delhivery-shrikant-bhv

March 6, 2024

[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 world-class 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 on it.

---

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-fa3d5c3...    Carting
1  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...    Carting
2  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)

  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]:

```python
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_time   osrm_time  osrm_distance      factor  \
count   144867.000  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_distance             0.00
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]:
```python
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-fa3d5c3…    Carting
1  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
2  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)

  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]
```

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

[114]:
```python
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
```

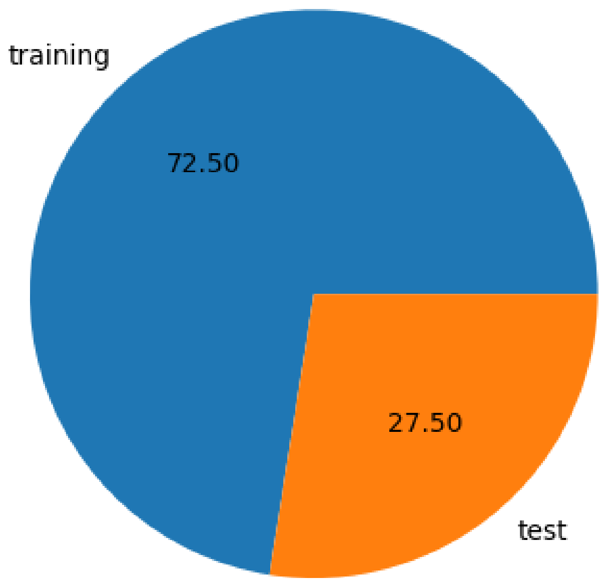
[115]:
```
df.head(3)
```

[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-fa3d5c3…    Carting
1  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
2  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)

  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]
```

