od,d__f_sod)
print("alpha:",0.05)
print("p_value:",p_value)
if p_value<alpha:
  print("Reject Null Hypothesis: Variance of the input datasets is not same")
else:
  print('Accept Null Hypothesis: Variance of the input datasets is Same/Close')
```

```
alpha: 0.05
p_value: 0.00021075232780577555
Reject Null Hypothesis: Variance of the input datasets is not same
```

Observations:

- As per result of Spearman's Rank Correlation test, both the samples data are independent.
- It is clear from Kruskal-Wallis H Test, samples are not identically distributed.
- Both sample data are not following normal distribution,it is clear from Q-Q plot.
- After boxcox transformation, it is clear from Q-Q plot, approximately 68% (+-1 sigma) of data points are following normally distribution.
- From levene test it is clear that,Variance of the samples are not same.

Student’s t-test:

- Tests whether the means of two samples are significantly different. ### **Interpretation:**
- H0: The means of the samples are equal.
- H1: The means of the samples are unequal.

In [204…

```
print(d__f["osrm_distance"].mean())
print(d__f["segment_osrm_distance"].mean())
```

```
204.4722385472973
223.34120322297298
```

In [220…

```
# Paired Student’s t-test
d__f_od=d__f["osrm_distance"].sample(14800)
d__f_sod=d__f["segment_osrm_distance"].sample(14800)
print("sample size d__f_at :",len(d__f_od))
print("sample size d__f_sat:",len(d__f_sod))
def t_test(CL):
  alpha=1-(CL/100) # significance level(alpha)
  t_stat,p_value=ttest_ind(d__f_od,d__f_sod,alternative='less')
  print("Alpha:",alpha)
  print("p value:",p_value)
  print("t statistics:",t_stat)
  if p_value<alpha:
    print("Reject Null Hypothesis: The means of the samples are unequal")
  else:
    print('Accept Null Hypothesis: The means of the samples are equal')
t_test(95)
```

```
sample size d__f_at : 14800
sample size d__f_sat: 14800
Alpha: 0.050000000000000044
p value: 1.9358793633779425e-05
t statistics: -4.115625507230605
Reject Null Hypothesis: The means of the samples are unequal
```

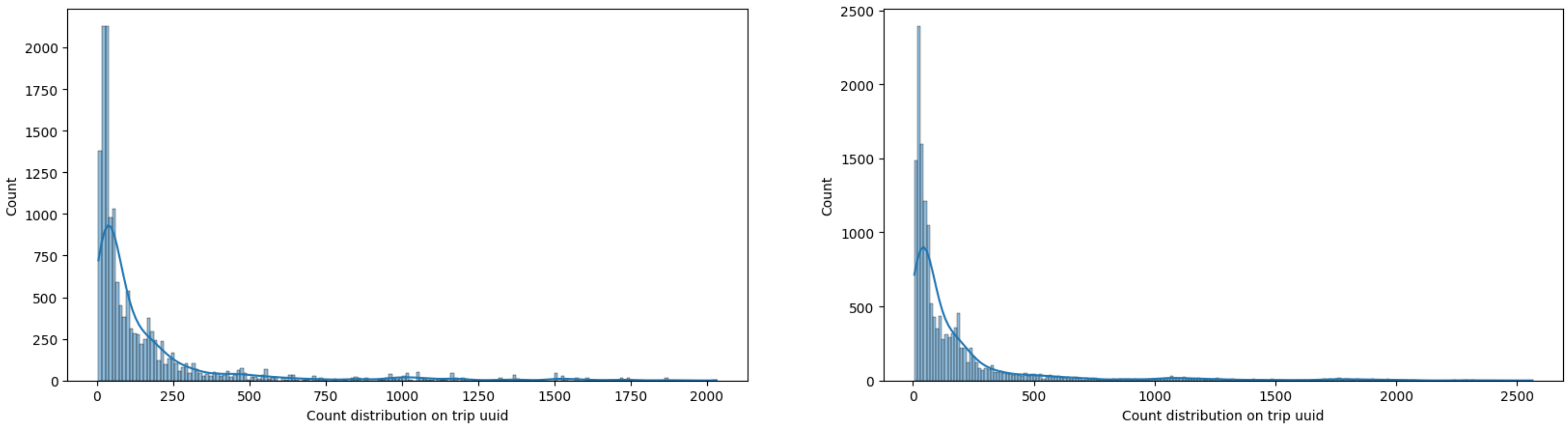
Observations:

- The calculated p-value : 1.9358793633779425e-05
- Which is lessar than the significance level.
- Null Hypothesis is Rejected.
- The means of the osrm distance lesser than the segment osrm distance.

CASE 5: hypothesis testing/ visual analysis between osrm time aggregated value and segment osrm time aggregated value

In [206…

```
# visual representation for normality test
d__f_ot=d__f["osrm_time"].reset_index(drop=True)
d__f_sot=d__f["segment_osrm_time"].reset_index(drop=True)
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
sns.histplot(d__f_ot,kde = True)
plt.xlabel('Count distribution on trip uuid',fontsize=10)
plt.subplot(1, 2, 2)
sns.histplot(d__f_sot,kde = True)
plt.xlabel('Count distribution on trip uuid',fontsize=10)
plt.show()
```



Assumptions under Student’s t-test:

- Observations in each sample are independent and identically distributed (iid).

- Observations in each sample are normally distributed.
- Observations in each sample have the same variance.

Validation of assumptions:

In [207…

