Delhivery

June 17, 2025

[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as scpy
```

[ ]:
```
from google.colab import files
data=files.upload()
```

```
<IPython.core.display.HTML object>
```

```
Saving delhivery_data.txt to delhivery_data.txt
```

[ ]:
```
df=pd.read_csv('delhivery_data.txt')
df.head()
```

[ ]:
```
       data          trip_creation_time  \
0  training  2018-09-20 02:35:36.476840
1  training  2018-09-20 02:35:36.476840
2  training  2018-09-20 02:35:36.476840
3  training  2018-09-20 02:35:36.476840
4  training  2018-09-20 02:35:36.476840

                              route_schedule_uuid route_type  \
0  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
1  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
2  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
3  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
4  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting

                 trip_uuid source_center                source_name  \
0  trip-153741093647649320  IND388121AAA  Anand_VUNagar_DC (Gujarat)
1  trip-153741093647649320  IND388121AAA  Anand_VUNagar_DC (Gujarat)
2  trip-153741093647649320  IND388121AAA  Anand_VUNagar_DC (Gujarat)
3  trip-153741093647649320  IND388121AAA  Anand_VUNagar_DC (Gujarat)
4  trip-153741093647649320  IND388121AAA  Anand_VUNagar_DC (Gujarat)

  destination_center              destination_name  \
```

```
0       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
1       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
2       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
3       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
4       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)

                od_start_time  …            cutoff_timestamp  \
0  2018-09-20 03:21:32.418600  …         2018-09-20 04:27:55
1  2018-09-20 03:21:32.418600  …         2018-09-20 04:17:55
2  2018-09-20 03:21:32.418600  …  2018-09-20 04:01:19.505586
3  2018-09-20 03:21:32.418600  …         2018-09-20 03:39:57
4  2018-09-20 03:21:32.418600  …         2018-09-20 03:33:55

   actual_distance_to_destination  actual_time  osrm_time osrm_distance  \
0                       10.435660         14.0       11.0       11.9653
1                       18.936842         24.0       20.0       21.7243
2                       27.637279         40.0       28.0       32.5395
3                       36.118028         62.0       40.0       45.5620
4                       39.386040         68.0       44.0       54.2181

     factor  segment_actual_time  segment_osrm_time  segment_osrm_distance  \
0  1.272727                 14.0               11.0                11.9653
1  1.200000                 10.0                9.0                 9.7590
2  1.428571                 16.0                7.0                10.8152
3  1.550000                 21.0               12.0                13.0224
4  1.545455                  6.0                5.0                 3.9153

   segment_factor
0        1.272727
1        1.111111
2        2.285714
3        1.750000
4        1.200000

[5 rows x 24 columns]
```

1. Basic data cleaning and EDA

Get shape of the data

[ ]:
```
df.shape
```

[ ]:
```
(144867, 24)
```

Data consisits of 144867 rows and 24 columns

Columns and Datatype

[ ]:
```
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  object 
 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  object 
 10  od_end_time                     144867 non-null  object 
 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  object 
 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), float64(10), int64(1), object(12)
memory usage: 25.6+ MB
```

[ ]:
```
#dropping unknown fields
unknown_feilds=["is_cutoff","cutoff_factor",'cutoff_timestamp',"factor","segment_factor"]
df=df.drop(unknown_feilds,axis=1)
```

These are the unknown fields shown in the dataset. Therefore, these columns are removed for further analysis.

[ ]:
```
# checking unique entities in each column
for col in df.columns:
  print(col, "=", df[col].nunique())
```

```
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
actual_distance_to_destination = 144515
actual_time = 3182
osrm_time = 1531
osrm_distance = 138046
segment_actual_time = 747
segment_osrm_time = 214
segment_osrm_distance = 113799
```

[ ]:
```
#converting cols to category
category=['data','route_type']
for col in category:
  df[col]=df[col].astype("category")
```

[ ]:
```
# converting cols to float
floating_columns=['segment_osrm_distance','start_scan_to_end_scan','actual_distance_to_destina
for col in floating_columns:
  df[col]=df[col].astype('float32')
```

[ ]:
```
# converting string to date 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.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144867 entries, 0 to 144866
Data columns (total 19 columns):
 #   Column                        Non-Null Count   Dtype
---  ------                        --------------   -----
 0   data                          144867 non-null  category
 1   trip_creation_time            144867 non-null  datetime64[ns]
 2   route_schedule_uuid           144867 non-null  object
 3   route_type                    144867 non-null  category
 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  float32
 12  actual_distance_to_destination   144867 non-null  float32
 13  actual_time                      144867 non-null  float32
 14  osrm_time                        144867 non-null  float32
 15  osrm_distance                    144867 non-null  float32
 16  segment_actual_time              144867 non-null  float32
 17  segment_osrm_time                144867 non-null  float32
 18  segment_osrm_distance            144867 non-null  float32
dtypes: category(2), datetime64[ns](3), float32(8), object(6)
memory usage: 14.6+ MB
```

Missing or null values

[ ]:
```
df.isnull().sum()
```

[ ]:
```
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
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
```

[ ]:
```
#filling null value in source_name
df['source_name']=df['source_name'].fillna('unknown')
df['destination_name']=df['destination_name'].fillna('unknown')
```

[ ]:
```
df.isnull().sum()
```

[ ]:
```
data                              0
trip_creation_time                0
route_schedule_uuid               0
route_type                        0
trip_uuid                         0
source_center                     0
```

```
source_name                          0
destination_center                   0
destination_name                     0
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
```

Basic description about the data

[ ]:
```
df.describe()
```

[ ]:
```
                trip_creation_time                 od_start_time  \
count                       144867                        144867
mean   2018-09-22 13:34:23.659819264  2018-09-22 18:02:45.855230720
min       2018-09-12 00:00:16.535741     2018-09-12 00:00:16.535741
25%    2018-09-17 03:20:51.775845888  2018-09-17 08:05:40.886155008
50%    2018-09-22 04:24:27.932764928  2018-09-22 08:53:00.116656128
75%    2018-09-27 17:57:56.350054912  2018-09-27 22:41:50.285857024
max       2018-10-03 23:59:42.701692     2018-10-06 04:27:23.392375
std                              NaN                           NaN

                        od_end_time  start_scan_to_end_scan  \
count                        144867           144867.000000
mean   2018-09-23 10:04:31.395393024              961.262939
min       2018-09-12 00:50:10.814399               20.000000
25%    2018-09-18 01:48:06.410121984              161.000000
50%    2018-09-23 03:13:03.520212992              449.000000
75%    2018-09-28 12:49:06.054018048             1634.000000
max       2018-10-08 03:00:24.353479             7898.000000
std                              NaN             1036.997803

       actual_distance_to_destination    actual_time      osrm_time  \
count                  144867.000000  144867.000000  144867.000000
mean                      234.073380     416.927521     213.868286
min                         9.000046       9.000000       6.000000
25%                        23.355875      51.000000      27.000000
50%                        66.126572     132.000000      64.000000
75%                       286.708878     513.000000     257.000000
max                      1927.447754    4532.000000    1686.000000
```

```
std                        344.979126     598.096069     308.004333

       osrm_distance  segment_actual_time  segment_osrm_time  \
count  144867.000000        144867.000000      144867.000000
mean      284.771301            36.196110          18.507547
min         9.008200          -244.000000           0.000000
25%        29.914701            20.000000          11.000000
50%        78.525803            29.000000          17.000000
75%       343.193253            40.000000          22.000000
max      2326.199219          3051.000000        1611.000000
std       421.117462            53.566002          14.770471

       segment_osrm_distance
count          144867.000000
mean               22.829018
min                 0.000000
25%                12.070100
50%                23.513000
75%                27.813250
max              2191.403809
std                17.860197
```

[ ]:
```
df.describe(include='object')
```

[ ]:
```
                                    route_schedule_uuid  \
count                                            144867
unique                                             1504
top     thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f…
freq                                               1812

                      trip_uuid source_center                    source_name  \
count                    144867        144867                         144867
unique                    14817          1508                           1499
top     trip-153759210483476123   IND000000ACB  Gurgaon_Bilaspur_HB (Haryana)
freq                        101         23347                          23347

       destination_center              destination_name
count              144867                        144867
unique               1481                          1469
top          IND000000ACB  Gurgaon_Bilaspur_HB (Haryana)
freq                15192                         15192
```

Merging rows and aggregration

[ ]:
```
segment_agg = df.groupby(['trip_uuid', 'source_center', 'destination_center']).
↪agg({
    # Meta info
```

```
    'data': 'first',
    'route_type': 'first',
    'trip_creation_time': 'first',

    # Location info
    'source_name': 'first',
    'destination_name': 'last',

    # Time info
    'od_start_time': 'min',     # Earliest segment start
    'od_end_time': 'max',       # Latest segment end
    'start_scan_to_end_scan': 'sum',  # Total scan-to-scan duration

    # Distance & time (actual and OSRM)
    'actual_distance_to_destination': 'first',  # Assume this is same for all␣
 ↪rows
    'actual_time': 'sum',
    'osrm_time':'sum',
    'osrm_distance': 'sum',

    # Segment-level aggregates
    'segment_actual_time': 'sum',
    'segment_osrm_time': 'sum',
    'segment_osrm_distance': 'sum'
}).reset_index()
segment_agg
```

[ ]:

	trip_uuid	source_center	destination_center	data	\
0	trip-153671041653548748	IND209304AAA	IND000000ACB	training	
1	trip-153671041653548748	IND462022AAA	IND209304AAA	training	
2	trip-153671042288605164	IND561203AAB	IND562101AAA	training	
3	trip-153671042288605164	IND572101AAA	IND561203AAB	training	
4	trip-153671043369099517	IND000000ACB	IND160002AAC	training	
…	…	…	…	…	
26363	trip-153861115439069069	IND628204AAA	IND627657AAA	test	
26364	trip-153861115439069069	IND628613AAA	IND627005AAA	test	
26365	trip-153861115439069069	IND628801AAA	IND628204AAA	test	
26366	trip-153861118270144424	IND583119AAA	IND583101AAA	test	
26367	trip-153861118270144424	IND583201AAA	IND583119AAA	test	

	route_type	trip_creation_time	\
0	FTL	2018-09-12 00:00:16.535741	
1	FTL	2018-09-12 00:00:16.535741	
2	Carting	2018-09-12 00:00:22.886430	
3	Carting	2018-09-12 00:00:22.886430	
4	FTL	2018-09-12 00:00:33.691250	
…	…	…	

```
26363    Carting 2018-10-03 23:59:14.390954
26364    Carting 2018-10-03 23:59:14.390954
26365    Carting 2018-10-03 23:59:14.390954
26366        FTL 2018-10-03 23:59:42.701692
26367        FTL 2018-10-03 23:59:42.701692

                             source_name  \
0      Kanpur_Central_H_6 (Uttar Pradesh)
1      Bhopal_Trnsport_H (Madhya Pradesh)
2       Doddablpur_ChikaDPP_D (Karnataka)
3           Tumkur_Veersagr_I (Karnataka)
4           Gurgaon_Bilaspur_HB (Haryana)
…                                     …
26363  Tirchchndr_Shnmgprm_D (Tamil Nadu)
26364   Peikulam_SriVnktpm_D (Tamil Nadu)
26365        Eral_Busstand_D (Tamil Nadu)
26366       Sandur_WrdN1DPP_D (Karnataka)
26367                  Hospet (Karnataka)

                           destination_name              od_start_time  \
0              Gurgaon_Bilaspur_HB (Haryana) 2018-09-12 16:39:46.858469
1         Kanpur_Central_H_6 (Uttar Pradesh) 2018-09-12 00:00:16.535741
2          Chikblapur_ShntiSgr_D (Karnataka) 2018-09-12 02:03:09.655591
3          Doddablpur_ChikaDPP_D (Karnataka) 2018-09-12 00:00:22.886430
4             Chandigarh_Mehmdpur_H (Punjab) 2018-09-14 03:40:17.106733
…                                       …                          …
26363  Thisayanvilai_UdnkdiRD_D (Tamil Nadu) 2018-10-04 02:29:04.272194
26364    Tirunelveli_VdkkuSrt_I (Tamil Nadu) 2018-10-04 04:16:39.894872
26365     Tirchchndr_Shnmgprm_D (Tamil Nadu) 2018-10-04 01:44:53.808000
26366                Bellary_Dc (Karnataka) 2018-10-04 03:58:40.726547
26367          Sandur_WrdN1DPP_D (Karnataka) 2018-10-04 02:51:44.712656

                    od_end_time  start_scan_to_end_scan  \
0     2018-09-13 13:40:23.123744                 22680.0
1     2018-09-12 16:39:46.858469                 20979.0
2     2018-09-12 03:01:59.598855                   174.0
3     2018-09-12 02:03:09.655591                   732.0
4     2018-09-14 17:34:55.442454                 10008.0
…                            …                       …
26363 2018-10-04 03:31:11.183797                   248.0
26364 2018-10-04 05:47:45.162682                   364.0
26365 2018-10-04 02:29:04.272194                    88.0
26366 2018-10-04 08:46:09.166940                   574.0
26367 2018-10-04 03:58:40.726547                   132.0

       actual_distance_to_destination  actual_time  osrm_time  osrm_distance  \
0                           34.015099       6484.0     3464.0    4540.125977
```

```
1                          22.812439       9198.0     4323.0    6037.638672
2                           9.357635         96.0       55.0      60.315701
3                           9.832310        303.0      155.0     209.115097
4                          24.680126       2601.0     1427.0    1975.740967
…                                …          …          …            …
26363                       9.167748        119.0      106.0     106.708405
26364                       9.393822        173.0      108.0     111.855499
26365                       9.010429         51.0       22.0      25.537100
26366                      22.000767        278.0       59.0      76.516899
26367                      22.156816         72.0       47.0      51.285103

       segment_actual_time  segment_osrm_time  segment_osrm_distance
0                    728.0              534.0             670.620483
1                    820.0              474.0             649.852783
2                     46.0               26.0              28.199501
3                     95.0               39.0              55.989899
4                    608.0              231.0             317.740784
…                        …                  …                  …
26363                 49.0               42.0              42.143101
26364                 89.0               77.0              78.586899
26365                 29.0               14.0              16.018400
26366                233.0               42.0              52.530300
26367                 41.0               25.0              28.048401

[26368 rows x 18 columns]
```

[ ]:
```
#Calculate the time taken between od_start_time and od_end_time and keep it as␣
 ↪a feature. Drop the original columns, if required
segment_agg['od_total_time']=segment_agg['od_end_time']-segment_agg['od_start_time']
segment_agg['od_total_time']=segment_agg['od_total_time'].apply(lambda x: x.
 ↪total_seconds()/60)
segment_agg.head()
```

[ ]:
```
                 trip_uuid source_center destination_center      data  \
0  trip-153671041653548748  IND209304AAA       IND000000ACB  training
1  trip-153671041653548748  IND462022AAA       IND209304AAA  training
2  trip-153671042288605164  IND561203AAB       IND562101AAA  training
3  trip-153671042288605164  IND572101AAA       IND561203AAB  training
4  trip-153671043369099517  IND000000ACB       IND160002AAC  training

  route_type         trip_creation_time                        source_name  \
0        FTL 2018-09-12 00:00:16.535741  Kanpur_Central_H_6 (Uttar Pradesh)
1        FTL 2018-09-12 00:00:16.535741  Bhopal_Trnsport_H (Madhya Pradesh)
2    Carting 2018-09-12 00:00:22.886430   Doddablpur_ChikaDPP_D (Karnataka)
3    Carting 2018-09-12 00:00:22.886430       Tumkur_Veersagr_I (Karnataka)
4        FTL 2018-09-12 00:00:33.691250       Gurgaon_Bilaspur_HB (Haryana)
```

```
                    destination_name             od_start_time  \
0       Gurgaon_Bilaspur_HB (Haryana) 2018-09-12 16:39:46.858469
1  Kanpur_Central_H_6 (Uttar Pradesh) 2018-09-12 00:00:16.535741
2   Chikblapur_ShntiSgr_D (Karnataka) 2018-09-12 02:03:09.655591
3   Doddablpur_ChikaDPP_D (Karnataka) 2018-09-12 00:00:22.886430
4      Chandigarh_Mehmdpur_H (Punjab) 2018-09-14 03:40:17.106733

                 od_end_time  start_scan_to_end_scan  \
0 2018-09-13 13:40:23.123744                 22680.0
1 2018-09-12 16:39:46.858469                 20979.0
2 2018-09-12 03:01:59.598855                   174.0
3 2018-09-12 02:03:09.655591                   732.0
4 2018-09-14 17:34:55.442454                 10008.0

   actual_distance_to_destination  actual_time  osrm_time  osrm_distance  \
0                       34.015099       6484.0     3464.0    4540.125977
1                       22.812439       9198.0     4323.0    6037.638672
2                        9.357635         96.0       55.0      60.315701
3                        9.832310        303.0      155.0     209.115097
4                       24.680126       2601.0     1427.0    1975.740967

   segment_actual_time  segment_osrm_time  segment_osrm_distance  \
0                728.0              534.0             670.620483
1                820.0              474.0             649.852783
2                 46.0               26.0              28.199501
3                 95.0               39.0              55.989899
4                608.0              231.0             317.740784

   od_total_time
0    1260.604421
1     999.505379
2      58.832388
3     122.779486
4     834.638929
```

[ ]:
```
#dropping unnecessary columns:
segment_agg=segment_agg.drop(['od_start_time','od_end_time'],axis=1)
segment_agg.head()
```

[ ]:
```
                trip_uuid source_center destination_center      data  \
0  trip-153671041653548748  IND209304AAA       IND000000ACB  training
1  trip-153671041653548748  IND462022AAA       IND209304AAA  training
2  trip-153671042288605164  IND561203AAB       IND562101AAA  training
3  trip-153671042288605164  IND572101AAA       IND561203AAB  training
4  trip-153671043369099517  IND000000ACB       IND160002AAC  training

  route_type         trip_creation_time                       source_name  \
```

```
0        FTL 2018-09-12 00:00:16.535741  Kanpur_Central_H_6 (Uttar Pradesh)
1        FTL 2018-09-12 00:00:16.535741  Bhopal_Trnsport_H (Madhya Pradesh)
2    Carting 2018-09-12 00:00:22.886430   Doddablpur_ChikaDPP_D (Karnataka)
3    Carting 2018-09-12 00:00:22.886430       Tumkur_Veersagr_I (Karnataka)
4        FTL 2018-09-12 00:00:33.691250       Gurgaon_Bilaspur_HB (Haryana)

                    destination_name  start_scan_to_end_scan  \
0       Gurgaon_Bilaspur_HB (Haryana)                 22680.0
1  Kanpur_Central_H_6 (Uttar Pradesh)                 20979.0
2   Chikblapur_ShntiSgr_D (Karnataka)                   174.0
3   Doddablpur_ChikaDPP_D (Karnataka)                   732.0
4      Chandigarh_Mehmdpur_H (Punjab)                 10008.0

   actual_distance_to_destination  actual_time  osrm_time  osrm_distance  \
0                       34.015099       6484.0     3464.0    4540.125977
1                       22.812439       9198.0     4323.0    6037.638672
2                        9.357635         96.0       55.0      60.315701
3                        9.832310        303.0      155.0     209.115097
4                       24.680126       2601.0     1427.0    1975.740967

   segment_actual_time  segment_osrm_time  segment_osrm_distance  \
0                728.0              534.0             670.620483
1                820.0              474.0             649.852783
2                 46.0               26.0              28.199501
3                 95.0               39.0              55.989899
4                608.0              231.0             317.740784

   od_total_time
0    1260.604421
1     999.505379
2      58.832388
3     122.779486
4     834.638929
```

[ ]:
```python
# second level aggregation only with trip_id
df_2 = segment_agg.groupby('trip_uuid').agg({
    # Meta info
    'data': 'first',
    'route_type': 'first',
    'trip_creation_time': 'first',

    # Location info (can vary if multiple hops, so pick first/last)
    'source_center': 'first',
    'destination_center': 'last',
    'source_name': 'first',
    'destination_name': 'last',
```

```
    # Time info
    'od_total_time':'sum',
    'start_scan_to_end_scan': 'sum',

    # Distance & time (actual and OSRM)
    'actual_distance_to_destination': 'sum',  # Sum of all legs
    'actual_time': 'sum',
    'osrm_time': 'sum',
    'osrm_distance': 'sum',

    # Segment aggregates
    'segment_actual_time': 'sum',
    'segment_osrm_time': 'sum',
    'segment_osrm_distance': 'sum'
}).reset_index()
df_2
```

[ ]:

```
                      trip_uuid      data route_type  \
0      trip-153671041653548748  training        FTL
1      trip-153671042288605164  training    Carting
2      trip-153671043369099517  training        FTL
3      trip-153671046011330457  training    Carting
4      trip-153671052974046625  training        FTL
…                          …       …        …
14812  trip-153861095625827784      test    Carting
14813  trip-153861104386292051      test    Carting
14814  trip-153861106442901555      test    Carting
14815  trip-153861115439069069      test    Carting
14816  trip-153861118270144424      test        FTL

              trip_creation_time source_center destination_center  \
0     2018-09-12 00:00:16.535741  IND209304AAA       IND209304AAA
1     2018-09-12 00:00:22.886430  IND561203AAB       IND561203AAB
2     2018-09-12 00:00:33.691250  IND000000ACB       IND000000ACB
3     2018-09-12 00:01:00.113710  IND400072AAB       IND401104AAA
4     2018-09-12 00:02:09.740725  IND583101AAA       IND583119AAA
…                            …           …                  …
14812 2018-10-03 23:55:56.258533  IND160002AAC       IND160002AAC
14813 2018-10-03 23:57:23.863155  IND121004AAB       IND121004AAA
14814 2018-10-03 23:57:44.429324  IND208006AAA       IND208006AAA
14815 2018-10-03 23:59:14.390954  IND627005AAA       IND628204AAA
14816 2018-10-03 23:59:42.701692  IND583119AAA       IND583119AAA

                               source_name  \
0       Kanpur_Central_H_6 (Uttar Pradesh)
1        Doddablpur_ChikaDPP_D (Karnataka)
2            Gurgaon_Bilaspur_HB (Haryana)
```

```
3                 Mumbai Hub (Maharashtra)
4                   Bellary_Dc (Karnataka)
…                                      …
14812       Chandigarh_Mehmdpur_H (Punjab)
14813         FBD_Balabhgarh_DPC (Haryana)
14814   Kanpur_GovndNgr_DC (Uttar Pradesh)
14815  Tirunelveli_VdkkuSrt_I (Tamil Nadu)
14816        Sandur_WrdN1DPP_D (Karnataka)

                        destination_name  od_total_time  \
0      Kanpur_Central_H_6 (Uttar Pradesh)    2260.109800
1       Doddablpur_ChikaDPP_D (Karnataka)     181.611874
2           Gurgaon_Bilaspur_HB (Haryana)    3934.362520
3          Mumbai_MiraRd_IP (Maharashtra)     100.494935
4           Sandur_WrdN1DPP_D (Karnataka)     718.349042
…                                     …            …
14812      Chandigarh_Mehmdpur_H (Punjab)     258.028928
14813      Faridabad_Blbgarh_DC (Haryana)      60.590521
14814  Kanpur_GovndNgr_DC (Uttar Pradesh)     422.119867
14815  Tirchchndr_Shnmgprm_D (Tamil Nadu)     348.512862
14816       Sandur_WrdN1DPP_D (Karnataka)     354.407571

       start_scan_to_end_scan  actual_distance_to_destination  actual_time  \
0                     43659.0                       56.827538      15682.0
1                       906.0                       19.189945        399.0
2                    248631.0                       51.588478     112225.0
3                       200.0                       11.354374         82.0
4                      1586.0                       67.150345        556.0
…                         …                             …          …
14812                   876.0                       18.853155        186.0
14813                   120.0                        9.616857         33.0
14814                  1263.0                       18.593136        549.0
14815                  1315.0                       46.175217        600.0
14816                   706.0                       44.157585        350.0

       osrm_time  osrm_distance  segment_actual_time  segment_osrm_time  \
0         7787.0   10577.764648               1548.0             1008.0
1          210.0     269.430786                141.0               65.0
2        65768.0   89447.250000               3308.0             1941.0
3           24.0      31.647499                 59.0               16.0
4          207.0     266.291382                340.0              115.0
…            …              …                    …                  …
14812      148.0     162.947296                 82.0               62.0
14813       19.0      26.533298                 21.0               11.0
14814      134.0     162.849899                281.0               88.0
14815      446.0     449.538300                258.0              221.0
14816      106.0     127.802002                274.0               67.0
```

```
       segment_osrm_distance
0                1320.473267
1                  84.189400
2                2545.267822
3                  19.876600
4                 146.791901
…                        …
14812              64.855103
14813              16.088299
14814             104.886597
14815             223.532394
14816              80.578705

[14817 rows x 17 columns]
```

Build some features to prepare the data for actual analysis. Extract features from the below fields:

[ ]:
```
#Trip_creation_time: Extract features like month, year and day etc
df_2['trip_creation_time']= pd.to_datetime(df_2['trip_creation_time'].dt.date)
df_2['trip_creation_time']
```

[ ]:
```
0       2018-09-12
1       2018-09-12
2       2018-09-12
3       2018-09-12
4       2018-09-12
           …
14812   2018-10-03
14813   2018-10-03
14814   2018-10-03
14815   2018-10-03
14816   2018-10-03
Name: trip_creation_time, Length: 14817, dtype: datetime64[ns]
```

[ ]:
```
df_2['trip_creation_month']=df_2['trip_creation_time'].dt.month
df_2['trip_creation_year']=df_2['trip_creation_time'].dt.year
df_2['trip_creation_day']=df_2['trip_creation_time'].dt.day
df_2['trip_creation_week']=df_2['trip_creation_time'].dt.isocalendar().week
df_2.drop(['trip_creation_time'],axis=1,inplace=True)
df_2.head()
```

[ ]:
```
                  trip_uuid      data route_type source_center  \
0  trip-153671041653548748  training        FTL  IND209304AAA
1  trip-153671042288605164  training    Carting  IND561203AAB
2  trip-153671043369099517  training        FTL  IND000000ACB
```

```
3  trip-153671046011330457  training    Carting  IND400072AAB
4  trip-153671052974046625  training        FTL  IND583101AAA

  destination_center                          source_name  \
0       IND209304AAA  Kanpur_Central_H_6 (Uttar Pradesh)
1       IND561203AAB   Doddablpur_ChikaDPP_D (Karnataka)
2       IND000000ACB       Gurgaon_Bilaspur_HB (Haryana)
3       IND401104AAA            Mumbai Hub (Maharashtra)
4       IND583119AAA              Bellary_Dc (Karnataka)

                    destination_name  od_total_time  start_scan_to_end_scan  \
0  Kanpur_Central_H_6 (Uttar Pradesh)    2260.109800                 43659.0
1   Doddablpur_ChikaDPP_D (Karnataka)     181.611874                   906.0
2       Gurgaon_Bilaspur_HB (Haryana)    3934.362520                248631.0
3      Mumbai_MiraRd_IP (Maharashtra)     100.494935                   200.0
4       Sandur_WrdN1DPP_D (Karnataka)     718.349042                  1586.0

   actual_distance_to_destination  actual_time  osrm_time  osrm_distance  \
0                       56.827538      15682.0     7787.0   10577.764648
1                       19.189945        399.0      210.0     269.430786
2                       51.588478     112225.0    65768.0   89447.250000
3                       11.354374         82.0       24.0      31.647499
4                       67.150345        556.0      207.0     266.291382

   segment_actual_time  segment_osrm_time  segment_osrm_distance  \
0               1548.0             1008.0            1320.473267
1                141.0               65.0              84.189400
2               3308.0             1941.0            2545.267822
3                 59.0               16.0              19.876600
4                340.0              115.0             146.791901

   trip_creation_month  trip_creation_year  trip_creation_day  \
0                    9                2018                 12
1                    9                2018                 12
2                    9                2018                 12
3                    9                2018                 12
4                    9                2018                 12

   trip_creation_week
0                  37
1                  37
2                  37
3                  37
4                  37
```

[ ]:
```
df_2[['destination_location', 'destination_state']] = df_2['destination_name'].
↪str.extract(r'^(.*?) \((.*?)\)$')
```

```
df_2[['destination_city', 'destination_place', 'destination_code']] =␣
 ↪df_2['destination_location'].str.split('_', n=2, expand=True)
df_2[['source_location', 'source_state']] = df_2['source_name'].str.
 ↪extract(r'^(.*?) \((.*?)\)$')
df_2[['source_city', 'source_place', 'source_code']] = df_2['source_location'].
 ↪str.split('_', n=2, expand=True)
df_2[['source_city', 'source_place', 'source_code']].head(10)
```

[ ]:

	source_city	source_place	source_code
0	Kanpur	Central	H_6
1	Doddablpur	ChikaDPP	D
2	Gurgaon	Bilaspur	HB
3	Mumbai Hub	None	None
4	Bellary	Dc	None
5	Chennai	Poonamallee	None
6	Chennai	Chrompet	DPC
7	HBR Layout PC	None	None
8	Surat	Central	D_12
9	Delhi	Lajpat	IP

[ ]:
```
df_2[['destination_city', 'destination_place', 'destination_code']].head(10)
```

[ ]:

	destination_city	destination_place	destination_code
0	Kanpur	Central	H_6
1	Doddablpur	ChikaDPP	D
2	Gurgaon	Bilaspur	HB
3	Mumbai	MiraRd	IP
4	Sandur	WrdN1DPP	D
5	Chennai	Poonamallee	None
6	Chennai	Vandalur	Dc
7	HBR Layout PC	None	None
8	Surat	Central	D_3
9	Delhi	Bhogal	None

[ ]:
```
df_2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14817 entries, 0 to 14816
Data columns (total 30 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   trip_uuid                     14817 non-null  object
 1   data                          14817 non-null  category
 2   route_type                    14817 non-null  category
 3   source_center                 14817 non-null  object
 4   destination_center            14817 non-null  object
 5   source_name                   14817 non-null  object
```