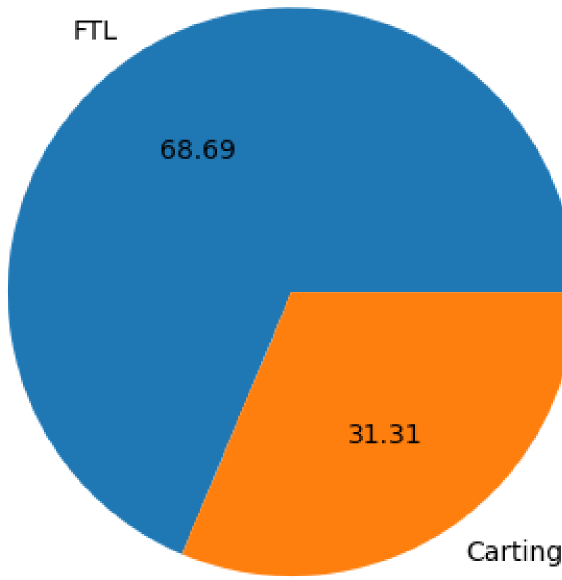
[116]:

```
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  \
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_end_time start_scan_to_end_scan  \
0       IND000000ACB  … 2018-09-13 13:40:23.123744                 1260.0
1       IND209304AAA  … 2018-09-12 16:39:46.858469                  999.0
2       IND562101AAA  … 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

   od_time_diff_hour
0        1260.604421
1         999.505379
2          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 *shapiro-wilk* 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

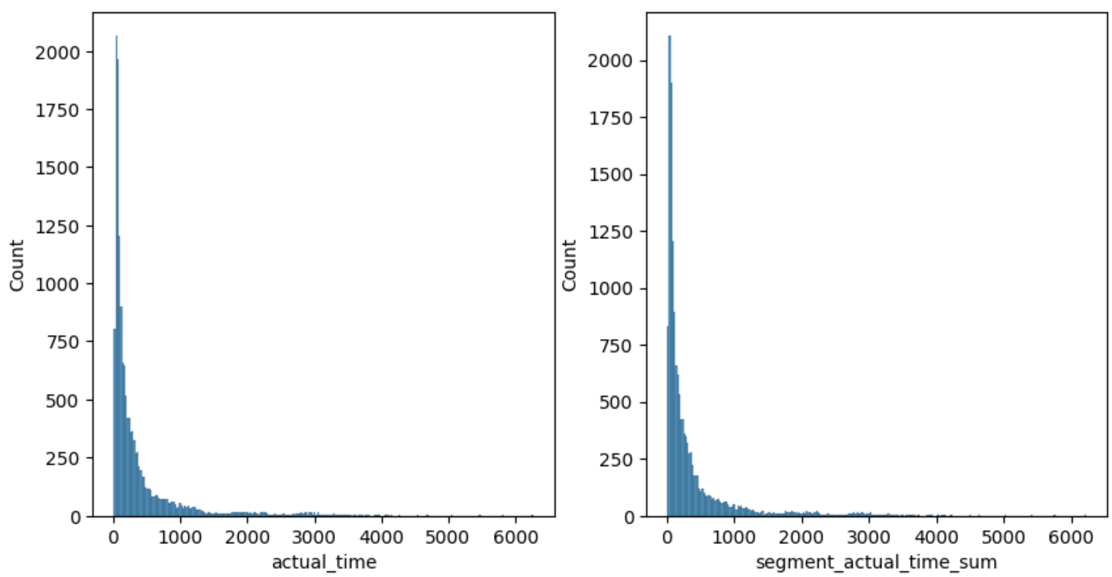
STEP-5: Compare p-value and alpha.

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

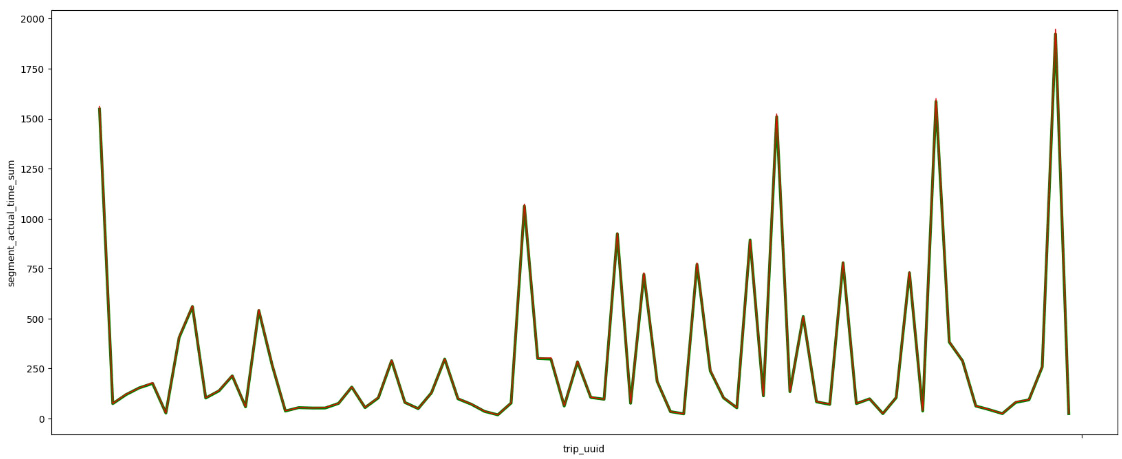
```
[135]: from scipy.stats import shapiro
p_val_1 = shapiro(trip_df['actual_time'])[1]
p_val_2 = shapiro(trip_df['segment_actual_time_sum'])[1]
print(f'p_value of actual_time is {p_val_1} and p_value of␣
 ↪segment_actual_time_sum is {p_val_2}')
```

```
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], y=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]:

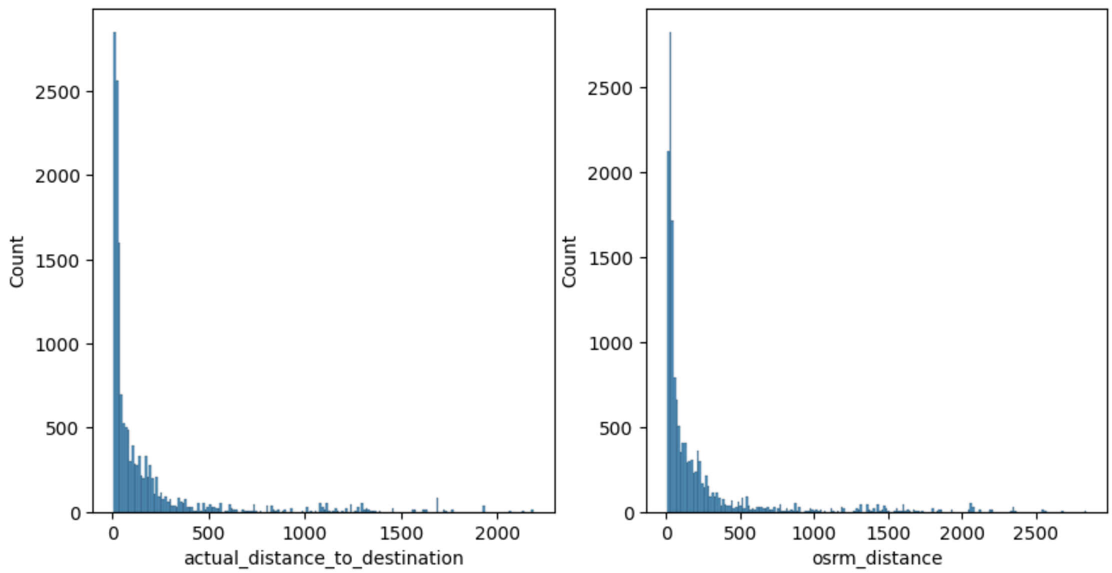
	actual_distance_to_destination	osrm_distance
0	824.732854	991.3523
1	73.186911	85.1110
2	1927.404273	2354.0665
3	17.175274	19.6800
4	127.448500	146.7918
5	24.597048	28.0647
6	9.100510	12.0184
7	22.424210	28.9203
8	25.454848	30.9359
9	9.872146	9.9566