```
# Validation of Assumption 1 by performing Spearman’s Rank Correlation:
# H0: the two samples are independent.
# H1: there is a dependency between the samples.
d__f_ot=d__f["osrm_time"].sample(14800)
d__f_sot=d__f["segment_osrm_time"].sample(14800)
print("sample size d__f_at :",len(d__f_ot))
print("sample size d__f_sat:",len(d__f_sot))
alpha=0.05
statistic,p_value=spearmanr(d__f_ot, d__f_sot)
print("alpha:",0.05)
print("p_value:",p_value)
print("stat:",statistic)
if p_value<alpha:
  print("Reject Null Hypothesis: There is a dependency between the samples")
else:
  print('Accept Null Hypothesis: The two samples are independent')
```

```
sample size d__f_at : 14800
sample size d__f_sat: 14800
alpha: 0.05
p_value: 0.47007907795218995
stat: 0.005938132859640371 5
Accept Null Hypothesis: The two samples are independent
```

In [208…

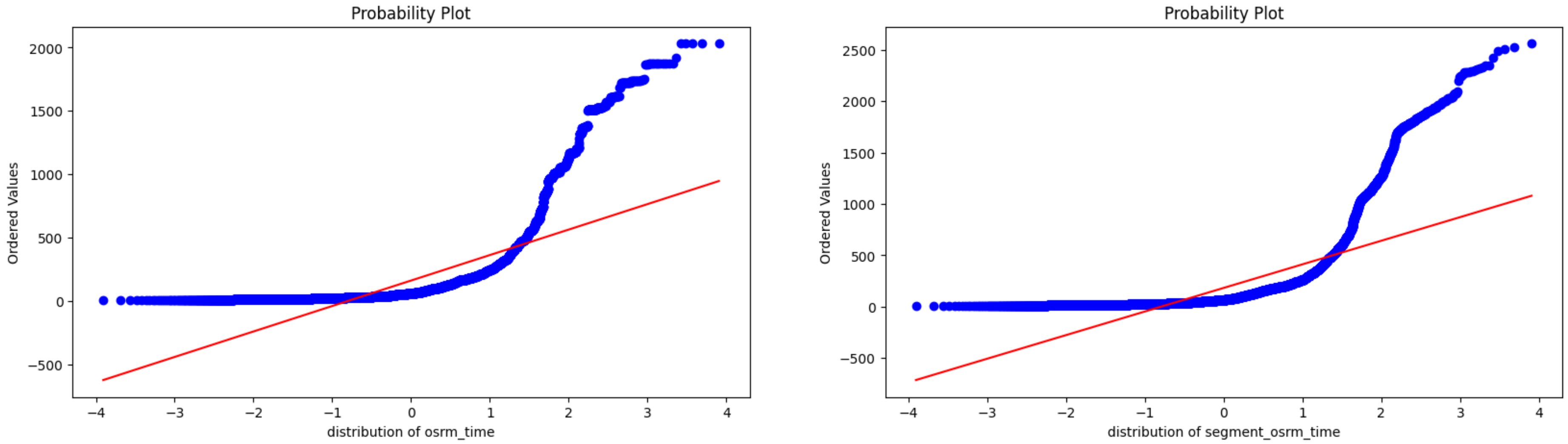
```
#  Validation of Assumption 1 by performing Kruskal-Wallis H Test:
# H0: The distributions of all samples are equal.
# H1: The distributions of one or more samples are not equal.
d__f_ot=d__f["osrm_time"].sample(14800)
d__f_sot=d__f["segment_osrm_time"].sample(14800)
print("sample size d__f_at :",len(d__f_ot))
print("sample size d__f_sat:",len(d__f_sot))
alpha=0.05
statistic,p_value=kruskal(d__f_ot, d__f_sot)
print("alpha:",0.05)
print("p_value:",p_value)
```

```
print("stat:",statistic)
if p_value<alpha:
  print("Reject Null Hypothesis: The distributions of one or more samples are not equal")
else:
  print('Accept Null Hypothesis: The distributions of all samples are equal')
```