```
 6   destination_name                14817 non-null  object
 7   od_total_time                   14817 non-null  float64
 8   start_scan_to_end_scan          14817 non-null  float32
 9   actual_distance_to_destination  14817 non-null  float32
 10  actual_time                     14817 non-null  float32
 11  osrm_time                       14817 non-null  float32
 12  osrm_distance                   14817 non-null  float32
 13  segment_actual_time             14817 non-null  float32
 14  segment_osrm_time               14817 non-null  float32
 15  segment_osrm_distance           14817 non-null  float32
 16  trip_creation_month             14817 non-null  int32
 17  trip_creation_year              14817 non-null  int32
 18  trip_creation_day               14817 non-null  int32
 19  trip_creation_week              14817 non-null  UInt32
 20  destination_location            14790 non-null  object
 21  destination_state               14790 non-null  object
 22  destination_city                14790 non-null  object
 23  destination_place               14033 non-null  object
 24  destination_code                12775 non-null  object
 25  source_location                 14801 non-null  object
 26  source_state                    14801 non-null  object
 27  source_city                     14801 non-null  object
 28  source_place                    14159 non-null  object
 29  source_code                     12884 non-null  object
dtypes: UInt32(1), category(2), float32(8), float64(1), int32(3), object(15)
memory usage: 2.5+ MB
```

[ ]:
```
df_2['trip_creation_day']=pd.to_datetime(df_2['trip_creation_day'])
df_2['trip_creation_week']=pd.to_datetime(df_2['trip_creation_week'])
df_2['trip_creation_month']=pd.to_datetime(df_2['trip_creation_month'])
df_2['trip_creation_year']=pd.to_datetime(df_2['trip_creation_year'])
```

[ ]:
```
df_2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14817 entries, 0 to 14816
Data columns (total 30 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   trip_uuid                       14817 non-null  object
 1   data                            14817 non-null  category
 2   route_type                      14817 non-null  category
 3   source_center                   14817 non-null  object
 4   destination_center              14817 non-null  object
 5   source_name                     14817 non-null  object
 6   destination_name                14817 non-null  object
 7   od_total_time                   14817 non-null  float64
 8   start_scan_to_end_scan          14817 non-null  float32
```

```
 9   actual_distance_to_destination  14817 non-null  float32
 10  actual_time                     14817 non-null  float32
 11  osrm_time                       14817 non-null  float32
 12  osrm_distance                   14817 non-null  float32
 13  segment_actual_time             14817 non-null  float32
 14  segment_osrm_time               14817 non-null  float32
 15  segment_osrm_distance           14817 non-null  float32
 16  trip_creation_month             14817 non-null  datetime64[ns]
 17  trip_creation_year              14817 non-null  datetime64[ns]
 18  trip_creation_day               14817 non-null  datetime64[ns]
 19  trip_creation_week              14817 non-null  datetime64[ns]
 20  destination_location            14790 non-null  object
 21  destination_state               14790 non-null  object
 22  destination_city                14790 non-null  object
 23  destination_place               14033 non-null  object
 24  destination_code                12775 non-null  object
 25  source_location                 14801 non-null  object
 26  source_state                    14801 non-null  object
 27  source_city                     14801 non-null  object
 28  source_place                    14159 non-null  object
 29  source_code                     12884 non-null  object
dtypes: category(2), datetime64[ns](4), float32(8), float64(1), object(15)
memory usage: 2.7+ MB
```

[ ]:
```
df_2.describe().T
```

[ ]:
```
                                 count                           mean  \
od_total_time                  14817.0                     531.795209
start_scan_to_end_scan         14817.0                    9398.344727
actual_distance_to_destination 14817.0                      32.067497
actual_time                    14817.0                    4076.333984
osrm_time                      14817.0                    2091.007324
osrm_distance                  14817.0                    2784.231934
segment_actual_time            14817.0                     353.892273
segment_osrm_time              14817.0                     180.949783
segment_osrm_distance          14817.0                     223.201157
trip_creation_month              14817  1970-01-01 00:00:00.000000009
trip_creation_year               14817  1970-01-01 00:00:00.000002018
trip_creation_day                14817  1970-01-01 00:00:00.000000018
trip_creation_week               14817  1970-01-01 00:00:00.000000038

                                        min  \
od_total_time                     23.461468
start_scan_to_end_scan                26.0
actual_distance_to_destination    9.000046
actual_time                            9.0
osrm_time                              6.0
```

```
osrm_distance                                    9.0729
segment_actual_time                                 9.0
segment_osrm_time                                   6.0
segment_osrm_distance                            9.0729
trip_creation_month          1970-01-01 00:00:00.000000009
trip_creation_year           1970-01-01 00:00:00.000002018
trip_creation_day            1970-01-01 00:00:00.000000001
trip_creation_week           1970-01-01 00:00:00.000000037

                                                     25%  \
od_total_time                                  149.930591
start_scan_to_end_scan                              408.0
actual_distance_to_destination                   9.631898
actual_time                                         142.0
osrm_time                                            62.0
osrm_distance                                   65.738602
segment_actual_time                                  66.0
segment_osrm_time                                    31.0
segment_osrm_distance                           32.654499
trip_creation_month          1970-01-01 00:00:00.000000009
trip_creation_year           1970-01-01 00:00:00.000002018
trip_creation_day            1970-01-01 00:00:00.000000014
trip_creation_week           1970-01-01 00:00:00.000000038

                                                     50%  \
od_total_time                                  280.765626
start_scan_to_end_scan                              985.0
actual_distance_to_destination                  19.435421
actual_time                                         348.0
osrm_time                                           167.0
osrm_distance                                  173.593597
segment_actual_time                                 147.0
segment_osrm_time                                    65.0
segment_osrm_distance                           70.154404
trip_creation_month          1970-01-01 00:00:00.000000009
trip_creation_year           1970-01-01 00:00:00.000002018
trip_creation_day            1970-01-01 00:00:00.000000019
trip_creation_week           1970-01-01 00:00:00.000000038

                                                     75%  \
od_total_time                                  638.199071
start_scan_to_end_scan                             2826.0
actual_distance_to_destination                   44.95438
actual_time                                         1063.0
osrm_time                                            516.0
osrm_distance                                  607.677368
segment_actual_time                                 367.0
```

segment_osrm_time		185.0
segment_osrm_distance		218.802399
trip_creation_month	1970-01-01 00:00:00.000000009	
trip_creation_year	1970-01-01 00:00:00.000002018	
trip_creation_day	1970-01-01 00:00:00.000000025	
trip_creation_week	1970-01-01 00:00:00.000000039	

	max	std
od_total_time	7898.551955	659.184525
start_scan_to_end_scan	396800.0	33701.675781
actual_distance_to_destination	1722.045532	39.296524
actual_time	167920.0	15216.874023
osrm_time	76953.0	7956.896484
osrm_distance	102415.867188	10759.12207
segment_actual_time	6230.0	556.246826
segment_osrm_time	2564.0	314.541412
segment_osrm_distance	3523.632324	416.628326
trip_creation_month	1970-01-01 00:00:00.000000010	NaN
trip_creation_year	1970-01-01 00:00:00.000002018	NaN
trip_creation_day	1970-01-01 00:00:00.000000030	NaN
trip_creation_week	1970-01-01 00:00:00.000000040	NaN

[ ]:
```
df_2.describe(include='object').T
```

[ ]:

	count	unique	top	freq
trip_uuid	14817	14817	trip-153861118270144424	1
source_center	14817	938	IND000000ACB	1063
destination_center	14817	1042	IND000000ACB	821
source_name	14817	934	Gurgaon_Bilaspur_HB (Haryana)	1063
destination_name	14817	1035	Gurgaon_Bilaspur_HB (Haryana)	821
destination_location	14790	1034	Gurgaon_Bilaspur_HB	821
destination_state	14790	31	Maharashtra	2561
destination_city	14790	846	Bengaluru	1088
destination_place	14033	794	Bilaspur	864
destination_code	12775	47	D	2868
source_location	14801	933	Gurgaon_Bilaspur_HB	1063
source_state	14801	29	Maharashtra	2714
source_city	14801	722	Gurgaon	1139
source_place	14159	703	Bilaspur	1085
source_code	12884	47	HB	3222

In-depth analysis and feature engineering:

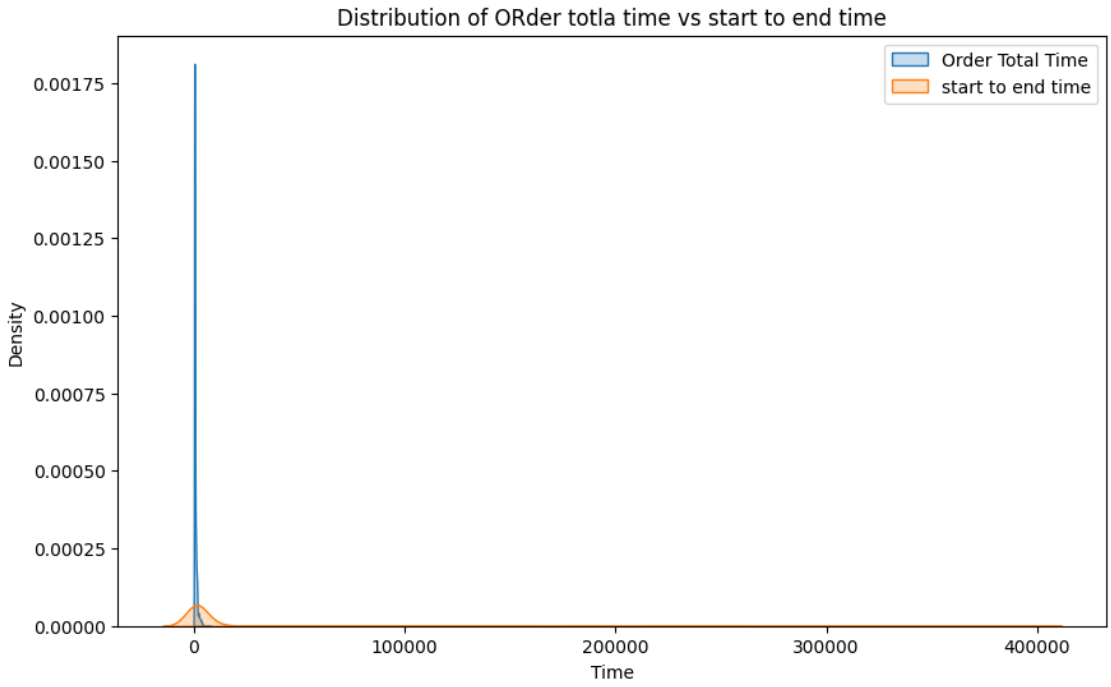
1. **Compare the difference between order_total_time and start_scan_to_end_scan. Do hypothesis testing/ Visual analysis to check.**

[ ]:
```
df_2[['od_total_time','start_scan_to_end_scan']].describe()
```

[ ]:

	od_total_time	start_scan_to_end_scan
count	14817.000000	14817.000000
mean	531.795209	9398.344727
std	659.184525	33701.675781
min	23.461468	26.000000
25%	149.930591	408.000000
50%	280.765626	985.000000
75%	638.199071	2826.000000
max	7898.551955	396800.000000

[ ]:
```
plt.figure(figsize=(10, 6))
sns.kdeplot(df_2['od_total_time'], label='Order Total Time', fill=True)
sns.kdeplot(df_2['start_scan_to_end_scan'], label='start to end time',␣
 ↪fill=True)
plt.title('Distribution of ORder totla time vs start to end time')
plt.xlabel('Time')
plt.legend()
plt.show()
```



[ ]:
```
test_stat, p_val = scpy.shapiro(df_2['od_total_time'])

print(f"Test_stat : {test_stat}")
print(f"p-value : {p_val}")
print()
if p_val < 0.05:
```

```
    print('Reject H0: Data does not follow normal distribution')
else:
    print('Fail to reject H0: Data follows a normal distribution')
```

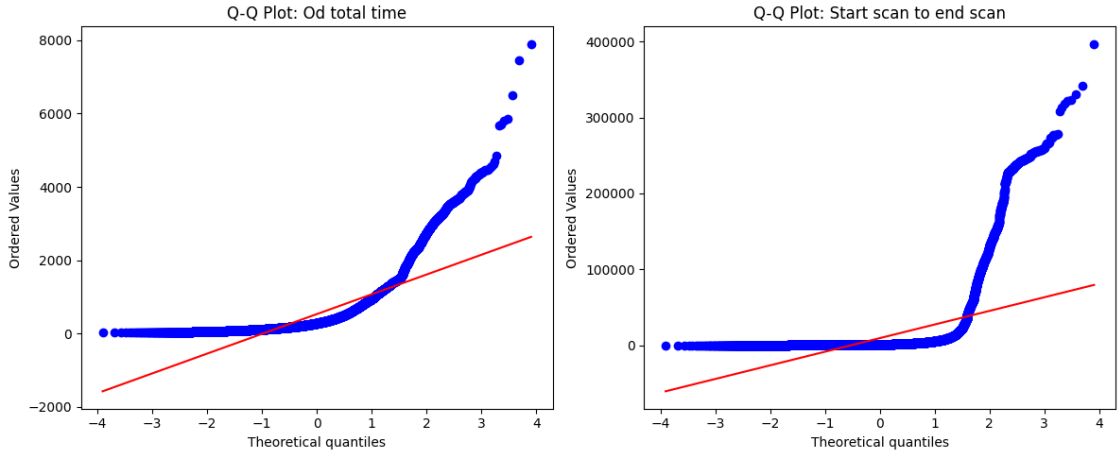
```
Test_stat : 0.6685213995508009
p-value : 1.1034623049567213e-97

Reject H0: Data does not follow normal distribution
```

```
/usr/local/lib/python3.11/dist-packages/scipy/stats/_axis_nan_policy.py:586:
UserWarning: scipy.stats.shapiro: For N > 5000, computed p-value may not be
accurate. Current N is 14817.
  res = hypotest_fun_out(*samples, **kwds)
```

[ ]:
```
test_stat, p_val = scpy.shapiro(df_2['start_scan_to_end_scan'])

print(f"Test_stat : {test_stat}")
print(f"p-value : {p_val}")
print()
if p_val < 0.05:
    print('Reject H0: Data does not follow normal distribution')
else:
    print('Fail to reject H0: Data follows a normal distribution')
```

```
Test_stat : 0.2830049771050981
p-value : 1.2055642806447882e-117

Reject H0: Data does not follow normal distribution
```

[ ]:
```
# Q-Q Plot for od total time
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
scpy.probplot(df_2['od_total_time'], dist="norm", plot=plt)
plt.title("Q-Q Plot: Od total time")

# Q-Q Plot for OSRM Time
plt.subplot(1, 2, 2)
scpy.probplot(df_2['start_scan_to_end_scan'], dist="norm", plot=plt)
plt.title("Q-Q Plot: Start scan to end scan")

plt.tight_layout()
plt.show()
```



Since, data is not normally distributed, two sample t test is not appropriate in this case. Therefore, non parametric test is most suitable method for further analysis.

[ ]:
```
stat, p_value = scpy.mannwhitneyu(df_2['od_total_time'],␣
 ↪df_2['start_scan_to_end_scan'])

print(f"test statistic: {stat}")
print(f"P-value: {p_value:.5f}")

if p_value < 0.05:
    print("There is a statistically significant difference between the od total␣
 ↪trip time and the start to end scan")
else:
    print("There is no statistically significant difference between the od␣
 ↪total trip time and the start to end scan")
```

```
test statistic: 51286069.0
P-value: 0.00000
There is a statistically significant difference between the od total trip time
and the start to end scan
```

The analysis reveals a significant difference between od_total_time and start_scan_to_end_scan.

This suggests these two time metrics capture different aspects of trip duration—od_total_time likely reflects the total origin-to-destination planned or estimated time, whereas start_scan_to_end_scan measures the actual time between scan events during the trip.

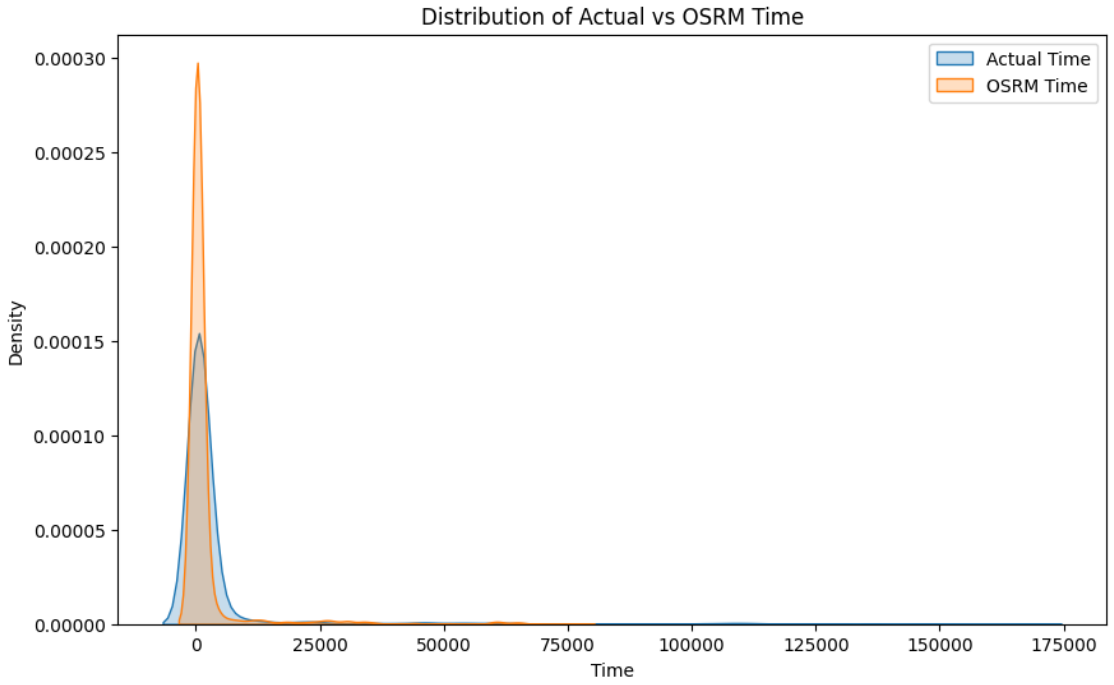
The discrepancy highlights potential differences in operational definitions or data recording processes, which should be addressed to ensure precise trip time measurement and improve delivery tracking accuracy.

2. Do hypothesis testing/ visual analysis between actual_time aggregated value and OSRM time aggregated value (aggregated values are the values you'll get after merging the rows on the basis of trip_uuid)

```
[ ]: df_2[['actual_time','osrm_time']].describe()
```

```
[ ]:          actual_time     osrm_time
     count   14817.000000  14817.000000
     mean     4076.333984   2091.007324
     std     15216.874023   7956.896484
     min         9.000000      6.000000
     25%       142.000000     62.000000
     50%       348.000000    167.000000
     75%      1063.000000    516.000000
     max    167920.000000  76953.000000
```

```
[ ]: plt.figure(figsize=(10, 6))
     sns.kdeplot(df_2['actual_time'], label='Actual Time', fill=True)
     sns.kdeplot(df_2['osrm_time'], label='OSRM Time', fill=True)
     plt.title('Distribution of Actual vs OSRM Time')
     plt.xlabel('Time')
     plt.legend()
     plt.show()
```



Both time distributions are right-skewed, meaning most trips take shorter times but some take much longer.

The OSRM time peaks earlier (i.e. has shorter typical durations), suggesting that OSRM often underestimates actual travel time—especially for longer trips.

[ ]:
```
test_stat, p_val = scpy.shapiro(df_2['actual_time'])

print(f"test_stat : {test_stat}")
print(f"p-value : {p_val}")
print()
if p_val < 0.05:
    print('Reject H0: Data does not follow normal distribution')
else:
    print('Fail to reject H0: Data follows a normal distribution')
```

```
test_stat : 0.27302197796332583
p-value : 5.084154046560269e-118

Reject H0: Data does not follow normal distribution
```

```
/usr/local/lib/python3.11/dist-packages/scipy/stats/_axis_nan_policy.py:586:
UserWarning: scipy.stats.shapiro: For N > 5000, computed p-value may not be
accurate. Current N is 14817.
  res = hypotest_fun_out(*samples, **kwds)
```

[ ]:
```
test_stat, p_val = scpy.shapiro(df_2['osrm_time'])

print(f"test_stat : {shap_stat}")
print(f"p-value : {p_val}")
print()
if p_val < 0.05:
    print('Reject H0: Data does not follow normal distribution')
else:
    print('Fail to reject H0: Data follows a normal distribution')
```

```
test_stat : 0.2685661543502248
p-value : 3.4699195378013362e-118

Reject H0: Data does not follow normal distribution
```

```
/usr/local/lib/python3.11/dist-packages/scipy/stats/_axis_nan_policy.py:586:
UserWarning: scipy.stats.shapiro: For N > 5000, computed p-value may not be
accurate. Current N is 14817.
  res = hypotest_fun_out(*samples, **kwds)
```

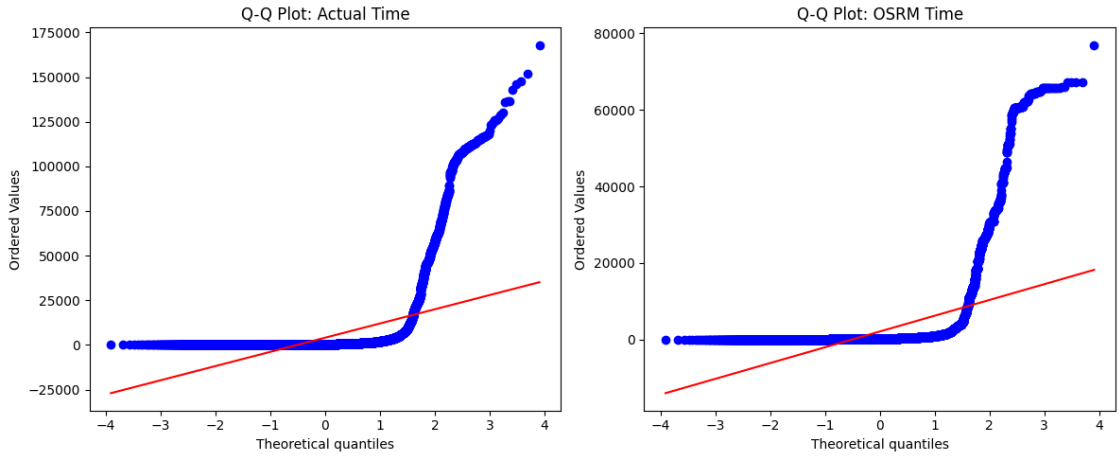
Both tests return very small p-values (< 0.05).

This rejects the assumption of normality for both distributions.

Therefore, non-parametric methods should be used for further comparison.

[ ]:
```
import scipy.stats as stats
import matplotlib.pyplot as plt

# Q-Q Plot for Actual Time
```

```
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
stats.probplot(df_2['actual_time'], dist="norm", plot=plt)
plt.title("Q-Q Plot: Actual Time")

# Q-Q Plot for OSRM Time
plt.subplot(1, 2, 2)
stats.probplot(df_2['osrm_time'], dist="norm", plot=plt)
plt.title("Q-Q Plot: OSRM Time")

plt.tight_layout()
plt.show()
```



The points deviate from the diagonal, especially in the upper tail (longer times), showing positive skew.

This confirms actual_time is not normally distributed

Like actual_time, OSRM time plot shows clear upward curvature in the upper tail.

This again indicates positive skewness and non-normal distribution of OSRM time estimates.

[ ]:
```
test_stat, p_value = stats.mannwhitneyu(df_2['actual_time'], df_2['osrm_time'])

print(f"test statistic: {test_stat}")
print(f"P-value: {p_value:.5f}")

if p_value < 0.05:
    print("There is a statistically significant difference between the actual␣
 ↪time and the osrm time")
else:
```

```
    print("There is no statistically significant difference between the actual␣
↪time and the osrm time")
```

```
test statistic: 141469729.0
P-value: 0.00000
There is a statistically significant difference between the actual time and the
osrm time
```

The hypothesis test shows a significant difference between actual time and OSRM estimated time (p-value = 0).

This means that the observed delivery durations differ substantially from the routing algorithm's estimates.

The OSRM model likely underestimates or fails to fully account for real-world factors such as traffic, delays, and operational variability, which affects the accuracy of estimated delivery times (ETAs).

Improving the estimation model is essential to better align predictions with actual delivery performance.

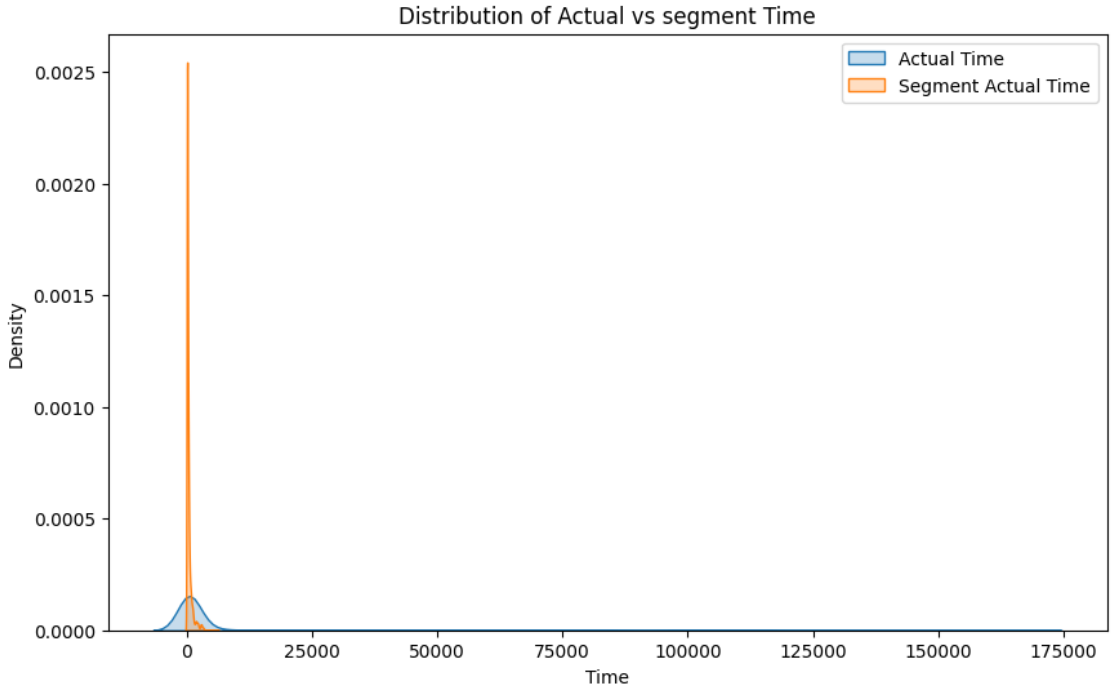
3. Do hypothesis testing/ visual analysis between actual_time aggregated value and segment actual time aggregated value (aggregated values are the values you'll get after merging the rows on the basis of trip_uuid)

[ ]:
```
df_2[['actual_time','segment_actual_time']].describe()
```

[ ]:

	actual_time	segment_actual_time
count	14817.000000	14817.000000
mean	4076.333984	353.892273
std	15216.874023	556.246826
min	9.000000	9.000000
25%	142.000000	66.000000
50%	348.000000	147.000000
75%	1063.000000	367.000000
max	167920.000000	6230.000000

[ ]:
```
plt.figure(figsize=(10, 6))
sns.kdeplot(df_2['actual_time'], label='Actual Time', fill=True)
sns.kdeplot(df_2['segment_actual_time'], label='Segment Actual Time', fill=True)
plt.title('Distribution of Actual vs segment Time')
plt.xlabel('Time')
plt.legend()
plt.show()
```



The KDE plot clearly shows that actual_time consistently exceeds segment_actual_time, revealing operational gaps like delays or idle times not captured at the segment level.

This has important implications for delivery performance analysis

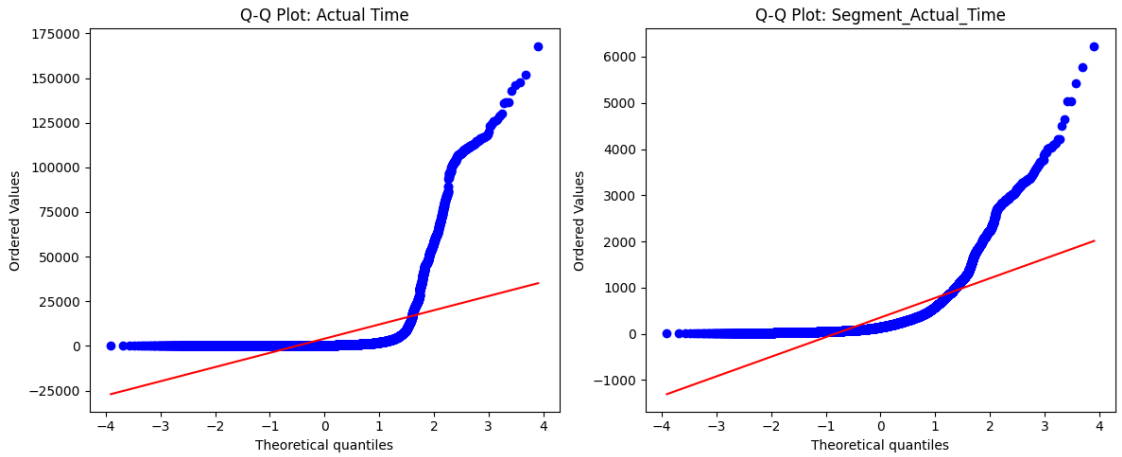
[ ]:
```
# checking normality
test_stat, p_val = scpy.shapiro(df_2['segment_actual_time'])

print(f"shapiro_stat : {test_stat}")
print(f"p-value : {p_val}")
print()
if p_val < 0.05:
    print('Reject H0: Data does not follow normal distribution')
else:
    print('Fail to reject H0: Data follows a normal distribution')
```

```
shapiro_stat : 0.5821857729098123
p-value : 1.785695134007935e-103

Reject H0: Data does not follow normal distribution

/usr/local/lib/python3.11/dist-packages/scipy/stats/_axis_nan_policy.py:586:
UserWarning: scipy.stats.shapiro: For N > 5000, computed p-value may not be
accurate. Current N is 14817.
  res = hypotest_fun_out(*samples, **kwds)
```

[ ]:
```
test_stat, p_val = scpy.shapiro(df_2['actual_time'])

print(f"shapiro_stat : {test_stat}")
print(f"p-value : {p_val}")
print()
if p_val < 0.05:
    print('Reject H0: Data does not follow normal distribution')
else:
    print('Fail to reject H0: Data follows a normal distribution')
```

```
shapiro_stat : 0.27302197796332583
p-value : 5.084154046560269e-118

Reject H0: Data does not follow normal distribution

/usr/local/lib/python3.11/dist-packages/scipy/stats/_axis_nan_policy.py:586:
UserWarning: scipy.stats.shapiro: For N > 5000, computed p-value may not be
accurate. Current N is 14817.
  res = hypotest_fun_out(*samples, **kwds)
```

[ ]:
```
# Q-Q Plot for Actual Time
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
stats.probplot(df_2['actual_time'], dist="norm", plot=plt)
plt.title("Q-Q Plot: Actual Time")

# Q-Q Plot for segment actual time
plt.subplot(1, 2, 2)
stats.probplot(df_2['segment_actual_time'], dist="norm", plot=plt)
plt.title("Q-Q Plot: Segment_Actual_Time")

plt.tight_layout()
plt.show()
```



Both variables, actual_time and segment_actual_time, show significant deviation from the normal distribution line in their Q-Q plots, particularly in the tails.

This visually confirms the results of the Shapiro-Wilk test, indicating that neither distribution is normal.

The upward curvature in the upper tails of both plots suggests that both actual_time and segment_actual_time distributions are right-skewed.

[ ]:
```
test_stat,p_val=scpy.
 ↪mannwhitneyu(df_2['actual_time'],df_2['segment_actual_time'])
print(f"test_statistic:{test_stat}")
print(f"p_value:{p_val}")
if p_val <0.05:
  print("There is a statistically significant difference between the actual␣
 ↪trip times and the aggregated segment times")
else:
  print("There is no statistically significant difference between the actual␣
 ↪trip times and the aggregated segment times")
```

```
test_statistic:150013130.5
p_value:0.0
There is a statistically significant difference between the actual trip times
and the aggregated segment times
```

The test shows a significant difference between the actual trip time and the sum of segment actual times (p-value = 0).

This indicates that adding up segment times does not fully account for the total trip duration.

Possible reasons include unrecorded waiting periods, delays between segments, or missing segment data. Addressing these gaps is important to accurately measure trip durations and improve operational insights.

4. Do hypothesis testing/ visual analysis between osrm distance aggregated value and segment osrm distance aggregated value (aggregated values are the values you'll get after merging the rows on the basis of trip_uuid)

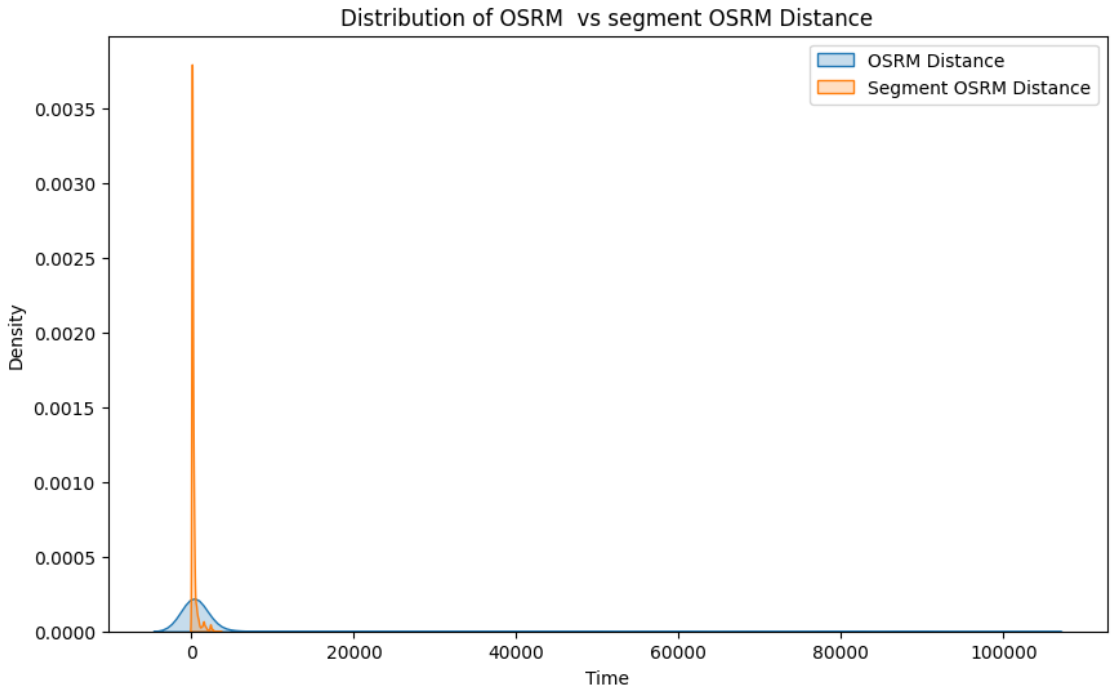
[ ]:
```
df_2[['osrm_distance','segment_osrm_distance']].describe()
```

[ ]:

	osrm_distance	segment_osrm_distance
count	14817.000000	14817.000000
mean	2784.231934	223.201157
std	10759.122070	416.628326
min	9.072900	9.072900
25%	65.738602	32.654499
50%	173.593597	70.154404
75%	607.677368	218.802399

```
max     102415.867188             3523.632324
```

[ ]:
```
plt.figure(figsize=(10, 6))
sns.kdeplot(df_2['osrm_distance'], label='OSRM Distance', fill=True)
sns.kdeplot(df_2['segment_osrm_distance'], label='Segment OSRM Distance',␣
 ↪fill=True)
plt.title('Distribution of OSRM  vs segment OSRM Distance')
plt.xlabel('Time')
plt.legend()
plt.show()
```



[ ]:
```
#shapiro test to find normality
test_stat,p_val=scpy.shapiro(df_2['osrm_distance'])
print(f"test_statistic:{test_stat}")
print(f"p_value:{p_val}")
if p_val <0.05:
  print('The data does not follow normal distribution')
else:
  print('The data follows normal distribution')
```

```
test_statistic:0.26662413484613046
p_value:2.939634036739815e-118
The data does not follow normal distribution
```

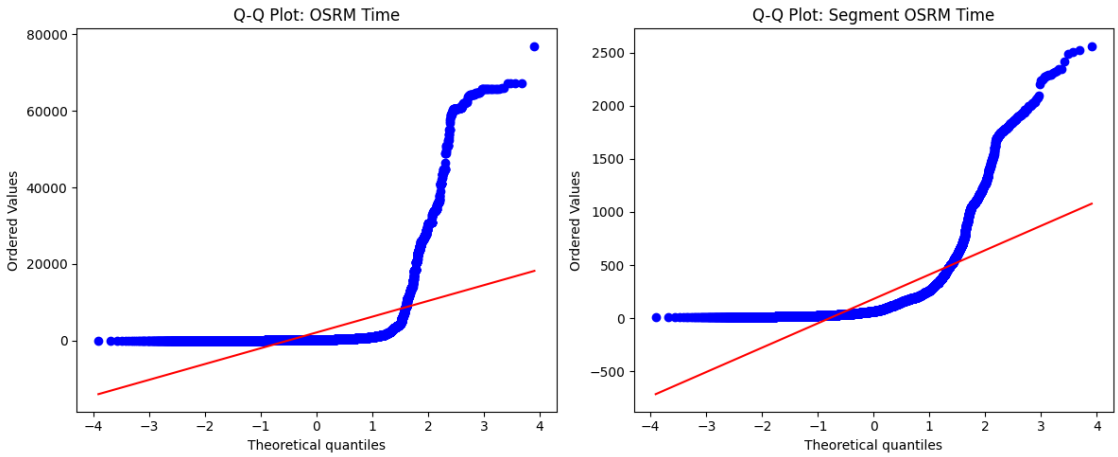
```
/usr/local/lib/python3.11/dist-packages/scipy/stats/_axis_nan_policy.py:586:
```

```
UserWarning: scipy.stats.shapiro: For N > 5000, computed p-value may not be
accurate. Current N is 14817.
  res = hypotest_fun_out(*samples, **kwds)
```

[ ]:
```
test_stat,p_val=scpy.shapiro(df_2['segment_osrm_distance'])
print(f"test_statistic:{test_stat}")
print(f"p_value:{p_val}")
if p_val <0.05:
  print('Reject Ho: The data does not follow normal distribution')
else:
  print('Fail to reject Ho: The data follows normal distribution')
```

```
test_statistic:0.5084269776547814
p_value:1.2107979713329913e-107
Reject Ho: The data does not follow normal distribution
```

[ ]:
```
# Q-Q Plot for Actual Time
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
stats.probplot(df_2['osrm_time'], dist="norm", plot=plt)
plt.title("Q-Q Plot: OSRM Time")

# Q-Q Plot for OSRM Time
plt.subplot(1, 2, 2)
stats.probplot(df_2['segment_osrm_time'], dist="norm", plot=plt)
plt.title("Q-Q Plot: Segment OSRM Time")

plt.tight_layout()
plt.show()
```



This show that data points deviate significantly from the straight diagonal line, especially in the

upper tail.

This indicates that neither the total OSRM time nor the sum of segment OSRM times is normally distributed.

The upward curvature suggests a right-skewed distribution for both.

This visual evidence supports the conclusions drawn from the Shapiro-Wilk tests, confirming that non-parametric tests are appropriate for comparing these two distributions.

[ ]:
```
test_stat, p_val =scpy.
 ↪mannwhitneyu(df_2['osrm_distance'],df_2['segment_osrm_distance'])
print(f'test_statistic:{test_stat}')
print(f'p_value:{p_val}')
if p_val <0.05:
  print('There is a statistically significant difference between the osrm␣
 ↪distance and segment osrm distance')
else:
  print('There is no statistically significant difference between osrm distance␣
 ↪and segment osrm distance')
```

```
test_statistic:146872393.5
p_value:0.0
There is a statistically significant difference between the osrm distance and
segment osrm distance
```

There is a significant difference between the OSRM total distance and the sum of segment OSRM distances (p-value = 0).

This suggests that the segment distances do not perfectly add up to the overall route distance.

This discrepancy could be due to inaccurate segmentation, route recalculations, or data inconsistencies. Resolving these issues will help improve route accuracy and logistics planning.

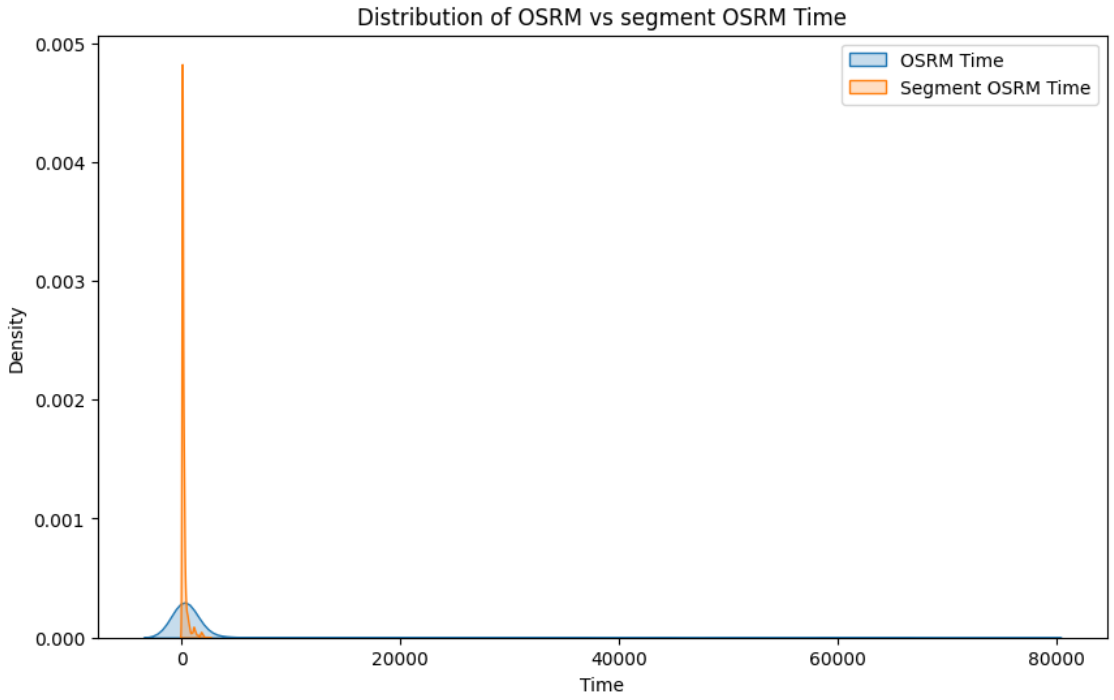
5. Do hypothesis testing/ visual analysis between osrm time aggregated value and segment osrm time aggregated value (aggregated values are the values you'll get after merging the rows on the basis of trip_uuid)

[ ]:
```
df_2[['osrm_time','segment_osrm_time']].describe()
```

[ ]:

	osrm_time	segment_osrm_time
count	14817.000000	14817.000000
mean	2091.007324	180.949783
std	7956.896484	314.541412
min	6.000000	6.000000
25%	62.000000	31.000000
50%	167.000000	65.000000
75%	516.000000	185.000000
max	76953.000000	2564.000000

[ ]:
```
#kde plot for visualization
plt.figure(figsize=(10,6))
sns.kdeplot(df_2['osrm_time'],label='OSRM Time', fill=True)
sns.kdeplot(df_2['segment_osrm_time'],label='Segment OSRM Time',fill=True)
plt.title('Distribution of OSRM vs segment OSRM Time')
plt.xlabel('Time')
plt.legend()
plt.show()
```



[ ]:
```
#checking normality
test_stat,p_val=scpy.shapiro(df_2['osrm_time'])
print(f"test_statistic:{test_stat}")
print(f"p_value:{p_val}")
if p_val <0.05:
  print('The data does not follow normal distribution')
else:
  print('The data follows normal distribution')
```

```
test_statistic:0.2685661543502248
p_value:3.4699195378013362e-118
The data does not follow normal distribution
```

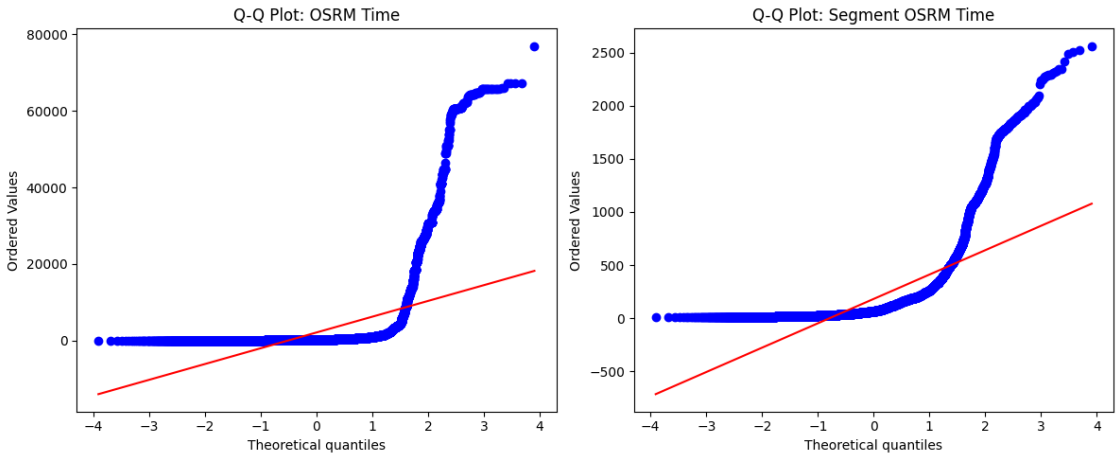
```
/usr/local/lib/python3.11/dist-packages/scipy/stats/_axis_nan_policy.py:586:
UserWarning: scipy.stats.shapiro: For N > 5000, computed p-value may not be
accurate. Current N is 14817.
```

```
  res = hypotest_fun_out(*samples, **kwds)
```

[ ]:
```
test_stat,p_val=scpy.shapiro(df_2['segment_osrm_time'])
print(f"test_statistic:{test_stat}")
print(f"p_value:{p_val}")
if p_val <0.05:
  print('The data does not follow normal distribution')
else:
  print('The data follows normal distribution')
```

```
test_statistic:0.5331972949207214
p_value:2.617893315832657e-106
The data does not follow normal distribution
```

[ ]:
```
# Q-Q Plot for Actual Time
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
stats.probplot(df_2['osrm_time'], dist="norm", plot=plt)
plt.title("Q-Q Plot: OSRM Time")

# Q-Q Plot for segment actual time
plt.subplot(1, 2, 2)
stats.probplot(df_2['segment_osrm_time'], dist="norm", plot=plt)
plt.title("Q-Q Plot: Segment OSRM Time")

plt.tight_layout()
plt.show()
```



Both Q-Q plots (OSRM Time and Segment OSRM Time) show significant deviation from the normal distribution line, particularly in the upper tail. This visually confirms the results of the Shapiro-Wilk test.

The upward curvature indicates a right-skewed distribution for both variables.

This visual evidence supports the conclusion that neither distribution is normal, and non-parametric tests are appropriate for comparison.

[ ]:
```
test_stat, p_val =scpy.mannwhitneyu(df_2['osrm_time'],df_2['segment_osrm_time'])
print(f'test_statistic:{test_stat}')
print(f'p_value:{p_val}')
if p_val <0.05:
  print('There is a statistically significant difference between the osrm time␣
 ↪and segment osrm time')
else:
  print('There is no statistically significant difference between osrm time and␣
 ↪segment osrm_time')
```

```
test_statistic:147916488.5
p_value:0.0
There is a statistically significant difference between the osrm time and
segment osrm time
```

The Mann-Whitney U test results show a statistically significant difference between OSRM estimated time and segment OSRM estimated times (p-value < 0.05).

This indicates that summing up the time estimates for individual segments does not perfectly match the total OSRM time estimated for the entire trip.

The difference suggests potential inconsistencies in how OSRM time is calculated at the segment versus the trip level, which could impact the accuracy of overall route time estimations.

6. Find outliers in the numerical variables (you might find outliers in almost all the variables), and check it using visual analysis

[ ]:
```
df_2.select_dtypes(include=['number']).columns
```

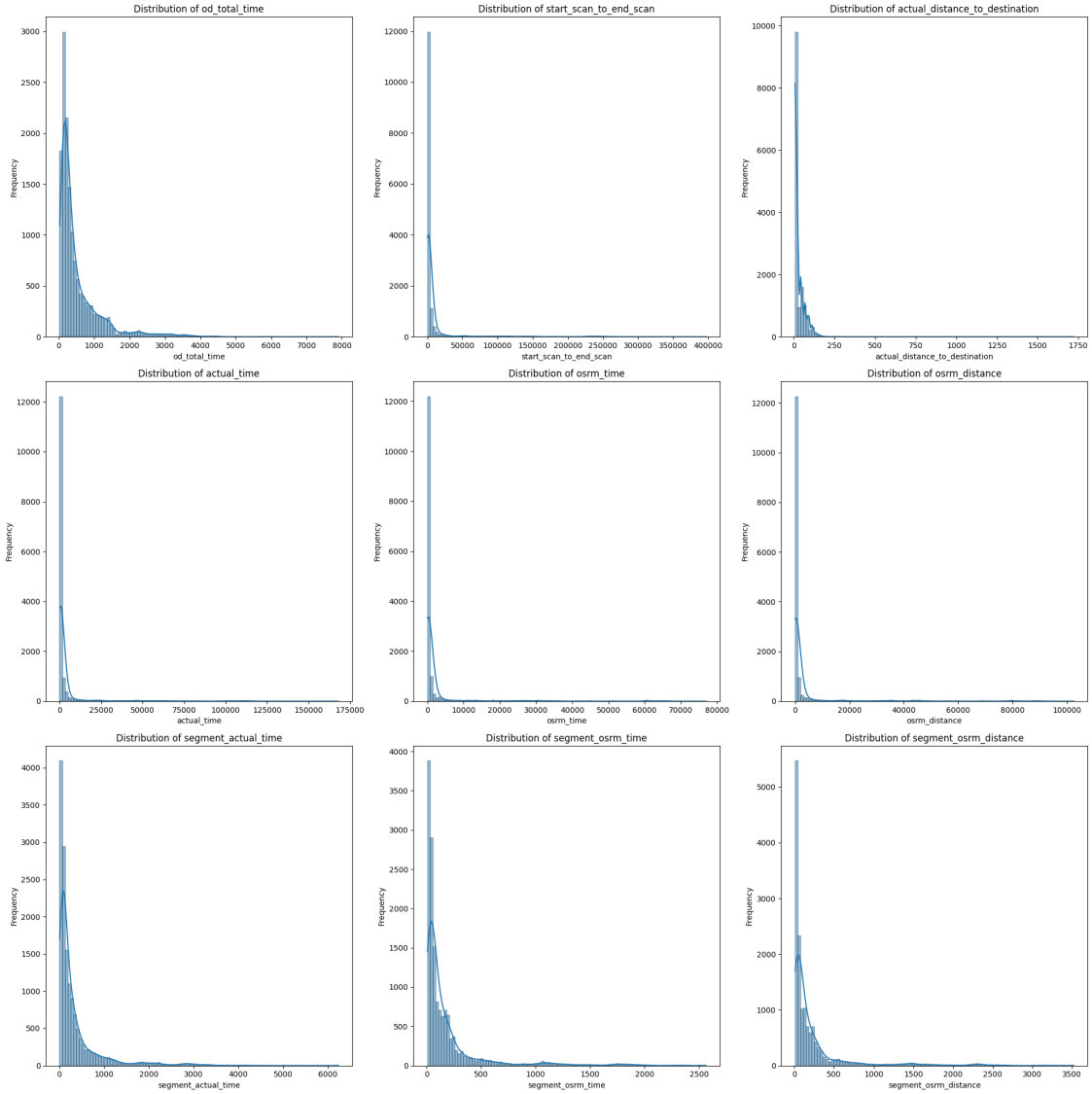
[ ]:
```
Index(['od_total_time', 'start_scan_to_end_scan',
       'actual_distance_to_destination', 'actual_time', 'osrm_time',
       'osrm_distance', 'segment_actual_time', 'segment_osrm_time',
       'segment_osrm_distance', 'start_scan_to_end_scan_min'],
      dtype='object')
```

[ ]:
```
numerical_columns=['od_total_time', 'start_scan_to_end_scan',
       'actual_distance_to_destination', 'actual_time', 'osrm_time',
       'osrm_distance', 'segment_actual_time', 'segment_osrm_time',
       'segment_osrm_distance']
df_2[numerical_columns].describe().T
```

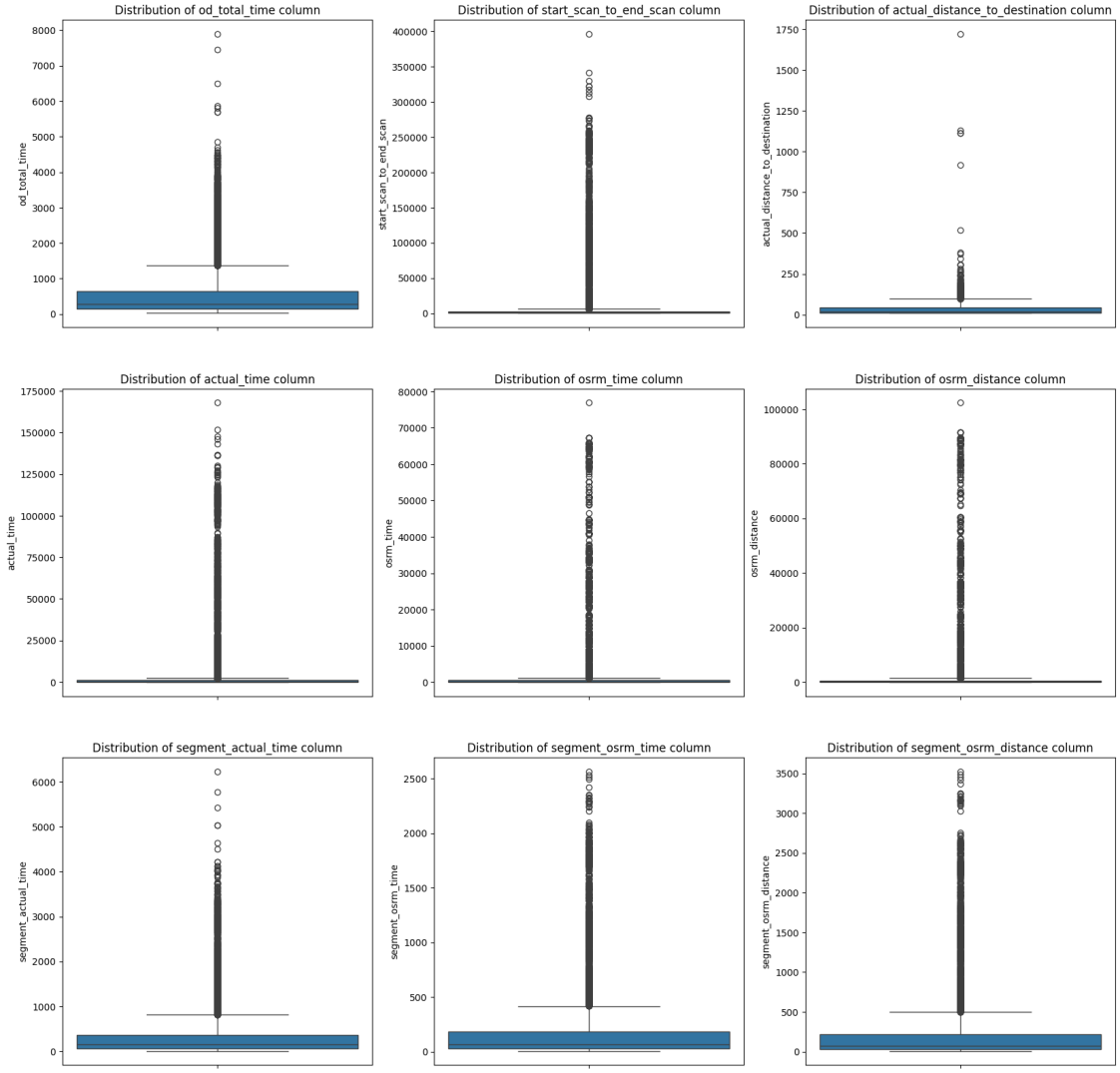
[ ]:
```
                                count         mean           std        min  \
od_total_time                 14817.0   531.795209    659.184525  23.461468
start_scan_to_end_scan        14817.0  9398.344727  33701.675781  26.000000
actual_distance_to_destination 14817.0    32.067497     39.296524   9.000046
```

```
actual_time                      14817.0  4076.333984  15216.874023   9.000000
osrm_time                        14817.0  2091.007324   7956.896484   6.000000
osrm_distance                    14817.0  2784.231934  10759.122070   9.072900
segment_actual_time              14817.0   353.892273    556.246826   9.000000
segment_osrm_time                14817.0   180.949783    314.541412   6.000000
segment_osrm_distance            14817.0   223.201157    416.628326   9.072900

                                        25%         50%          75%  \
od_total_time                    149.930591  280.765626   638.199071
start_scan_to_end_scan           408.000000  985.000000  2826.000000
actual_distance_to_destination     9.631898   19.435421    44.954380
actual_time                      142.000000  348.000000  1063.000000
osrm_time                         62.000000  167.000000   516.000000
osrm_distance                     65.738602  173.593597   607.677368
segment_actual_time               66.000000  147.000000   367.000000
segment_osrm_time                 31.000000   65.000000   185.000000
segment_osrm_distance             32.654499   70.154404   218.802399

                                         max
od_total_time                    7898.551955
start_scan_to_end_scan         396800.000000
actual_distance_to_destination    1722.045532
actual_time                     167920.000000
osrm_time                        76953.000000
osrm_distance                   102415.867188
segment_actual_time               6230.000000
segment_osrm_time                 2564.000000
segment_osrm_distance             3523.632324
```

[ ]:
```
plt.figure(figsize=(20,20))

for i, col in enumerate(numerical_columns, 1):
    plt.subplot(3, 3, i)
    sns.histplot(df_2[col], bins=100, kde=True)
    plt.title(f'Distribution of {col}')
    plt.xlabel(col)
    plt.ylabel('Frequency')

plt.tight_layout()
plt.show()
```



[ ]:
```
plt.figure(figsize = (20, 20))
for i in range(len(numerical_columns)):
    plt.subplot(3, 3, i + 1)
    sns.boxplot(df_2[numerical_columns[i]])
    plt.title(f"Distribution of {numerical_columns[i]} column")
    plt.plot()
```



It can be observed from the above plots that data in all the numerical columns are right skewed. It can be infered that outliers are present in the data set.

7. Handle the outliers using the IQR method.

[ ]:
```
# prompt: generate code for outliers in numerical columns

def identify_outliers_iqr(df, column):
  Q1 = df[column].quantile(0.25)
  Q3 = df[column].quantile(0.75)
  IQR = Q3 - Q1
  lower_bound = Q1 - 1.5 * IQR
  upper_bound = Q3 + 1.5 * IQR
  outliers_df = df[(df[column] < lower_bound) | (df[column] > upper_bound)]
  return lower_bound, upper_bound, outliers_df
```

```python
# Apply the function to each numerical column and print the results
print("Identifying Outliers using IQR Method:")
for col in numerical_columns:
    lower, upper, outliers = identify_outliers_iqr(df_2, col)
    print(f"\n--- Outliers in '{col}' ---")
    print(f"  Lower Bound (IQR): {lower:.2f}")
    print(f"  Upper Bound (IQR): {upper:.2f}")
    print(f"  Number of Outliers: {len(outliers)}")
    if len(outliers) > 0:
        print("  Sample Outliers:")
        print(outliers[[col]].head())
```

```
Identifying Outliers using IQR Method:

--- Outliers in 'od_total_time' ---
  Lower Bound (IQR): -582.47
  Upper Bound (IQR): 1370.60
  Number of Outliers: 1266
  Sample Outliers:
    od_total_time
0     2260.109800
2     3934.362520
41    2338.380200
43    2302.995534
62    1795.279778

--- Outliers in 'start_scan_to_end_scan' ---
  Lower Bound (IQR): -3219.00
  Upper Bound (IQR): 6453.00
  Number of Outliers: 2026
  Sample Outliers:
    start_scan_to_end_scan
0                  43659.0
2                 248631.0
13                 11435.0
39                 11500.0
41                114562.0

--- Outliers in 'actual_distance_to_destination' ---
  Lower Bound (IQR): -43.35
  Upper Bound (IQR): 97.94
  Number of Outliers: 706
  Sample Outliers:
    actual_distance_to_destination
30                      114.507141
42                      132.176636
```

```
57                      107.864494
62                      164.736755
68                      112.162735

--- Outliers in 'actual_time' ---
  Lower Bound (IQR): -1239.50
  Upper Bound (IQR): 2444.50
  Number of Outliers: 2070
  Sample Outliers:
    actual_time
0       15682.0
2      112225.0
13       5503.0
20       2534.0
39       4793.0

--- Outliers in 'osrm_time' ---
  Lower Bound (IQR): -619.00
  Upper Bound (IQR): 1197.00
  Number of Outliers: 1948
  Sample Outliers:
    osrm_time
0      7787.0
2     65768.0
13     3010.0
39     2948.0
41    23589.0

--- Outliers in 'osrm_distance' ---
  Lower Bound (IQR): -747.17
  Upper Bound (IQR): 1420.59
  Number of Outliers: 2069
  Sample Outliers:
    osrm_distance
0    10577.764648
2    89447.250000
13    3814.062256
39    3846.499512
41   31927.496094

--- Outliers in 'segment_actual_time' ---
  Lower Bound (IQR): -385.50
  Upper Bound (IQR): 818.50
  Number of Outliers: 1643
  Sample Outliers:
    segment_actual_time
0                1548.0
2                3308.0
```

```
20                 843.0
41                2073.0
43                1963.0

--- Outliers in 'segment_osrm_time' ---
  Lower Bound (IQR): -200.00
  Upper Bound (IQR): 416.00
  Number of Outliers: 1492
  Sample Outliers:
    segment_osrm_time
0              1008.0
2              1941.0
13              492.0
39              471.0
41             1003.0

--- Outliers in 'segment_osrm_distance' ---
  Lower Bound (IQR): -246.57
  Upper Bound (IQR): 498.02
  Number of Outliers: 1548
  Sample Outliers:
    segment_osrm_distance
0             1320.473267
2             2545.267822
13             623.379211
39             596.815430
41            1360.305298
```

8.Do one-hot encoding of categorical variables (like route_type)

[ ]:
```
# One-hot encode 'data' and 'route_type' columns
df_encoded = pd.get_dummies(df_2, columns=['data', 'route_type'],␣
 ↪prefix=['data', 'route'])
# View the result
df_encoded.head()
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-2-4287706567> in <cell line: 0>()
      1 # One-hot encode 'data' and 'route_type' columns
----> 2 df_encoded = pd.get_dummies(df_2, columns=['data', 'route_type'],␣
 ↪prefix=['data', 'route'])
      3 # View the result
      4 df_encoded.head()

NameError: name 'pd' is not defined
```

[ ]:
```
from sklearn.preprocessing import MinMaxScaler

numerical_columns = ['od_total_time', 'start_scan_to_end_scan',
                     'actual_distance_to_destination', 'actual_time',␣
 ↪'osrm_time',
                     'osrm_distance', 'segment_actual_time',␣
 ↪'segment_osrm_time',
                     'segment_osrm_distance']
scaler = MinMaxScaler()
df_normalized = df_2.copy()
df_normalized[numerical_columns] = scaler.fit_transform(df_2[numerical_columns])
df_normalized[numerical_columns].head()
```

[ ]:

	od_total_time	start_scan_to_end_scan	actual_distance_to_destination	actual_time	osrm_time	osrm_distance	segment_actual_time	segment_osrm_time	segment_osrm_distance
0	0.284016	0.109969	0.027920	0.093341	0.101122	0.103203	0.247388	0.391712	0.373134
1	0.020082	0.002218	0.005948	0.002323	0.002651	0.002542	0.021218	0.023065	0.021373
2	0.496617	0.626566	0.024861	0.668306	0.854640	0.873362	0.530301	0.756450	0.721625
3	0.009782	0.000439	0.001374	0.000435	0.000234	0.000220	0.008037	0.003909	0.003074
4	0.088239	0.003932	0.033946	0.003258	0.002612	0.002512	0.053207	0.042611	0.039185

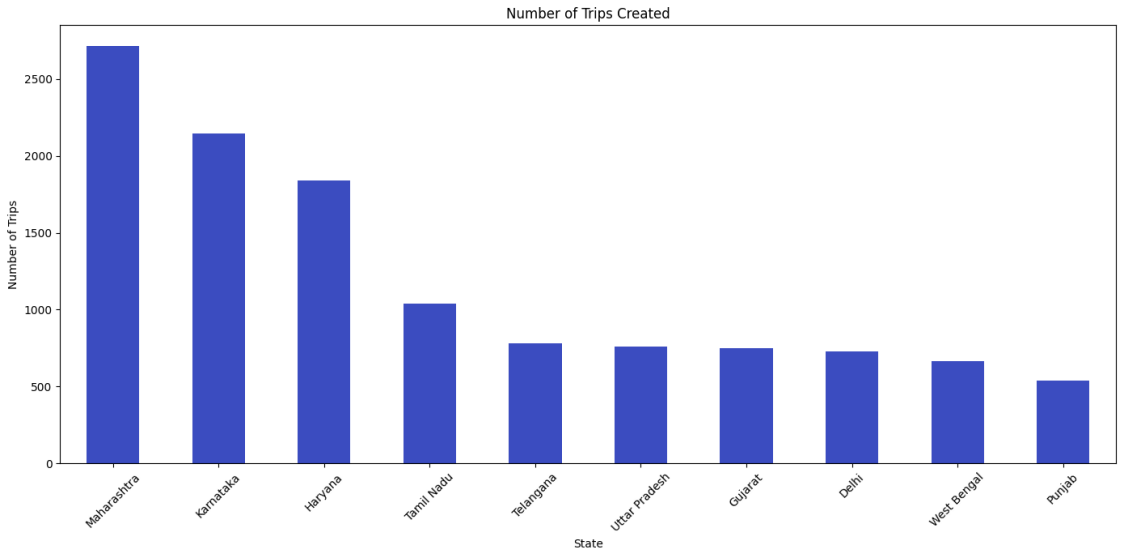
Basic Analysis

[ ]:
```
#Check from where most orders are coming from (State, Corridor etc)
state_counts = df_2['source_state'].value_counts().sort_values(ascending=False)
state_counts
```

[ ]:
```
source_state
Maharashtra          2714
Karnataka            2143
Haryana              1838
Tamil Nadu           1039
Telangana             781
Uttar Pradesh         762
```

```
Gujarat                    750
Delhi                      728
West Bengal                665
Punjab                     536
Rajasthan                  514
Andhra Pradesh             434
Bihar                      350
Madhya Pradesh             317
Kerala                     289
Assam                      268
Jharkhand                  160
Uttarakhand                114
Orissa                     107
Chandigarh                  93
Goa                         65
Chhattisgarh                43
Himachal Pradesh            34
Jammu & Kashmir             17
Dadra and Nagar Haveli      15
Pondicherry                 12
Nagaland                     5
Arunachal Pradesh            4
Mizoram                      4
Name: count, dtype: int64
```

[ ]:
```
state_counts.head(10).plot(kind='bar', figsize=(14, 7), colormap='coolwarm')
plt.title('Number of Trips Created')
plt.xlabel('State')
plt.ylabel('Number of Trips')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



The highest trips created by maharastra followed by karnataka and haryana. These states shows stronger seller base.

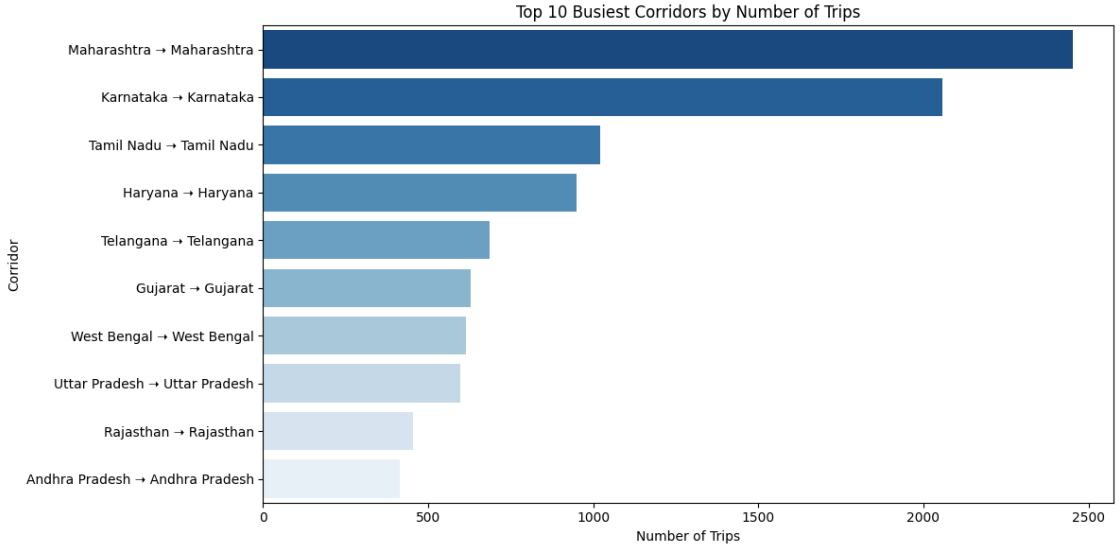
[ ]:
```
# Group by source and destination state to find busiest corridors
df_corridors = df_2.groupby(['source_state', 'destination_state'])['trip_uuid'].
 ↪count().reset_index()

# Rename the column for clarity
df_corridors.rename(columns={'trip_uuid': 'trip_count'}, inplace=True)

# Sort to get the top busiest corridors
df_corridors = df_corridors.sort_values(by='trip_count', ascending=False)

# Display top 10 busiest corridors
df_corridors.head(10)
```

[ ]:

	source_state	destination_state	trip_count
88	Maharashtra	Maharashtra	2453
65	Karnataka	Karnataka	2056
114	Tamil Nadu	Tamil Nadu	1021
42	Haryana	Haryana	949
123	Telangana	Telangana	685
32	Gujarat	Gujarat	629
140	West Bengal	West Bengal	615
130	Uttar Pradesh	Uttar Pradesh	597
110	Rajasthan	Rajasthan	453
0	Andhra Pradesh	Andhra Pradesh	414

[ ]:
```
top_corridors = df_corridors.head(10)

# Combine source and destination into one label for better visualization
top_corridors['corridor'] = top_corridors['source_state'] + '   ' +␣
 ↪top_corridors['destination_state']

# Plot
plt.figure(figsize=(12, 6))
sns.barplot(data=top_corridors, x='trip_count', y='corridor', palette='Blues_r')
plt.title('Top 10 Busiest Corridors by Number of Trips')
plt.xlabel('Number of Trips')
plt.ylabel('Corridor')
plt.tight_layout()
plt.show()
```

```
<ipython-input-75-14e21fdc29f5>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  top_corridors['corridor'] = top_corridors['source_state'] + '   ' +
top_corridors['destination_state']
<ipython-input-75-14e21fdc29f5>:8: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(data=top_corridors, x='trip_count', y='corridor',
palette='Blues_r')
```



Business Activity:

The fact that the top 10 corridors represent a significant portion of the total trip volume indicates a concentration of logistics business in specific geographic areas and routes.

This suggests that optimizing operations, infrastructure, and resources along these high-volume corridors should be a strategic priority.

Potential for Targeted Investment:

Understanding these busiest routes allows for targeted investment in infrastructure, such as warehouses, sorting centers, and vehicle fleets, in or near these key source and destination states.

This can improve efficiency and reduce costs on the most frequent routes.

[ ]:
```
#trips created on day basis
df_2['trip_creation_day'].unique()
```

[ ]:
```
array([12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28,
       29, 30,  1,  2,  3], dtype=int32)
```

[ ]:
```
df_day=df_2.groupby('trip_creation_day')['trip_uuid'].count().reset_index()
df_day.T
```

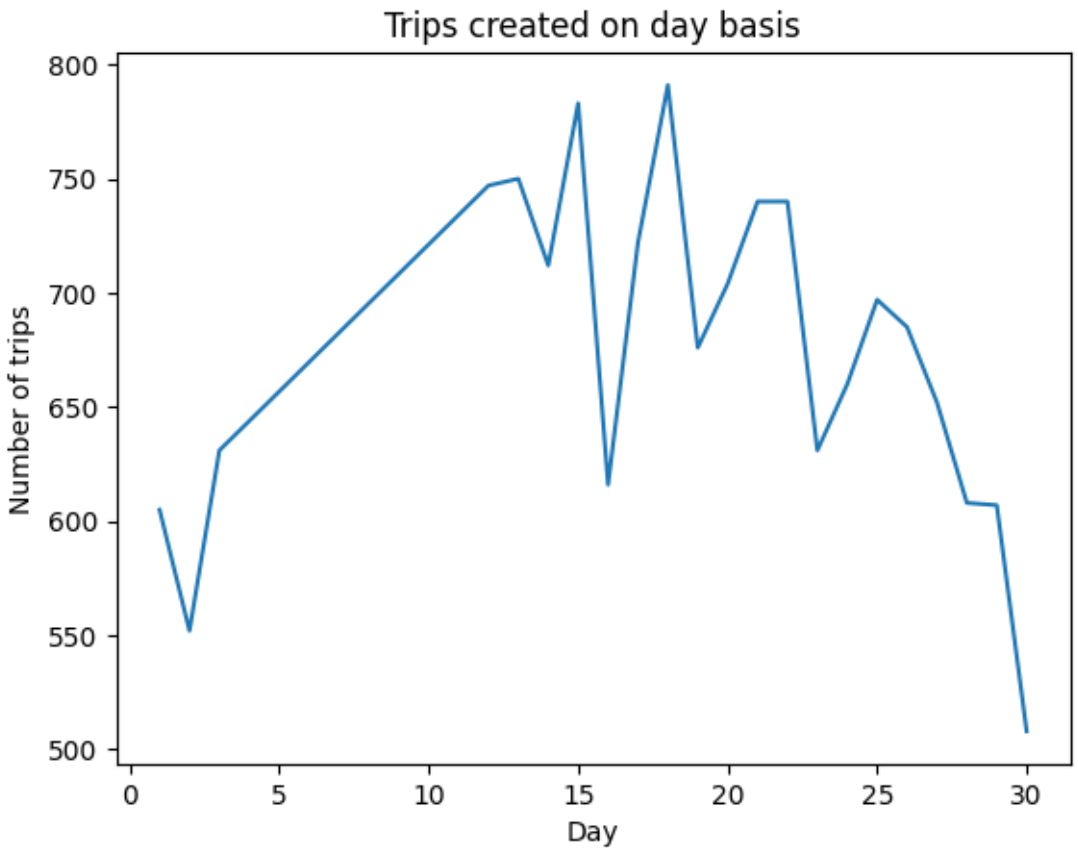
[ ]:

	0	1	2	3	4	5	6	7	8	9	…	12	\
trip_creation_day	1	2	3	12	13	14	15	16	17	18	…	21	
trip_uuid	605	552	631	747	750	712	783	616	722	791	…	740	

	13	14	15	16	17	18	19	20	21
trip_creation_day	22	23	24	25	26	27	28	29	30
trip_uuid	740	631	660	697	685	652	608	607	508

[2 rows x 22 columns]

[ ]:
```
sns.lineplot(data=df_day,x='trip_creation_day', y='trip_uuid')
plt.title('Trips created on day basis')
plt.xlabel('Day')
plt.ylabel('Number of trips')
plt.show()
```



Customers usually perfer to make more orders in the mid of the month.

[ ]:
```
#weekly basis
df_2['trip_creation_week'].unique()
```

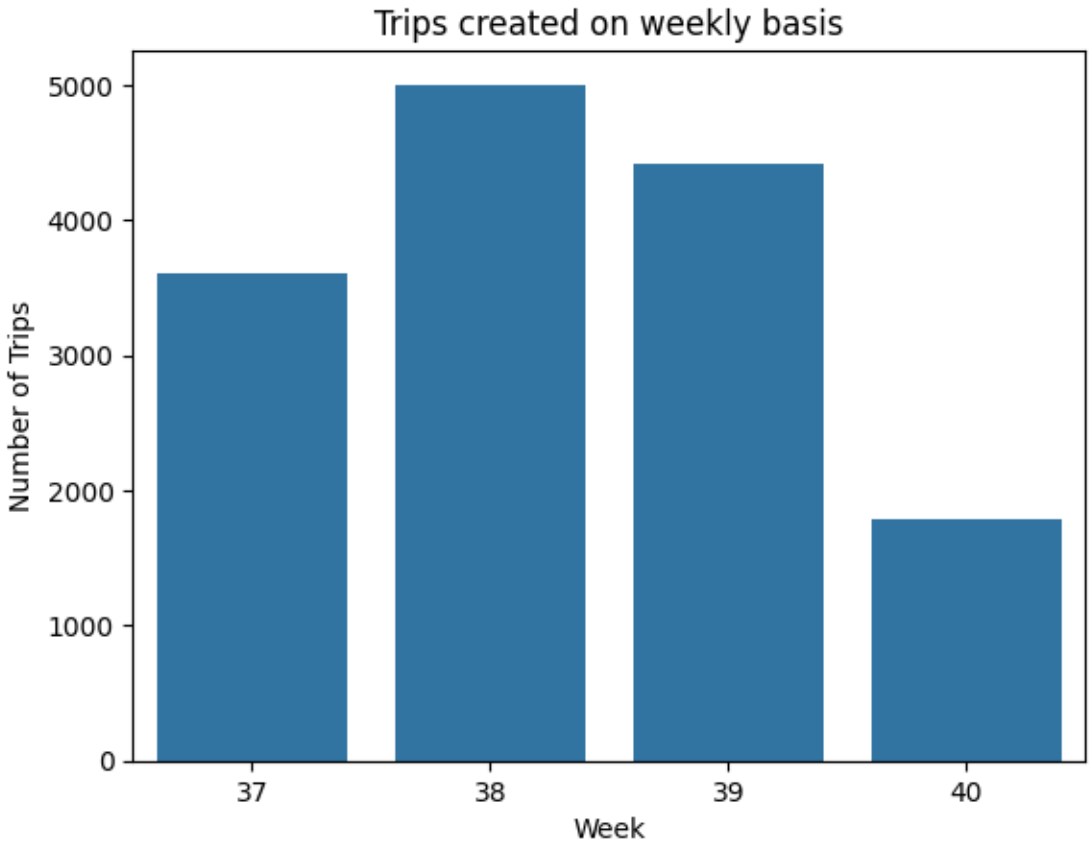
[ ]:
```
<IntegerArray>
[37, 38, 39, 40]
Length: 4, dtype: UInt32
```

[ ]:
```
df_week=df_2.groupby('trip_creation_week')['trip_uuid'].count().reset_index()
df_week.T
```

[ ]:
```
                        0     1     2     3
trip_creation_week     37    38    39    40
trip_uuid            3608  5004  4417  1788
```

[ ]:
```
sns.barplot(data=df_week,x='trip_creation_week',y='trip_uuid')
plt.title('Trips created on weekly basis')
plt.xlabel('Week')
plt.ylabel('Number of Trips')
```

```
plt.show()
```



Trip created on weekly basis found to be highest in 38th week followed by 39th week.

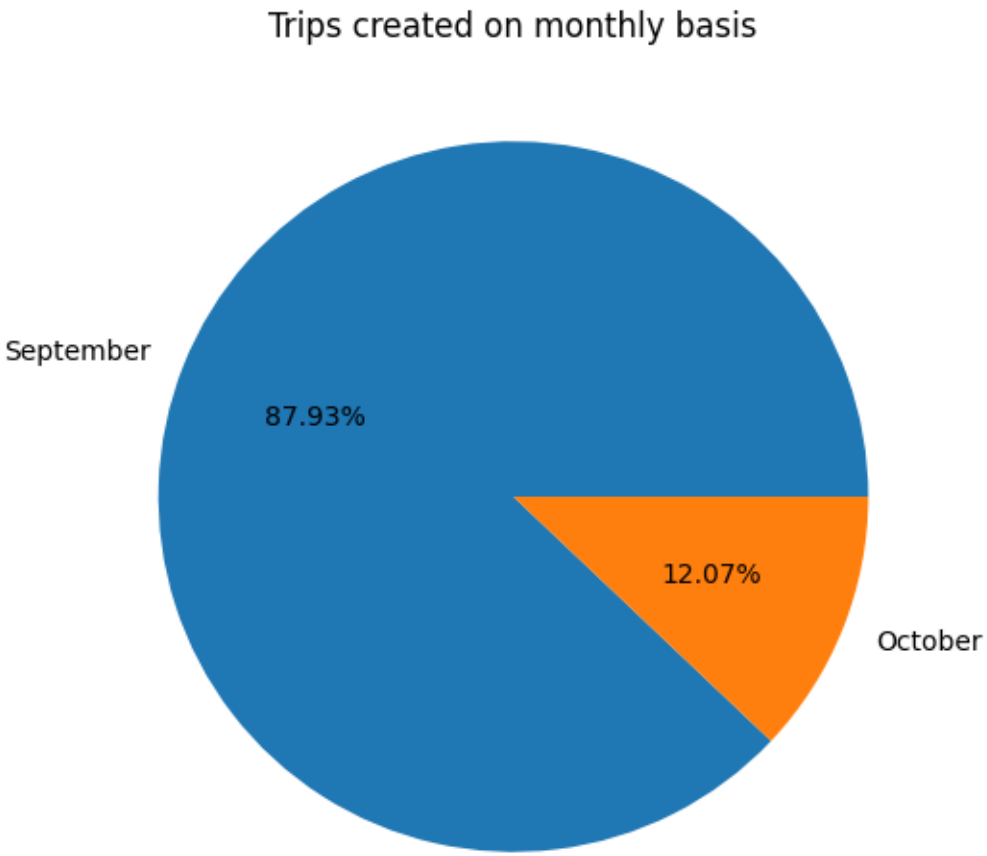
[ ]:
```
#trip created on mothly basis

df_month=df_2.groupby('trip_creation_month')['trip_uuid'].count().to_frame().
 ↪reset_index()
df_month['percent']=np.round(df_month['trip_uuid']*100/df_month['trip_uuid'].
 ↪sum(),2)
df_month['trip_creation_month']=df_month['trip_creation_month'].apply(lambda x:␣
 ↪calendar.month_name[x])
df_month.T
```

[ ]:

	0	1
trip_creation_month	September	October
trip_uuid	13029	1788
percent	87.93	12.07

[ ]:
```
#pie chart
plt.figure(figsize=(6,6))
plt.pie(df_month['trip_uuid'],labels=df_month['trip_creation_month'],autopct='%.
  ↪2f%%')
plt.title('Trips created on monthly basis')
plt.plot()
plt.plot()
```

[ ]:
```
[]
```



88% of orders created during the month of september

[ ]:
```
#didtribution of trip data for the orders
df_data=df_2.groupby('data')['trip_uuid'].count().to_frame().reset_index()
df_data['percent']=np.round(df_data['trip_uuid']*100/df_data['trip_uuid'].
  ↪sum(),2)
df_data
```

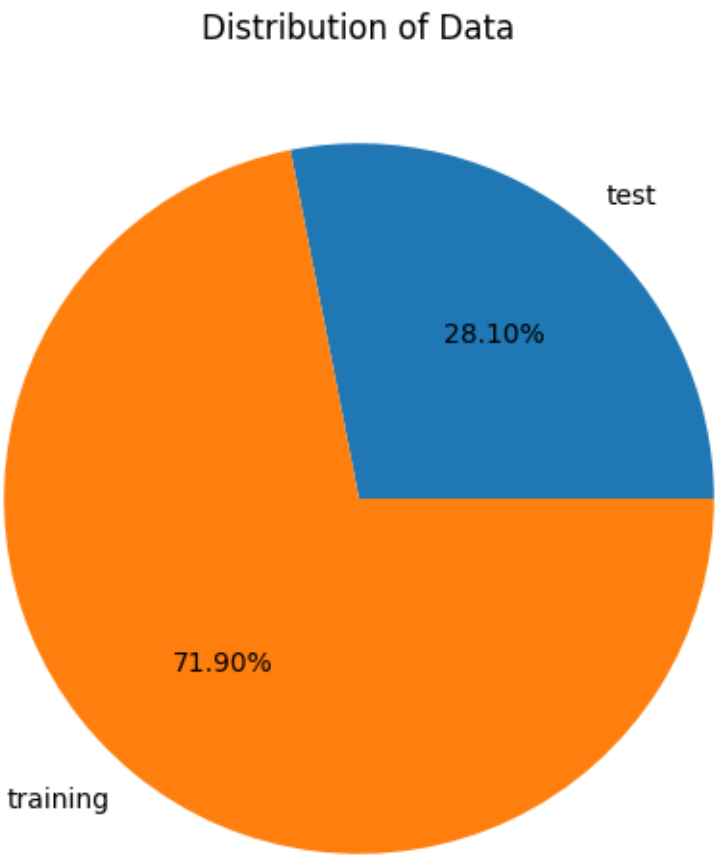
```
<ipython-input-120-69ec52e72ced>:2: FutureWarning: The default of observed=False
is deprecated and will be changed to True in a future version of pandas. Pass
observed=False to retain current behavior or observed=True to adopt the future
default and silence this warning.
  df_data=df_2.groupby('data')['trip_uuid'].count().to_frame().reset_index()
```

[ ]:

	data	trip_uuid	percent
0	test	4163	28.1
1	training	10654	71.9

[ ]:
```
plt.figure(figsize=(6,6))
plt.pie(df_data['trip_uuid'],labels=df_data['data'],autopct='%.2f%%')
plt.title('Distribution of Data')
plt.plot()
plt.plot()
```

[ ]: []



~72% of data derived from training category.

[ ]:
```
#distribution of orders by route type
df_route_type=df_2.groupby('route_type')['trip_uuid'].count().to_frame().
 ↪reset_index()
df_route_type['percent']=np.round(df_data['trip_uuid']*100/df_data['trip_uuid'].
 ↪sum(),2)
df_route_type
```

```
<ipython-input-124-9d7542920432>:2: FutureWarning: The default of observed=False
is deprecated and will be changed to True in a future version of pandas. Pass
observed=False to retain current behavior or observed=True to adopt the future
default and silence this warning.
  df_route_type=df_2.groupby('route_type')['trip_uuid'].count().to_frame().reset
_index()
```

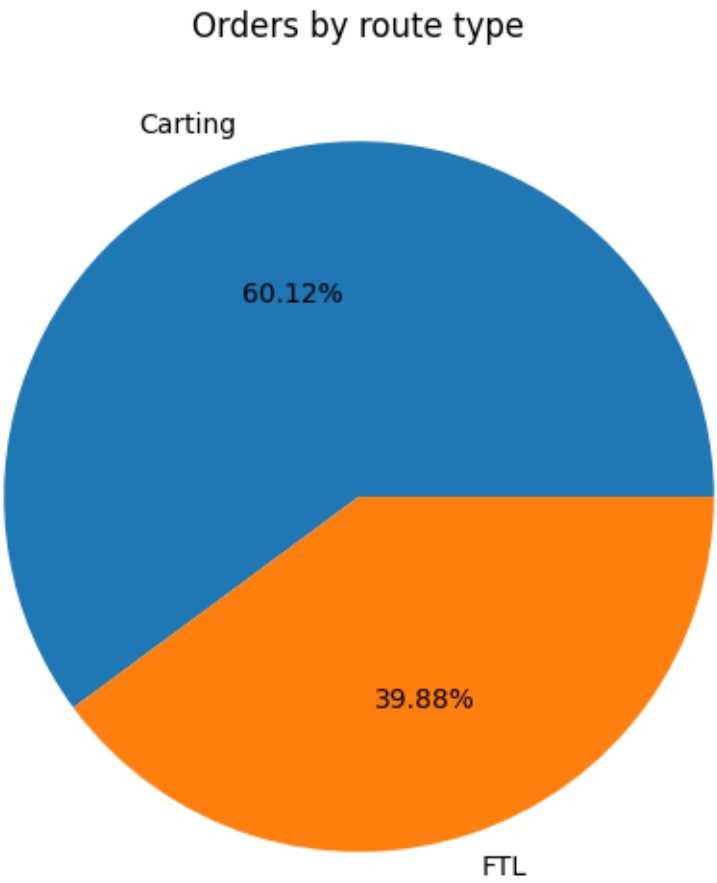
[ ]:

	route_type	trip_uuid	percent
0	Carting	8908	60.12
1	FTL	5909	39.88

[ ]:
```

```

[ ]:
```
plt.figure(figsize=(6,6))
plt.pie(df_route_type['trip_uuid'],labels=df_data['route_type'],autopct='%.
 ↪2f%%')
plt.title('Orders by route type')
plt.plot()
plt.plot()
```

[ ]: []



60.12% of orders are delivered through carting route type.

Business Insights for Delhivery Logistics

1.**OSRM Trip Planning Needs Improvement**

Delivery trips take ~27% longer than planned (OSRM predictions), causing delays. For example, a 3-hour planned trip often takes over 6 hours.

Recommendation: Fix routing engine configurations to better account for real-world factors like traffic or road conditions.

2. Focus on High-Volume States

Key hubs: Gurgaon (Haryana), Karnataka, Tamil Nadu, and Uttar Pradesh are major sources/destinations.

Recommendation: Optimize routes in these states to reduce delays and improve delivery efficiency.

3. Address Distance Discrepancies

Actual routes are sometimes shorter than OSRM-planned distances (e.g., 234 km vs. 285 km on average). Drivers might be taking shortcuts or avoiding traffic.

Recommendation: Investigate why drivers deviate from planned routes and update OSRM with real-world insights.

4. Prepare for State-Specific Challenges

States like Karnataka and Tamil Nadu have mixed terrain (e.g., cities and rural areas), which may cause delays.

Recommendation: Plan for traffic and terrain issues, especially during festivals or peak seasons.

5. Extend Data Collection Period

Current data covers only 2 months (Sep-Oct 2018), limiting trend analysis.

Recommendation: Collect data for 6–12 months to identify seasonal patterns (e.g., holiday rush).

6. Improve Delivery Time Predictions

The average delay per trip segment is 27%, hurting customer trust.

Recommendation: Use real-time traffic data to align OSRM predictions with actual delivery times.

Summary:

Delhivery's biggest opportunities lie in fixing route-planning inaccuracies, standardizing location data, and focusing on high-demand states. Addressing these will reduce delays, lower costs, and improve customer satisfaction.