Delhivery

March 19, 2022

[1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from scipy import stats

import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)

pd.set_option('display.max_columns', None)
```

0.0.1 Problem Statement :

Delhivery wants to understand and process the data coming out of data engineering pipelines. The two main tasks involved are :

- Cleaning, sanitizing and manipulating data to get useful features out of raw fields.
- Making sense out of the raw data to provide business insights/recommendations and to help data science team to build forecasting models on it.

[2]:
```
df = pd.read_csv("data/delhivery_data.csv")
df.head(10)
```

[2]:
```
       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
5  training  2018-09-20 02:35:36.476840
6  training  2018-09-20 02:35:36.476840
7  training  2018-09-20 02:35:36.476840
8  training  2018-09-20 02:35:36.476840
9  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
5  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
6  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
7  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
8  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
9  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)
5  trip-153741093647649320  IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
6  trip-153741093647649320  IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
7  trip-153741093647649320  IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
8  trip-153741093647649320  IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
9  trip-153741093647649320  IND388620AAB  Khambhat_MotvdDPP_D (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)
5       IND388320AAA     Anand_Vaghasi_IP (Gujarat)
6       IND388320AAA     Anand_Vaghasi_IP (Gujarat)
7       IND388320AAA     Anand_Vaghasi_IP (Gujarat)
8       IND388320AAA     Anand_Vaghasi_IP (Gujarat)
9       IND388320AAA     Anand_Vaghasi_IP (Gujarat)

               od_start_time                 od_end_time  \
0  2018-09-20 03:21:32.418600  2018-09-20 04:47:45.236797
1  2018-09-20 03:21:32.418600  2018-09-20 04:47:45.236797
2  2018-09-20 03:21:32.418600  2018-09-20 04:47:45.236797
3  2018-09-20 03:21:32.418600  2018-09-20 04:47:45.236797
4  2018-09-20 03:21:32.418600  2018-09-20 04:47:45.236797
5  2018-09-20 04:47:45.236797  2018-09-20 06:36:55.627764
6  2018-09-20 04:47:45.236797  2018-09-20 06:36:55.627764
7  2018-09-20 04:47:45.236797  2018-09-20 06:36:55.627764
8  2018-09-20 04:47:45.236797  2018-09-20 06:36:55.627764
9  2018-09-20 04:47:45.236797  2018-09-20 06:36:55.627764

   start_scan_to_end_scan  is_cutoff  cutoff_factor  \
0                    86.0       True              9
```

```
1                   86.0       True            18
2                   86.0       True            27
3                   86.0       True            36
4                   86.0      False            39
5                  109.0       True             9
6                  109.0       True            18
7                  109.0       True            27
8                  109.0       True            36
9                  109.0      False            43

             cutoff_timestamp  actual_distance_to_destination  actual_time  \
0         2018-09-20 04:27:55                       10.435660         14.0
1         2018-09-20 04:17:55                       18.936842         24.0
2  2018-09-20 04:01:19.505586                       27.637279         40.0
3         2018-09-20 03:39:57                       36.118028         62.0
4         2018-09-20 03:33:55                       39.386040         68.0
5         2018-09-20 06:15:58                       10.403038         15.0
6         2018-09-20 05:47:29                       18.045481         44.0
7         2018-09-20 05:25:58                       28.061896         65.0
8         2018-09-20 05:15:56                       38.939167         76.0
9         2018-09-20 04:49:20                       43.595802        102.0

   osrm_time  osrm_distance    factor  segment_actual_time  segment_osrm_time  \
0       11.0        11.9653  1.272727                 14.0               11.0
1       20.0        21.7243  1.200000                 10.0                9.0
2       28.0        32.5395  1.428571                 16.0                7.0
3       40.0        45.5620  1.550000                 21.0               12.0
4       44.0        54.2181  1.545455                  6.0                5.0
5       11.0        12.1171  1.363636                 15.0               11.0
6       17.0        21.2890  2.588235                 28.0                6.0
7       29.0        35.8252  2.241379                 21.0               11.0
8       39.0        47.1900  1.948718                 10.0               10.0
9       45.0        53.2334  2.266667                 26.0                6.0

   segment_osrm_distance  segment_factor
0                11.9653        1.272727
1                 9.7590        1.111111
2                10.8152        2.285714
3                13.0224        1.750000
4                 3.9153        1.200000
5                12.1171        1.363636
6                 9.1719        4.666667
7                14.5362        1.909091
8                11.3648        1.000000
9                 6.0434        4.333333
```

[3]:
```
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
```

0.0.2 1. Basic Data Cleaning and Exploration

1.1 Handling Missing Values

[4]:
```python
for col in df.columns:
    n_nulls = df[col].isna().sum()
    if(n_nulls>0):
        print("Column '" + str(col)+"' has "+str(n_nulls)+" null values.")
```

```
Column 'source_name' has 293 null values.
Column 'destination_name' has 261 null values.
```

We see that the 'source_name' and 'destination_name' columns have null values (about 290 + 258 + 3 = 551, we subtract 3 because of common rows which have both columns null). We remove those 551 rows. These constitute of only 0.38% of total rows.

```
[5]: df[(df["destination_name"].isna()) & (df["source_name"].isna())]
```

```
[5]:            data          trip_creation_time  \
68006  training  2018-09-26 22:21:56.619259
68007  training  2018-09-26 22:21:56.619259
68008  training  2018-09-26 22:21:56.619259

                                     route_schedule_uuid route_type  \
68006  thanos::sroute:cfb575b8-df26-48f5-8427-6f48f9d…        FTL
68007  thanos::sroute:cfb575b8-df26-48f5-8427-6f48f9d…        FTL
68008  thanos::sroute:cfb575b8-df26-48f5-8427-6f48f9d…        FTL

                     trip_uuid source_center source_name destination_center  \
68006  trip-153800051661903546  IND331022A1B         NaN       IND331001A1C
68007  trip-153800051661903546  IND331022A1B         NaN       IND331001A1C
68008  trip-153800051661903546  IND331022A1B         NaN       IND331001A1C

      destination_name               od_start_time  \
68006              NaN  2018-09-27 03:19:14.797080
68007              NaN  2018-09-27 03:19:14.797080
68008              NaN  2018-09-27 03:19:14.797080

                      od_end_time  start_scan_to_end_scan  is_cutoff  \
68006  2018-09-27 05:28:00.922915                   128.0       True
68007  2018-09-27 05:28:00.922915                   128.0       True
68008  2018-09-27 05:28:00.922915                   128.0      False

       cutoff_factor            cutoff_timestamp  \
68006             22         2018-09-27 05:01:28
68007             44         2018-09-27 03:33:17
68008             50  2018-09-27 03:19:19.935198

       actual_distance_to_destination  actual_time  osrm_time  osrm_distance  \
68006                       25.178605         26.0       23.0        25.7246
68007                       45.101167        114.0       44.0        54.6110
68008                       50.844665        128.0       49.0        60.9205

         factor  segment_actual_time  segment_osrm_time  \
68006  1.130435                 26.0               23.0
68007  2.590909                 88.0               21.0
68008  2.612245                 13.0                4.0

       segment_osrm_distance  segment_factor
68006                25.7246        1.130435
68007                28.8863        4.190476
```

```
68008                    6.3096        3.250000
```

[6]:
```
df = df.dropna(subset = ['destination_name','source_name'])
```

[7]:
```
df.head(2)
```

[7]:
```
       data          trip_creation_time  \
0  training  2018-09-20 02:35:36.476840
1  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

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

  destination_center               destination_name  \
0       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
1       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)

               od_start_time                 od_end_time  \
0  2018-09-20 03:21:32.418600  2018-09-20 04:47:45.236797
1  2018-09-20 03:21:32.418600  2018-09-20 04:47:45.236797

   start_scan_to_end_scan  is_cutoff  cutoff_factor     cutoff_timestamp  \
0                    86.0       True              9  2018-09-20 04:27:55
1                    86.0       True             18  2018-09-20 04:17:55

   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

     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

   segment_factor
0        1.272727
1        1.111111
```

1.2 Analysing the structure of the data

[8]:
```
df.shape
```

[8]: (144316, 24)

So we see that there are 144316 rows and 24 columns. We can see the detailed description of the columns as given below:

Column Profiling

- data - tells whether the data is testing or training data

- trip_creation_time – Timestamp of trip creation
- route_schedule_uuid – Unique Id for a particular route schedule
- route_type – Transportation type
  - FTL – Full Truck Load: FTL shipments get to the destination sooner, as the truck is making no other pickups or drop-offs along the way
  - Carting: Handling system consisting of small vehicles (carts)
- trip_uuid - Unique ID given to a particular trip (A trip may include different source and destination centers)

- source_center - Source ID of trip origin

- source_name - Source Name of trip origin

- destination_cente – Destination ID

- destination_name – Destination Name

- od_start_time – Trip start time

- od_end_time – Trip end time

- start_scan_to_end_scan – Time taken to deliver from source to destination

- is_cutoff – Unknown field

- cutoff_factor – Unknown field

- cutoff_timestamp – Unknown field

- actual_distance_to_destination – Distance in Kms between source and destination warehouse
- actual_time – Actual time taken to complete the delivery (Cumulative)
- osrm_time – An open-source routing engine time calculator which computes the shortest path between points in a given map (Includes usual traffic, distance through major and minor roads) and gives the time (Cumulative)
- osrm_distance – An open-source routing engine which computes the shortest path between points in a given map (Includes usual traffic, distance through major and minor roads) (Cumulative)
- factor – Unknown field

- segment_actual_time – This is a segment time. Time taken by the subset of the package delivery
- segment_osrm_time – This is the OSRM segment time. Time taken by the subset of the package delivery

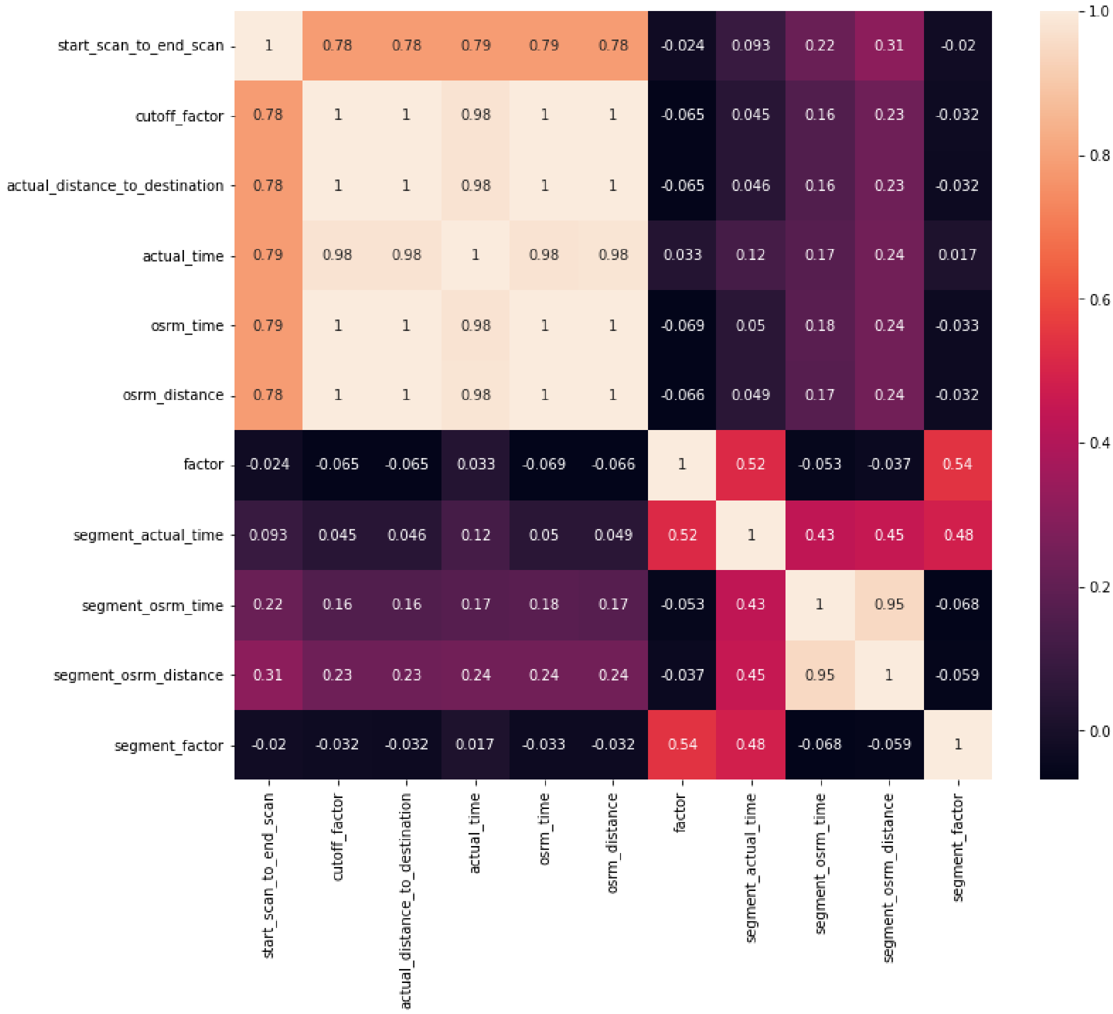
- segment_osrm_distance – This is the OSRM distance. Distance covered by subset of the package delivery

- segment_factor – Unknown field

We convert the 'trip_creation_time', trip start time ('od_start_time') and end time ('od_end_time') to datetime format.

[9]:
```
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"])
```

[10]:
```
numeric_columns =['start_scan_to_end_scan', 'cutoff_factor',
       'actual_distance_to_destination', 'actual_time', 'osrm_time',
       'osrm_distance', 'factor', 'segment_actual_time', 'segment_osrm_time',
       'segment_osrm_distance', 'segment_factor']

plt.figure(figsize=(12,10))
sns.heatmap(df[numeric_columns].corr(), annot=True)
plt.show()
```



So we see that certain fields are highly correlated : - cut-off factor : osrm_time, actual_time, osrm_distance, actual_distance_to_destination, start_scan_to_end_scan. - start_scan_to_end_scan : osrm_time, actual_time, osrm_distance, actual_distance_to_destination.

- osrm_time, actual_time, osrm_distance, actual_distance_to_destination are all highly correlated to each other, which is expected because distance will effect time, and osrm calculation will be somewhat close to actual (even if not perfect).
- segment_osrm_time and segment_osrm_distance are also highly correlated as expected.
- we see poor correlation between segment_actual_time and segment_osrm_time (even though overall actual_time and osrm_time are highly correlated). ####

[11]:
```
df.describe(datetime_is_numeric=True).transpose()
```

[11]:
```
                                 count                           mean  \
trip_creation_time              144316  2018-09-22 13:05:09.454117120
```

```
od_start_time                    144316  2018-09-22 17:32:42.435769344
od_end_time                      144316  2018-09-23 09:36:54.057172224
start_scan_to_end_scan         144316.0                     963.697698
cutoff_factor                  144316.0                     233.561345
actual_distance_to_destination 144316.0                     234.708498
actual_time                    144316.0                     417.996237
osrm_time                      144316.0                     214.437055
osrm_distance                  144316.0                     285.549785
factor                         144316.0                       2.120178
segment_actual_time            144316.0                      36.175379
segment_osrm_time              144316.0                      18.495697
segment_osrm_distance          144316.0                      22.818993
segment_factor                 144316.0                       2.218707

                                                      min  \
trip_creation_time             2018-09-12 00:00:16.535741
od_start_time                  2018-09-12 00:00:16.535741
od_end_time                    2018-09-12 00:50:10.814399
start_scan_to_end_scan                               20.0
cutoff_factor                                         9.0
actual_distance_to_destination                   9.000045
actual_time                                           9.0
osrm_time                                             6.0
osrm_distance                                      9.0082
factor                                              0.144
segment_actual_time                                -244.0
segment_osrm_time                                     0.0
segment_osrm_distance                                 0.0
segment_factor                                 -23.444444

                                                         25%  \
trip_creation_time             2018-09-17 02:46:11.004421120
od_start_time                  2018-09-17 07:37:35.014584832
od_end_time                       2018-09-18 01:29:56.978912
start_scan_to_end_scan                                 161.0
cutoff_factor                                           22.0
actual_distance_to_destination                     23.352027
actual_time                                             51.0
osrm_time                                               27.0
osrm_distance                                       29.89625
factor                                              1.604545
segment_actual_time                                     20.0
segment_osrm_time                                       11.0
segment_osrm_distance                              12.053975
segment_factor                                      1.347826

                                                         50%  \
```

```
trip_creation_time              2018-09-22 03:36:19.186585088
od_start_time                   2018-09-22 07:35:23.038482944
od_end_time                     2018-09-23 02:49:00.936600064
start_scan_to_end_scan                                  451.0
cutoff_factor                                            66.0
actual_distance_to_destination                      66.135322
actual_time                                             132.0
osrm_time                                                64.0
osrm_distance                                         78.6244
factor                                               1.857143
segment_actual_time                                      28.0
segment_osrm_time                                        17.0
segment_osrm_distance                                 23.5083
segment_factor                                       1.684211

                                                          75%  \
trip_creation_time              2018-09-27 17:53:19.027942912
od_start_time                   2018-09-27 22:01:30.861209088
od_end_time                     2018-09-28 12:13:41.675546112
start_scan_to_end_scan                                 1645.0
cutoff_factor                                           286.0
actual_distance_to_destination                     286.919294
actual_time                                             516.0
osrm_time                                               259.0
osrm_distance                                        346.3054
factor                                                2.21228
segment_actual_time                                      40.0
segment_osrm_time                                        22.0
segment_osrm_distance                               27.813325
segment_factor                                           2.25

                                                       max          std
trip_creation_time              2018-10-03 23:59:42.701692          NaN
od_start_time                   2018-10-06 04:27:23.392375          NaN
od_end_time                     2018-10-08 03:00:24.353479          NaN
start_scan_to_end_scan                              7898.0  1038.082976
cutoff_factor                                       1927.0   345.245823
actual_distance_to_destination                 1927.447705   345.480571
actual_time                                         4532.0   598.940065
osrm_time                                           1686.0   308.448543
osrm_distance                                    2326.1991   421.717826
factor                                           77.387097     1.717065
segment_actual_time                                 3051.0    53.524298
segment_osrm_time                                   1611.0    14.774008
segment_osrm_distance                            2191.4037    17.866367
segment_factor                                      574.25     4.854804
```

[12]:
```
df.describe(include=['object']).transpose()
```

[12]:
```
                      count unique  \
data                 144316      2
route_schedule_uuid  144316   1497
route_type           144316      2
trip_uuid            144316  14787
source_center        144316   1496
source_name          144316   1496
destination_center   144316   1466
destination_name     144316   1466
cutoff_timestamp     144316  92894

                                                                   top    freq
data                                                          training  104632
route_schedule_uuid  thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f…    1812
route_type                                                         FTL   99132
trip_uuid                                      trip-153837029526866991     101
source_center                                             IND000000ACB   23267
source_name                                 Gurgaon_Bilaspur_HB (Haryana)   23267
destination_center                                        IND000000ACB   15192
destination_name                            Gurgaon_Bilaspur_HB (Haryana)   15192
cutoff_timestamp                                   2018-09-24 05:19:20      39
```

1.3 Merging the Rows and Condensing and Further Preparing the Data. A trip may include different source and destination centers. So, the delivery details of one package is divided into several rows (like connecting flights to reach a particular destination). We shall combine these rows to prepare our data for analysing overall time and distances.

We will use different aggregations like cumulative sums, first/last element, sums, etc to merge the rows. This merging will be done in 2 phases :

1. Merging rows based on a unique <'segment_key' made of 'trip_uuid', 'source_center', 'destination_center'>
2. Further aggregate on the basis of only 'trip_uuid'.

[13]:
```
df['segment_key'] = df["trip_uuid"]+df["source_center"]+df["destination_center"]

segment_cols =␣
↪['segment_actual_time','segment_osrm_time','segment_osrm_distance']

for col in segment_cols:
    df[col + '_sum'] = df.groupby(['segment_key'])[col].cumsum()

df[[col + '_sum' for col in segment_cols]]
```

[13]:
```
        segment_actual_time_sum  segment_osrm_time_sum  \
0                          14.0                   11.0
1                          24.0                   20.0
2                          40.0                   27.0
3                          61.0                   39.0
4                          67.0                   44.0
…                           …                    …
144862                     92.0                   94.0
144863                    118.0                  115.0
144864                    138.0                  149.0
144865                    155.0                  176.0
144866                    423.0                  185.0

        segment_osrm_distance_sum
0                         11.9653
1                         21.7243
2                         32.5395
3                         45.5619
4                         49.4772
…                           …
144862                    65.3487
144863                    82.7212
144864                   103.4265
144865                   122.3150
144866                   131.1238

[144316 rows x 3 columns]
```

So, above, we have aggregated the time and distances of each segment using cumulative sum. So, <segment_actual_time_sum, segment_osrm_time_sum and segment_osrm_distance_sum> should ideally be equal <to actual_time, osrm_time and osrm_distance>, but that is not the case actually. ####

[14]:
```python
df.head(4)
```

[14]:
```
       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

                                 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

                 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)

  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)

                od_start_time                od_end_time  \
0 2018-09-20 03:21:32.418600 2018-09-20 04:47:45.236797
1 2018-09-20 03:21:32.418600 2018-09-20 04:47:45.236797
2 2018-09-20 03:21:32.418600 2018-09-20 04:47:45.236797
3 2018-09-20 03:21:32.418600 2018-09-20 04:47:45.236797

   start_scan_to_end_scan  is_cutoff  cutoff_factor  \
0                    86.0       True              9
1                    86.0       True             18
2                    86.0       True             27
3                    86.0       True             36

             cutoff_timestamp  actual_distance_to_destination  actual_time  \
0         2018-09-20 04:27:55                       10.435660         14.0
1         2018-09-20 04:17:55                       18.936842         24.0
2  2018-09-20 04:01:19.505586                       27.637279         40.0
3         2018-09-20 03:39:57                       36.118028         62.0

   osrm_time  osrm_distance    factor  segment_actual_time  segment_osrm_time  \
0       11.0        11.9653  1.272727                 14.0               11.0
1       20.0        21.7243  1.200000                 10.0                9.0
2       28.0        32.5395  1.428571                 16.0                7.0
3       40.0        45.5620  1.550000                 21.0               12.0

   segment_osrm_distance  segment_factor  \
0                11.9653        1.272727
1                 9.7590        1.111111
2                10.8152        2.285714
3                13.0224        1.750000

                                    segment_key  segment_actual_time_sum  \
0  trip-153741093647649320IND388121AAAIND388620AAB                     14.0
1  trip-153741093647649320IND388121AAAIND388620AAB                     24.0
2  trip-153741093647649320IND388121AAAIND388620AAB                     40.0
3  trip-153741093647649320IND388121AAAIND388620AAB                     61.0
```

```
   segment_osrm_time_sum  segment_osrm_distance_sum
0                   11.0                    11.9653
1                   20.0                    21.7243
2                   27.0                    32.5395
3                   39.0                    45.5619
```

Next we perform our first level of aggregations using segment_key defined above.

[15]:
```
create_segment_dict = {
    'data' : 'first',
    'trip_creation_time' : 'first',
    'route_schedule_uuid' : 'first',
    'route_type' : 'first',
    'trip_uuid' : 'first',

    'source_center' : 'first',
    'source_name' : 'first',

    'destination_center' : 'last', #we need to take the last destination for␣
↪this trip segment
    'destination_name' : 'last',

    'od_start_time' : 'first',
    'od_end_time' : 'first',
    'start_scan_to_end_scan' : 'first',

    'actual_distance_to_destination' : 'last', #since it is already cumulative
    'actual_time' : 'last', #since it is already cumulative

    'osrm_time' : 'last', #since it is already cumulative
    'osrm_distance' : 'last', #since it is already cumulative

    'segment_actual_time_sum' : 'last', #we calculated it above using␣
↪cumulative sums
    'segment_osrm_time_sum' : 'last', #we calculated it above using cumulative␣
↪sums
    'segment_osrm_distance_sum' : 'last' #we calculated it above using␣
↪cumulative sums
}
```

[16]:
```
segment = df.groupby(['segment_key']).agg(create_segment_dict).reset_index()
segment = segment.sort_values(by = ['segment_key','od_end_time'],␣
↪ascending=True).reset_index()
```

[17]:
```
segment[segment['trip_uuid']=='trip-153741093647649320']
```

[17]:
```
        index                                    segment_key      data  \
10370  10370  trip-153741093647649320IND388121AAAIND388620AAB  training
10371  10371  trip-153741093647649320IND388620AABIND388320AAA  training

              trip_creation_time  \
10370 2018-09-20 02:35:36.476840
10371 2018-09-20 02:35:36.476840

                                 route_schedule_uuid route_type  \
10370  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
10371  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting

                     trip_uuid source_center                   source_name  \
10370  trip-153741093647649320  IND388121AAA     Anand_VUNagar_DC (Gujarat)
10371  trip-153741093647649320  IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)

      destination_center               destination_name  \
10370       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
10371       IND388320AAA     Anand_Vaghasi_IP (Gujarat)

                   od_start_time                od_end_time  \
10370 2018-09-20 03:21:32.418600 2018-09-20 04:47:45.236797
10371 2018-09-20 04:47:45.236797 2018-09-20 06:36:55.627764

       start_scan_to_end_scan  actual_distance_to_destination  actual_time  \
10370                    86.0                       39.386040         68.0
10371                   109.0                       43.595802        102.0

       osrm_time  osrm_distance  segment_actual_time_sum  \
10370       44.0        54.2181                     67.0
10371       45.0        53.2334                    100.0

       segment_osrm_time_sum  segment_osrm_distance_sum
10370                   44.0                    49.4772
10371                   44.0                    53.2334
```

Now, as we see above, the particular trip-uuid has two entries associated with it. We will further aggregate using only trip-uuid to have just one entry for each uuid.

[18]:
```
segment.shape
```

[18]: (26222, 21)

[19]:
```
segment.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26222 entries, 0 to 26221
Data columns (total 21 columns):
```

```
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   index                           26222 non-null  int64
 1   segment_key                     26222 non-null  object
 2   data                            26222 non-null  object
 3   trip_creation_time              26222 non-null  datetime64[ns]
 4   route_schedule_uuid             26222 non-null  object
 5   route_type                      26222 non-null  object
 6   trip_uuid                       26222 non-null  object
 7   source_center                   26222 non-null  object
 8   source_name                     26222 non-null  object
 9   destination_center              26222 non-null  object
 10  destination_name                26222 non-null  object
 11  od_start_time                   26222 non-null  datetime64[ns]
 12  od_end_time                     26222 non-null  datetime64[ns]
 13  start_scan_to_end_scan          26222 non-null  float64
 14  actual_distance_to_destination  26222 non-null  float64
 15  actual_time                     26222 non-null  float64
 16  osrm_time                       26222 non-null  float64
 17  osrm_distance                   26222 non-null  float64
 18  segment_actual_time_sum         26222 non-null  float64
 19  segment_osrm_time_sum           26222 non-null  float64
 20  segment_osrm_distance_sum       26222 non-null  float64
dtypes: datetime64[ns](3), float64(8), int64(1), object(9)
memory usage: 4.2+ MB
```

So we have reduced the number of rows from 144316 to just 26222. We now have 22 columns.

We calculate time taken between od_start_time and od_end_time and keep it as a feature. We will later check if od_time_diff_hour is matching with start_scan_to_end_scan.

[20]:
```
segment["od_time_diff_hour"] = (segment["od_end_time"] -␣
 ↪segment["od_start_time"]).dt.total_seconds()/(60)
segment["od_time_diff_hour"]
```

[20]:
```
0        1260.604421
1         999.505379
2          58.832388
3         122.779486
4         834.638929
             …
26217      62.115193
26218      91.087797
26219      44.174403
26220     287.474007
26221      66.933565
Name: od_time_diff_hour, Length: 26222, dtype: float64
```

[21]:
```
segment[segment['trip_uuid']=='trip-153741093647649320']
```

[21]:
```
       index                                   segment_key      data  \
10370  10370  trip-153741093647649320IND388121AAAIND388620AAB  training
10371  10371  trip-153741093647649320IND388620AABIND388320AAA  training

             trip_creation_time  \
10370 2018-09-20 02:35:36.476840
10371 2018-09-20 02:35:36.476840

                                   route_schedule_uuid route_type  \
10370  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
10371  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting

                     trip_uuid source_center                   source_name  \
10370  trip-153741093647649320  IND388121AAA     Anand_VUNagar_DC (Gujarat)
10371  trip-153741093647649320  IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)

      destination_center              destination_name  \
10370       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
10371       IND388320AAA     Anand_Vaghasi_IP (Gujarat)

                   od_start_time                od_end_time  \
10370 2018-09-20 03:21:32.418600 2018-09-20 04:47:45.236797
10371 2018-09-20 04:47:45.236797 2018-09-20 06:36:55.627764

       start_scan_to_end_scan  actual_distance_to_destination  actual_time  \
10370                    86.0                       39.386040         68.0
10371                   109.0                       43.595802        102.0

       osrm_time  osrm_distance  segment_actual_time_sum  \
10370       44.0        54.2181                     67.0
10371       45.0        53.2334                    100.0

       segment_osrm_time_sum  segment_osrm_distance_sum  od_time_diff_hour
10370                   44.0                    49.4772          86.213637
10371                   44.0                    53.2334         109.173183
```

We now perform the second level of aggregations using only 'trip_uuid'. This will mostly involve summing up the individual segments for certain fields involving time and distances.

[22]:
```
create_trip_dict = {
    'data' : 'first',
    'trip_creation_time' : 'first',
    'route_schedule_uuid' : 'first',
    'route_type' : 'first',
    'trip_uuid' : 'first',
```

```
    'source_center' : 'first',
    'source_name' : 'first',

    'destination_center' : 'last',
    'destination_name' : 'last',

    'start_scan_to_end_scan' : 'sum',
    'od_time_diff_hour' : 'sum',

    'actual_distance_to_destination' : 'sum',
    'actual_time' : 'sum',
    'osrm_time' : 'sum',
    'osrm_distance' : 'sum',

    'segment_actual_time_sum' : 'sum',
    'segment_osrm_time_sum' : 'sum',
    'segment_osrm_distance_sum' : 'sum'
}
```

[23]:
```
trip = segment.groupby('trip_uuid').agg(create_trip_dict).reset_index(drop=True)
trip.shape
```

[23]:
```
(14787, 18)
```

So, now we have only 14787 rows and 18 columns.

[24]:
```
trip
```

[24]:
```
            data          trip_creation_time  \
0      training 2018-09-12 00:00:16.535741
1      training 2018-09-12 00:00:22.886430
2      training 2018-09-12 00:00:33.691250
3      training 2018-09-12 00:01:00.113710
4      training 2018-09-12 00:02:09.740725
…          …                         …
14782      test 2018-10-03 23:55:56.258533
14783      test 2018-10-03 23:57:23.863155
14784      test 2018-10-03 23:57:44.429324
14785      test 2018-10-03 23:59:14.390954
14786      test 2018-10-03 23:59:42.701692

                                     route_schedule_uuid route_type  \
0      thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6…        FTL
1      thanos::sroute:3a1b0ab2-bb0b-4c53-8c59-eb2a2c0…    Carting
2      thanos::sroute:de5e208e-7641-45e6-8100-4d9fb1e…        FTL
3      thanos::sroute:f0176492-a679-4597-8332-bbd1c7f…    Carting
4      thanos::sroute:d9f07b12-65e0-4f3b-bec8-df06134…        FTL
…                                                    …          …
```

```
14782  thanos::sroute:8a120994-f577-4491-9e4b-b7e4a14…    Carting
14783  thanos::sroute:b30e1ec3-3bfa-4bd2-a7fb-3b75769…    Carting
14784  thanos::sroute:5609c268-e436-4e0a-8180-3db4a74…    Carting
14785  thanos::sroute:c5f2ba2c-8486-4940-8af6-d1d2a6a…    Carting
14786  thanos::sroute:412fea14-6d1f-4222-8a5f-a517042…        FTL

                    trip_uuid source_center  \
0      trip-153671041653548748  IND209304AAA
1      trip-153671042288605164  IND561203AAB
2      trip-153671043369099517  IND000000ACB
3      trip-153671046011330457  IND400072AAB
4      trip-153671052974046625  IND583101AAA
…                          …             …
14782  trip-153861095625827784  IND160002AAC
14783  trip-153861104386292051  IND121004AAB
14784  trip-153861106442901555  IND208006AAA
14785  trip-153861115439069069  IND627005AAA
14786  trip-153861118270144424  IND583119AAA

                                source_name destination_center  \
0        Kanpur_Central_H_6 (Uttar Pradesh)       IND209304AAA
1         Doddablpur_ChikaDPP_D (Karnataka)       IND561203AAB
2             Gurgaon_Bilaspur_HB (Haryana)       IND000000ACB
3                  Mumbai Hub (Maharashtra)       IND401104AAA
4                    Bellary_Dc (Karnataka)       IND583119AAA
…                                        …                …
14782        Chandigarh_Mehmdpur_H (Punjab)       IND160002AAC
14783          FBD_Balabhgarh_DPC (Haryana)       IND121004AAA
14784    Kanpur_GovndNgr_DC (Uttar Pradesh)       IND208006AAA
14785  Tirunelveli_VdkkuSrt_I (Tamil Nadu)       IND628204AAA
14786         Sandur_WrdN1DPP_D (Karnataka)       IND583119AAA

                           destination_name  start_scan_to_end_scan  \
0        Kanpur_Central_H_6 (Uttar Pradesh)                  2259.0
1         Doddablpur_ChikaDPP_D (Karnataka)                   180.0
2             Gurgaon_Bilaspur_HB (Haryana)                  3933.0
3            Mumbai_MiraRd_IP (Maharashtra)                   100.0
4             Sandur_WrdN1DPP_D (Karnataka)                   717.0
…                                        …                     …
14782        Chandigarh_Mehmdpur_H (Punjab)                   257.0
14783         Faridabad_Blbgarh_DC (Haryana)                   60.0
14784    Kanpur_GovndNgr_DC (Uttar Pradesh)                   421.0
14785    Tirchchndr_Shnmgprm_D (Tamil Nadu)                   347.0
14786         Sandur_WrdN1DPP_D (Karnataka)                   353.0

       od_time_diff_hour  actual_distance_to_destination  actual_time  \
0            2260.109800                      824.732854       1562.0
```

```
1            181.611874                          73.186911        143.0
2           3934.362520                        1927.404273       3347.0
3            100.494935                          17.175274         59.0
4            718.349042                         127.448500        341.0
…                 …                                …          …
14782        258.028928                          57.762332         83.0
14783         60.590521                          15.513784         21.0
14784        422.119867                          38.684839        282.0
14785        348.512862                         134.723836        264.0
14786        354.407571                          66.081533        275.0

       osrm_time  osrm_distance  segment_actual_time_sum  \
0          717.0       991.3523                   1548.0
1           68.0        85.1110                    141.0
2         1740.0      2354.0665                   3308.0
3           15.0        19.6800                     59.0
4          117.0       146.7918                    340.0
…            …            …                      …
14782       62.0        73.4630                     82.0
14783       12.0        16.0882                     21.0
14784       48.0        58.9037                    281.0
14785      179.0       171.1103                    258.0
14786       68.0        80.5787                    274.0

       segment_osrm_time_sum  segment_osrm_distance_sum
0                     1008.0                  1320.4733
1                       65.0                    84.1894
2                     1941.0                  2545.2678
3                       16.0                    19.8766
4                      115.0                   146.7919
…                       …                         …
14782                   62.0                    64.8551
14783                   11.0                    16.0883
14784                   88.0                   104.8866
14785                  221.0                   223.5324
14786                   67.0                    80.5787

[14787 rows x 18 columns]
```

[25]:
```
trip[trip['trip_uuid']=='trip-153741093647649320']
```

[25]:
```
          data          trip_creation_time  \
5917  training 2018-09-20 02:35:36.476840

                                    route_schedule_uuid route_type  \
5917  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
```

```
                   trip_uuid source_center                  source_name  \
5917  trip-153741093647649320  IND388121AAA  Anand_VUNagar_DC (Gujarat)

     destination_center            destination_name  start_scan_to_end_scan  \
5917       IND388320AAA  Anand_Vaghasi_IP (Gujarat)                   195.0

      od_time_diff_hour  actual_distance_to_destination  actual_time  \
5917         195.386819                       82.981842        170.0

      osrm_time  osrm_distance  segment_actual_time_sum  \
5917       89.0       107.4515                    167.0

      segment_osrm_time_sum  segment_osrm_distance_sum
5917                   88.0                   102.7106
```

[26]:
```python
trip[['actual_distance_to_destination','osrm_distance']]
```

[26]:
```
       actual_distance_to_destination  osrm_distance
0                          824.732854       991.3523
1                           73.186911        85.1110
2                         1927.404273      2354.0665
3                           17.175274        19.6800
4                          127.448500       146.7918
…                                 …            …
14782                       57.762332        73.4630
14783                       15.513784        16.0882
14784                       38.684839        58.9037
14785                      134.723836       171.1103
14786                       66.081533        80.5787

[14787 rows x 2 columns]
```

[27]:
```python
trip["destination_name"] = trip["destination_name"].str.lower()
trip["source_name"] = trip["source_name"].str.lower()
```

[28]:
```python
trip.head(4)
```

[28]:
```
       data          trip_creation_time  \
0  training 2018-09-12 00:00:16.535741
1  training 2018-09-12 00:00:22.886430
2  training 2018-09-12 00:00:33.691250
3  training 2018-09-12 00:01:00.113710

                                 route_schedule_uuid route_type  \
0  thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6…        FTL
1  thanos::sroute:3a1b0ab2-bb0b-4c53-8c59-eb2a2c0…    Carting
2  thanos::sroute:de5e208e-7641-45e6-8100-4d9fb1e…        FTL
```

```
3  thanos::sroute:f0176492-a679-4597-8332-bbd1c7f…    Carting

                 trip_uuid source_center                         source_name  \
0  trip-153671041653548748   IND209304AAA  kanpur_central_h_6 (uttar pradesh)
1  trip-153671042288605164   IND561203AAB   doddablpur_chikadpp_d (karnataka)
2  trip-153671043369099517   IND000000ACB       gurgaon_bilaspur_hb (haryana)
3  trip-153671046011330457   IND400072AAB           mumbai hub (maharashtra)

  destination_center                    destination_name  \
0       IND209304AAA  kanpur_central_h_6 (uttar pradesh)
1       IND561203AAB   doddablpur_chikadpp_d (karnataka)
2       IND000000ACB       gurgaon_bilaspur_hb (haryana)
3       IND401104AAA      mumbai_mirard_ip (maharashtra)

   start_scan_to_end_scan  od_time_diff_hour  actual_distance_to_destination  \
0                  2259.0        2260.109800                      824.732854
1                   180.0         181.611874                       73.186911
2                  3933.0        3934.362520                     1927.404273
3                   100.0         100.494935                       17.175274

   actual_time  osrm_time  osrm_distance  segment_actual_time_sum  \
0       1562.0      717.0       991.3523                   1548.0
1        143.0       68.0        85.1110                    141.0
2       3347.0     1740.0      2354.0665                   3308.0
3         59.0       15.0        19.6800                     59.0

   segment_osrm_time_sum  segment_osrm_distance_sum
0                 1008.0                  1320.4733
1                   65.0                    84.1894
2                 1941.0                  2545.2678
3                   16.0                    19.8766
```

0.0.3 2. Building Features to Prepare the Data for Actual Analysis

We first look at the following two features and extract relevant information from those : - Destination Name: We split and extract features out of destination. City-place-code (State) - Source Name: We split and extract features out of destination. City-place-code (State)

[29]:
```
#One way to extract the data would be to use regular expressions.

import re

def getstate(x):
```

```
    if x is not np.nan:
        st = re.search("\([a-zA-Z]*( \&)?( [a-zA-Z]*){0,3}\)",x)
        if st is not None:
            return st.group()[1:-1]

#df["destination_state"] = df["destination_name"].apply(getstate)
#df["source_state"] = df["source_name"].apply(getstate)


def getcity(x):
    if x is not np.nan:
        st = re.search("^[a-zA-Z]*(_| )?",x)
        if st is not None:
            return st.group()[:-1]

#df["destination_city"] = df["destination_name"].apply(getcity)
#df["source_city"] = df["source_name"].apply(getcity)
```

[30]:
```
def place2state(x):
    state = x.split('(')[1]
    return state[:-1]

def place2city(x):
    city = x.split('(')[0]
    city=city.split('_')[0]

    #dealing with edge cases
    if city == "pnq vadgaon shei dpc" : city = "vadgaonsheri"
    if city in ["pnq pashan dpc", "pnq rahatani dpc", "pune balaji nagar"] :␣
↪city = 'pune'

    if city == "hbr layout pc" : city = "bengaluru"
    if city == "bhopal mp nagar" : city = "bhopal"
    if city == "mumbai antop hill" : city = "mumbai"
    if city == "bangalore" : city = "bengaluru"
    if city == "mumbai hub " : city = "mumbai"

    return city


def place2city_place(x):
    #removing state
    x = x.split('(')[0]

    len_ = len(x.split('_'))

    if len_ >= 3:
```

```
        return x.split('_')[1]

    #small cities have same city and place name
    if len_ == 2:
        return x.split('_')[0]

    #dealing with edge cases or improper naming conventions
    return x.split(' ')[0]


def place2code(x):
    #removing state
    x = x.split('(')[0]

    if(len(x.split('_')) >=3):
        return x.split('_')[-1]

    return 'none'
```

[31]:
```
trip["destination_state"] = trip["destination_name"].apply(lambda x:␣
 ↪place2state(x))
trip["destination_city"] = trip["destination_name"].apply(lambda x:␣
 ↪place2city(x))
trip["destination_place"] = trip["destination_name"].apply(lambda x:␣
 ↪place2city_place(x))
trip["destination_code"] = trip["destination_name"].apply(lambda x:␣
 ↪place2code(x))
```

[32]:
```
trip["source_state"] = trip["source_name"].apply(lambda x: place2state(x))
trip["source_city"] = trip["source_name"].apply(lambda x: place2city(x))
trip["source_place"] = trip["source_name"].apply(lambda x: place2city_place(x))
trip["source_code"] = trip["source_name"].apply(lambda x: place2code(x))
```

[33]:
```
trip[["destination_state","destination_city","destination_place","destination_code"]]
```

[33]:

	destination_state	destination_city	destination_place	destination_code
0	uttar pradesh	kanpur	central	6
1	karnataka	doddablpur	chikadpp	d
2	haryana	gurgaon	bilaspur	hb
3	maharashtra	mumbai	mirard	ip
4	karnataka	sandur	wrdn1dpp	d
…	…	…	…	…
14782	punjab	chandigarh	mehmdpur	h
14783	haryana	faridabad	blbgarh	dc
14784	uttar pradesh	kanpur	govndngr	dc
14785	tamil nadu	tirchchndr	shnmgprm	d
14786	karnataka	sandur	wrdn1dpp	d

```
[14787 rows x 4 columns]
```

Next we extract features from trip_creation_time. These features include : Year, Month, Day, Week, DayofWeek, Hour.

[34]:
```python
trip["trip_creation_time"] = pd.to_datetime(trip["trip_creation_time"])

trip["trip_year"] = trip["trip_creation_time"].dt.year
trip["trip_month"] = trip["trip_creation_time"].dt.month
trip["trip_hour"] = trip["trip_creation_time"].dt.hour
trip["trip_day"] = trip["trip_creation_time"].dt.day
trip["trip_week"] = trip["trip_creation_time"].dt.isocalendar().week
trip["trip_dayofweek"] = trip["trip_creation_time"].dt.dayofweek
```

[35]:
```python
trip[['trip_year','trip_month','trip_hour','trip_day','trip_week','trip_dayofweek']]
```

[35]:

	trip_year	trip_month	trip_hour	trip_day	trip_week	trip_dayofweek
0	2018	9	0	12	37	2
1	2018	9	0	12	37	2
2	2018	9	0	12	37	2
3	2018	9	0	12	37	2
4	2018	9	0	12	37	2
…	…	…	…	…	…	…
14782	2018	10	23	3	40	2
14783	2018	10	23	3	40	2
14784	2018	10	23	3	40	2
14785	2018	10	23	3	40	2
14786	2018	10	23	3	40	2

```
[14787 rows x 6 columns]
```

0.0.4 3. In-Depth Analysis and Feature Engineering

Finding, visualizing and removing outliers (using IQR) from numeric variables

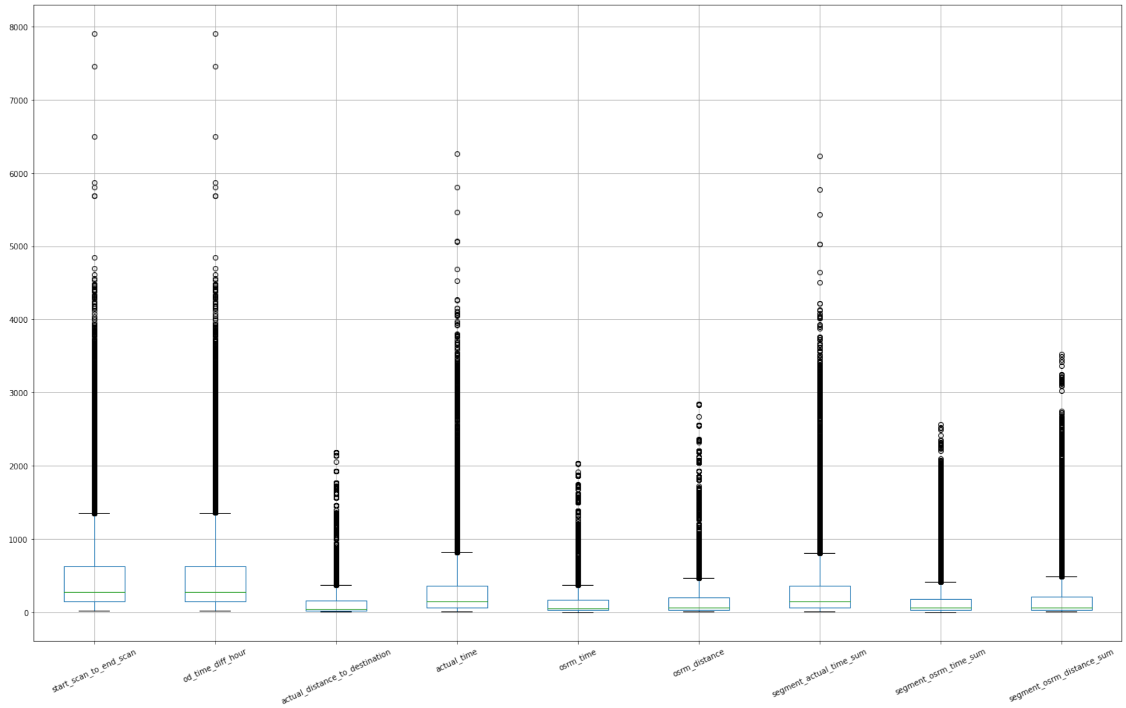
[36]:
```python
trip.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14787 entries, 0 to 14786
Data columns (total 32 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   data                            14787 non-null  object
 1   trip_creation_time              14787 non-null  datetime64[ns]
 2   route_schedule_uuid             14787 non-null  object
 3   route_type                      14787 non-null  object
```

```
 4   trip_uuid                        14787 non-null  object
 5   source_center                    14787 non-null  object
 6   source_name                      14787 non-null  object
 7   destination_center               14787 non-null  object
 8   destination_name                 14787 non-null  object
 9   start_scan_to_end_scan           14787 non-null  float64
 10  od_time_diff_hour                14787 non-null  float64
 11  actual_distance_to_destination   14787 non-null  float64
 12  actual_time                      14787 non-null  float64
 13  osrm_time                        14787 non-null  float64
 14  osrm_distance                    14787 non-null  float64
 15  segment_actual_time_sum          14787 non-null  float64
 16  segment_osrm_time_sum            14787 non-null  float64
 17  segment_osrm_distance_sum        14787 non-null  float64
 18  destination_state                14787 non-null  object
 19  destination_city                 14787 non-null  object
 20  destination_place                14787 non-null  object
 21  destination_code                 14787 non-null  object
 22  source_state                     14787 non-null  object
 23  source_city                      14787 non-null  object
 24  source_place                     14787 non-null  object
 25  source_code                      14787 non-null  object
 26  trip_year                        14787 non-null  int64
 27  trip_month                       14787 non-null  int64
 28  trip_hour                        14787 non-null  int64
 29  trip_day                         14787 non-null  int64
 30  trip_week                        14787 non-null  UInt32
 31  trip_dayofweek                   14787 non-null  int64
dtypes: UInt32(1), datetime64[ns](1), float64(9), int64(5), object(16)
memory usage: 3.6+ MB
```

[37]:

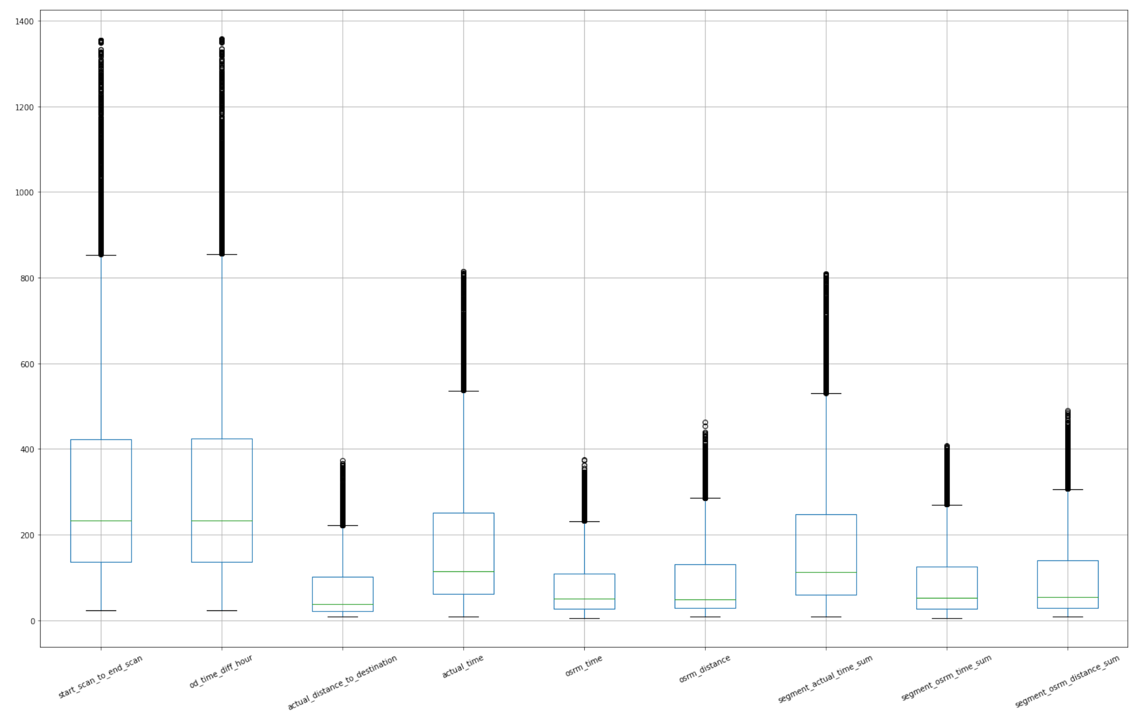
```
num_cols =␣
↪['start_scan_to_end_scan','od_time_diff_hour','actual_distance_to_destination',
            'actual_time','osrm_time',␣
↪'osrm_distance','segment_actual_time_sum',
            'segment_osrm_time_sum', 'segment_osrm_distance_sum']

trip[num_cols].boxplot(rot=25, figsize=(25,15))
plt.show()
```



[38]:
```
Q1 = trip[num_cols].quantile(0.25)
Q3 = trip[num_cols].quantile(0.75)
IQR = Q3-Q1
```

[39]:
```
trip = trip[~((trip[num_cols] < (Q1 - 1.5 * IQR))|(trip[num_cols] > (Q3 + 1.5 *␣
↪IQR))).any(axis=1)]
trip = trip.reset_index(drop=True)
```

[40]:
```
trip[num_cols].boxplot(rot=25, figsize=(25,15))
plt.show()
```



Handling Categorical Variables Since there are only two types of routes, we encode one of those as 0 and the other as 1.

[41]:
```
trip['route_type'].value_counts()
```

[41]:
```
Carting    8812
FTL        3911
Name: route_type, dtype: int64
```

[42]:
```
trip["route_type"] = trip["route_type"].map({'FTL':0,'Carting':1})
```

[43]:
```
trip.head()
```

[43]:
```
       data          trip_creation_time  \
0  training 2018-09-12 00:00:22.886430
1  training 2018-09-12 00:01:00.113710
2  training 2018-09-12 00:02:09.740725
3  training 2018-09-12 00:02:34.161600
4  training 2018-09-12 00:04:22.011653

                                 route_schedule_uuid  route_type  \
0  thanos::sroute:3a1b0ab2-bb0b-4c53-8c59-eb2a2c0…           1
1  thanos::sroute:f0176492-a679-4597-8332-bbd1c7f…           1
2  thanos::sroute:d9f07b12-65e0-4f3b-bec8-df06134…           0
```

```
3  thanos::sroute:9bf03170-d0a2-4a3f-aa4d-9aaab3d…           1
4  thanos::sroute:a97698cc-846e-41a7-916b-88b1741…           1

               trip_uuid source_center                         source_name  \
0  trip-153671042288605164  IND561203AAB  doddablpur_chikadpp_d (karnataka)
1  trip-153671046011330457  IND400072AAB          mumbai hub (maharashtra)
2  trip-153671052974046625  IND583101AAA            bellary_dc (karnataka)
3  trip-153671055416136166  IND600056AAA   chennai_poonamallee (tamil nadu)
4  trip-153671066201138152  IND600044AAD  chennai_chrompet_dpc (tamil nadu)

  destination_center                   destination_name  \
0       IND561203AAB  doddablpur_chikadpp_d (karnataka)
1       IND401104AAA     mumbai_mirard_ip (maharashtra)
2       IND583119AAA      sandur_wrdn1dpp_d (karnataka)
3       IND600056AAA   chennai_poonamallee (tamil nadu)
4       IND600048AAA   chennai_vandalur_dc (tamil nadu)

   start_scan_to_end_scan  od_time_diff_hour  actual_distance_to_destination  \
0                   180.0         181.611874                       73.186911
1                   100.0         100.494935                       17.175274
2                   717.0         718.349042                      127.448500
3                   189.0         190.487849                       24.597048
4                    98.0          98.005634                        9.100510

   actual_time  osrm_time  osrm_distance  segment_actual_time_sum  \
0        143.0       68.0        85.1110                    141.0
1         59.0       15.0        19.6800                     59.0
2        341.0      117.0       146.7918                    340.0
3         61.0       23.0        28.0647                     60.0
4         24.0       13.0        12.0184                     24.0

   segment_osrm_time_sum  segment_osrm_distance_sum destination_state  \
0                   65.0                    84.1894         karnataka
1                   16.0                    19.8766       maharashtra
2                  115.0                   146.7919         karnataka
3                   23.0                    28.0647        tamil nadu
4                   13.0                    12.0184        tamil nadu

  destination_city destination_place destination_code source_state  \
0       doddablpur          chikadpp                d    karnataka
1           mumbai            mirard               ip  maharashtra
2           sandur          wrdn1dpp                d    karnataka
3          chennai           chennai             none   tamil nadu
4          chennai          vandalur               dc   tamil nadu

  source_city source_place source_code  trip_year  trip_month  trip_hour  \
0  doddablpur     chikadpp           d       2018           9          0
```

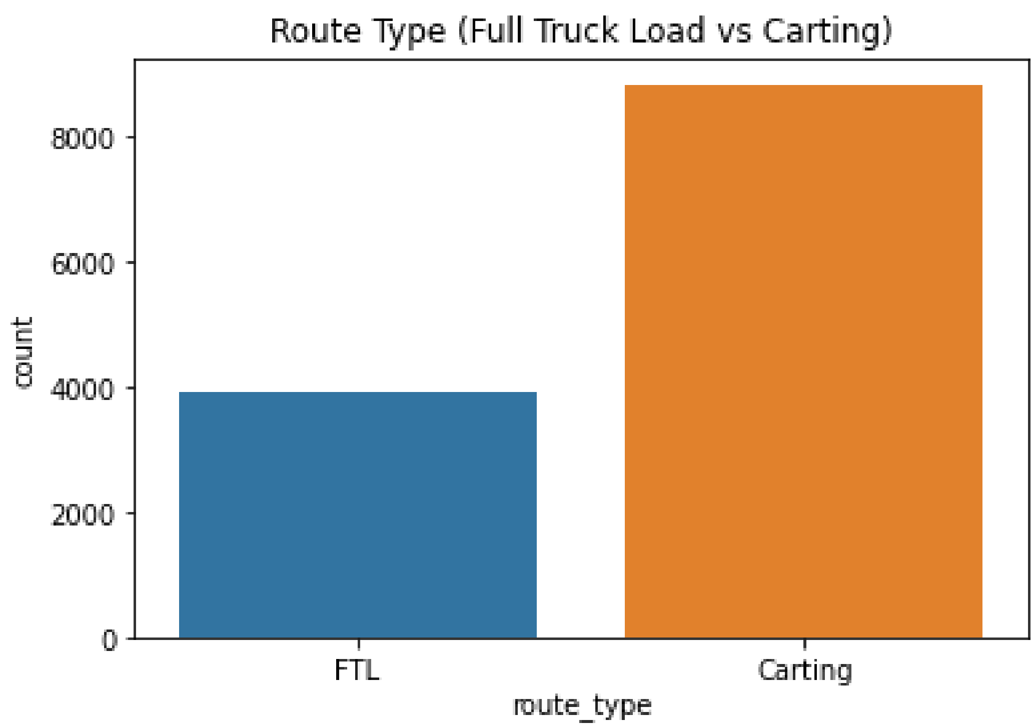
```
1      mumbai        mumbai         none       2018              9           0
2    bellary       bellary          none       2018              9           0
3    chennai       chennai          none       2018              9           0
4    chennai      chrompet          dpc        2018              9           0

   trip_day  trip_week  trip_dayofweek
0        12         37               2
1        12         37               2
2        12         37               2
3        12         37               2
4        12         37               2
```

Some more EDA on the cleaned and condensed data.

Univariate Analysis

Distribution of Route Types

[44]:
```python
ax = sns.countplot(x = "route_type", data = trip)
ax.set_xticklabels(["FTL","Carting"])
plt.title("Route Type (Full Truck Load vs Carting)")
plt.show()
```



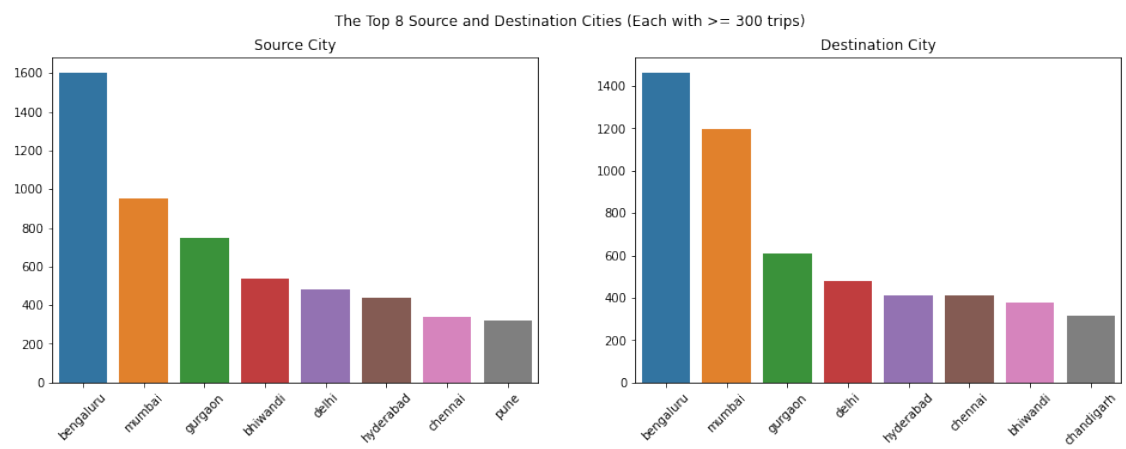
The majority of trips (8812) involved handling systems made of small vehicles (carts).

The rest of the trips (3911) involved Full Truck Load: FTL shipments get to the destination sooner, as the truck is making no other pickups or drop-offs along the way.

Top source and destination cities.

[45]:
```
source300 = trip["source_city"].value_counts()[0:8]
destination300 = trip["destination_city"].value_counts()[0:8]
```

[46]:
```
fig, ax = plt.subplots(1,2,figsize=(16,5))

sns.barplot(x = np.linspace(0,1,8), y = source300.values, data = source300, ax␣
↪= ax[0])
ax[0].set_xticklabels(source300.index,rotation=45)
ax[0].set_title("Source City")

sns.barplot(x = np.linspace(0,1,8), y = destination300.values, data =␣
↪destination300, ax = ax[1])
ax[1].set_xticklabels(destination300.index,rotation=45)
ax[1].set_title("Destination City")

plt.suptitle("The Top 8 Source and Destination Cities (Each with >= 300 trips)")

plt.show()
```



So we see that Bengaluru, Mumbai and Gurgaon are both the top source and destination cities. More trips are starting at Bhiwandi than ending there. Delhi, Hyderabad and Chennai also maintain their relative ordering in source and destination.

[47]:
```
trip.groupby(['destination_city','source_city'])['actual_time'].sum().
↪reset_index().sort_values(by='actual_time', ascending=False)
```

[47]:
```
     destination_city    source_city  actual_time
186          bengaluru      bengaluru     121144.0
1053            mumbai         mumbai      50277.0
645          hyderabad      hyderabad      44130.0
1049            mumbai       bhiwandi      32402.0
565            gurgaon          delhi      30993.0
…                  …            …          …
300             chabua      dibrugarh         24.0
302          chalakudy       angamaly         23.0
631             howrah        kolkata         19.0
1055            mumbai   mumbai mahim         18.0
1186          phagwara      jalandhar         17.0

[1561 rows x 3 columns]
```

[48]:
```
trip.
↪groupby(['destination_city','source_city'])['actual_distance_to_destination'].
↪sum().reset_index().sort_values(by='actual_distance_to_destination',␣
↪ascending=False)
```

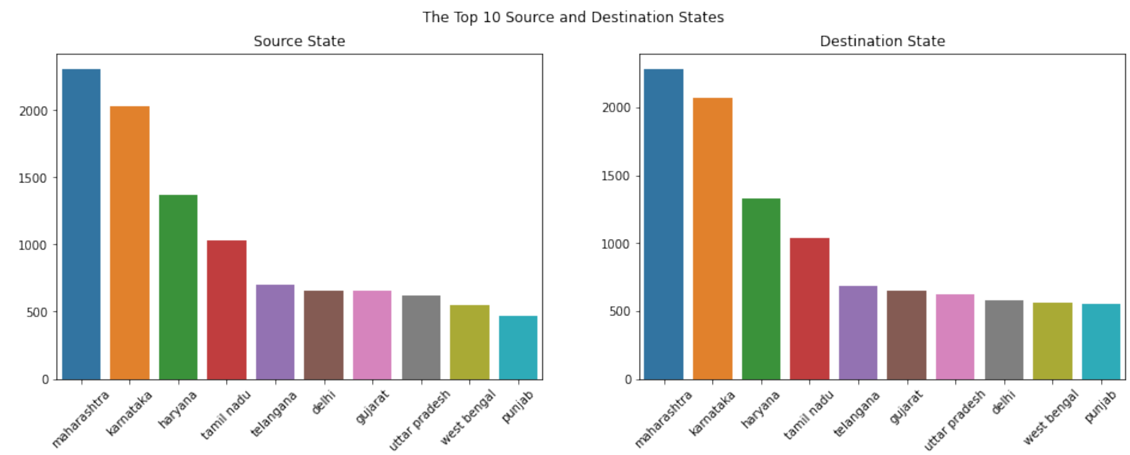
[48]:
```
     destination_city    source_city  actual_distance_to_destination
186          bengaluru      bengaluru                    42937.780295
645          hyderabad      hyderabad                    15461.602801
1053            mumbai         mumbai                    12524.846027
409              delhi        gurgaon                    11063.119871
1049            mumbai       bhiwandi                     9864.383562
…                  …            …                               …
386              daman           vapi                        9.376028
1055            mumbai   mumbai mahim                        9.362187
1160          paranpur      manikchak                        9.100748
1120       north delhi          delhi                        9.045083
1316             salem          salem                        9.040986

[1561 rows x 3 columns]
```

Top source and destination states.

[49]:
```
sourcestate10 = trip["source_state"].value_counts()[0:10]
destinationstate10 = trip["destination_state"].value_counts()[0:10]
```

[50]:
```
fig, ax = plt.subplots(1,2,figsize=(16,5))

sns.barplot(x = np.linspace(0,1,10), y = sourcestate10.values, data =␣
↪sourcestate10, ax = ax[0])
ax[0].set_xticklabels(sourcestate10.index,rotation=45)
ax[0].set_title("Source State")
```

```
sns.barplot(x = np.linspace(0,1,10), y = destinationstate10.values, data =␣
↪destinationstate10, ax = ax[1])
ax[1].set_xticklabels(destinationstate10.index,rotation=45)
ax[1].set_title("Destination State")

plt.suptitle("The Top 10 Source and Destination States")
plt.show()
```



We see that the same 10 states are the top source and destination states for the trips. Maharashtra is the highest, followed by Karnataka, Haryana, Tamil Nadu and Telengana.

[51]:
```
trip.groupby(['source_state','destination_state'])['actual_time'].sum().
↪reset_index().sort_values(by='actual_time', ascending=False)
```

[51]:

	source_state	destination_state	actual_time
56	maharashtra	maharashtra	268491.0
43	karnataka	karnataka	261334.0
75	tamil nadu	tamil nadu	153442.0
79	telangana	telangana	130197.0
84	uttar pradesh	uttar pradesh	122282.0
..	…	…	…
9	assam	nagaland	306.0
74	tamil nadu	kerala	249.0
72	tamil nadu	andhra pradesh	234.0
85	uttar pradesh	uttarakhand	152.0
23	gujarat	daman & diu	43.0

[90 rows x 3 columns]

[52]:

```
trip.
 ↪groupby(['destination_state','source_state'])['actual_distance_to_destination'].
 ↪sum().reset_index().sort_values(by='actual_distance_to_destination',␣
 ↪ascending=False)
```

[52]:

```
   destination_state    source_state  actual_distance_to_destination
40         karnataka       karnataka                   103882.587719
56       maharashtra     maharashtra                    97873.000720
77        tamil nadu      tamil nadu                    70873.071768
80         telangana       telangana                    56633.784572
0     andhra pradesh  andhra pradesh                    50976.404367
..               …               …                             …
59           mizoram           assam                      128.424011
47            kerala      tamil nadu                       99.858307
86       uttarakhand   uttar pradesh                       70.772628
60          nagaland           assam                       58.732392
13       daman & diu         gujarat                        9.376028

[90 rows x 3 columns]
```

Trip month

[53]:

```
trip["trip_month"].value_counts()
```

[53]:

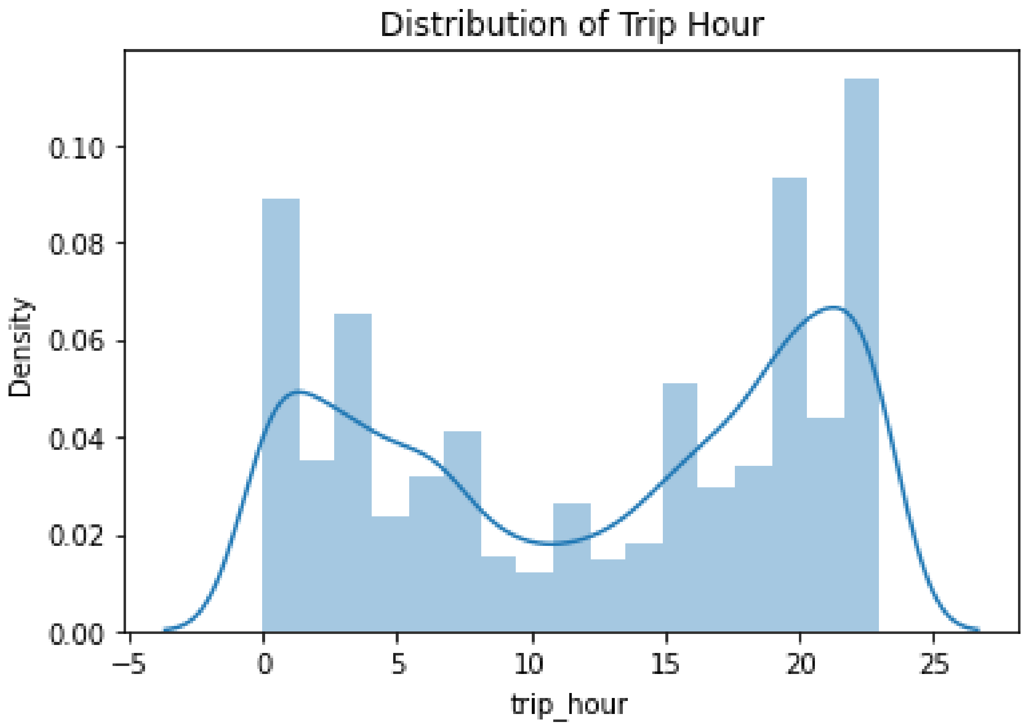
```
9     11172
10     1551
Name: trip_month, dtype: int64
```

The trips are recorded only for the months of September and October. The recording perhaps stopped after that. So we do not analyse further on the basis of month.

Trip Hour Distribution.

[54]:

```
sns.distplot(trip["trip_hour"])
plt.title("Distribution of Trip Hour")
plt.show()
```



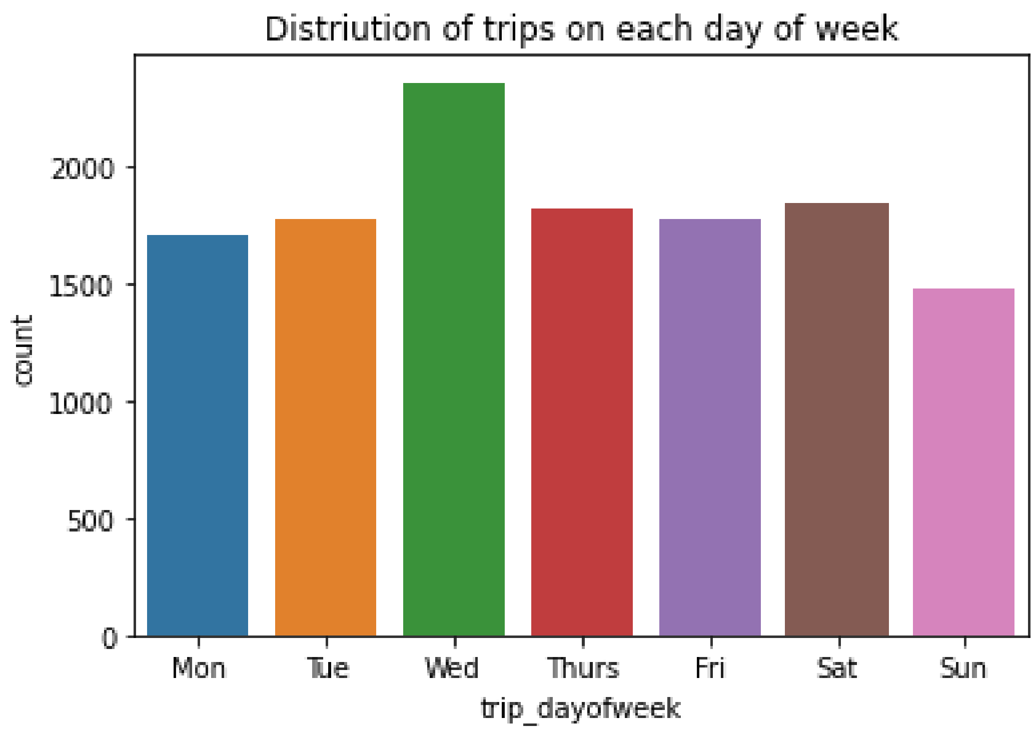
So, we observe a kind of bimodal distribution with minimum trips occuring during the day hours (8 AM to 1 PM) and maximum occuring during late night or early morning hours (8 PM to 2 AM).

Trip Day of Week Distribution

[55]:
```
trip["trip_dayofweek"] = trip["trip_dayofweek"].map({0:'Mon',1:'Tue',2:'Wed',3:
↪'Thurs',4:'Fri',5:'Sat',6:'Sun'})
trip["trip_dayofweek"].value_counts()
```

[55]:
```
Wed      2352
Sat      1836
Thurs    1819
Fri      1774
Tue      1766
Mon      1697
Sun      1479
Name: trip_dayofweek, dtype: int64
```

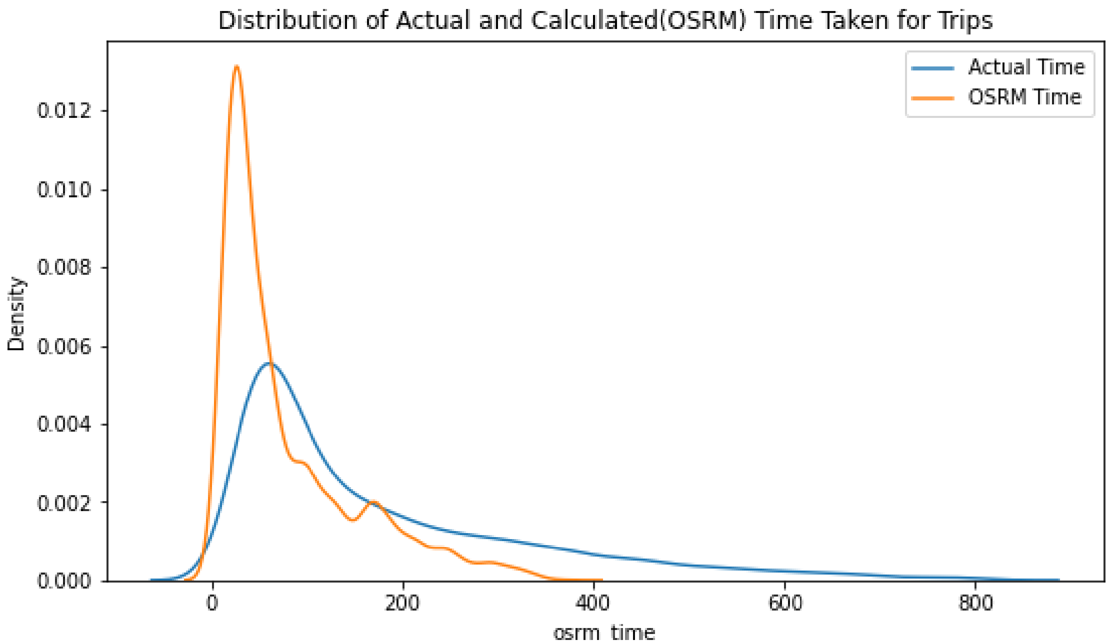
[56]:
```
sns.countplot(x = "trip_dayofweek",data=trip,␣
↪order=['Mon','Tue','Wed','Thurs','Fri','Sat','Sun'])
plt.title("Distriution of trips on each day of week")
plt.show()
```



So we see that maximum number of trips are happening on Wednesday and minimum on Sunday.

Distribution of Actual and Calculated(OSRM) Time Taken for Trips

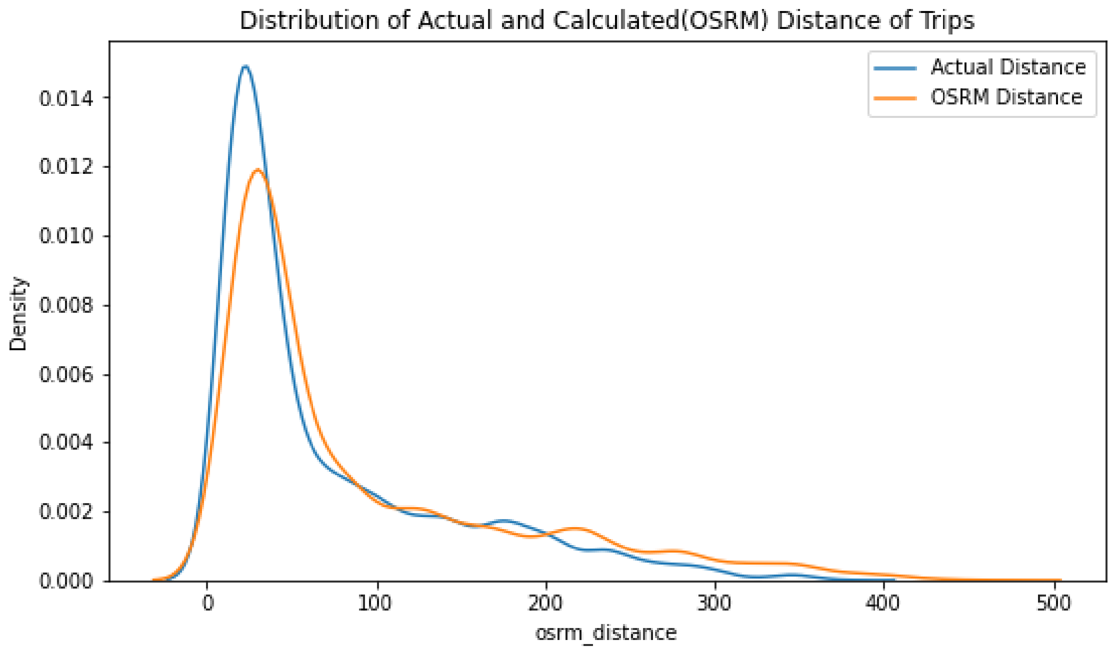
[57]:
```
plt.figure(figsize=(9,5))
sns.distplot(trip["actual_time"], hist=False, label = "Actual Time")
sns.distplot(trip["osrm_time"], hist=False, label = "OSRM Time")

plt.legend()
plt.title("Distribution of Actual and Calculated(OSRM) Time Taken for Trips")
plt.show()
```



So we see that actual time distribution has a kind of skewed distribution. Also, OSRM seems to be calculating time taken as less than what time it actually takes. This might be because in actual scenario, there might be delays caused by unprecedented traffic or other delays.

Distribution of Actual and Calculated(OSRM) Distance of Trips

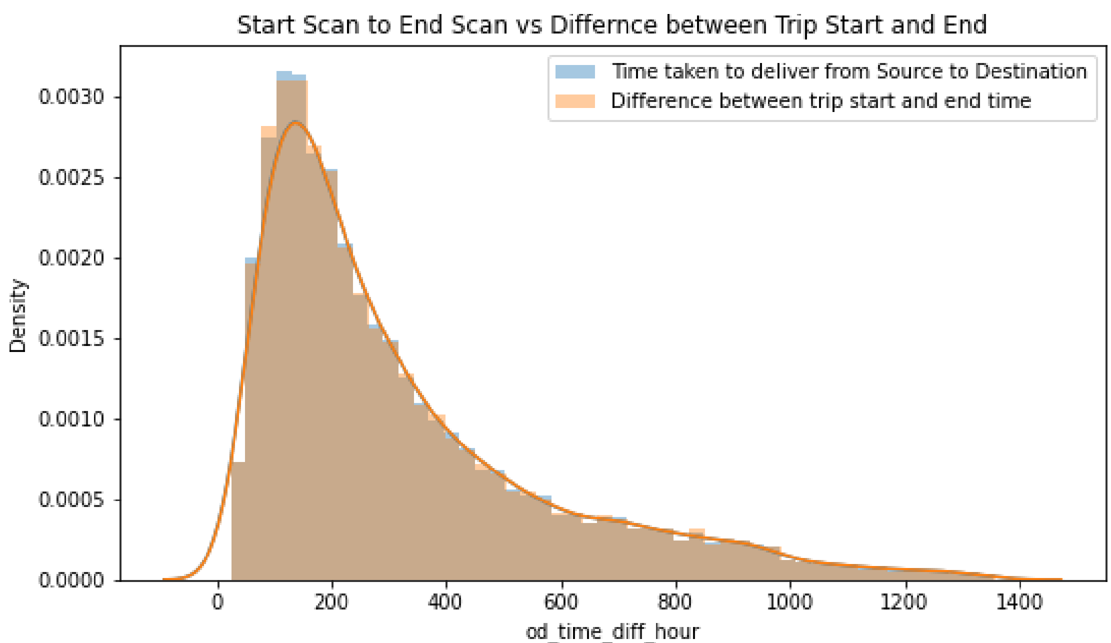
[58]:
```
plt.figure(figsize=(9,5))
sns.distplot(trip["actual_distance_to_destination"], hist=False, label =␣
↪"Actual Distance")
sns.distplot(trip["osrm_distance"], hist=False, label = "OSRM Distance")

plt.legend()
plt.title("Distribution of Actual and Calculated(OSRM) Distance of Trips")
plt.show()
```



As we can see, the distributions are similar, however, OSRM distance has greater spread than actual (which means distance covered actually is on the lower side as compared to OSRM calculated).

Start Scan to End Scan vs Differnce between Trip Start and End

[59]:
```
plt.figure(figsize=(9,5))
sns.distplot(trip["start_scan_to_end_scan"],  label = "Time taken to deliver␣
↪from Source to Destination")
sns.distplot(trip["od_time_diff_hour"],  label = "Difference between trip start␣
↪and end time")

plt.legend()
plt.title("Start Scan to End Scan vs Differnce between Trip Start and End")
plt.show()
```



There is not much difference between the above two variables.

Bivariate Analysis

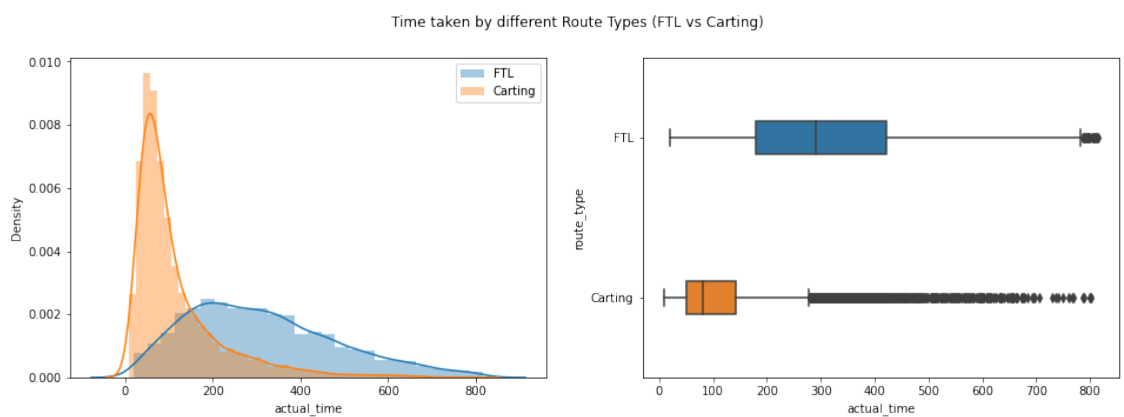
[60]:
```
trip.head(1)
```

[60]:
```
       data          trip_creation_time  \
0  training 2018-09-12 00:00:22.886430

                                  route_schedule_uuid  route_type  \
0  thanos::sroute:3a1b0ab2-bb0b-4c53-8c59-eb2a2c0…           1

                 trip_uuid source_center                       source_name  \
0  trip-153671042288605164  IND561203AAB  doddablpur_chikadpp_d (karnataka)

  destination_center                  destination_name  \
0       IND561203AAB  doddablpur_chikadpp_d (karnataka)

   start_scan_to_end_scan  od_time_diff_hour  actual_distance_to_destination  \
0                   180.0         181.611874                       73.186911

   actual_time  osrm_time  osrm_distance  segment_actual_time_sum  \
0        143.0       68.0         85.111                    141.0

   segment_osrm_time_sum  segment_osrm_distance_sum destination_state  \
```

```
0                   65.0                        84.1894         karnataka

  destination_city destination_place destination_code source_state  \
0       doddablpur          chikadpp                d    karnataka

  source_city source_place source_code  trip_year  trip_month  trip_hour  \
0  doddablpur     chikadpp           d       2018           9          0

   trip_day  trip_week trip_dayofweek
0        12         37            Wed
```

Does the distribution of time taken depend on the route type (carting vs full truck load) ?

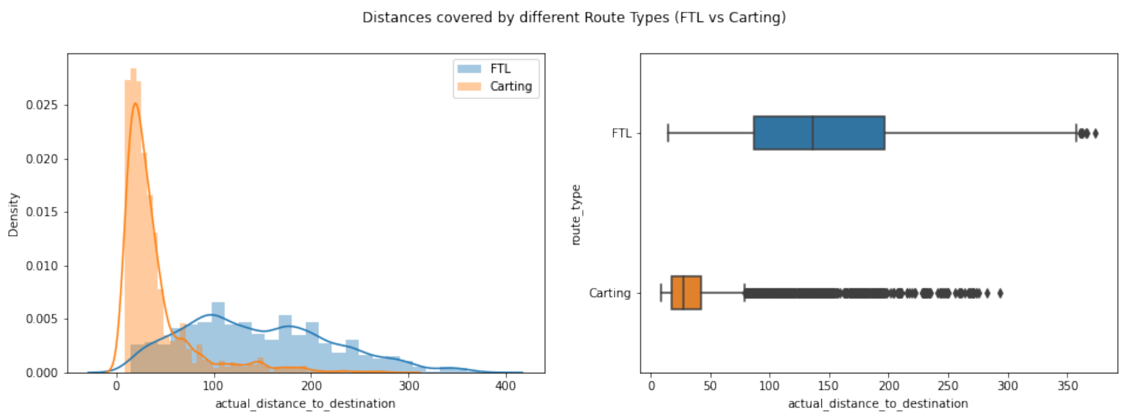
[61]:
```python
fig, ax = plt.subplots(1,2,figsize=(16,5))
sns.distplot(trip[trip["route_type"]==0]["actual_time"],  label = "FTL", ax =␣
 ↪ax[0])
sns.distplot(trip[trip["route_type"]==1]["actual_time"],  label = "Carting", ax␣
 ↪= ax[0])

sns.boxplot(x = "actual_time", y = "route_type", data = trip, orient='h',␣
 ↪width=0.2, ax=ax[1])

ax[0].legend()
ax[1].set_yticklabels(["FTL","Carting"])
plt.suptitle("Time taken by different Route Types (FTL vs Carting)")
plt.show()
```



So we see that the time taken by full truck load deliveries is on average, a lot higher (>300 hours) (probably because the distance covered by trucks is also mucvh higher since they don't make stops) than the cart deliveries (<100 hours).

Does the distribution of distance covered depend on the route type (carting vs full truck load) ?

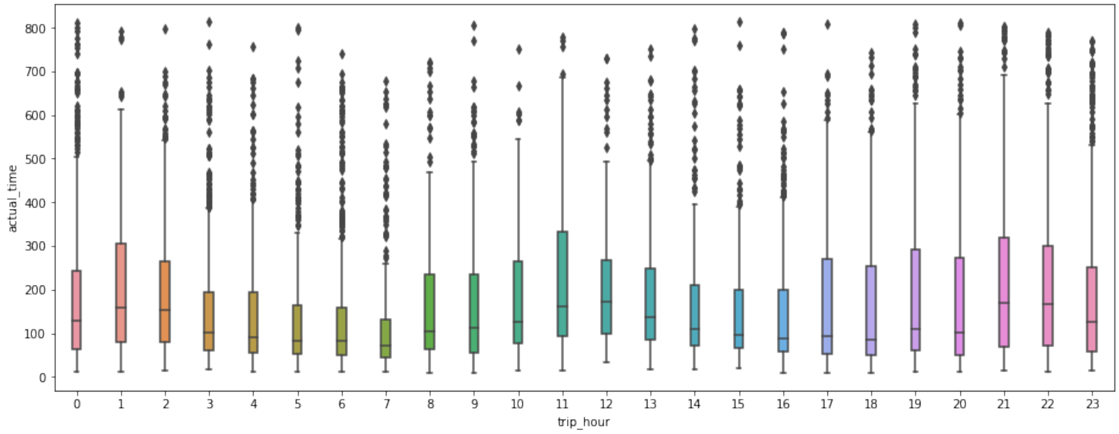
[62]:
```
fig, ax = plt.subplots(1,2,figsize=(16,5))
sns.distplot(trip[trip["route_type"]==0]["actual_distance_to_destination"], ␣
↪label = "FTL", ax = ax[0])
sns.distplot(trip[trip["route_type"]==1]["actual_distance_to_destination"], ␣
↪label = "Carting", ax = ax[0])

sns.boxplot(x = "actual_distance_to_destination", y = "route_type", data =␣
↪trip, orient='h', width=0.2, ax=ax[1])

ax[0].legend()
ax[1].set_yticklabels(["FTL","Carting"])
plt.suptitle("Distances covered by different Route Types (FTL vs Carting)")
plt.show()
```



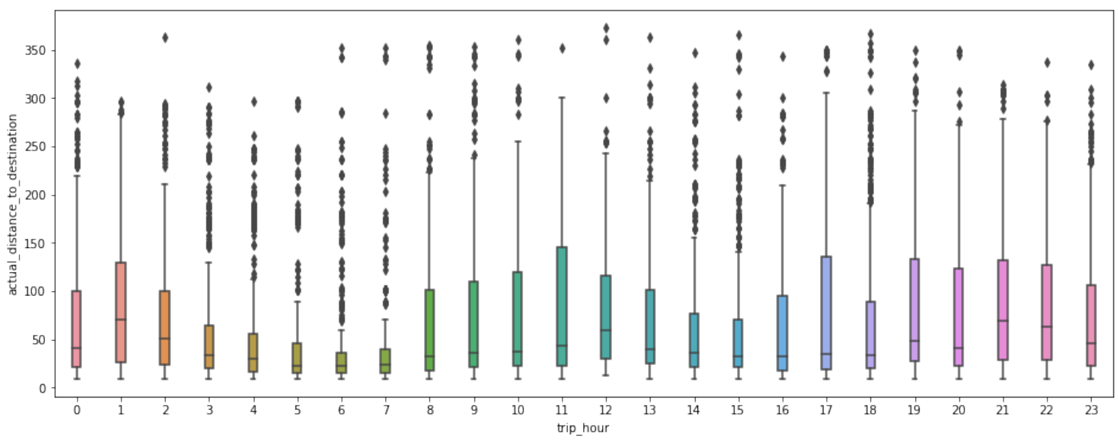
So our initial assumption is correct. The full truck load deliveries cover much longer distances on average (>150 kms) than carting deliveries (~ 25 kms).

Distribution of time taken and distance covered by deliveries depending on the hour of the day

[63]:
```
plt.figure(figsize=(16,6))
sns.boxplot(x = "trip_hour", y = "actual_time", data = trip, width=0.2)
plt.show()
```



[64]:
```
plt.figure(figsize=(16,6))
sns.boxplot(x = "trip_hour", y = "actual_distance_to_destination", data = trip,␣
↪width=0.2)
plt.show()
```

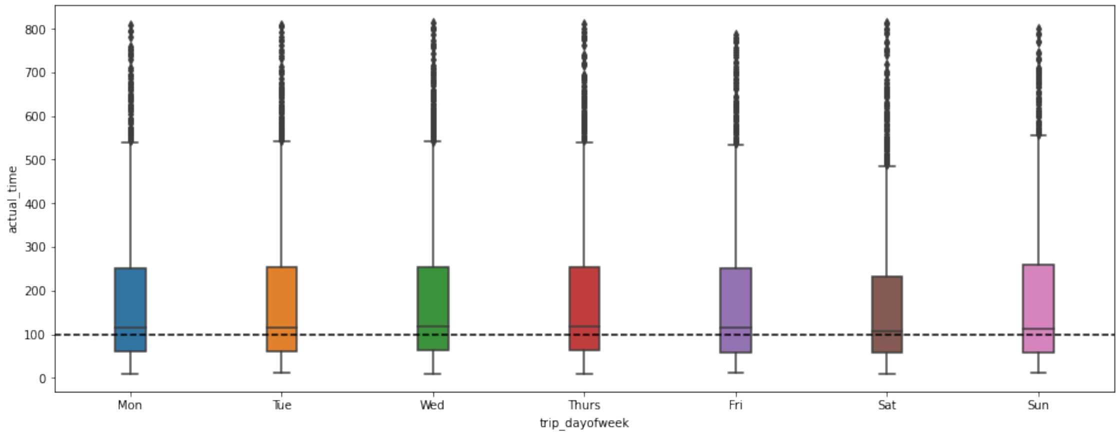


Time and distances follow similar trends against the hour of the day. Maximum time and distance deliveries are likely to be made during peak morning hours of 10 AM to 12 PM as well as 5 PM, 7 PM and 1 AM.

Distribution of time taken and distance covered by deliveries depending on the day of the week

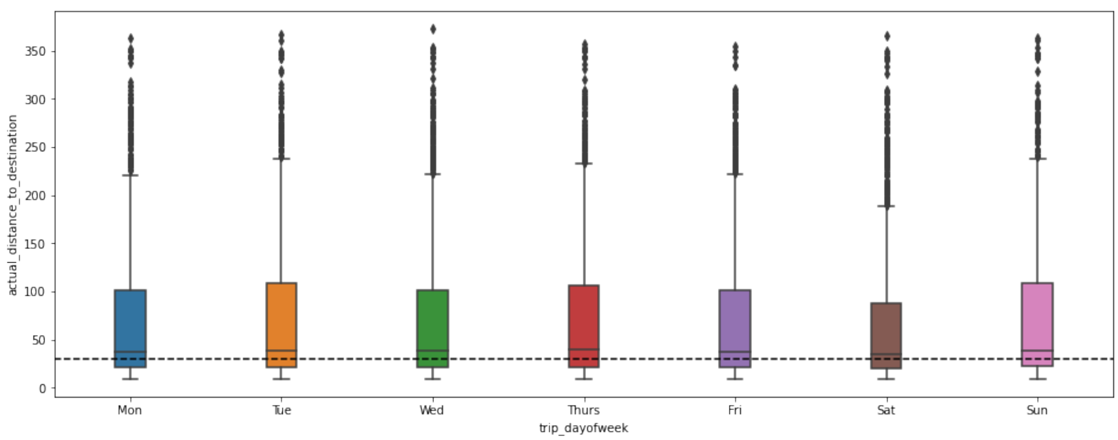
[65]:
```
plt.figure(figsize=(16,6))
sns.boxplot(x = "trip_dayofweek", y = "actual_time", data = trip, width=0.2,␣
↪order = ['Mon','Tue','Wed','Thurs','Fri','Sat','Sun'])
```

```
plt.axhline(y=100, color='k', ls = '--')
plt.show()
```



On average, time taken is slightly more on weekdays and Sunday as compared to Saturday. However, they are very similar.

[66]:
```
plt.figure(figsize=(16,6))
sns.boxplot(x = "trip_dayofweek", y = "actual_distance_to_destination", data =␣
↪trip, width=0.2, order = ['Mon','Tue','Wed','Thurs','Fri','Sat','Sun'])
plt.axhline(y=30, color='k', ls = '--')
plt.show()
```

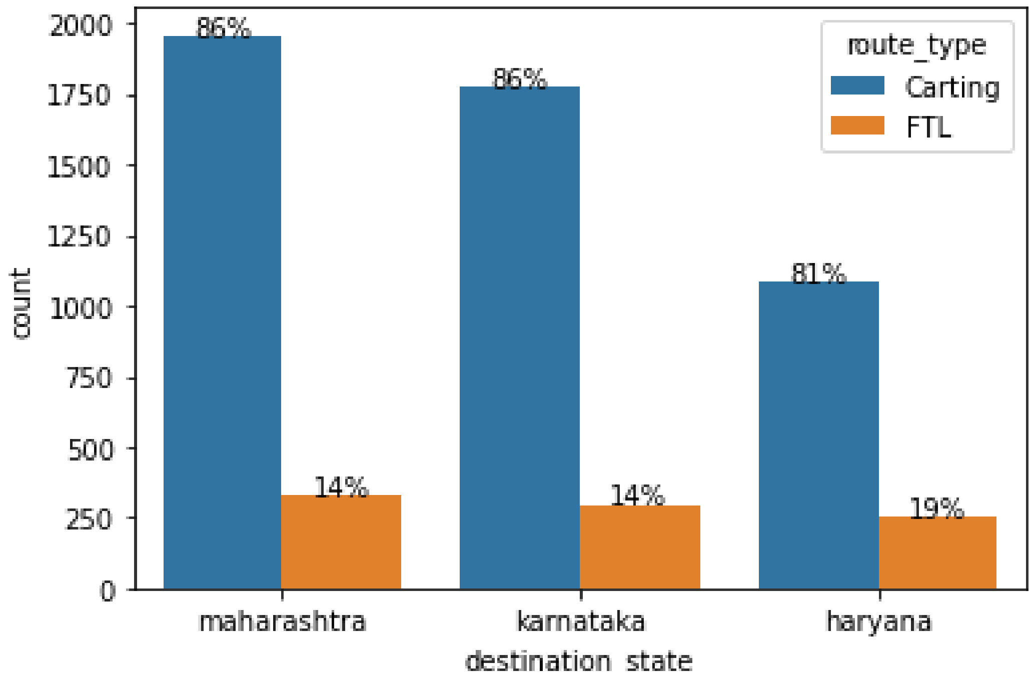


Distance covered is also lowest on Saturday.

Route Type Distributions for Top 3 States

Destination States

[67]:
```
top3d =␣
↪trip[(trip["destination_state"]=='maharashtra')|(trip["destination_state"]=='karnataka')|(t
top3d = top3d[['route_type','destination_state']]
top3d['route_type'] = top3d['route_type'].map({0:'FTL',1:'Carting'})

st = ['maharashtra','karnataka','haryana']

g = sns.countplot(x='destination_state',hue='route_type', data=top3d, order =␣
↪st)

percx = []

for e in st:
    percx.
↪append(top3d[(top3d['destination_state']==e)&(top3d["route_type"]=="Carting")].
↪shape[0]/top3d[top3d['destination_state']==e].shape[0])
for e in st:
    percx.
↪append(top3d[(top3d['destination_state']==e)&(top3d["route_type"]=="FTL")].
↪shape[0]/top3d[top3d['destination_state']==e].shape[0])

i=0
for p in g.patches:
    txt = str((round(percx[i]*100))) + '%'
    txt_x = p.get_x()
    txt_y = p.get_height()
    g.text(txt_x+0.1,txt_y,txt)
    i+=1
plt.show()
```

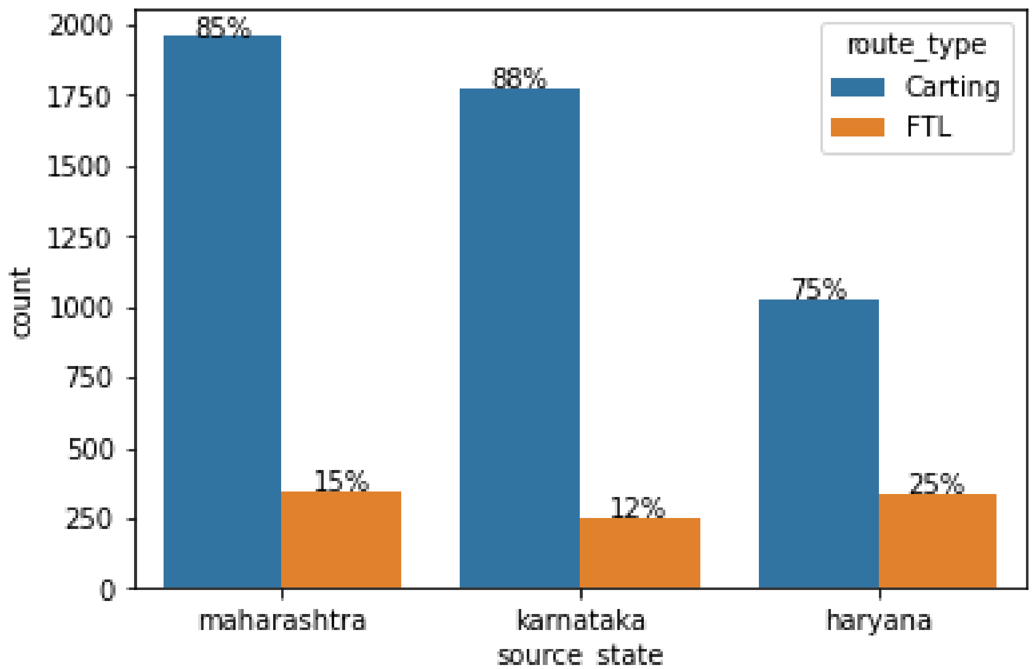


So we see that for top 3 destination states, Maharashtra hs 86% Carting and 14% FTL, Karnataka has 86% Carting and 14% FTL, Haryana has 81% Carting and 19% FTL.

Source States

[68]:
```
top3s =␣
↪trip[(trip["source_state"]=='maharashtra')|(trip["source_state"]=='karnataka')|(trip["sourc
top3s = top3s[['route_type','source_state']]
top3s['route_type'] = top3s['route_type'].map({0:'FTL',1:'Carting'})

g = sns.countplot(x='source_state',hue='route_type', data=top3s, order = st)

percx = []

for e in st:
    percx.
↪append(top3s[(top3s['source_state']==e)&(top3s["route_type"]=="Carting")].
↪shape[0]/top3s[top3s['source_state']==e].shape[0])
for e in st:
    percx.append(top3s[(top3s['source_state']==e)&(top3s["route_type"]=="FTL")].
↪shape[0]/top3s[top3s['source_state']==e].shape[0])

i=0
for p in g.patches:
    txt = str((round(percx[i]*100))) + '%'
```

```
    txt_x = p.get_x()
    txt_y = p.get_height()
    g.text(txt_x+0.1,txt_y,txt)
    i+=1
plt.show()
```



So we see that for top 3 source states, Maharashtra hs 85% Carting and 15% FTL, Karnataka has 88% Carting and 12% FTL, Haryana has 75% Carting and 25% FTL.

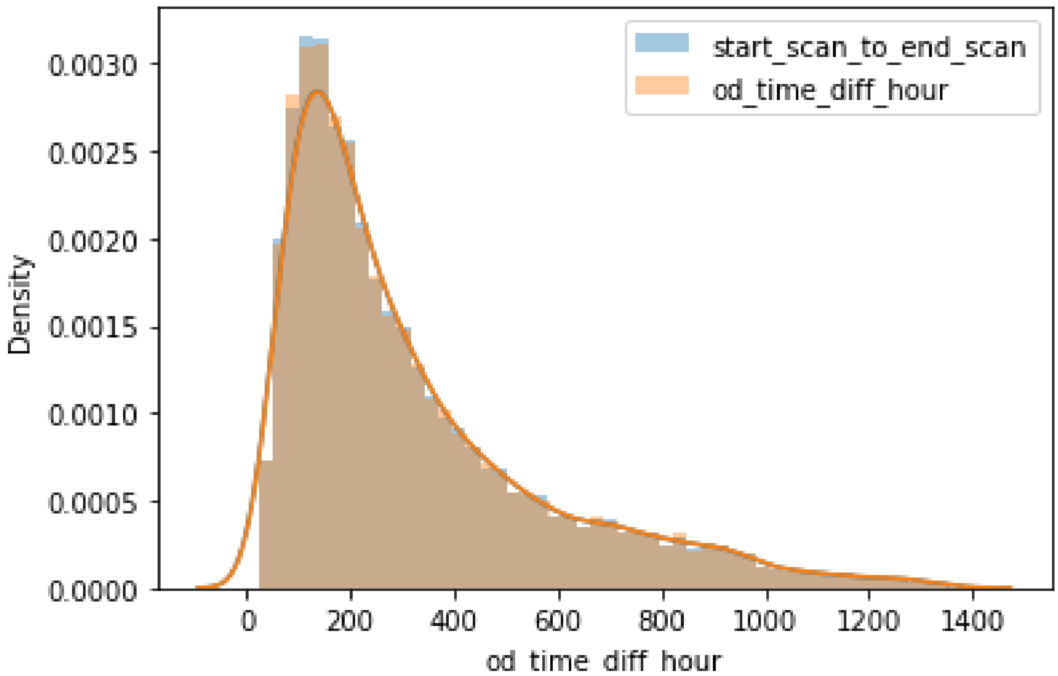
0.0.5 Hypothesis Testing

1. start_scan_to_end_scan v/s od_time_diff_hour H0 : The mean of both groups are equal.

H1: The mean are not equal.

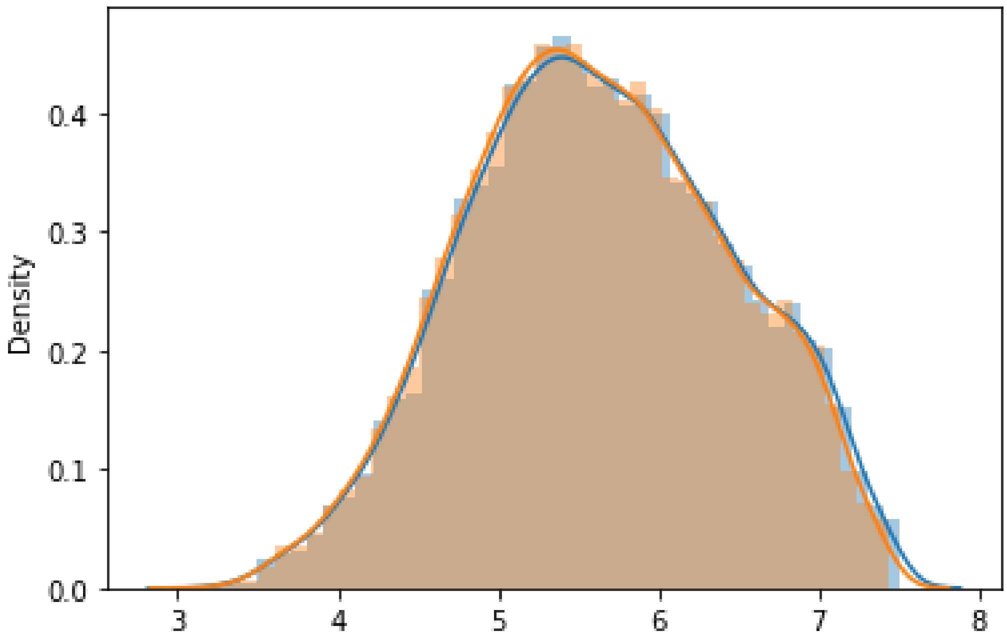
$\alpha = 0.05$

[69]:
```
sns.distplot(trip["start_scan_to_end_scan"], label="start_scan_to_end_scan")
sns.distplot(trip["od_time_diff_hour"], label="od_time_diff_hour")
plt.legend()
plt.show()
```

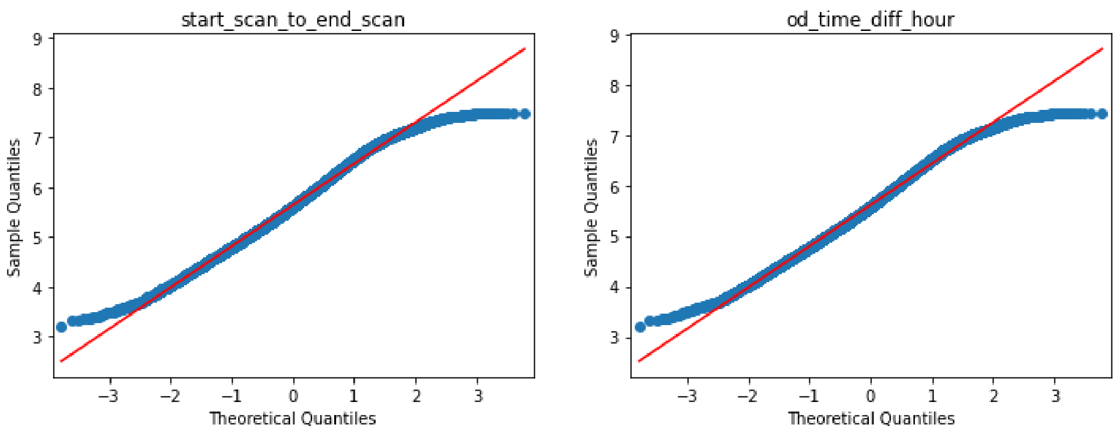


From the above plot, the means indeed appear to be the same. We will perform 2-sample t-test to find out. But first we shall convert our data to a normal distribution using boxcox transformation.

[70]:
```
from scipy.stats import boxcox

x_trf1 , lambda1 = boxcox(trip["start_scan_to_end_scan"])
x_trf2 , lambda2 = boxcox(trip["od_time_diff_hour"])

sns.distplot(x_trf1)
sns.distplot(x_trf2)
plt.show()
```



[71]:
```
import statsmodels.api as sms

fig, ax = plt.subplots(1,2,figsize=(12,4))
sms.qqplot(x_trf1, line='s', ax = ax[0])
sms.qqplot(x_trf2, line='s', label='od_time_diff_hour', ax = ax[1])

ax[0].set_title('start_scan_to_end_scan')
ax[1].set_title('od_time_diff_hour')

plt.show()
```



Since our data is not normal even after trying BoxCox transform, we perform a non-parametric test (Mann-Whitney). Now our H0 and H1 become :

H0 : The median of both groups are equal.

H1: The median are not equal.

[72]:
```
from scipy.stats import mannwhitneyu
```

[73]:
```
stat, p = mannwhitneyu(trip["start_scan_to_end_scan"],␣
 ↪trip["od_time_diff_hour"])
```

[74]:
```
p
```

[74]:
```
0.7366629968419203
```

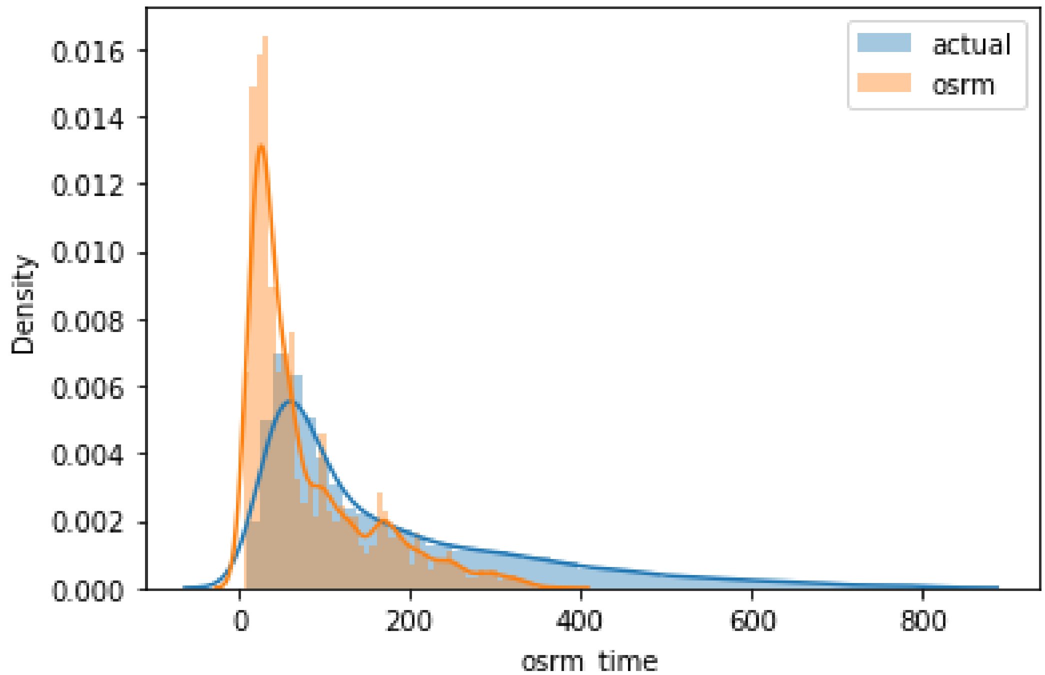
Since p > α (0.05), we fail to reject the null hypothesis. Hence, the sample distributions seem to be the same for 'start_scan_to_end_scan' and 'od_time_diff_hour'. So, the trip duration and the difference between trip start and end are indeed the same.

2. actual_time v/s osrm_time H0 : The mean of actual_time and calculated(osrm) time are equal.

H1: The mean are not equal.

$\alpha = 0.05$

[75]:
```
sns.distplot(trip["actual_time"], label="actual")
sns.distplot(trip["osrm_time"], label="osrm")
plt.legend()
plt.show()
```



From the plot above, it is clear that these do not follow normal distribution. So we go for the non-parametric Mann-Whitney test. Now our H0 and H1 become :

H0 : The median of both groups are equal.

H1: The median are not equal.

[76]:
```
stat, p = mannwhitneyu(trip["actual_time"].sample(1000), trip["osrm_time"].
 ↪sample(1000))
p
```

[76]: 7.98073622371822e-72

Since p $<$ α (0.05), we reject the null hypothesis. Hence, the sample distributions are different. So, the actual time and th time calculated by algorithm (osrm) are very different.

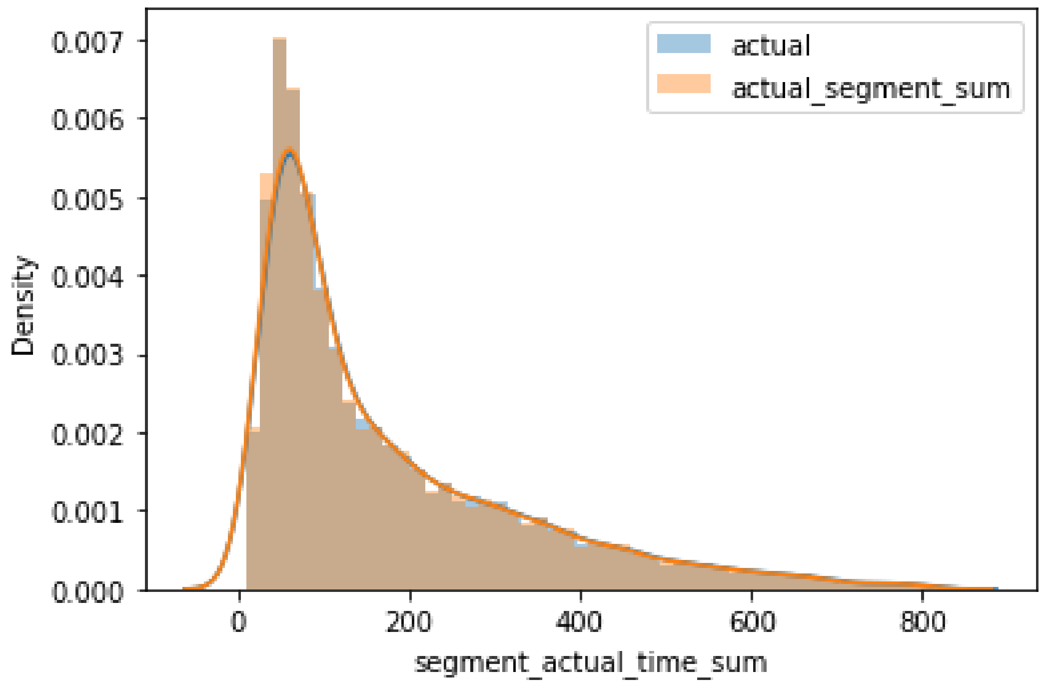
3. actual_time v/s segment_actual_time H0 : The mean of actual_time and segment_actual_time are equal.

H1: The mean are not equal.

$\alpha = 0.05$

[77]:
```
sns.distplot(trip["actual_time"], label="actual")
sns.distplot(trip["segment_actual_time_sum"], label="actual_segment_sum")
```

```
plt.legend()
plt.show()
```



Once again, we see that the times are not normally distributed. However, the distributions look similar. We use the non parametric Mann-Whitney test again. Now our H0 and H1 become :

H0 : The median of both groups are equal.

H1: The median are not equal.

[78]:
```
stat, p = mannwhitneyu(trip["actual_time"].sample(1000),␣
↪trip["segment_actual_time_sum"].sample(1000))
p
```

[78]: 0.141952881812958

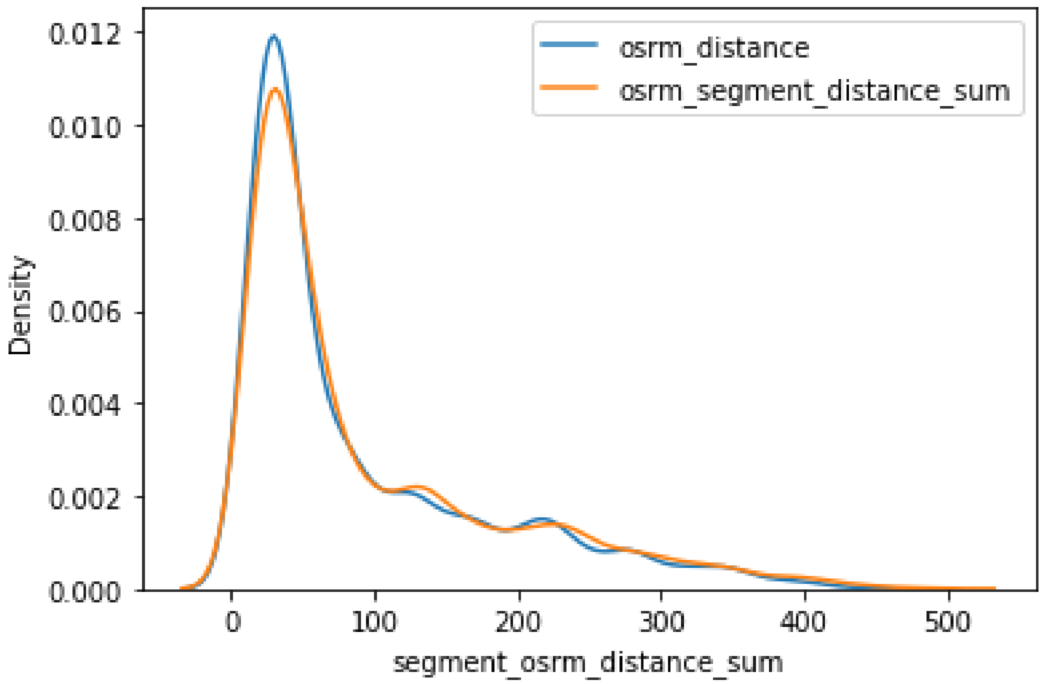
Since p > α (0.05), we fail to reject the null hypothesis. Hence, the sample distributions seem to be the same for 'segment_actual_time' and 'actual_time'. So, the actual total time taken for a trip is similar to the sum of the distances of a trip's segments.

4. osrm_distance v/s segment_osrm_distance_sum H0 : The mean of osrm_distance and segment_osrm_distance_sum are equal.

H1: The mean are not equal.

$\alpha = 0.05$

[79]:
```
sns.distplot(trip["osrm_distance"], hist=False, label="osrm_distance")
sns.distplot(trip["segment_osrm_distance_sum"], hist=False,␣
↪label="osrm_segment_distance_sum")
plt.legend()
plt.show()
```



Once again, these distributions look slightly different. Also, they are not normal. We use the non paramteric Mann-Whitney test. Now our H0 and H1 become :

H0 : The median of both groups are equal.

H1: The median are not equal.

[80]:
```
stat, p = mannwhitneyu(trip["osrm_distance"], trip["segment_osrm_distance_sum"])
p
```

[80]: 1.8349406474411988e-08

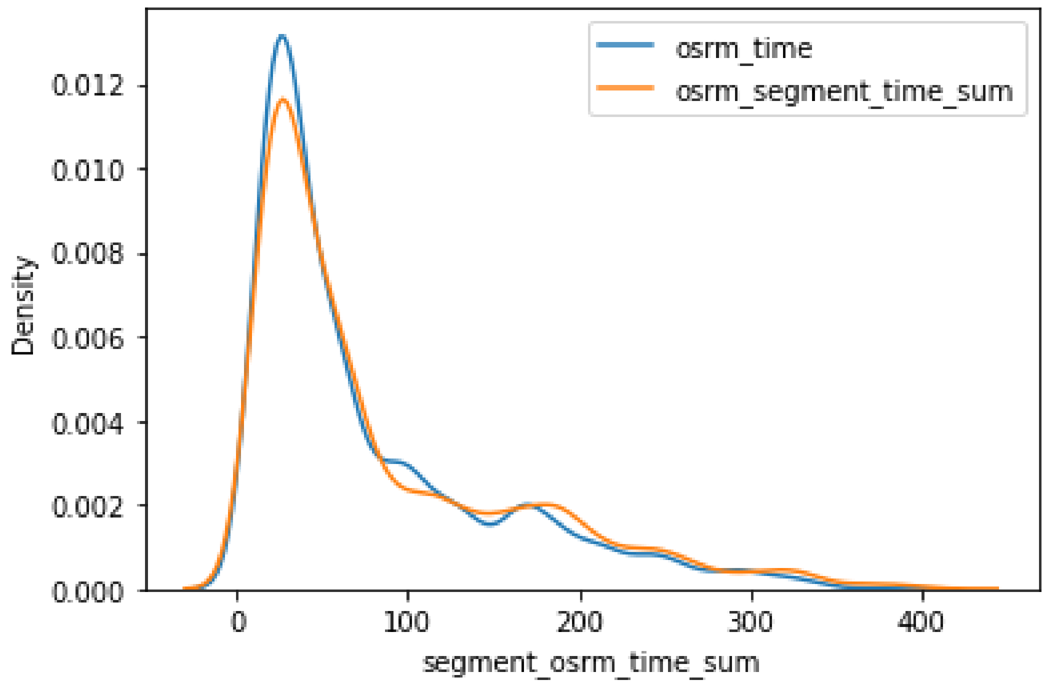
Since p < (0.05), we reject the null hypothesis. Hence, the sample distributions are different. So, the overall distance calculated by osrm and the sum of individual segment distances caluclated by osrm are different.

5. osrm_time v/s segment_osrm_time_sum H0 : The mean of osrm_time and segment_osrm_time_sum are equal.

H1: The mean are not equal.

$\alpha = 0.05$

[81]:
```
sns.distplot(trip["osrm_time"], hist=False, label="osrm_time")
sns.distplot(trip["segment_osrm_time_sum"], hist=False,␣
 ↪label="osrm_segment_time_sum")
plt.legend()
plt.show()
```



The distributions look slightly different and are not normal. We use non parametric Mann-Whitney test. Now our H0 and H1 become :

H0 : The median of both groups are equal.

H1: The median are not equal.

[82]:
```
stat, p = mannwhitneyu(trip["osrm_time"], trip["segment_osrm_time_sum"])
p
```

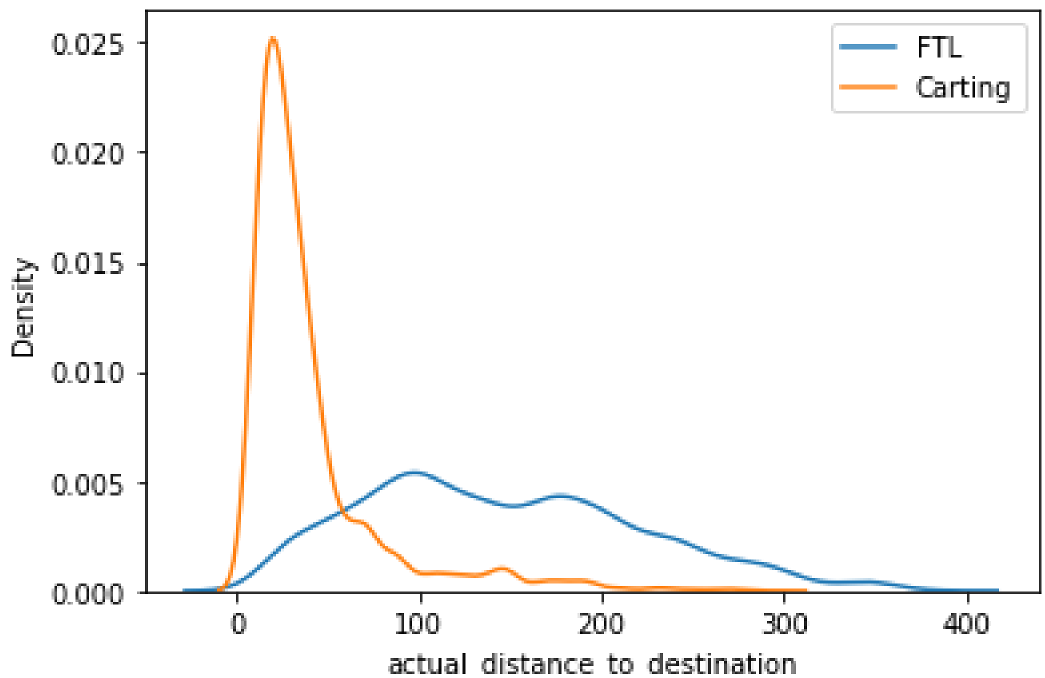
[82]: 3.7243838320849166e-10

Since p < (0.05), we reject the null hypothesis. Hence, the sample distributions are different. So, the overall time calculated by osrm and the sum of individual segment time caluclated by osrm are different.

6. Does distance depend on route type? H0: The median distance of FTL and Carting is same.

H1: The median are different.

[83]:
```
sns.distplot(trip[trip["route_type"]==0]["actual_distance_to_destination"],␣
 ↪hist=False, label="FTL")
sns.distplot(trip[trip["route_type"]==1]["actual_distance_to_destination"],␣
 ↪hist=False, label="Carting")
plt.legend()
plt.show()
```



The ditributions are clearly different and not normal. So we use non paramteric Mann-Whitney test.

[84]:
```
stat, p =␣
 ↪mannwhitneyu(trip[trip["route_type"]==0]["actual_distance_to_destination"],␣
 ↪trip[trip["route_type"]==1]["actual_distance_to_destination"])
p
```

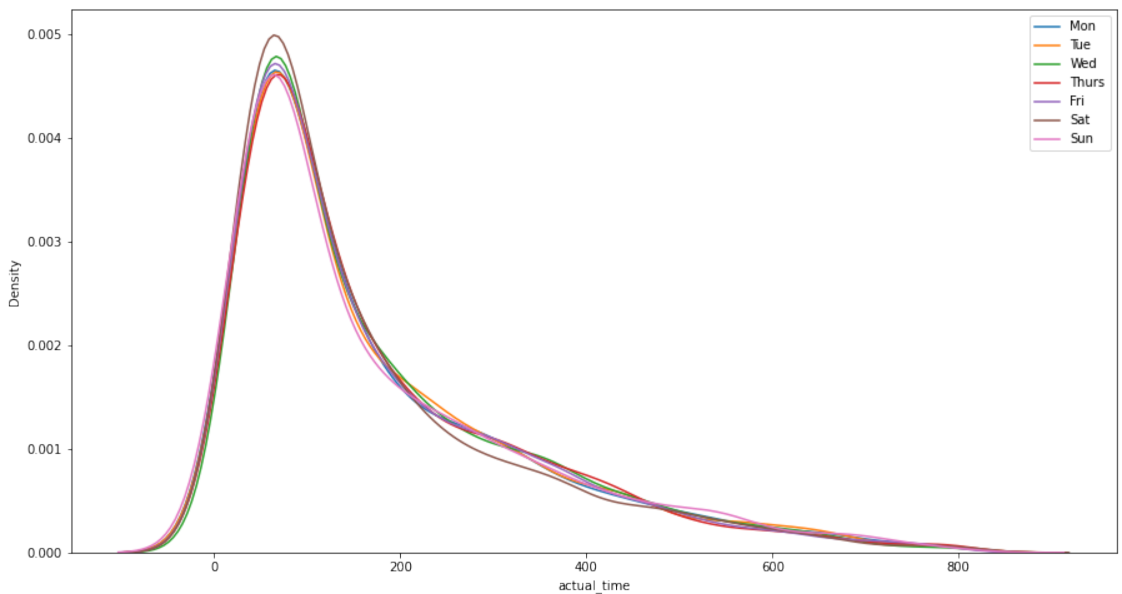
[84]: 0.0

Since p < (0.05), we reject the null hypothesis. Hence, the sample distributions are different. So, the actual distances covered for FTL routes is different from that of Carting routes.

7. Does time taken depend on day of week? H0: The median time taken of all week days are same.

H1: The median are different.

[85]:
```
plt.figure(figsize=(15,8))
days = ['Mon','Tue','Wed','Thurs','Fri','Sat','Sun']

daydist=[]

for day in days:
    daydist.append(trip[trip["trip_dayofweek"]==day]["actual_time"])
    sns.distplot(trip[trip["trip_dayofweek"]==day]["actual_time"], hist=False,␣
 ↪label=day)

plt.legend()
plt.show()
```



The distributions look slightly different. We will perform the non-parametric counterpart to one way ANOVA, the Kruskal Willis Test (and hence the medians in our hypothesis).

[86]:
```
stats.
 ↪kruskal(daydist[0],daydist[1],daydist[2],daydist[3],daydist[4],daydist[5],daydist[6])
```

[86]:
```
KruskalResult(statistic=8.743242607332519, pvalue=0.18854113288304772)
```

Since p > (0.05), we fail to reject the null hypothesis. Hence, the sample distributions of time taken seem to be the same for all week days.

Normalize/Standardize the numerical features using MinMax Scaler/ Standard Scaler

[87]:
```
from sklearn.preprocessing import StandardScaler
```

[88]:
```
scaler = StandardScaler()
scaler.fit(trip[num_cols])
```

[88]:
```
StandardScaler()
```

[89]:
```
trip[num_cols] = scaler.transform(trip[num_cols])
trip[num_cols]
```

[89]:
```
       start_scan_to_end_scan  od_time_diff_hour  \
0                   -0.548546          -0.544839
1                   -0.861602          -0.861856
2                    1.552838           1.552812
3                   -0.513328          -0.510150
4                   -0.869428          -0.871585
…                        …                  …
12718               -0.247231          -0.246189
12719               -1.018130          -1.017809
12720                0.394533           0.395103
12721                0.104957           0.107436
12722                0.128436           0.130473

       actual_distance_to_destination  actual_time  osrm_time  osrm_distance  \
0                            0.012060    -0.217856  -0.144341      -0.073948
1                           -0.765152    -0.749015  -0.877085      -0.804506
2                            0.764988     1.034163   0.533102       0.614738
3                           -0.662169    -0.736369  -0.766482      -0.710888
4                           -0.877197    -0.970332  -0.904736      -0.890050
…                                 …          …         …             …
12718                       -0.201970    -0.597255  -0.227293      -0.204002
12719                       -0.788207    -0.989302  -0.918561      -0.844610
12720                       -0.466688     0.661086  -0.420848      -0.366561
12721                        0.865940     0.547267   1.390274       0.886261
12722                       -0.086534     0.616823  -0.144341      -0.124553

       segment_actual_time_sum  segment_osrm_time_sum  \
0                    -0.221500              -0.262662
1                    -0.743482              -0.878225
2                     1.045260               0.365464
3                    -0.737116              -0.790288
```

```
4                     -0.966279             -0.915913
…                           …                     …
12718                 -0.597073             -0.300349
12719                 -0.985376             -0.941038
12720                  0.669688              0.026276
12721                  0.523279              1.697092
12722                  0.625129             -0.237537

       segment_osrm_distance_sum
0                      -0.145358
1                      -0.823653
2                       0.514899
3                      -0.737295
4                      -0.906532
…                            …
12718                  -0.349273
12719                  -0.863608
12720                   0.072932
12721                   1.324267
12722                  -0.183439

[12723 rows x 9 columns]
```

[90]:
```
trip[num_cols].describe()
```

[90]:
```
       start_scan_to_end_scan  od_time_diff_hour  \
count            1.272300e+04       1.272300e+04
mean            -1.619566e-17      -1.452025e-16
std              1.000039e+00       1.000039e+00
min             -1.162918e+00      -1.162915e+00
25%             -7.207269e-01      -7.210516e-01
50%             -3.411472e-01      -3.418602e-01
75%              4.023595e-01       4.020802e-01
max              4.049455e+00       4.050310e+00

       actual_distance_to_destination   actual_time     osrm_time  \
count                    1.272300e+04  1.272300e+04  1.272300e+04
mean                    -7.371818e-17 -8.041983e-17  4.467769e-17
std                      1.000039e+00  1.000039e+00  1.000039e+00
min                     -8.785574e-01 -1.065181e+00 -1.001514e+00
25%                     -7.065920e-01 -7.363685e-01 -7.111809e-01
50%                     -4.689012e-01 -4.012322e-01 -3.931975e-01
75%                      4.073375e-01  4.650634e-01  4.224989e-01
max                      4.178358e+00  4.031419e+00  4.113871e+00

       osrm_distance  segment_actual_time_sum  segment_osrm_time_sum  \
count   1.272300e+04             1.272300e+04           1.272300e+04
```

```
mean    3.797603e-17             -3.127438e-17           6.031487e-17
std     1.000039e+00              1.000039e+00           1.000039e+00
min    -9.229378e-01             -1.061764e+00          -1.003850e+00
25%    -7.077649e-01             -7.371165e-01          -7.274750e-01
50%    -4.836339e-01             -3.997380e-01          -4.134119e-01
75%     4.419548e-01              4.596223e-01           4.910897e-01
max     4.150641e+00              4.037107e+00           4.046283e+00

       segment_osrm_distance_sum
count               1.272300e+04
mean               -8.488760e-17
std                 1.000039e+00
min                -9.375981e-01
25%                -7.228116e-01
50%                -4.628077e-01
75%                 4.488499e-01
max                 4.130135e+00
```

0.1 Business Insights

1. Most trips use "Carting" (~8K) transportation type as opposed to "FTL" (~4K).
2. Bengaluru, Mumbai and Gurgaon are both the top source and destination cities. Bhiwandi, Delhi, Hyderabad, Chennai, Pune and Chandigarh are also some of the top contributors. So we see that the Southern, Western and Northern corridors have the top contributing cities.
3. The top contributor states (both source and destination) are : Maharashtra is the highest, followed by Karnataka, Haryana, Tamil Nadu and Telengana, Delhi, Gujarat, UP and West Bengal. Again we see Western, Southern and Northern corridors have significant contribution to the traffic.
4. The greatest amount of time was spent in intra-state trips within Maharashtra,Karnataka, Tamil Nadu, Telengana, UP.
5. The greatest amount of distance was covered on inter-state trips in Karnaataka, Maharashtra, amil Nadu, Telengana and Andhra.
6. Similarly, the greatest amount of time was spent in intra-city trips within Bangalore, Mumbai, Hyderabad. A significant time is also spent in inter-city trips from Mumbai to Bhiwandi and Guragon to Delhi. These routes also contributed to the greatest amount of distance covered on trips.
7. Hourly distribution of number of trips in a day : minimum trips occuring during the day hours (8 AM to 1 PM) and maximum occuring during late night or early morning hours (8 PM to 2 AM).
8. Week Day : we see that maximum number of trips are happening on Wednesday and minimum on Sunday.
9. OSRM seems to be calculating time taken as less than what time it actually takes. This might be because in actual scenario, there might be delays caused by unprecedented traffic or other delays.
10. OSRM seems to be calculating distance as less than what distance is actually covered. So,

OSRM is underestimating time and overestimting the distance.

11. The time taken by full truck load deliveries is on average, a lot higher (>300 hours) (this is because the distance covered by trucks is also mucvh higher since they don't make stops) than the cart deliveries (<100 hours). The full truck load deliveries cover much longer distances on average (>150 kms) than carting deliveries (~ 25 kms).
12. Hourly distribution of trip time and distances : Time and distances follow similar trends against the hour of the day. Maximum time and distance deliveries are likely to be made during peak morning hours of 10 AM to 12 PM as well as 5 PM, 7 PM and 1 AM.
13. Weekday distribution of trip time and distances : On average, time taken is slightly more on weekdays and Sunday as compared to Saturday. However, they are very similar. Distances covered is also lowest on Saturday.
14. Route type of top 3 Destination states : Maharashtra has 86% Carting and 14% FTL, Karnataka has 86% Carting and 14% FTL, Haryana has 81% Carting and 19% FTL.
15. Route type of top 3 Source states : Maharashtra hs 85% Carting and 15% FTL, Karnataka has 88% Carting and 12% FTL, Haryana has 75% Carting and 25% FTL.

0.2 Recommendations

1. Since there is significant dfference between the time and distances calculated by OSRM with actual time and distances, it might make sense to revisit the information which is fed to the routing engine for trip planning. We need to check for discrrepancies with transporters nd to check if the routing engine is configured for optimum performance.

2. We have seen that the Western, Southern and Northern corridors have significant traffic, however, not so much in Eastern, Central and North Eastern corridors. Increasing the presence in these corridors is worth investigating.

3. There is a need to plan resources (specifically during regional festivities) in the states/cities which have highest contribution to traffic.

4. Road network can be taken into consideration to increase the number of FTL deliveries inter state and to connect the states where there is lower traffic.

5. Since intra state or intra city trips are more likely to be using "carting" as mehod of transport, the number of hubs could be increased in those cities and states which have highest contribution to traffic.