```
sample size d__f_at : 14800
sample size d__f_sat: 14800
alpha: 0.05
p_value: 2.388694733325058e-08
stat: 31.14975528566642
Reject Null Hypothesis: The distributions of one or more samples are not equal
```

In [209…

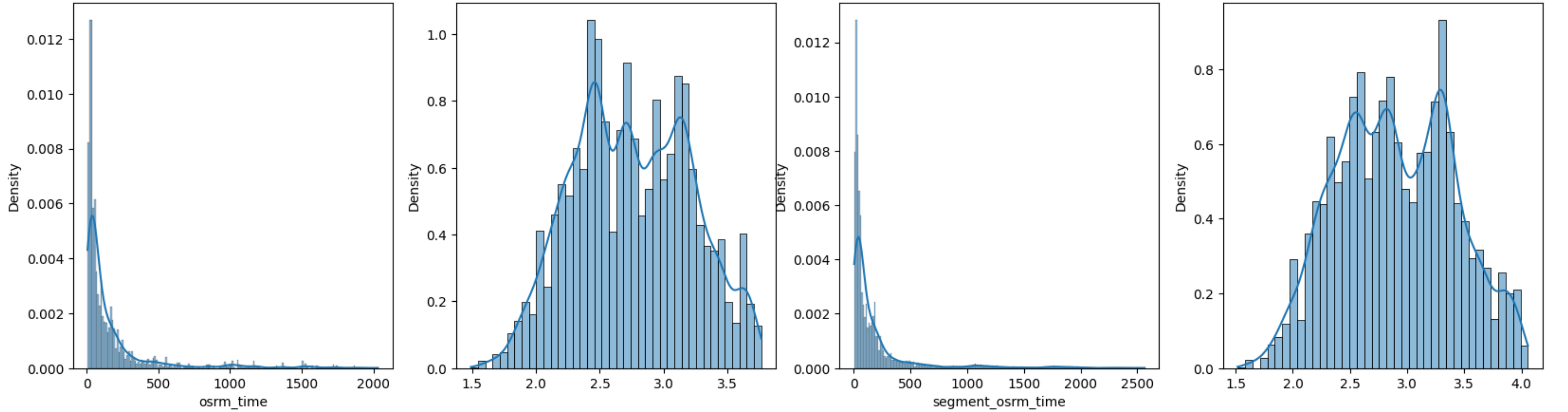
```
# Validation of Assumption 2 by performing Quantile-Quantile Plot Test:
# H0: The sample has a Gaussian distribution.
# H1: The sample does not have a Gaussian distribution.
d__f_ot=d__f["osrm_time"].sample(14800)
d__f_sot=d__f["segment_osrm_time"].sample(14800)
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
probplot(d__f_ot,dist="norm",plot=plt)
plt.xlabel('distribution of osrm_time',fontsize=10)
plt.subplot(1, 2, 2)
probplot(d__f_sot,dist="norm",plot=plt)
plt.xlabel('distribution of segment_osrm_time',fontsize=10)
plt.show()
```



In [210…

```
# Transforming data by using boxcox transformation:
original_data1=d__f_ot
fitted_data1, fitted_lambda1 = boxcox(d__f_ot)
original_data2=d__f_sot
fitted_data2, fitted_lambda2 = boxcox(d__f_sot)
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 4, 1)
sns.histplot(original_data1, kde=True, stat="density")
plt.subplot(1, 4, 2)
sns.histplot(fitted_data1, kde=True, stat="density")
print(f"Lambda value used for Transformation of actual time data: {fitted_lambda1}")
plt.subplot(1, 4, 3)
sns.histplot(original_data2, kde=True, stat="density")
plt.subplot(1, 4, 4)
sns.histplot(fitted_data2, kde=True, stat="density")
print(f"Lambda value used for Transformation of segment actual time data : {fitted_lambda2}")
plt.show()
```

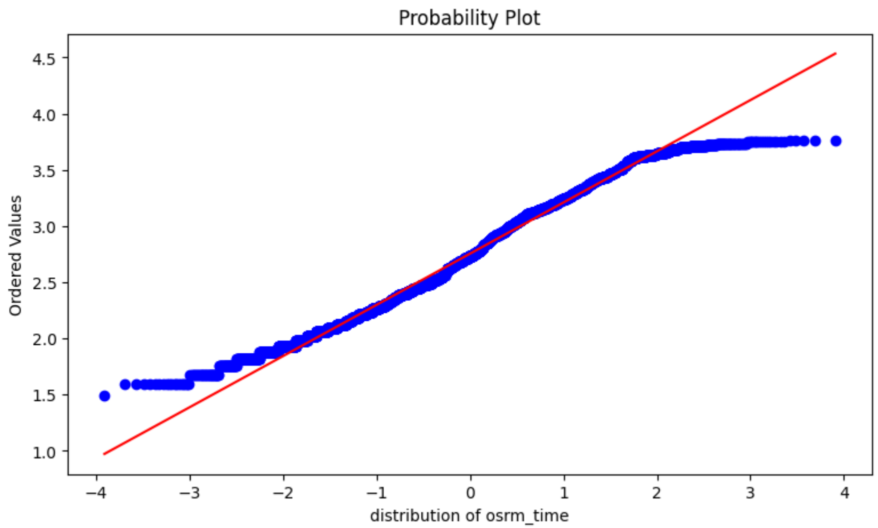
```
Lambda value used for Transformation of actual time data: -0.21319194452961855
Lambda value used for Transformation of segment actual time data : -0.19181266458171708
```

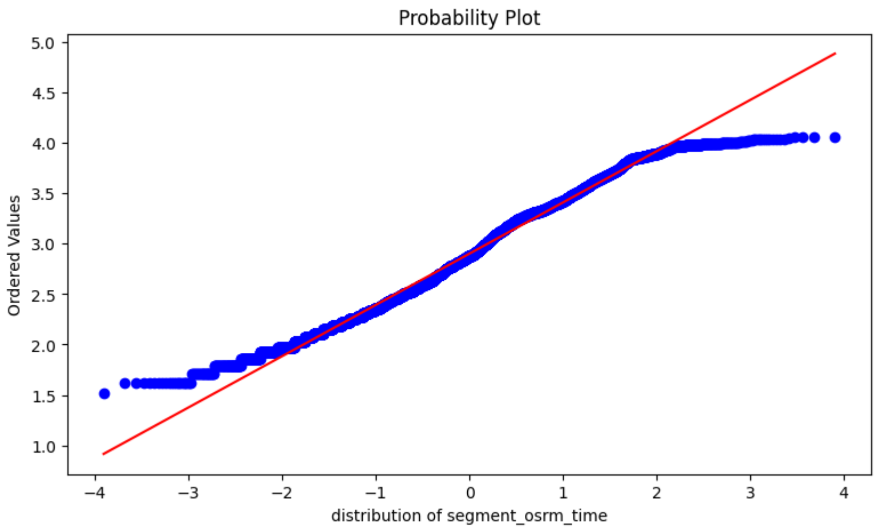


In [211…

```
# Quantile-Quantile Plot after data transformation:
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
probplot(fitted_data1,dist="norm",plot=plt)
plt.xlabel('distribution of osrm_time',fontsize=10)
plt.subplot(1, 2, 2)
```

```
probplot(fitted_data2,dist="norm",plot=plt)
plt.xlabel('distribution of segment_osrm_time',fontsize=10)
plt.show()
```





In [212…

```
#  Validation of Assumption 3:
# H0:variance of the sample is same.
# Ha:variances of the sample is not same.
alpha=0.05
levene_stat,p_value=levene(d__f_ot,d__f_sot)
print("alpha:",0.05)
print("p_value:",p_value)
if p_value<alpha:
  print("Reject Null Hypothesis: Variance of the input datasets is not same")
else:
  print('Accept Null Hypothesis: Variance of the input datasets is Same/Close')
```

```
alpha: 0.05
p_value: 8.434382972244705e-08
Reject Null Hypothesis: Variance of the input datasets is not same
```

Observations:

- As per result of Spearman's Rank Correlation test, both the samples data are independent.
- It is clear from Kruskal-Wallis H Test, samples are not identically distributed.
- Both sample data are not following normal distribution,it is clear from Q-Q plot.

- After boxcox transformation, it is clear from Q-Q plot, approximately 68% (+-1 sigma) of data points are following normally distribution.
- From levene test it is clear that,Variance of the samples are not same.

Student's t-test:

- Tests whether the means of two samples are significantly different. ### **Interpretation:**
- H0: The means of the samples are equal.
- H1: The means of the samples are unequal.

In [213…

```
print(d__f["osrm_time"].mean())
print(d__f["segment_osrm_time"].mean())
```

```
161.47885135135135
181.05628378378378
```

In [214…

```
# Student's t-test
d__f_ot=d__f["osrm_time"].sample(14800)
d__f_sot=d__f["segment_osrm_time"].sample(14800)
print("sample size d__f_at :",len(d__f_ot))
print("sample size d__f_sat:",len(d__f_sot))
def t_test(CL):
  alpha=1-(CL/100) # significance level(alpha)
  t_stat,p_value=ttest_rel(d__f_ot,d__f_sot,alternative='less')
  print("Alpha:",alpha)
  print("p value:",p_value)
  print("t statistics:",t_stat)
  if p_value<alpha:
    print("Reject Null Hypothesis: The means of the samples are unequal")
  else:
    print('Accept Null Hypothesis: The means of the samples are equal')
t_test(95)
```

```
sample size d__f_at : 14800
sample size d__f_sat: 14800
Alpha: 0.050000000000000044
p value: 5.2537368011304388e-09
t statistics: -5.725590783077166
Reject Null Hypothesis: The means of the samples are unequal
```

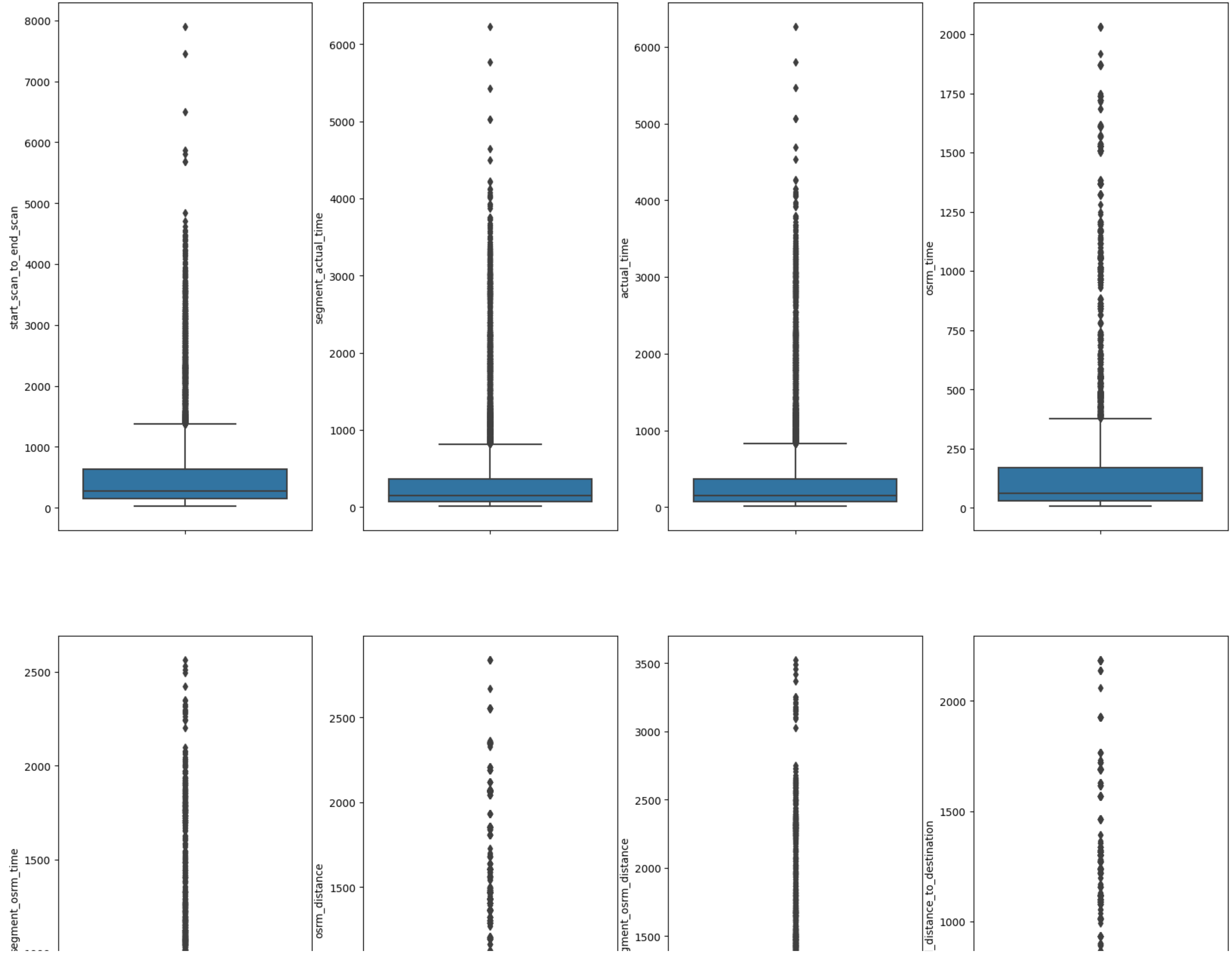
Observations:

- The calculated p-value : 5.045903058766468e-09
- Which is lessar than the significance level.
- Null Hypothesis is Rejected.
- The means of the osrm time is lesser than segment osrm time.

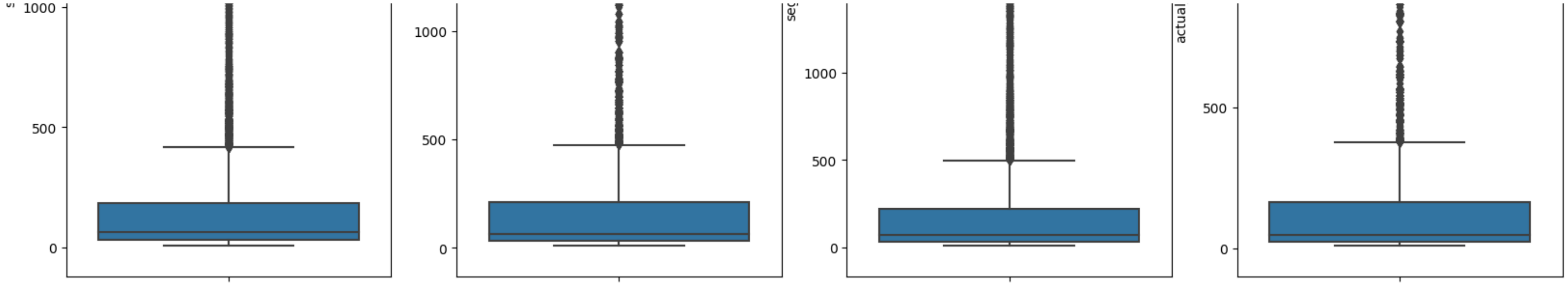
Outlier Treatment:

In [215…

```
# outlier detection
fig = plt.figure(figsize=(20,20))
plt.subplot(2, 4, 1)
sns.boxplot(data=d__f,y='start_scan_to_end_scan')
plt.subplot(2, 4, 2)
sns.boxplot(data=d__f,y='segment_actual_time')
plt.subplot(2, 4, 3)
sns.boxplot(data=d__f,y='actual_time')
plt.subplot(2, 4, 4)
sns.boxplot(data=d__f,y='osrm_time')
plt.subplot(2, 4, 5)
sns.boxplot(data=d__f,y='segment_osrm_time')
plt.subplot(2, 4, 6)
sns.boxplot(data=d__f,y='osrm_distance')
plt.subplot(2, 4, 7)
sns.boxplot(data=d__f,y='segment_osrm_distance')
plt.subplot(2, 4, 8)
sns.boxplot(data=d__f,y='actual_distance_to_destination')
plt.show()
```

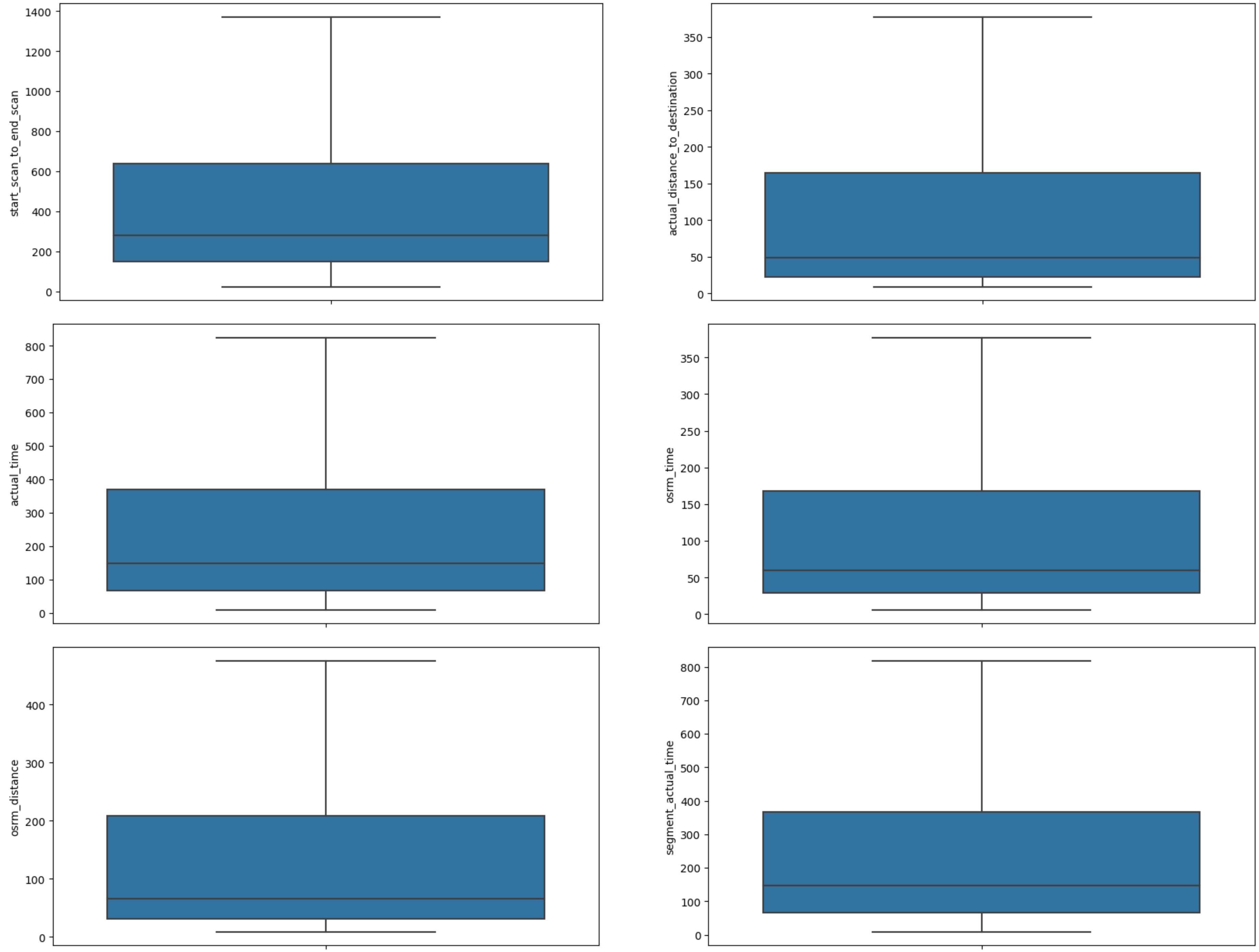


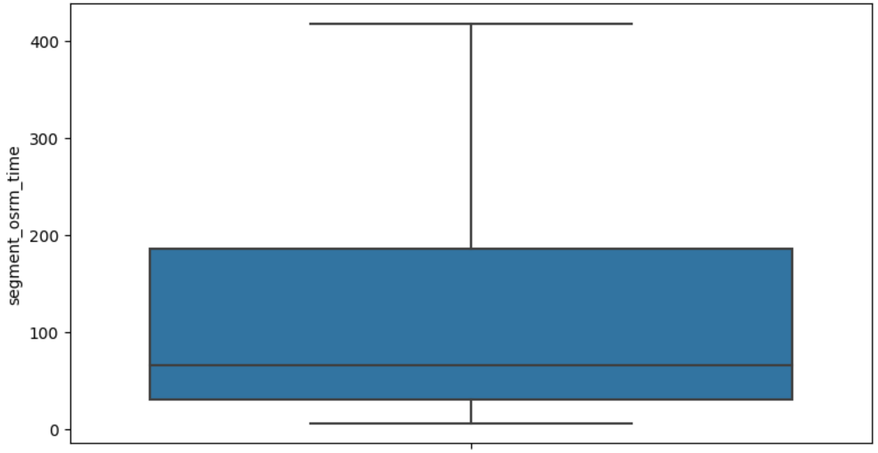
start_scan_to_end_scan
0
1000
2000
3000
4000
5000
6000
7000
8000
segment_actual_time
0
1000
2000
3000
4000
5000
6000
actual_time
0
1000
2000
3000
4000
5000
6000
osrm_time
0
250
500
750
1000
1250
1500
1750
2000
egment_osrm_time
1500
2000
2500
osrm_distance
1500
2000
2500
gment_osrm_distance
1500
2000
2500
3000
3500
_distance_to_destination
1000
1500
2000

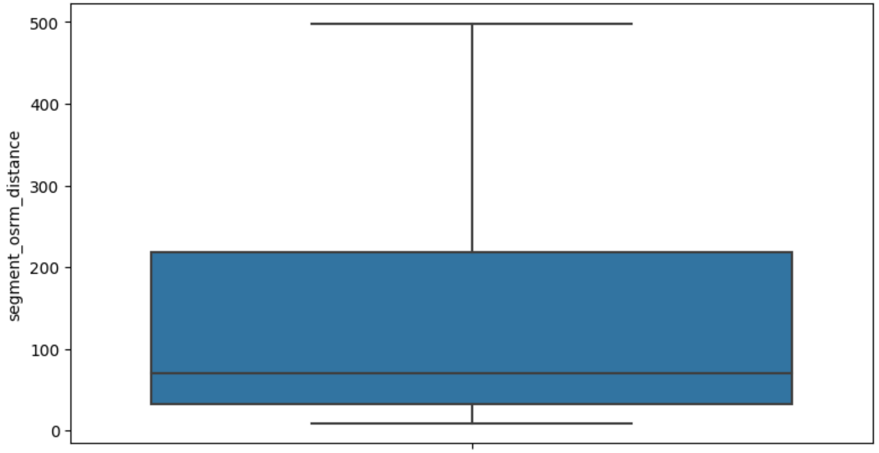


In [216…

```
# Outlier Removal:
new_df=d__f.copy()
def outlier(a,b,c,d):
  Q25 = new_df[b].quantile(0.25)
  Q75 = new_df[b].quantile(0.75)
  IQR = Q75-Q25
  fig = plt.figure(figsize=(20,5))
  plt.subplot(1, 2, a)
  new_df.loc[(new_df[b]>(Q75 + 1.5*IQR)),b]=(Q75 + 1.5*IQR)
  new_df.loc[(new_df[b]<(Q25 - 1.5*IQR)),b]=(Q25 - 1.5*IQR)
  sns.boxplot(data=new_df,y=b)
  Q25 = new_df[d].quantile(0.25)
  Q75 = new_df[d].quantile(0.75)
  IQR = Q75-Q25
  plt.subplot(1, 2, c )
  new_df.loc[(new_df[d]>(Q75 + 1.5*IQR)),d]=(Q75 + 1.5*IQR)
  new_df.loc[(new_df[d]<(Q25 - 1.5*IQR)),d]=(Q25 - 1.5*IQR)
  sns.boxplot(data=new_df,y=d)
  plt.show()
outlier(1,'start_scan_to_end_scan',2,'actual_distance_to_destination')
outlier(1,'actual_time',2,'osrm_time')
outlier(1,'osrm_distance',2,'segment_actual_time')
outlier(1,'segment_osrm_time',2,'segment_osrm_distance')
```


start_scan_to_end_scan
actual_distance_to_destination
actual_time
osrm_time
osrm_distance
segment_actual_time





Observations:

- It is clear from boxplot, outlier has been removed.

Hot encoding of categorical variables:

In [217…

```
d__f1=d__f.copy()
pd.get_dummies(d__f1, columns = ['data', 'route_type'])
```

Out[217]:

	trip_uuid	source_center	destination_center	start_scan_to_end_scan	actual_distance_to_destination	actual_time	osrm_time	osrm_dista
0	trip-153671041653548748	IND462022AAA	IND000000ACB	2259.0	824.732854	1562.0	717.0	991.3
1	trip-153671042288605164	IND572101AAA	IND562101AAA	180.0	73.186911	143.0	68.0	85.1
2	trip-153671043369099517	IND562132AAA	IND160002AAC	3933.0	1927.404273	3347.0	1740.0	2354.0
3	trip-153671046011330457	IND400072AAB	IND401104AAA	100.0	17.175274	59.0	15.0	19.6
4	trip-153671052974046625	IND583101AAA	IND583101AAA	717.0	127.448500	341.0	117.0	146.7
...	...	...	...	...	...	...	...	
14812	trip-153861095625827784	IND160002AAC	IND160002AAC	257.0	57.762332	83.0	62.0	73.4
14813	trip-153861104386292051	IND121004AAB	IND121004AAA	60.0	15.513784	21.0	12.0	16.0
14814	trip-153861106442901555	IND209304AAA	IND209304AAA	421.0	38.684839	282.0	48.0	58.9
14815	trip-153861115439069069	IND627005AAA	IND627005AAA	347.0	134.723836	264.0	179.0	171.1
14816	trip-153861118270144424	IND583201AAA	IND583101AAA	353.0	66.081533	275.0	68.0	80.5

14800 rows × 24 columns

Normalize/ Standardize the numerical features using MinMaxScaler or StandardScaler:

In [218…

```
# Normalization of numerical data_set
# Using MinMax Scaler
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
```

```
d__f1[['start_scan_to_end_scan',
       'actual_distance_to_destination', 'actual_time', 'osrm_time',
       'osrm_distance', 'segment_actual_time', 'segment_osrm_time',
       'segment_osrm_distance', 'diff']]=scaler.fit_transform(d__f1[['start_scan_to_end_scan',
       'actual_distance_to_destination', 'actual_time', 'osrm_time',
       'osrm_distance', 'segment_actual_time', 'segment_osrm_time',
       'segment_osrm_distance', 'diff']])
d__f1
```

Out[218]:

	trip_uuid	data	source_center	destination_center	route_type	start_scan_to_end_scan	actual_distance_to_destination	actual_time	o
0	trip-153671041653548748	training	IND462022AAA	IND000000ACB	FTL	0.283937	0.374613	0.248242	
1	trip-153671042288605164	training	IND572101AAA	IND562101AAA	Carting	0.019937	0.029476	0.021419	
2	trip-153671043369099517	training	IND562132AAA	IND160002AAC	FTL	0.496508	0.880999	0.533568	
3	trip-153671046011330457	training	IND400072AAB	IND401104AAA	Carting	0.009778	0.003753	0.007992	
4	trip-153671052974046625	training	IND583101AAA	IND583101AAA	FTL	0.088127	0.054395	0.053069	
...	...	...	...	...	...	...	...	...	
14812	trip-153861095625827784	test	IND160002AAC	IND160002AAC	Carting	0.029714	0.022392	0.011829	
14813	trip-153861104386292051	test	IND121004AAB	IND121004AAA	Carting	0.004698	0.002990	0.001918	
14814	trip-153861106442901555	test	IND209304AAA	IND209304AAA	Carting	0.050540	0.013631	0.043638	
14815	trip-153861115439069069	test	IND627005AAA	IND627005AAA	Carting	0.041143	0.057736	0.040761	
14816	trip-153861118270144424	test	IND583201AAA	IND583101AAA	FTL	0.041905	0.026213	0.042519	

14800 rows × 22 columns

Observations:

- After Normalization of numerical dataset, all values are converted within the new range of 0 and 1.
- It is done by the help of this expression y = (x – min) / (max – min).

In [219…

```
# Using StandardScaler
d__f2=d__f.copy()
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
d__f2[['start_scan_to_end_scan',
       'actual_distance_to_destination', 'actual_time', 'osrm_time',
       'osrm_distance', 'segment_actual_time', 'segment_osrm_time',
       'segment_osrm_distance', 'diff']]=scaler.fit_transform(d__f2[['start_scan_to_end_scan',
       'actual_distance_to_destination', 'actual_time', 'osrm_time',
       'osrm_distance', 'segment_actual_time', 'segment_osrm_time',
       'segment_osrm_distance', 'diff']])
d__f2
```

Out[219]:

	trip_uuid	data	source_center	destination_center	route_type	start_scan_to_end_scan	actual_distance_to_destination	actual_time	o
0	trip-153671041653548748	training	IND462022AAA	IND000000ACB	FTL	2.623454	2.160648	2.145243	
1	trip-153671042288605164	training	IND572101AAA	IND562101AAA	Carting	-0.532810	-0.299138	-0.381574	
2	trip-153671043369099517	training	IND562132AAA	IND160002AAC	FTL	5.164863	5.769657	5.323797	
3	trip-153671046011330457	training	IND400072AAB	IND401104AAA	Carting	-0.654264	-0.482462	-0.531153	
4	trip-153671052974046625	training	IND583101AAA	IND583101AAA	FTL	0.282444	-0.121541	-0.028995	
...	...	...	...	...	...	...	...	...	
14812	trip-153861095625827784	test	IND160002AAC	IND160002AAC	Carting	-0.415912	-0.349622	-0.488416	
14813	trip-153861104386292051	test	IND121004AAB	IND121004AAA	Carting	-0.714990	-0.487900	-0.598820	
14814	trip-153861106442901555	test	IND209304AAA	IND209304AAA	Carting	-0.166933	-0.412062	-0.134056	
14815	trip-153861115439069069	test	IND627005AAA	IND627005AAA	Carting	-0.279277	-0.097729	-0.166109	
14816	trip-153861118270144424	test	IND583201AAA	IND583101AAA	FTL	-0.270168	-0.322393	-0.146521	

14800 rows × 22 columns

Observations:

- Standardizing a dataset involves rescaling the distribution of values so that the mean of observed values is 0 and the standard deviation is 1.

Business Insights:

1. Delhivery Bussines case study having 144867 rows and 24 columns.
2. After performing aggregation on dataset,14817 unique trip id has beed found.
3. In this data set, total 868 unique source centre has been detected.
4. Total observed Unique destination centre are 956.
5. Highest order received by Mumbai city.
6. Highest order received by state-wise is Maharashtra.
7. Top 5 source states are Maharashtra, Karnataka, Haryana, Tamil Nadu, and Delhi.
8. Top 5 source cities are Gurgaon, Bengaluru ,Mumbai, Bhiwandi and Bangalore
9. Busiest corridors are Mumbai to Mumbai having average distance is 16Km taking approximately 63 minutes.
10. Longest Corridor between cities is Guwahati to Bhiwandi having distance of 2140 Km and taking average time around 5457 minutes to delivered order.
11. Based on two sample t-test, there is no significant difference between mean of Actual time and segment actual time.
12. Based on two sample t-test the mean of the difference between order start time to order end time & start scan to end scan is higher.
13. Based on two sample t-test, there is significant difference between mean of Actual time and osrm time has been observed.
14. Based on two sample t-test, the means of the actual time is significantly greater than osrm time
15. Based on two sample t-test, there is significant difference between mean of osrm distance and segment osrm distance has been observed. And mean of segment osrm distance is higher than the osrm distance.
16. Based on two sample t-test, the mean of the osrm time is lesser than segment osrm time.

Recommendations:

1. As the actual time is more than the osrm time therefore scheduling of order has to be done on the basis of actual time.
2. As the segment osrm distance is more than osrm distance trip planning must done by taking care of segment osrm distance.
3. Proper selections of the distribution centre can reduce average travel time to the customers.
4. All products picked up at the same source city and destined to the same destination city are aggregated together.
5. Sometimes there may be need to aggregate not only by distribution pattern but also by logistics characteristics,such as weight and volume.
6. Distribution centers and check points must be linked with advanced information systems to ensure that all pickups and deliveries are made within the schedule time.