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}')
```

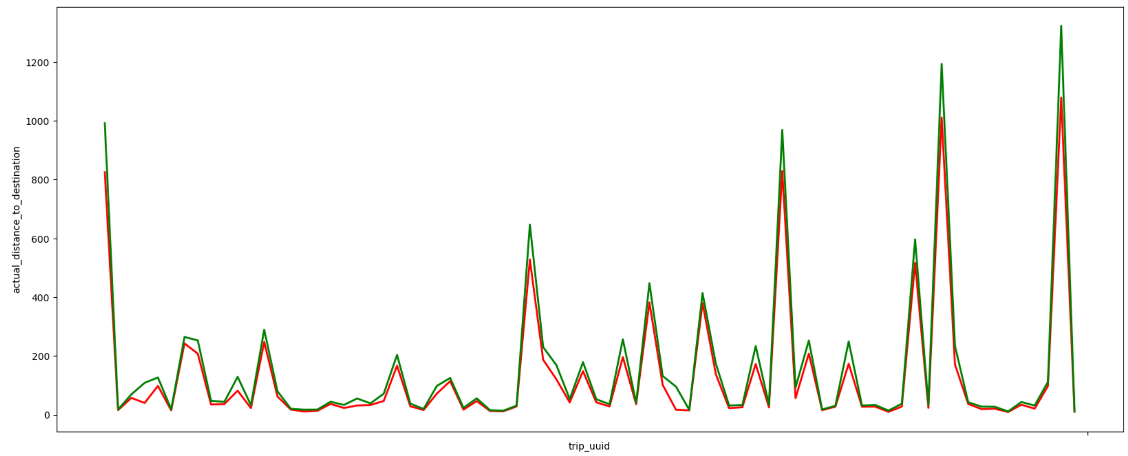
```
p_value of actual_distance_to_destination is 0.0 and p_value of osrm_distance is
0.0
```

```
/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]:

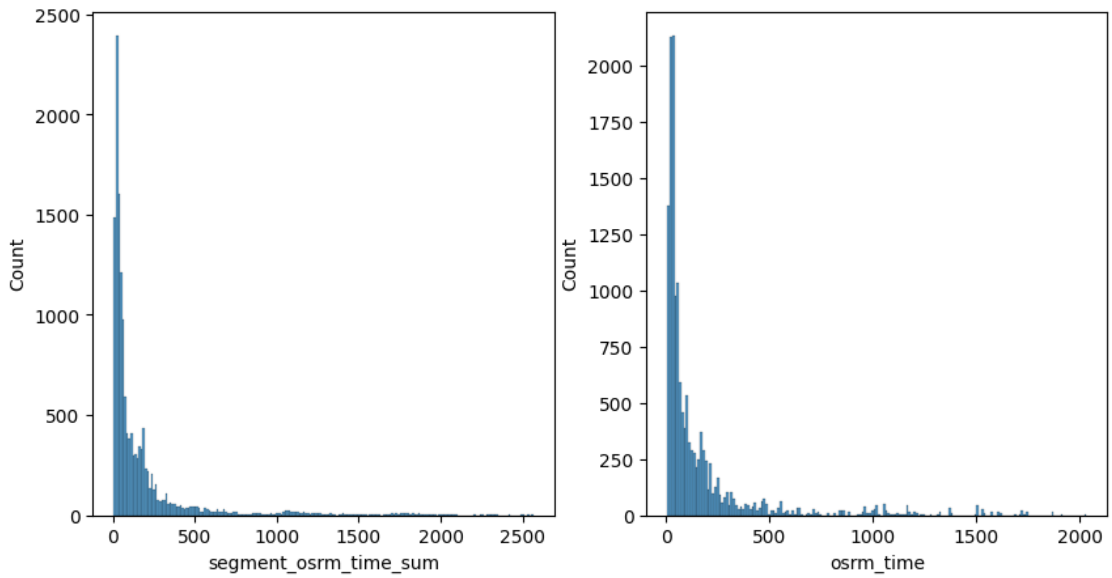
	osrm_time	segment_osrm_time_sum
0	717.0	1008.0
1	68.0	65.0
2	1740.0	1941.0
3	15.0	16.0
4	117.0	115.0
5	23.0	23.0
6	13.0	13.0
7	34.0	34.0
8	29.0	29.0
9	8.0	14.0

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}')
```

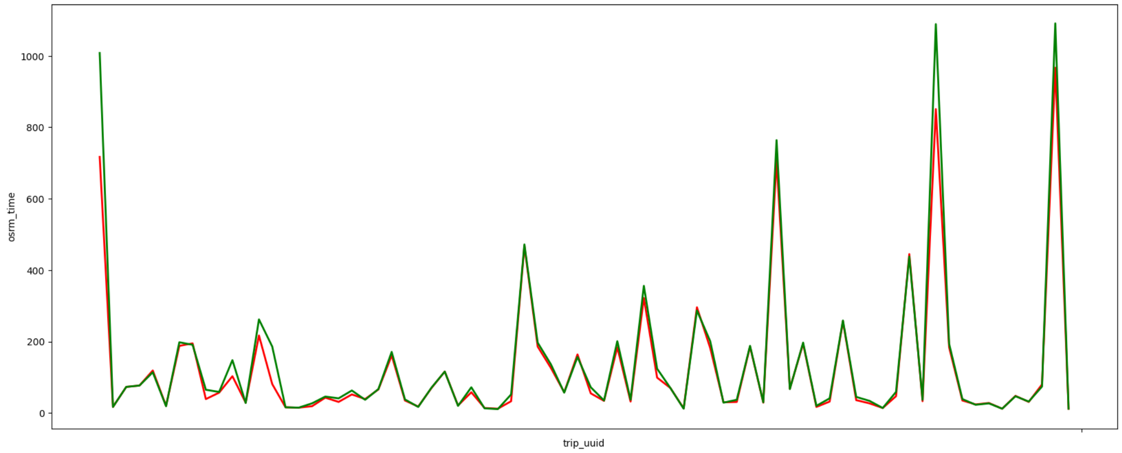
```
p_value of segment_osrm_time_sum is 0.0 and p_value of osrm_time is 0.0
```

```
/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], y=trip_df['osrm_time'][::200],␣
↪color='r', lw=2)
sns.lineplot(x=trip_df['trip_uuid'][::200], y=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]:
```python
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
```

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

[151]:

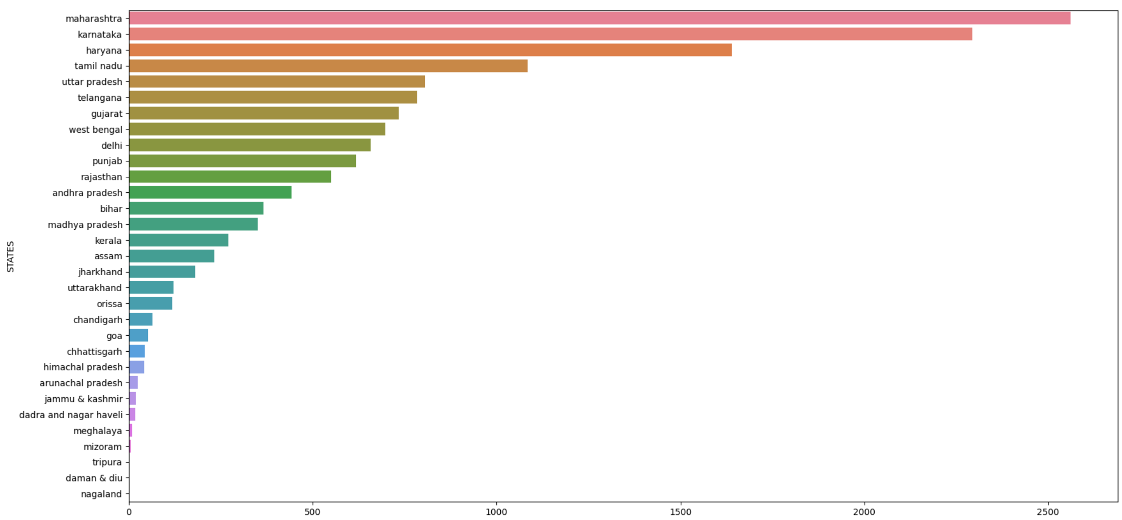
	destination_state	destination_city	destination_place	destination_code
0	uttar pradesh	kanpur	central	6
1	karnataka	doddablpur	chikadpp	d
2	haryana	gurgaon	bilaspur	hb
3	maharashtra	mumbai	mirard	ip
4	karnataka	sandur	wrdn1dpp	d
…	…	…	…	…
14782	punjab	chandigarh	mehmdpur	h
14783	haryana	faridabad	blbgarh	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_week','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]:

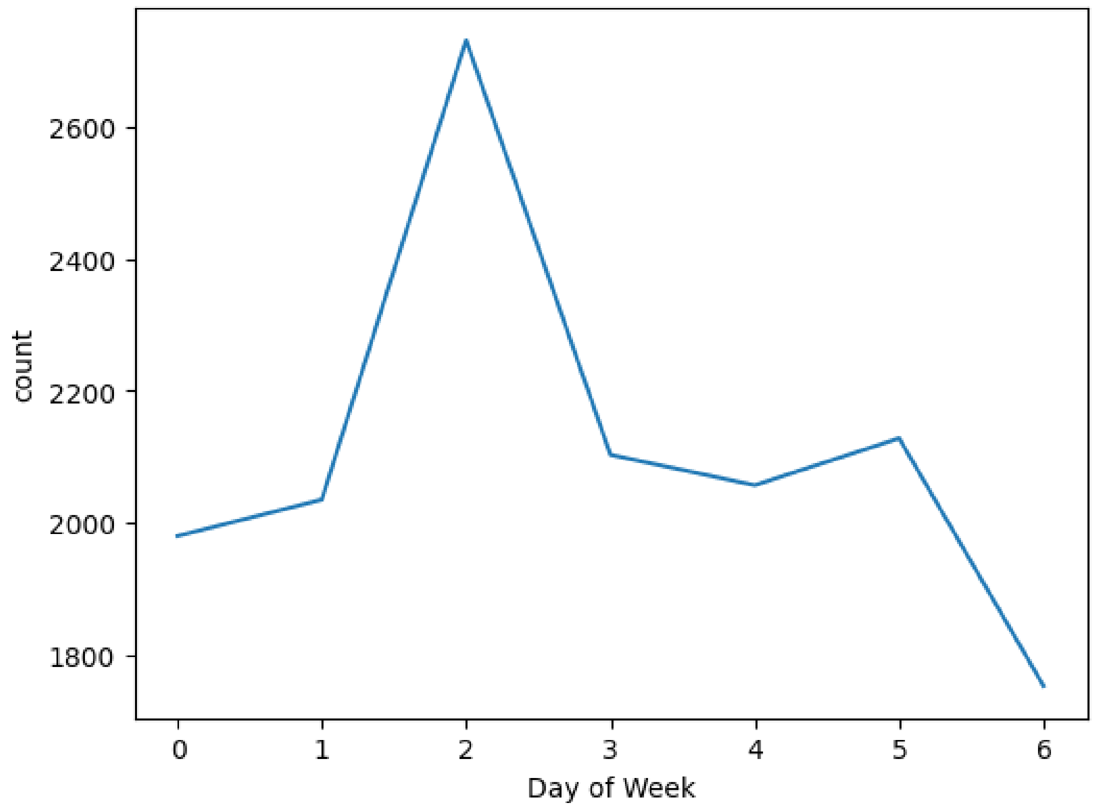
```
# {'0':'Monday', '1':'Tuesday', '2':'Wednesday', '3':'Thursday', '4':'Friday',␣
 ↪'5':'Saturday', '6':'Sunday'}
trip_df.groupby('trip_dayofweek').aggregate({'trip_uuid':'count'}).reset_index()
```

[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_dayofweek']
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

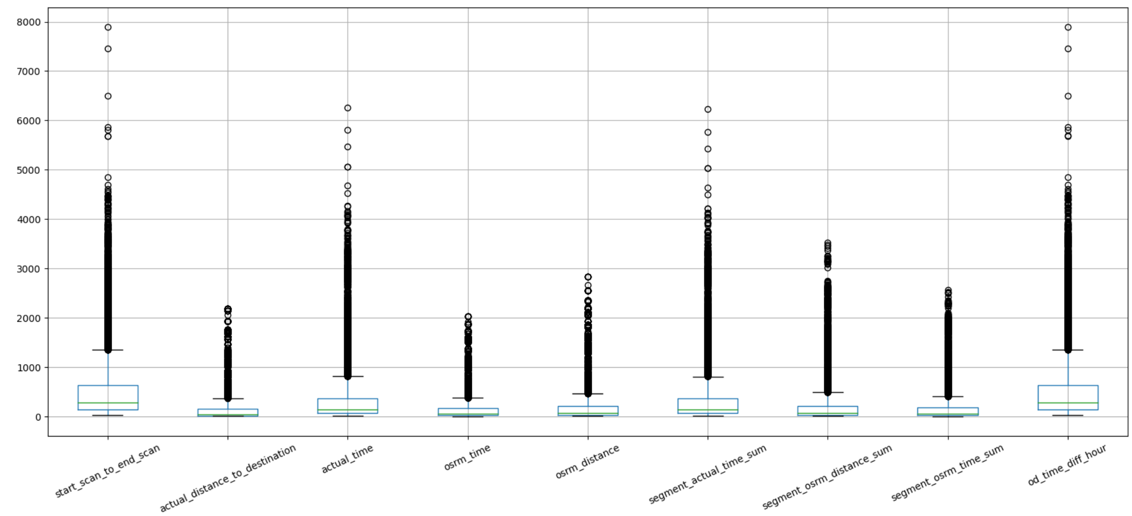
[158]:
```
trip_df.shape
```

[158]: (14787, 28)

[159]:
```
num_cols =␣
↪['start_scan_to_end_scan','actual_distance_to_destination','actual_time',
            '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()
```

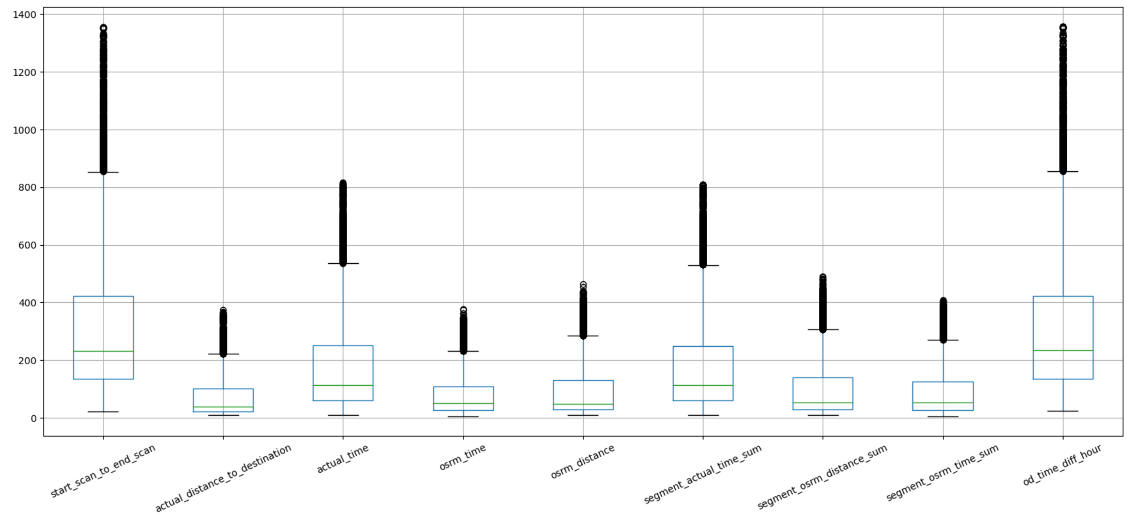


[161]:
```
Q1 = trip_df[num_cols].quantile(0.25)
Q3 = trip_df[num_cols].quantile(0.75)
IQR = Q3-Q1
```

[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  \
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

                                 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]
```

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

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

[171]:
```python
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]:
```python
trip_df[num_cols].describe()
```

[172]:
```
       start_scan_to_end_scan  actual_distance_to_destination   actual_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-17   3.797603e-17            -3.127438e-17
std    1.000039e+00   1.000039e+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.

[ ]: