Delhivery

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[106]:
```
!gdown '12cyX1cS1pnzJHXP1U9tdWNyR4aFqHYq9'
```

```
Downloading…
From: https://drive.google.com/uc?id=12cyX1cS1pnzJHXP1U9tdWNyR4aFqHYq9
To:    /content/delhivery_data.csv
100%   55.6M/55.6M   [00:00<00:00,
132MB/s] #Defining the problem statement:
```

Introduction:

Delhivery is the largest and fastest-growing fully integrated player in India by revenue in Fiscal 2021. They aim to build the operating system for commerce, through a combination of worldclass infrastructure, logistics operations of the highest quality, and cutting-edge engineering and technology capabilities.

The Data team builds intelligence and capabilities using this data that helps them to widen the gap between the quality, efficiency, and profitability of their business versus their competitors.

The Problem Statement

The company wants to understand and process the data coming out of data engineering pipelines:

- Clean, sanitize and manipulate data to get useful features out of raw fields
- Make sense out of the raw data and help the data science team to build forecasting models onit.

---

1 Basic EDA and Handling Missing Values

[107]:
```
import pandas as pd, numpy as np, seaborn as sns, matplotlib.pyplot as plt
```

[108]:
```
df = pd.read_csv('delhivery_data.csv')
df.head(3)
```

[108]:
```
      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

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

              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)

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

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

   actual_distance_to_destination actual_time osrm_time osrm_distance
   \
0                      10.435660  14.0  11.0  11.9653
1                      18.936842  24.0  20.0  21.7243
2                      27.637279  40.0  28.0  32.5395

factor segment_actual_time segment_osrm_time segment_osrm_distance \
 0 1.272727              14.0            11.0             11.9653
 1 1.200000              10.0             9.0              9.7590
 2 1.428571              16.0             7.0             10.8152
   segment_factor
 0    1.272727 1
      1.111111
 2       2.285714

 [3 rows x 24 columns]
```

[109]:
```
print(f'Number of rows : {df.shape[0]}, Number of columns : {df.shape[1]}')
print('Number of rows containing training data :
',df[df['data']=='training'].
 ↪shape[0]) print('Number of rows containing testing data :
',df[df['data']!='test'].
```

```
  ↪shape[0])
Number of rows : 144867, Number of columns : 24
Number of rows containing training data : 104858
Number of rows containing testing data : 104858
```

[110]:
```
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
```

[111]:
```
np.round(df.describe(),3)
```

[111]:

	start_scan_to_end_scan	cutoff_factor	actual_distance_to_destination
count	144867.000	144867.000	144867.000
mean	961.263	232.927	234.073
std	1037.013	344.756	344.990
min	20.000	9.000	9.000
25%	161.000	22.000	23.356
50%	449.000	66.000	66.127
75%	1634.000	286.000	286.709
max	7898.000	1927.000	1927.448

	actual_timeosrm_time	osrm_distance	factor
count	144867.000	144867.000	144867.000
mean	416.928	213.868	284.771	2.120
std	598.104	308.011	421.119	1.715
min	9.000	6.000	9.008	0.144
25%	51.000	27.000	29.915	1.604
50%	132.000	64.000	78.526	1.857
75%	513.000	257.000	343.193	2.213
max	4532.000	1686.000	2326.199	77.387

	segment_actual_time	segment_osrm_time	segment_osrm_distance
count	144867.000	144867.000	144867.000
mean	36.196	18.508	22.829
std	53.571	14.776	17.861
min	-244.000	0.000	0.000
25%	20.000	11.000	12.070
50%	29.000	17.000	23.513
75%	40.000	22.000	27.813

```
max             3051.000         1611.000            2191.404

       segment_factor
count     144867.000

mean           2.218

std            4.848

min          -23.444

25%            1.348

50%            1.684

75%            2.250

max          574.250
```

[112]:
```
np.round(df.isna().sum()/len(df) * 100,2)
```

[112]:
```
data                          0.00
trip_creation_time            0.00
 route_schedule_uuid          0.00
 route_type                   0.00
 trip_uuid                    0.00
 source_center                0.00
 source_name                  0.20
destination_center            0.00
destination_name              0.18
 od_start_time                0.00
 od_end_time                  0.00
 start_scan_to_end_scan       0.00
 is_cutoff  0.00 cutoff_factor    0.00
 cutoff_timestamp     0.00
 actual_distance_to_destination  0.00
 actual_time     0.00 osrm_time   0.00
 osrm_distance   0.00 factor      0.00
 segment_actual_time  0.00
 segment_osrm_time    0.00
 segment_osrm_distance0.00
 segment_factor  0.00
 dtype: float64
```

Since, the missing values are present only in 2 features and their percentages are 0.2% and 0.18%, therefore let's drop these rows.

[113]:
```
df = df.dropna(how='any')
df = df.reset_index(drop=True)
df.head(3)
```

[113]:
```
      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

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

              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)

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

              od_start_time …          cutoff_timestamp \
0  2018-09-20 03:21:32.418600 … 2018-09-20 04:27:55
1  2018-09-20 03:21:32.418600 … 2018-09-20 04:17:55
2  2018-09-20 03:21:32.418600 … 2018-09-20

   04:01:19.505586actual_distance_to_destination actual_time osrm_time

   osrm_distance \

0                   10.435660       14.0      11.0      11.9653
1                   18.936842       24.0      20.0      21.7243
2                   27.637279       40.0      28.0      32.5395
     factor segment_actual_time segment_osrm_time
     segment_osrm_distance \
0 1.272727              14.0            11.0             11.9653
1 1.200000              10.0             9.0              9.7590
2 1.428571              16.0             7.0             10.8152
   segment_factor
0    1.272727 1
     1.111111
2       2.285714

[3 rows x 24 columns]
```

For proper treatment of the data, let's convert data type of time-based-data columns

[114]:
```
df['trip_creation_time'] =
pd.to_datetime(df['trip_creation_time']) df['od_start_time'] =
pd.to_datetime(df['od_start_time']) df['od_end_time'] =
pd.to_datetime(df['od_end_time']) df['cutoff_timestamp'] =
pd.to_datetime(df['cutoff_timestamp']) df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144316 entries, 0 to
144315 Data columns (total 24
columns):
#   Column                        Non-Null Count Dtype
--- ------                        -------------- -----
0   data                          144316 non-null object
1  trip_creation_time             144316             non-null
                                  datetime64[ns]
2  route_schedule_uuid            144316 non-null object
3   route_type                    144316 non-null object
4   trip_uuid                     144316 non-null object
5   source_center                 144316 non-null object
6   source_name                   144316 non-null object
7  destination_center             144316 non-null object
8  destination_name               144316 non-null object
9   od_start_time                 144316             non-null
                                  datetime64[ns]
 10 od_end_time                   144316             non-null
                                  datetime64[ns]
 11 start_scan_to_end_scan        144316 non-null float64
 12 is_cutoff                     144316 non-null bool
 13 cutoff_factor                 144316 non-null int64
 14 cutoff_timestamp              144316             non-null
                                  datetime64[ns]
 15 actual_distance_to_destination 144316 non-null float64
 16 actual_time                   144316       non-null
                                  float64
 17 osrm_time                     144316       non-null
                                  float64
 18 osrm_distance                 144316       non-null
                                  float64
 19 factor                        144316       non-null
                                  float64
 20 segment_actual_time           144316       non-null
                                  float64
 21 segment_osrm_time             144316       non-null
                                  float64
```

```
 22 segment_osrm_distance       144316       non-null
                                float64
 23 segment_factor              144316       non-null
                                float64
dtypes: bool(1), datetime64[ns](4), float64(10), int64(1),
object(8) memory usage: 25.5+ MB
```

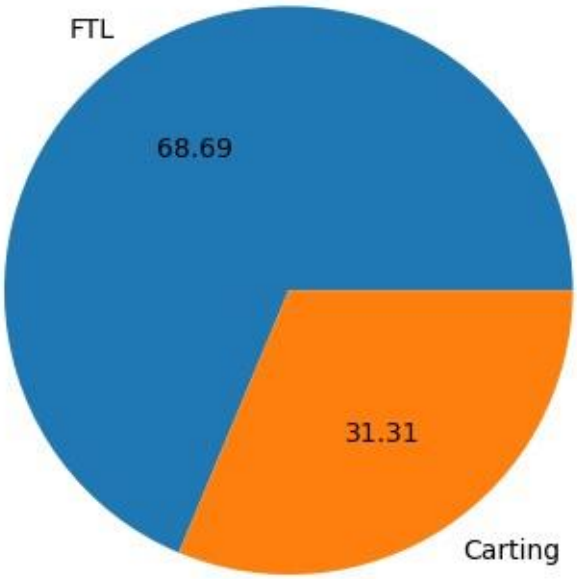
[115]:
```
df.head(3)
```

[115]:
```
      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

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

              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)

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

             od_start_time …         cutoff_timestamp \
0 2018-09-20 03:21:32.418600 … 2018-09-20 04:27:55.000000
1 2018-09-20 03:21:32.418600 … 2018-09-20 04:17:55.000000
2 2018-09-20 03:21:32.418600 … 2018-09-20 04:01:19.505586

   actual_distance_to_destination actual_time osrm_time osrm_distance
   \
0                      10.435660  14.0  11.0  11.9653
1                      18.936842  24.0  20.0  21.7243
2                      27.637279  40.0  28.0  32.5395

factor segment_actual_time segment_osrm_time segment_osrm_distance \
 0 1.272727              14.0            11.0             11.9653
 1 1.200000              10.0             9.0              9.7590
 2 1.428571              16.0             7.0             10.8152
   segment_factor
```

```
0       1.272727
1       1.111111
2       2.285714
[3 rows x 24 columns]
```

[116]:
```
data_distribution = df['data'].value_counts(normalize=True)*100
plt.pie(x = data_distribution, labels = data_distribution.index,autopct = '%.
 ↪2f')
plt.show()
```

[117]:
```
 route_type_distribution =
df['route_type'].value_counts(normalize=True)*100 plt.pie(x =
route_type_distribution, labels = route_type_distribution.
 ↪index,autopct = '%.2f')
plt.show()
```



2 Grouping the data into sub-journey

Let's first create a unique identifier for each subjourney. This identifier will consist of trip_uuid, source_center and destination_center

[120]:
```
df['segment_key'] = df['trip_uuid'] + df['source_center'] +␣
 ↪df['destination_center']
df[['segment_key']].head(3)
```

[120]:

	segment_key
0	trip-153741093647649320IND388121AAAIND388620AAB
1	trip-153741093647649320IND388121AAAIND388620AAB
2	trip-153741093647649320IND388121AAAIND388620AAB

Now, let's use this identifier for groupby to create cleaner data

[121]:
```
segment_columns = ['segment_actual_time', 'segment_osrm_distance',␣
 ↪'segment_osrm_time']

for i in segment_columns:
  df[i + '_sum'] = df.groupby('segment_key').aggregate({i:'cumsum'})

df[[i+'_sum' for i in segment_columns]].head(3)
```

[121]:
	segment_actual_time_sum	segment_osrm_distance_sum	segment_osrm_time_sum
0	14.0	11.9653	11.0
1	24.0	21.7243	20.0
2	40.0	32.5395	27.0

[122]:
```
df.columns
```

[122]:
```
Index(['data', 'trip_creation_time', 'route_schedule_uuid',
       'route_type', 'trip_uuid', 'source_center', 'source_name',
                                                  'destination_center',
       'destination_name', 'od_start_time', 'od_end_time',
       'start_scan_to_end_scan', 'is_cutoff', 'cutoff_factor',
       'cutoff_timestamp', 'actual_distance_to_destination',
       'actual_time',
       'osrm_time', 'osrm_distance', 'factor', 'segment_actual_time',
       'segment_osrm_time', 'segment_osrm_distance', 'segment_factor',
       'segment_key', 'segment_actual_time_sum',
       'segment_osrm_distance_sum',
       'segment_osrm_time_sum'],
      dtype='object')
```

Aggregation at sub-journey level

[123]:
```
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',
    'destination_name' : 'last',
    'od_start_time' : 'first',
    'od_end_time' : 'first',
    'start_scan_to_end_scan' : 'first',
    'actual_distance_to_destination' : 'last',
    'actual_time' : 'last',
    'osrm_time' : 'last',
    'osrm_distance' : 'last',
    'segment_actual_time_sum' : 'last',
    'segment_osrm_distance_sum' : 'last',
    'segment_osrm_time_sum' : 'last',
}
```

Grouping mini trips and sorting them by time

```
                        [124]: segment_df =
df.groupby('segment_key').aggregate(segment_dict).reset_index() segment_df =
    segment_df.sort_values(by=['segment_key','od_end_time']).
 ↪reset_index()
segment_df.head(3) [124]:
     index segment_key
     data \
0      0 trip-153671041653548748IND209304AAAIND000000ACB training
1      1 trip-153671041653548748IND462022AAAIND209304AAA training
2      2 trip-153671042288605164IND561203AABIND562101AAA training

         trip_creation_time \
0 2018-09-12 00:00:16.535741
1 2018-09-12 00:00:16.535741
2 2018-09-12 00:00:22.886430

                              route_schedule_uuid route_type \
0  thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6…     FTL
1  thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6…     FTL
2  thanos::sroute:3a1b0ab2-bb0b-4c53-8c59-eb2a2c0…     Carting

              trip_uuid source_center                    source_name \
0  trip-153671041653548748 IND209304AAA Kanpur_Central_H_6 (Uttar
   Pradesh)
1  trip-153671041653548748 IND462022AAA Bhopal_Trnsport_H (Madhya
   Pradesh)
2  trip-153671042288605164 IND561203AAB    Doddablpur_ChikaDPP_D
   (Karnataka)

 destination_center …           od_start_time \
0      IND000000ACB … 2018-09-12 16:39:46.858469
1      IND209304AAA … 2018-09-12 00:00:16.535741
2      IND562101AAA … 2018-09-12 02:03:09.655591

             od_end_time start_scan_to_end_scan \
0 2018-09-13 13:40:23.123744    1260.0
1 2018-09-12 16:39:46.858469    999.0
2 2018-09-12 03:01:59.598855    58.0

   actual_distance_to_destination actual_time osrm_time osrm_distance
   \
0                   383.759164  732.0 329.0 446.5496
1                   440.973689  830.0 388.0 544.8027
2                   24.644021   47.0  26.0  28.1994
```

```
   segment_actual_time_sum segment_osrm_distance_sum
   segment_osrm_time_sum
0                    728.0                  670.6205                   534.0
1                    820.0                  649.8528                   474.0
2                     46.0                   28.1995                    26.0
[3 rows x 21 columns]
```

[125]:
```
segment_df.shape
```

[125]: (26222, 21)

Example

[126]:
```
segment_df[segment_df['trip_uuid']=='trip-153671074033284934']
```

[126]:
```
   index                                  segment_key     data \
15    15 trip-153671074033284934IND395009AAAIND395023AAD training
16    16 trip-153671074033284934IND395023AADIND395004AAB training

          trip_creation_time \
15 2018-09-12 00:05:40.333071
16 2018-09-12 00:05:40.333071

                             route_schedule_uuid route_type \
15  thanos::sroute:a0e60427-16ad-4b17-b3b0-6a06643…    Carting
16  thanos::sroute:a0e60427-16ad-4b17-b3b0-6a06643…    Carting

               trip_uuid source_center               source_name \
15  trip-153671074033284934 IND395009AAA Surat_Central_D_12 (Gujarat)
16  trip-153671074033284934 IND395023AAD    Surat_Central_I_4
    (Gujarat)

  destination_center …           od_start_time \
15      IND395023AAD … 2018-09-12 02:31:39.246238
16      IND395004AAB … 2018-09-12 00:05:40.333071

              od_end_time start_scan_to_end_scan \
15 2018-09-12 05:16:28.581141    164.0
16 2018-09-12 02:01:41.638015    116.0

   actual_distance_to_destination actual_time osrm_time osrm_distance \
15                    12.264924  128.0 16.0  17.0225
16                    13.189924  33.0  13.0  13.9134

  segment_actual_time_sum segment_osrm_distance_sum segment_osrm_time_sum
15                  128.0  17.0225    16.0
16                  33.0   13.9133    13.0
```

```
[2 rows x 21 columns]
```

[127]:
```
segment_df.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_distance_sum    26222       non-null
                                 float64
 20 segment_osrm_time_sum        26222       non-null
                                 float64
dtypes: datetime64[ns](3), float64(8), int64(1),
object(9) memory usage: 4.2+ MB
```

#Feature Engineering

Let's create a fearture "od_time_diff_hour" using od_start_time and od_end_time and convert it to hours.

[128]:
```
segment_df['od_time_diff_hour'] = (segment_df['od_end_time'] -␣
```

```
 ↪segment_df['od_start_time']).dt.total_seconds()/60
segment_df.head(3)
```

[128]:

	index	segment_key	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_center	…	od_end_time	start_scan_to_end_scan	actual_distance_to_destination	actual_time	osrm_time	osrm_distance	segment_actual_time_sum	segment_osrm_distance_sum	segment_osrm_time_sum	od_time_diff_hour
0	0	trip-153671041653548748IND209304AAAIND000000ACB	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6…	FTL	trip-153671041653548748	IND209304AAA	Kanpur_Central_H_6 (Uttar Pradesh)	IND000000ACB	…	2018-09-13 13:40:23.123744	1260.0	383.759164	732.0	329.0	446.5496	728.0	670.6205	534.0	1260.604421
1	1	trip-153671041653548748IND462022AAAIND209304AAA	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6…	FTL	trip-153671041653548748	IND462022AAA	Bhopal_Trnsport_H (Madhya Pradesh)	IND209304AAA	…	2018-09-12 16:39:46.858469	999.0	440.973689	830.0	388.0	544.8027	820.0	649.8528	474.0	999.505379
2	2	trip-153671042288605164IND561203AABIND562101AAA	training	2018-09-12 00:00:22.886430	thanos::sroute:3a1b0ab2-bb0b-4c53-8c59-eb2a2c0…	Carting	trip-153671042288605164	IND561203AAB	Doddablpur_ChikaDPP_D (Karnataka)	IND562101AAA	…	2018-09-12 03:01:59.598855	58.0	47.0	26.0	28.1994	2	24.644021	46.0	28.1995	26.0	58.832388

[3 rows x 22 columns]

Aggregation at sub-journey level

[129]:
```
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_distance_sum' : 'sum',
    'segment_osrm_time_sum' : 'sum',
}
```

[130]:
```
trip_df = segment_df.groupby('trip_uuid').aggregate(trip_dict).reset_index(drop
 ↪= True)
```

```
trip_df.head(3)
```

[130]:

```
      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

                                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

              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)
```

```
 destination_center                destination_name \
0       IND209304AAA Kanpur_Central_H_6 (Uttar Pradesh)
1       IND561203AAB  Doddablpur_ChikaDPP_D (Karnataka)
2       IND000000ACB  Gurgaon_Bilaspur_HB (Haryana)

  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

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

[131]:
```
trip_df.shape
```

[131]: (14787, 18)

[132]:
```
trip_df[['actual_time','segment_actual_time_sum']].head(10)
```

[132]:
```
   actual_time segment_actual_time_sum
0      1562.0                1548.0
1       143.0                 141.0
2      3347.0                3308.0
3                  59.0     59.0 4 341.0     340.0
5         61.0    60.0
6         24.0    24.0
7         64.0    64.0 8 161.0     161.0
9         23.0                   23.0
```

Example

[133]:
```
trip_df[trip_df['trip_uuid'] == 'trip-153671074033284934']
```

[133]:
```
      data       trip_creation_time \
8 training 2018-09-12 00:05:40.333071

                                 route_schedule_uuid
route_type \ 8 thanos::sroute:a0e60427-16ad-4b17-b3b0-
6a06643…  Carting

               trip_uuid source_center               source_name \
```

```
8 trip-153671074033284934 IND395009AAA Surat_Central_D_12 (Gujarat)

  destination_center destination_name start_scan_to_end_scan \ 8
IND395004AAB Surat_Central_D_3 (Gujarat) 280.0

   od_time_diff_hour actual_distance_to_destination actual_time
   osrm_time \
8       280.843997                   25.454848      161.0      29.0

osrm_distance segment_actual_time_sum segment_osrm_distance_sum \
8       30.9359                 161.0                 30.9358

   segment_osrm_time_sum
8                 29.0
```

Notice that the values in these two columns don't necessarily match. So, let's test this hypothesis.

Step-1

Null Hypothesis(H0) –> There is no difference in *actual_time* and *segment_actual_time_sum*.

Alternate Hypothesis(HA) –> There is statistically significant difference in *actual_time* and *segment_actual_time_sum*.

STEP-2 : Checking for basic assumpitons for the hypothesis

Plot the histogram to visually see whether it follows normal distribution. If it doesn't, use *shapirowilk* test to confirm.

STEP-3: Define Test statistics; Distribution of T under H0.

If the assumptions of T Test are met then we can proceed performing T Test for independent samples else we will perform the non parametric test equivalent to T Test for independent sample i.e., Mann-Whitney U test for two independent samples.

STEP-4: Compute the p-value and compare with the value of alpha. alpha = 0.05

STEP-5: Compare p-value and alpha. Based on p-

value, we will accept or reject H0. `p-val  >`

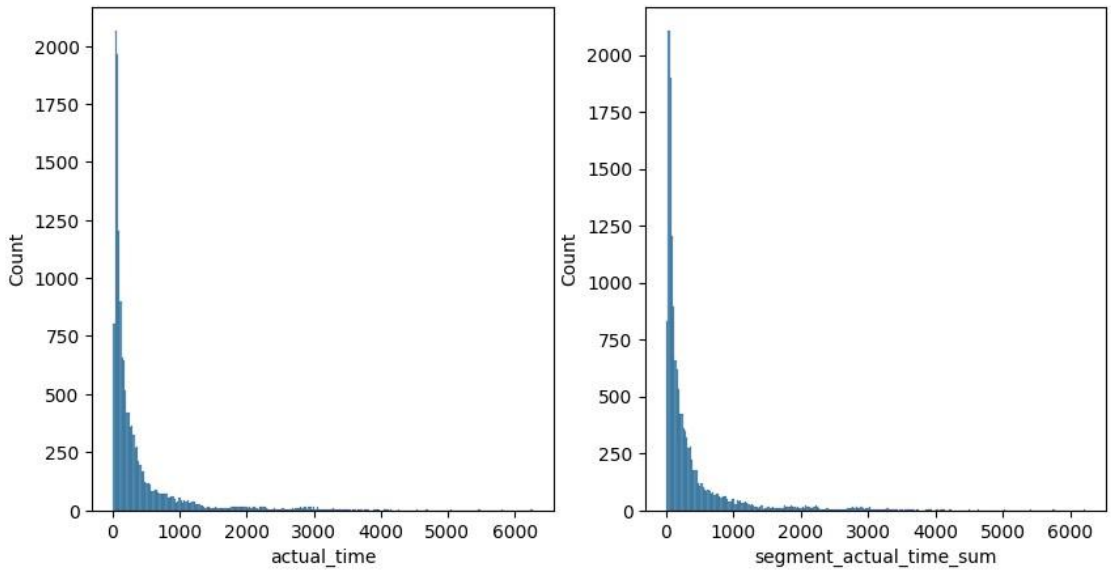
`alpha : Accept H0`

---

p-val < alpha : Reject H0

---

[134]:
```
plt.figure(figsize=(10,5))
plt.subplot(1,2,1)
sns.histplot(x='actual_time', data=trip_df)
plt.subplot(1,2,2)
sns.histplot(x='segment_actual_time_sum', data=trip_df)
plt.show()
```



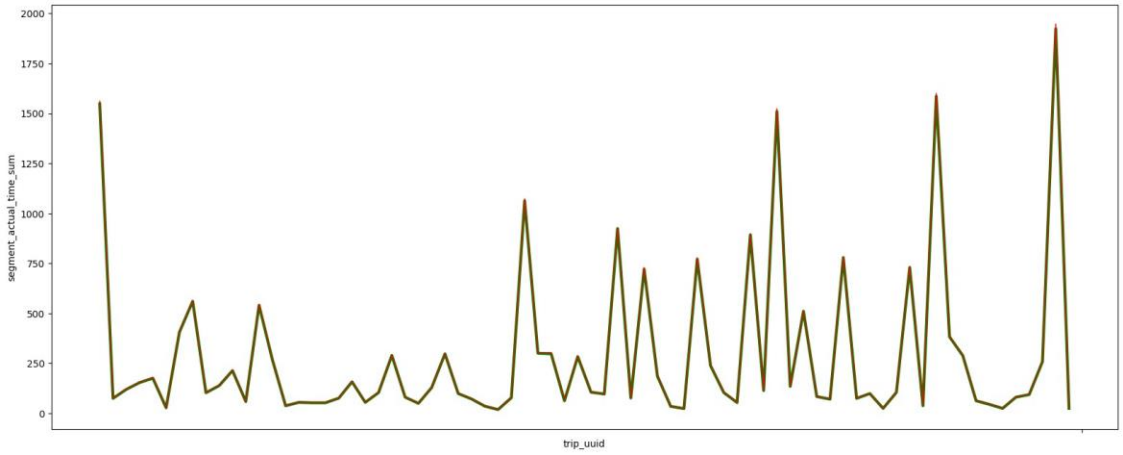
Neither of the graphs follow *normal* distribution So, let's use *shapiro-wilk* test to confirm the same

[135]:
```
from scipy.stats import shapiro p_val_1 =
shapiro(trip_df['actual_time'])[1] p_val_2 =
shapiro(trip_df['segment_actual_time_sum'])[1] print(f'p_value of
actual_time is {p_val_1} and p_value of␣
↪segment_actual_time_sum is {p_val_2}') p_value of actual_time is
0.0 and p_value of segment_actual_time_sum is 0.0
/usr/local/lib/python3.10/dist-
packages/scipy/stats/_morestats.py:1882:
UserWarning: p-value may not be accurate for N > 5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

This confirms that the graphs don't follow normal distribution.

Let's test our hypothesis both visually and statistically (non-parametric test).

[136]:
```
plt.figure(figsize=(20,8))
sns.lineplot(x=trip_df['trip_uuid'][::200],
 ↪y=trip_df['segment_actual_time_sum'][::200], color='g', lw=3)
sns.lineplot(x=trip_df['trip_uuid'][::200],  =trip_df['actual_time'][::200],
 ↪color='r', lw=1)
plt.xticks('')
plt.show()
```



As, the samples are related/paired, let's use wilcoxon signed rank test

[137]:
```
from scipy.stats import wilcoxon p_value =
wilcoxon(trip_df['actual_time'],trip_df['segment_actual_time_sum'])[1
]

if p_value >= 0.05:
  print('Fail to reject Null Hypothesis')
  print('There is no difference in actual_time and
segment_actual_time_sum') else:
  print('Reject Null Hypothesis') print('There is statistically
  significant difference in actual_time and
 ↪segment_actual_time_sum.')
```

```
Reject Null Hypothesis
There is statistically significant difference in actual_time and
segment_actual_time_sum.
```

Now, let's check for actual_distance_to_destination and osrm_distance

[138]:
```
trip_df[['actual_distance_to_destination','osrm_distance']].head(10)
```

[138]:
```
actual_distance_to_destination osrm_distance
```

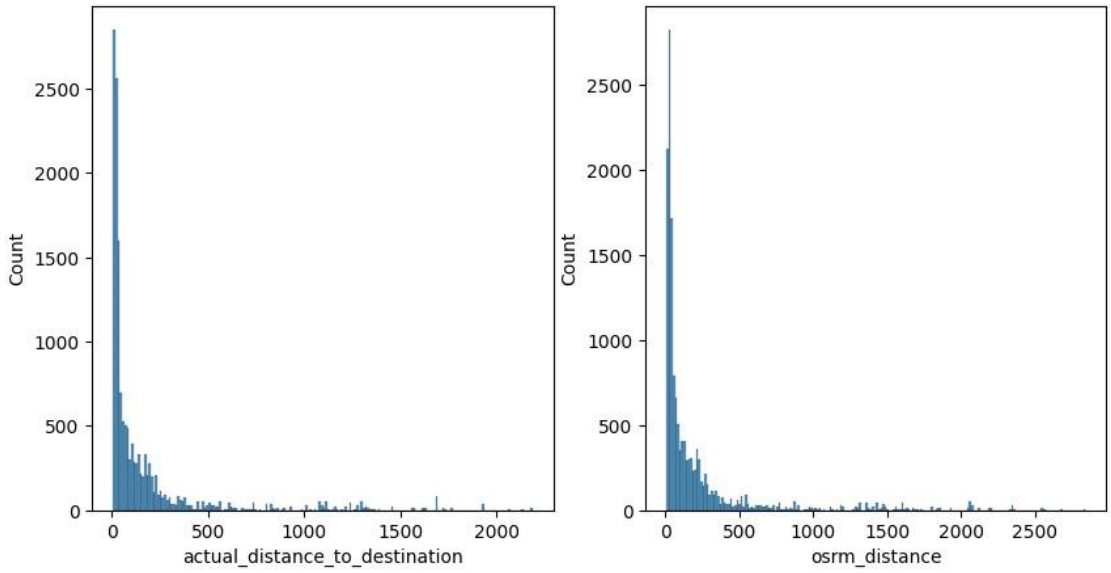
```
0                    824.732854     991.3523
1                     73.186911      85.1110
2                   1927.404273    2354.0665
3                     17.175274      19.6800
4                    127.448500     146.7918
5                     24.597048      28.0647
6                      9.100510      12.0184
7                     22.424210      28.9203
8                     25.454848      30.9359
9                      9.872146       9.9566
```

Notice that the values in these two columns don't necessarily match. So, let's test this hypothesis.

Null Hypothesis(H0) –> There is no difference in *actual_distance_to_destination* and *osrm_distance*

Alternate Hypothesis(HA) –> There is statistically significant difference in *actual_distance_to_destination* and *osrm_distance*.

[139]:
```
plt.figure(figsize=(10,5))
plt.subplot(1,2,1)
sns.histplot(x='actual_distance_to_destination', data=trip_df)
plt.subplot(1,2,2)
sns.histplot(x='osrm_distance', data=trip_df)
plt.show()
```



Neither of the graphs follow *normal* distribution So, let's use *shapiro-wilk* test to confirm the same

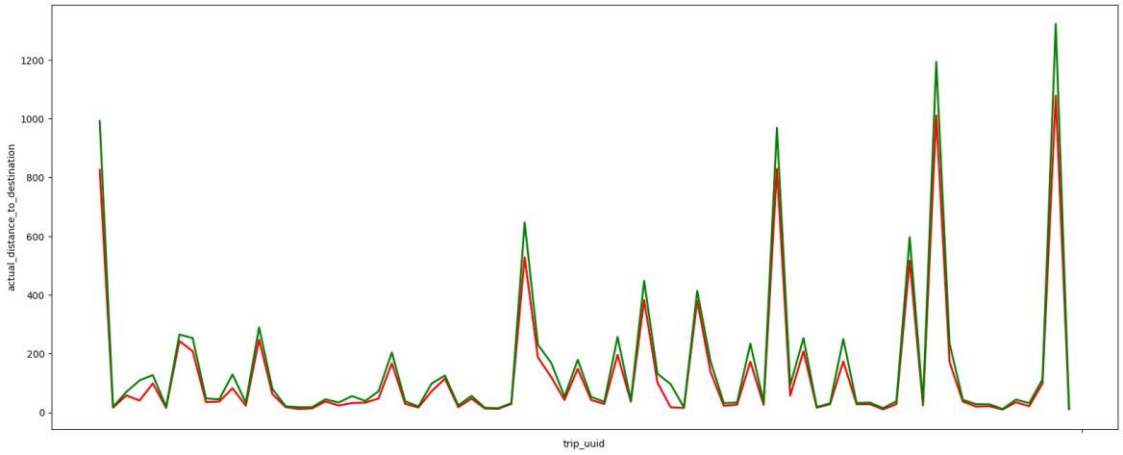
[140]:
```
p_val_1 = shapiro(trip_df['actual_distance_to_destination'])[1]
p_val_2 = shapiro(trip_df['osrm_distance'])[1] print(f'p_value of
actual_distance_to_destination is {p_val_1} and p_value of␣
↪osrm_distance is {p_val_2}')
```

```
p_value of actual_distance_to_destination is 0.0 and p_value of
osrm_distance is 0.0

/usr/local/lib/python3.10/dist-
packages/scipy/stats/_morestats.py:1882:
UserWarning: p-value may not be accurate for N > 5000.

warnings.warn("p-value may not be accurate for N >

5000.")
```

This confirms that the graphs don't follow normal distribution.

Let's test our hypothesis both visually and statistically.

[141]:
```
plt.figure(figsize=(20,8))
sns.lineplot(x=trip_df['trip_uuid'][::200],␣
↪y=trip_df['actual_distance_to_destination'][::200], color='r',
lw=2) sns.lineplot(x=trip_df['trip_uuid'][::200],
y=trip_df['osrm_distance'][::200],␣
↪color='g', lw=2)
plt.xticks('')
plt.show()
```



[142]:
```
p_value =␣
↪wilcoxon(trip_df['actual_distance_to_destination'],trip_df['osrm_distance'])
                                                                    [1]


if p_value >= 0.05:
  print('Fail to reject Null Hypothesis') print('There is no
  difference in actual_distance_to_destination and␣
 ↪osrm_distance')
else:
  print('Reject Null Hypothesis')
  print('There is statistically significant difference in␣
```

```
    ↪actual_distance_to_destination and osrm_distance.')

Reject Null Hypothesis
There is statistically significant difference in
actual_distance_to_destination and osrm_distance.
```

Now, let's check if the features *osrm_time* and *segment_osrm_time_sum* are same or not

[143]:
```
trip_df[['osrm_time','segment_osrm_time_sum']].head(10)
```

[143]:

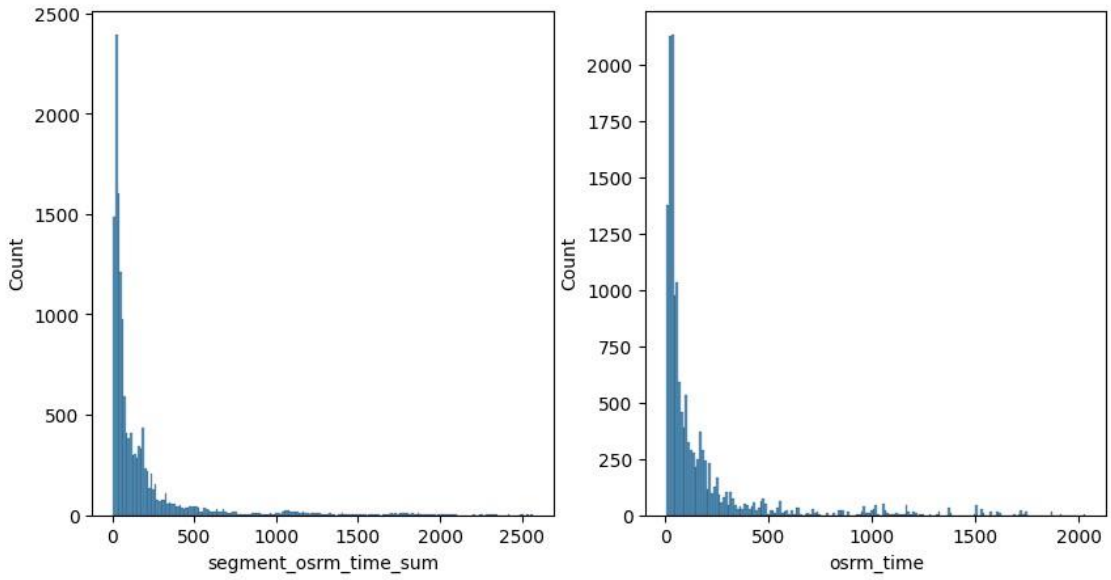
	osrm_time	segment_osrm_time_sum
0	717.0	1008.0
1	68.0	65.0
2	1740.0	1941.0
3	15.0	16.0
4	117.0	115.0
5	23.0	23.0
6	13.0	13.0
7	34.0	34.0
8	29.0	29.0
9	8.0	14.0

Notice that the values in these two columns don't necessarily match. So, let's test this hypothesis.

Null Hypothesis(H0) –> There is no difference in *actual_distance_to_destination* and *osrm_distance*

Alternate Hypothesis(HA) –> There is statistically significant difference in *actual_distance_to_destination* and *osrm_distance*.

[144]:
```
plt.figure(figsize=(10,5))
plt.subplot(1,2,1)
sns.histplot(x='segment_osrm_time_sum', data=trip_df)
plt.subplot(1,2,2)
sns.histplot(x='osrm_time', data=trip_df)
plt.show()
```



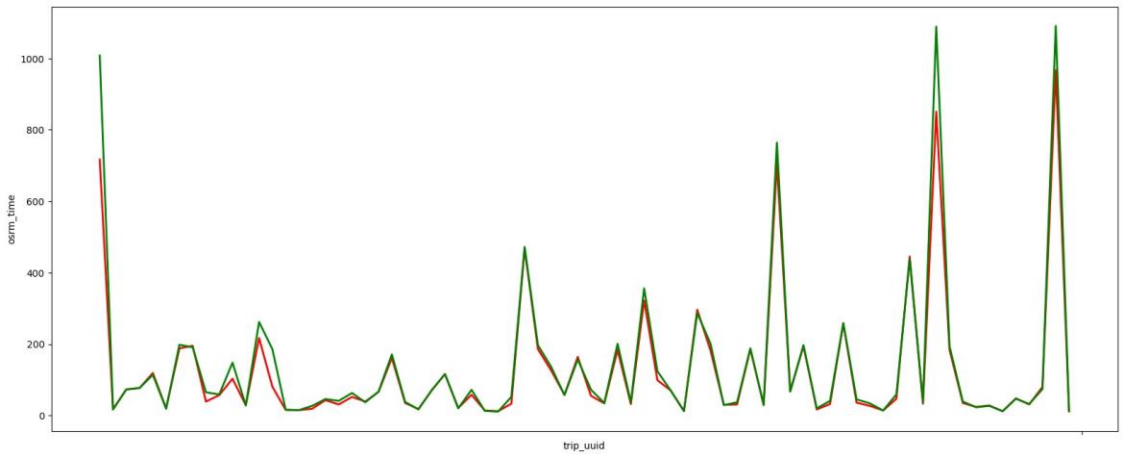
Neither of the graphs follow normal distribution So, let's use shapiro-wilk test to confirm the same

[145]:
```
p_val_1 = shapiro(trip_df['segment_osrm_time_sum'])[1] p_val_2 =
shapiro(trip_df['osrm_time'])[1] print(f'p_value of
segment_osrm_time_sum is {p_val_1} and p_value of osrm_time␣ ↪is
{p_val_2}') p_value of segment_osrm_time_sum is 0.0 and p_value of
osrm_time is 0.0
```

```
/usr/local/lib/python3.10/dist-
packages/scipy/stats/_morestats.py:1882:
UserWarning: p-value may not be accurate for N > 5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

This confirms that the graphs doesn't follow normal distribution.
Let's test our hypothesis both visually and statistically.

[146]:
```
plt.figure(figsize=(20,8))
sns.lineplot(x=trip_df['trip_uuid'][::200],  =trip_df['osrm_time'][::200],␣
↪color='r', lw=2)
sns.lineplot(x=trip_df['trip_uuid'][::200],  =trip_df['segment_osrm_time_sum'][:
↪:200], color='g', lw=2)
plt.xticks('')
plt.show()
```



[147]:
```
p_value = wilcoxon(trip_df['osrm_time'],
trip_df['segment_osrm_time_sum'])[1]

if p_value >= 0.05:
  print('Fail to reject Null Hypothesis')
print('There is no difference in osrm_time and segment_osrm_time_sum')
else:
  print('Reject Null Hypothesis') print('There is
  statistically significant difference in osrm_time and␣
  ↪segment_osrm_time_sum.')
```

```
Reject Null Hypothesis
There is statistically significant difference in osrm_time and
segment_osrm_time_sum.
```

Now, let's change source_name and destination_name into lower case for futher processing.

[148]:
```
 trip_df['destination_name'] =
trip_df['destination_name'].str.lower() trip_df['source_name'] =
trip_df['source_name'].str.lower() trip_df.head(3)
```

[148]:

	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

                                  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

                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)

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

  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

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

Let's transaform destiname_name into more meaningful data Let's break down destination_name into state and city

[149]:
```
def dest_to_state(destination_name):
  state = destination_name.split('(')[1]
  return state[:-1] # to remove the last character ')'


def dest_to_city(destination_name):
  city = destination_name.split('_')[0]
  return city
```

```
def dest_to_place(destination_name):
  x = destination_name.split('(')[0]
  lst = x.split('_')

  if len(lst)>=3:
    return lst[1]
  elif len(lst)==2:
    return lst[0]
  else:
    return x.split(' ')[0]


def dest_to_code(destination_name):
  x = destination_name.split('(')[0]
  lst = x.split('_')
  code = lst[-1]
  return code
```

[150]:
```
trip_df['destination_state'] = trip_df['destination_name'].apply(lambda x:␣
 ↪dest_to_state(x))
trip_df['destination_city']  = trip_df['destination_name'].apply(lambda x:␣
 ↪dest_to_city(x))
trip_df['destination_place'] = trip_df['destination_name'].apply(lambda x:␣
 ↪dest_to_place(x))
trip_df['destination_code']  = trip_df['destination_name'].apply(lambda x:␣
 ↪dest_to_code(x))
```

[151]:
```
trip_df[['destination_state','destination_city','destination_place','destination_code']]
```

[151]:

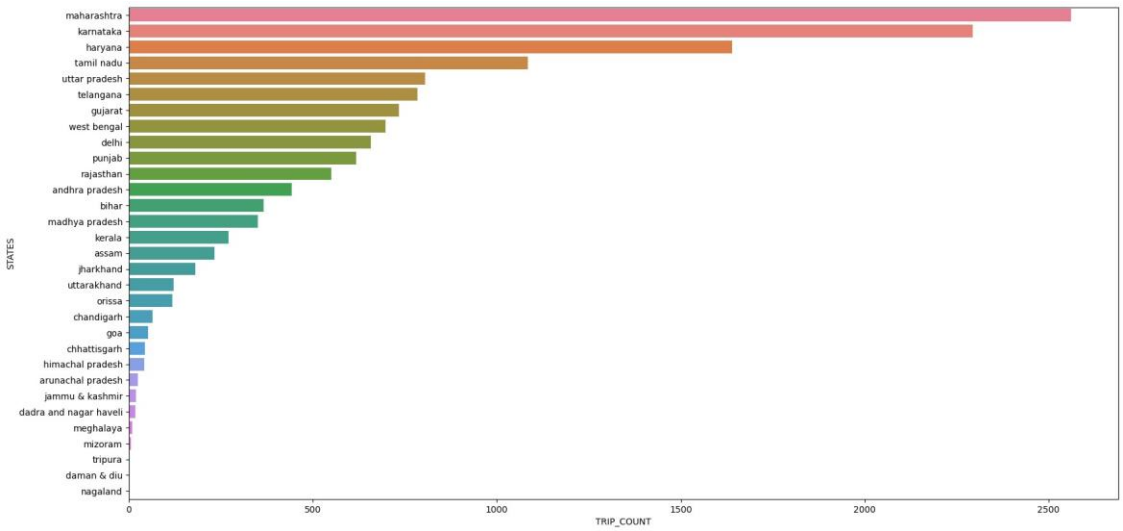
	destination_state	destination_city	destination_place	destination_code
0	uttar pradesh	kanpur	central	6
1	karnataka	doddablpur	chikadpp	d
2	haryana	gurgaon	bilaspur	hb
3	maharashtra	mumbai	mirard	ip
4	karnataka	sandur	wrdn1dpp	d
…	…	…	…	…
14782	punjab	chandigarh	mehmdpur	h
14783	haryana	faridabad	blbgarh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

```
      14786       karnataka          sandur        wrdn1dpp             d

      [14787 rows x 4 columns]
```

[152]:
```
top_states = trip_df.groupby('destination_state').aggregate({'trip_uuid':
 ↪'count'}).reset_index().
 ↪sort_values(by='trip_uuid',ascending=False)['destination_state']
print(f'The top 5 states are :{top_states[:5].values}')

top_cities = trip_df.groupby('destination_city').aggregate({'trip_uuid':
 ↪'count'}).reset_index().
 ↪sort_values(by='trip_uuid',ascending=False)['destination_city']
print(f'The top 5 cities are :{top_cities[:5].values}')
```

```
The top 5 states are :['maharashtra' 'karnataka' 'haryana' 'tamil
nadu' 'uttar pradesh']
The top 5 cities are :['bengaluru' 'mumbai' 'gurgaon' 'delhi'
'bangalore']
```

[153]:
```
state_wise_count = trip_df.groupby('destination_state').aggregate({'trip_uuid':
 ↪'count'}).reset_index().
 ↪sort_values(by='trip_uuid',ascending=False)['trip_uuid']
plt.figure(figsize=(20,10))
sns.barplot(y=top_states, x=state_wise_count, hue = top_states)
plt.xlabel('TRIP_COUNT')
plt.ylabel('STATES')
plt.show()
```



[154]:
```
trip_df['trip_year'] = trip_df['trip_creation_time'].dt.year
trip_df['trip_month'] = trip_df['trip_creation_time'].dt.month
```

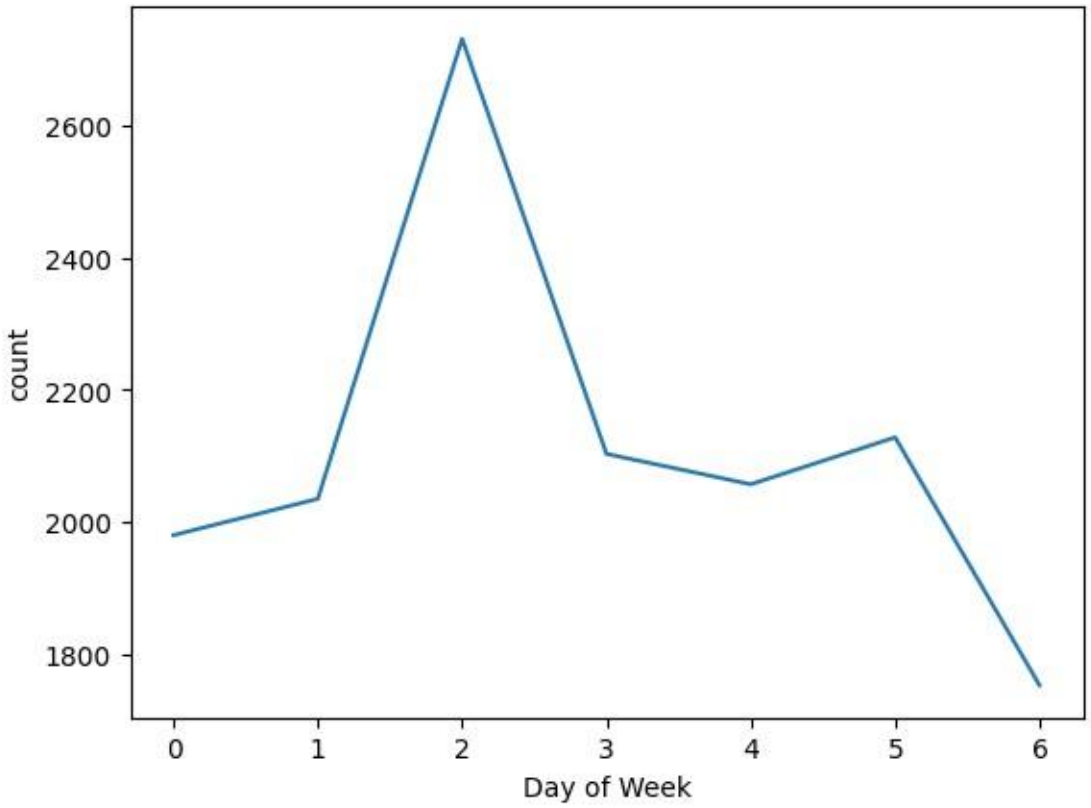
```
trip_df['trip_hour'] = trip_df['trip_creation_time'].dt.hour
trip_df['trip_day'] = trip_df['trip_creation_time'].dt.day
trip_df['trip_week'] =
trip_df['trip_creation_time'].dt.isocalendar().week
trip_df['trip_dayofweek'] =
trip_df['trip_creation_time'].dt.dayofweek
trip_df[['trip_year','trip_month','trip_hour','trip_day','trip_wee
k','trip_dayofweek']]. ↪head(3)
```

[154]:
```
  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
```

[155]:
```
# {'0':'Monday', '1':'Tuesday', '2':'Wednesday', '3':'Thursday',
'4':'Friday',␣
 ↪'5':'Saturday', '6':'Sunday'}
trip_df.groupby('trip_dayofweek').aggregate({'trip_uuid':'count'}).re
set_index()
```

[155]:
```
  trip_dayofweek trip_uuid
0              0 1980
1              1 2035
2              2 2731
3              3 2103
4              4 2057
5              5 2128
6              6      1753
```

[156]:
```
plt.xlabel('Day of Week')
plt.ylabel('count')
sns.lineplot(trip_df.groupby('trip_dayofweek').aggregate({'trip_uuid':'count'}).
 ↪reset_index()['trip_uuid'])
plt.show()
```



The day that recieves peak orders is *Wednesday*

[157]:
```
date_cols =␣
↪['trip_year','trip_month','trip_hour','trip_day','trip_week','trip_day
ofweek'] for i in date_cols:
 print('The data belongs to ',trip_df[i].nunique(), '
 ',i.split('_')[1],'s',␣ ↪sep='')
```

```
The data belongs to 1 years
The data belongs to 2 months
The data belongs to 24 hours
The data belongs to 22 days
The data belongs to 4 weeks
The data belongs to 7 dayofweeks
```

#Outlier Detection and Treatment

[158]:
```
trip_df.shape
```

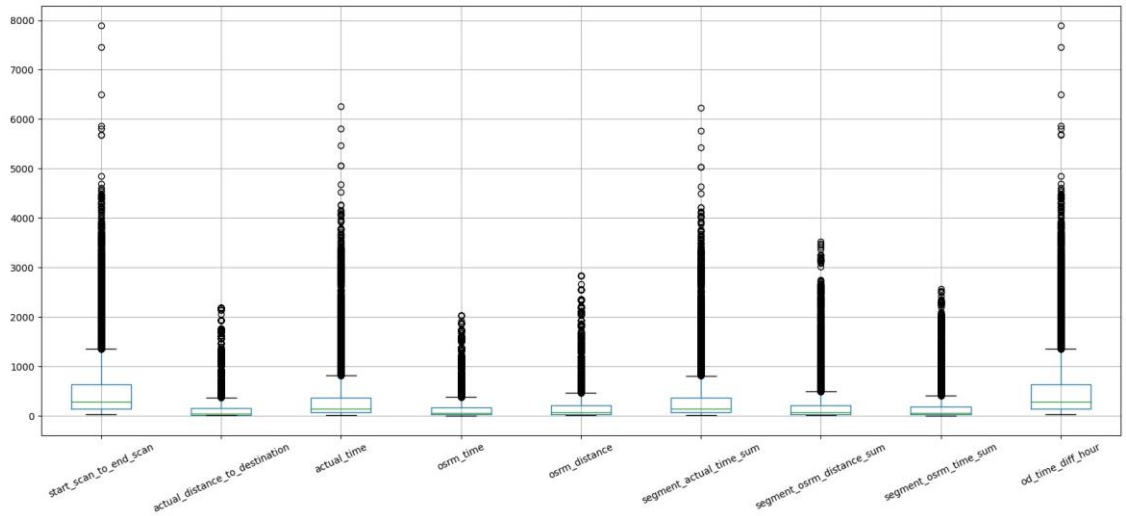
[158]: (14787, 28)

[159]:
```
num_cols =␣
```

```
↪['start_scan_to_end_scan','actual_distance_to_destination','actual_tim
                                                                    e',
          'osrm_time', 'osrm_distance','segment_actual_time_sum',
          'segment_osrm_distance_sum', 'segment_osrm_time_sum',␣
 ↪'od_time_diff_hour']
```

Box-Plot

[160]:
```
trip_df[num_cols].boxplot(rot=25, figsize=(20,8))
plt.show()
```

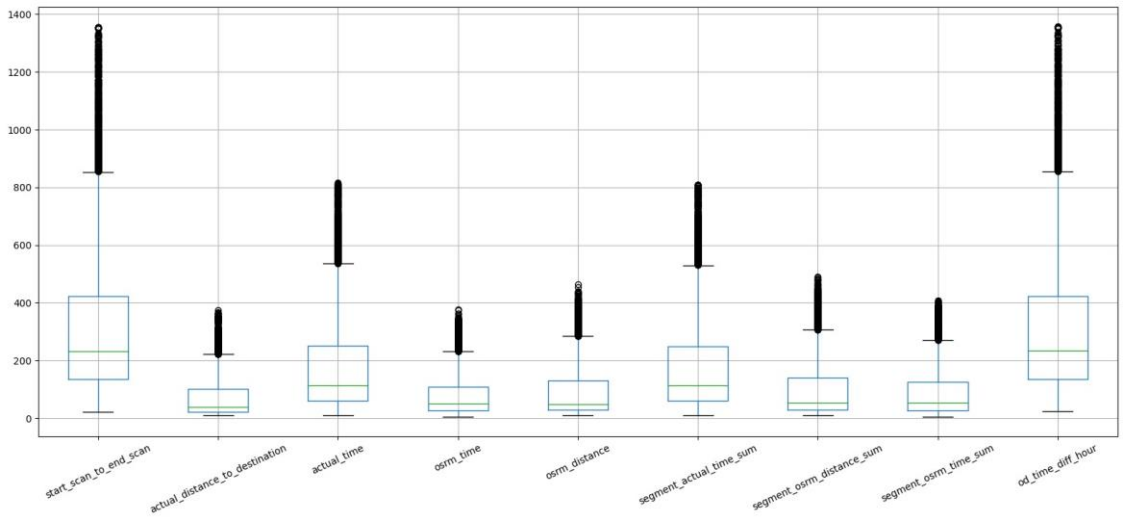


[161]:
```
Q1 = trip_df[num_cols].quantile(0.25)
Q3 = trip_df[num_cols].quantile(0.75)
IQR = Q3-Q1
```

[162]:
```
trip_df = trip_df[-((trip_df[num_cols] < (Q1 - IQR*1.5)) | (trip_df[num_cols] >␣
 ↪(Q3 + IQR*1.5))).any(axis=1)]
trip_df = trip_df.reset_index(drop=True)
trip_df.shape
```

[162]:
```
(12723, 28)
```

[163]:
```
trip_df[num_cols].boxplot(rot=25, figsize=(20,8))
plt.show()
```



#Handling Categorical & Numerical Variables

[164]:
```
trip_df['route_type'].unique()
```

[164]:
```
array(['Carting', 'FTL'], dtype=object)
```

As there are only 2 categories for 'route_type', so let's do *One-Hot Encoding*

[165]:
```
trip_df['route_type'] =
trip_df['route_type'].map({'Carting':0,'FTL':1})
trip_df['route_type'].unique()
```

[165]:
```
array([0, 1])
```

[166]:
```
trip_df.head(3)
```

[166]:

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name
0	training	2018-09-12 00:00:22.886430	thanos::sroute:3a1b0ab2-bb0b-4c53-8c59-eb2a2c0…	0	trip-153671042288605164	IND561203AAB	doddablpur_chikadpp_d (karnataka)
1	training	2018-09-12 00:01:00.113710	thanos::sroute:f0176492-a679-4597-8332-bbd1c7f…	0	trip-153671046011330457	IND400072AAB	mumbai hub (maharashtra)
2	training	2018-09-12 00:02:09.740725	thanos::sroute:d9f07b12-65e0-4f3b-bec8-df06134…	1			

```
2  trip-153671052974046625 IND583101AAA     bellary_dc (karnataka)
   destination_center destination_name \
0      IND561203AAB doddablpur_chikadpp_d (karnataka)
1      IND401104AAA   mumbai_mirard_ip (maharashtra)
2      IND583119AAA   sandur_wrdn1dpp_d (karnataka)

 start_scan_to_end_scan … destination_state destination_city \
0                 180.0 …   karnataka  doddablpur
1                 100.0 …   maharashtra      mumbai
2                 717.0 …   karnataka  sandur

   destination_place destination_code trip_year trip_month trip_hour \
0         chikadpp              d       2018         9         0
1           mirard             ip       2018         9         0
2         wrdn1dpp              d       2018         9         0

   trip_day trip_week trip_dayofweek
0       12  37    2
1       12  37    2
2       12  37    2
[3 rows x 28 columns]
```

Let's do this for *data* feature too

[167]:
```
trip_df['data'].unique()
```

[167]:
```
array(['training', 'test'], dtype=object)
```

As there are only 2 categories for *'route_type'*, so let's do One-Hot Encoding

[168]:
```
trip_df['data'] = trip_df['data'].map({'training':0,'test':1})
trip_df['data'].unique()
```

[168]:
```
array([0, 1])
```

[169]:
```
trip_df.head(3)
```

[169]:
```
data trip_creation_time \ 0
     0 2018-09-12 00:00:22.886430
1    0 2018-09-12 00:01:00.113710
2    0 2018-09-12 00:02:09.740725

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

 destination_center              destination_name \
0      IND561203AAB doddablpur_chikadpp_d (karnataka)
1      IND401104AAA  mumbai_mirard_ip (maharashtra)
2      IND583119AAA  sandur_wrdn1dpp_d (karnataka)

 start_scan_to_end_scan … destination_state destination_city \
0                 180.0 …  karnataka  doddablpur
1                 100.0 …  maharashtra     mumbai
2                 717.0 …  karnataka  sandur

destination_place destination_code trip_year trip_month trip_hour \
0         chikadpp              d       2018          9         0
1           mirard             ip       2018          9         0
2         wrdn1dpp              d       2018          9         0

   trip_day trip_week trip_dayofweek
0       12  37    2
1       12  37    2
2       12  37    2
[3 rows x 28 columns]
```

Normalizing/ Standardizing the numerical features using StandardScaler

[170]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(trip_df[num_cols])
```

[170]:
```
StandardScaler()
```

[171]:
```
trip_df[num_cols] = scaler.transform(trip_df[num_cols])
trip_df[num_cols]
```

[171]:
```
   start_scan_to_end_scan actual_distance_to_destination actual_time \
0               -0.548546                      0.012060  -
                                                         0.217856
1               -0.861602                     -0.765152  -
                                                         0.749015
2                1.552838                      0.764988   1.034163
3               -0.513328                     -0.662169  -
                                                         0.736369
4               -0.869428                     -0.877197  -
                                                         0.970332
…                     …                             …         …
```

```
12718            -0.247231                  -0.201970  -
                                                        0.597255
12719            -1.018130                  -0.788207  -
                                                        0.989302
12720             0.394533                  -0.466688   0.661086
12721             0.104957                   0.865940   0.547267
12722             0.128436                  -0.086534   0.616823
      osrm_time osrm_distance segment_actual_time_sum \
0     -0.144341    -0.073948            -
                                        0.221500
1     -0.877085    -0.804506            -
                                        0.743482
2      0.533102     0.614738             1.045260
3     -0.766482    -0.710888            -
                                        0.737116
4     -0.904736    -0.890050            -
                                        0.966279
…         …          …                  …
12718 -0.227293    -0.204002            -
                                        0.597073
12719 -0.918561    -0.844610            -
                                        0.985376
12720 -0.420848    -0.366561             0.669688
12721  1.390274     0.886261             0.523279
12722 -0.144341    -0.124553             0.625129
      segment_osrm_distance_sum segment_osrm_time_sum
      od_time_diff_hour
0                  -0.145358          -0.262662       -
                                                       0.544839
1                  -0.823653          -0.878225       -
                                                       0.861856
2                   0.514899           0.365464        1.552812
3                  -0.737295          -0.790288       -
                                                       0.510150
4                  -0.906532          -0.915913       -
                                                       0.871585
…                        …                  …         …
12718              -0.349273          -0.300349       -
                                                       0.246189
12719              -0.863608          -0.941038       -
                                                       1.017809
12720               0.072932           0.026276        0.395103
12721               1.324267           1.697092        0.107436
12722              -0.183439          -0.237537        0.130473
[12723 rows x 9 columns]
```

[172]:
```
trip_df[num_cols].describe()
```

```
[172]:   start_scan_to_end_scan actual_distance_to_destinationactual_time \
count          1.272300e+04                1.272300e+04
                                           1.272300e+04
mean          -1.619566e-17               -7.371818e-17          -
                                          8.041983e-17
std            1.000039e+00                1.000039e+00
                                           1.000039e+00
min           -1.162918e+00               -8.785574e-01          -
                                          1.065181e+00
25%           -7.207269e-01               -7.065920e-01          -
                                          7.363685e-01
50%           -3.411472e-01               -4.689012e-01          -
                                          4.012322e-01
75%            4.023595e-01                4.073375e-01
                                           4.650634e-01
max            4.049455e+00                4.178358e+00
                                           4.031419e+00
       osrm_time osrm_distance segment_actual_time_sum \
count           1.272300e+04     1.272300e+04
1.272300e+04
mean 4.467769e-173.797603e-17    -3.127438e-
                                 17
std  1.000039e+001.000039e+00     1.000039e+00
min   -1.001514e+00 -9.229378e-01      -1.061764e+00
25%   -7.111809e-01 -7.077649e-01      -7.371165e-01
50%   -3.931975e-01 -4.836339e-01      -3.997380e-01
75%   4.224989e-01  4.419548e-01        4.596223e-01
max   4.113871e+00  4.150641e+00        4.037107e+00

      segment_osrm_distance_sum
      segment_osrm_time_sum od_time_diff_hour
count            1.272300e+04        1.272300e+04
                 1.272300e+04
mean            -8.488760e-17        6.031487e-17
                 7.818595e-18
std              1.000039e+00        1.000039e+00
                 1.000039e+00
min             -9.375981e-01       -1.003850e+00  -
     1.162915e+00
25%             -7.228116e-01       -7.274750e-01  -
     7.210516e-01
50%             -4.628077e-01       -4.134119e-01  -
     3.418602e-01
75%              4.488499e-01        4.910897e-01
                 4.020802e-01
max              4.130135e+00        4.046283e+00
                 4.050310e+00
```

#Insights

1. The data set is corresponding to only 2 months, so not much can be concluded about the seasonal or month-over-month or year-over-year patterns.
2. There is a significant difference between *actual_time* and *segment_actual_time_sum* which shows there is discrepancy in data entry.
3. There is a significant difference between *actual_distance_to_destination* and *osrm_distance* which shows that the ML model's prediction is statistically significantly wrong or the delivery executives are not following the predetermined route.
4. There is a significant difference between *segment_osrm_time_sum* and *osrm_time* which shows that the ML model's prediction is statistically significantly wrong.
5. The top 5 states are : ***maharashtra, karnataka, haryana, tamil nadu, telangana***
6. The top 5 cities are : ***bengaluru, mumbai, gurgaon, delhi, hyderabad***
7. The day on which most orders are generated is a ***Wednesday***.

3 Recomendations

- We should work on imroving the ML model to improve business.
- We should focus more on those states and cities that provide us with more business by enabling more carries and better infrastructure.
- We should be ready with more orders on Wednesday by enabling long-shifts and getting more work force.

[ ]: