Business Case_ Delhivery - Feature Engineering

September 25, 2024

1 Business Case: Delhivery - Feature Engineering

About Delhivery

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.

How can you help here?

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

1.1 Importing modules and Loading dataset

[ ]:
```
# importing required modules
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import warnings
warnings.filterwarnings('ignore')

# Loading dataset
!wget 'https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/551/
↪original/delhivery_data.csv?1642751181' -O delhivery_data.csv
df = pd.read_csv('/content/delhivery_data.csv')
```

```
--2024-09-25 14:11:25--  https://d2beiqkhq929f0.cloudfront.net/public_assets/ass
ets/000/001/551/original/delhivery_data.csv?1642751181
Resolving d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)…
65.8.234.72, 65.8.234.36, 65.8.234.174, …
Connecting to d2beiqkhq929f0.cloudfront.net
```

```
(d2beiqkhq929f0.cloudfront.net)|65.8.234.72|:443… connected.
HTTP request sent, awaiting response… 200 OK
Length: 55617130 (53M) [text/plain]
Saving to: 'delhivery_data.csv'

delhivery_data.csv  100%[===================>]  53.04M  65.8MB/s    in 0.8s

2024-09-25 14:11:26 (65.8 MB/s) - 'delhivery_data.csv' saved [55617130/55617130]
```

1.2 Basic Metrics

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

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

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

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

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

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

```
4  2018-09-20 03:21:32.418600  …        2018-09-20 03:33:55

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

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

   segment_factor
0        1.272727
1        1.111111
2        2.285714
3        1.750000
4        1.200000

[5 rows x 24 columns]
```

[ ]:
```python
# shape
df.shape
```

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

[ ]:
```python
# information of the dataset
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
```

1.3 Basic Data Cleaning

1.3.1 Dropping unknown fields

[ ]:
```
unknown_fields = ['is_cutoff', 'cutoff_factor', 'cutoff_timestamp', 'factor',␣
↪'segment_factor']
df = df.drop(columns = unknown_fields)
```

1.3.2 Reducing Memory

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

[ ]:
```
data                                   2
trip_creation_time                 14817
route_schedule_uuid                 1504
route_type                             2
trip_uuid                          14817
source_center                       1508
source_name                         1498
destination_center                  1481
destination_name                    1468
od_start_time                      26369
od_end_time                        26369
start_scan_to_end_scan              1915
actual_distance_to_destination    144515
actual_time                         3182
osrm_time                           1531
osrm_distance                     138046
segment_actual_time                  747
```

```
segment_osrm_time                     214
segment_osrm_distance              113799
dtype: int64
```

[ ]:
```python
# Converting the datatype of columns having 2 unique entries to Category
df['data'] = df['data'].astype('category')
df['route_type'] = df['route_type'].astype('category')
```

[ ]:
```python
df.select_dtypes(include='float64').max()
```

[ ]:
```
start_scan_to_end_scan            7898.000000
actual_distance_to_destination    1927.447705
actual_time                       4532.000000
osrm_time                         1686.000000
osrm_distance                     2326.199100
segment_actual_time               3051.000000
segment_osrm_time                 1611.000000
segment_osrm_distance             2191.403700
dtype: float64
```

[ ]:
```python
# Updating the float64 datatype to float32 since the maximum value entry is␣
 ↪small
for i in df.select_dtypes(include='float64').columns:
  df[i] = df[i].astype('float32')
```

[ ]:
```python
# Updating the datatype of the datetime columns
datetime_columns = ['trip_creation_time', 'od_start_time', 'od_end_time']
for i in datetime_columns:
    df[i] = pd.to_datetime(df[i])
```

[ ]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144867 entries, 0 to 144866
Data columns (total 19 columns):
 #   Column                          Non-Null Count   Dtype
---  ------                          --------------   -----
 0   data                            144867 non-null  category
 1   trip_creation_time              144867 non-null  datetime64[ns]
 2   route_schedule_uuid             144867 non-null  object
 3   route_type                      144867 non-null  category
 4   trip_uuid                       144867 non-null  object
 5   source_center                   144867 non-null  object
 6   source_name                     144574 non-null  object
 7   destination_center              144867 non-null  object
 8   destination_name                144606 non-null  object
 9   od_start_time                   144867 non-null  datetime64[ns]
```

```
 10  od_end_time                     144867 non-null  datetime64[ns]
 11  start_scan_to_end_scan          144867 non-null  float32
 12  actual_distance_to_destination  144867 non-null  float32
 13  actual_time                     144867 non-null  float32
 14  osrm_time                       144867 non-null  float32
 15  osrm_distance                   144867 non-null  float32
 16  segment_actual_time             144867 non-null  float32
 17  segment_osrm_time               144867 non-null  float32
 18  segment_osrm_distance           144867 non-null  float32
dtypes: category(2), datetime64[ns](3), float32(8), object(6)
memory usage: 14.6+ MB
```

Earlier the dataset was using 25.6+ MB of memory but now it has been reduced to 14.6+ MB i.e., around 40% reduction in memory usage.

1.3.3 Checking duplicates

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

[ ]:
```
0
```

1.3.4 Handling Null values

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

[ ]:
```
data                                0
trip_creation_time                  0
route_schedule_uuid                 0
route_type                          0
trip_uuid                           0
source_center                       0
source_name                       293
destination_center                  0
destination_name                  261
od_start_time                       0
od_end_time                         0
start_scan_to_end_scan              0
actual_distance_to_destination      0
actual_time                         0
osrm_time                           0
osrm_distance                       0
segment_actual_time                 0
segment_osrm_time                   0
segment_osrm_distance               0
dtype: int64
```

[ ]:
```
missing_source_center = df.loc[df['source_name'].isnull(), 'source_center'].
 ↪unique()
missing_destination_center = df.loc[df['destination_name'].isnull(),␣
 ↪'destination_center'].unique()
missing_center = np.union1d(missing_source_center,missing_destination_center)
missing_center
```

[ ]:
```
array(['IND122015AAC', 'IND126116AAA', 'IND221005A1A', 'IND250002AAC',
       'IND282002AAD', 'IND331001A1C', 'IND331022A1B', 'IND342902A1B',
       'IND465333A1B', 'IND505326AAB', 'IND509103AAC', 'IND577116AAA',
       'IND841301AAC', 'IND852118A1B'], dtype=object)
```

[ ]:
```
df_ms = df.loc[df['source_center'].isin(missing_center)]
df_md = df.loc[df['destination_center'].isin(missing_center)]
df_mc = pd.concat([df_ms, df_md])
```

[ ]:
```
# percentage of the rows containing null values
(df_mc.size/df.size)*100
```

[ ]:
```
0.3824197367240296
```

We can see that only 0.3% of the data contains some null values. Hence dropping them cannot cause an issue.

[ ]:
```
# drpping null values
df.dropna(inplace = True)
```

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

[ ]:
```
data                              0
trip_creation_time                0
route_schedule_uuid               0
route_type                        0
trip_uuid                         0
source_center                     0
source_name                       0
destination_center                0
destination_name                  0
od_start_time                     0
od_end_time                       0
start_scan_to_end_scan            0
actual_distance_to_destination    0
actual_time                       0
osrm_time                         0
osrm_distance                     0
segment_actual_time               0
segment_osrm_time                 0
```

```
segment_osrm_distance              0
dtype: int64
```

1.4 Merging of rows and aggregation of fields

Since delivery details of one package are divided into several rows i.e., consists of intermediate destinations (like that of connecting flights to reach a particular destination), performing grouping of rows to get delivery details of each order per row.

```
[ ]: cols = ['trip_uuid', 'source_center', 'destination_center']
df1 = df.groupby(by = cols, as_index = False).agg({'data' : 'first',
                                                  'route_type' : 'first',
                                                  'trip_creation_time' :␣
 ↪'first',
                                                  'source_name' : 'first',
                                                  'destination_name' : 'last',
                                                  'od_start_time' : 'first',
                                                  'od_end_time' : 'first',
                                                  'start_scan_to_end_scan' :␣
 ↪'first',
                                                 ␣
 ↪'actual_distance_to_destination' : 'last',
                                                  'actual_time' : 'last',
                                                  'osrm_time' : 'last',
                                                  'osrm_distance' : 'last',
                                                  'segment_actual_time' :␣
 ↪'sum',
                                                  'segment_osrm_time' : 'sum',
                                                  'segment_osrm_distance' :␣
 ↪'sum'})
df1
```

```
[ ]:                     trip_uuid source_center destination_center      data  \
0      trip-153671041653548748  IND209304AAA       IND000000ACB  training
1      trip-153671041653548748  IND462022AAA       IND209304AAA  training
2      trip-153671042288605164  IND561203AAB       IND562101AAA  training
3      trip-153671042288605164  IND572101AAA       IND561203AAB  training
4      trip-153671043369099517  IND000000ACB       IND160002AAC  training
…                          …             …                  …         …
26217  trip-153861115439069069  IND628204AAA       IND627657AAA      test
26218  trip-153861115439069069  IND628613AAA       IND627005AAA      test
26219  trip-153861115439069069  IND628801AAA       IND628204AAA      test
26220  trip-153861118270144424  IND583119AAA       IND583101AAA      test
26221  trip-153861118270144424  IND583201AAA       IND583119AAA      test

      route_type         trip_creation_time  \
0            FTL 2018-09-12 00:00:16.535741
```

```
1           FTL 2018-09-12 00:00:16.535741
2       Carting 2018-09-12 00:00:22.886430
3       Carting 2018-09-12 00:00:22.886430
4           FTL 2018-09-12 00:00:33.691250
…           …                          …
26217   Carting 2018-10-03 23:59:14.390954
26218   Carting 2018-10-03 23:59:14.390954
26219   Carting 2018-10-03 23:59:14.390954
26220       FTL 2018-10-03 23:59:42.701692
26221       FTL 2018-10-03 23:59:42.701692

                              source_name  \
0      Kanpur_Central_H_6 (Uttar Pradesh)
1      Bhopal_Trnsport_H (Madhya Pradesh)
2       Doddablpur_ChikaDPP_D (Karnataka)
3           Tumkur_Veersagr_I (Karnataka)
4           Gurgaon_Bilaspur_HB (Haryana)
…                                      …
26217  Tirchchndr_Shnmgprm_D (Tamil Nadu)
26218   Peikulam_SriVnktpm_D (Tamil Nadu)
26219         Eral_Busstand_D (Tamil Nadu)
26220        Sandur_WrdN1DPP_D (Karnataka)
26221                   Hospet (Karnataka)

                           destination_name               od_start_time  \
0             Gurgaon_Bilaspur_HB (Haryana) 2018-09-12 16:39:46.858469
1        Kanpur_Central_H_6 (Uttar Pradesh) 2018-09-12 00:00:16.535741
2         Chikblapur_ShntiSgr_D (Karnataka) 2018-09-12 02:03:09.655591
3         Doddablpur_ChikaDPP_D (Karnataka) 2018-09-12 00:00:22.886430
4            Chandigarh_Mehmdpur_H (Punjab) 2018-09-14 03:40:17.106733
…                                         …                          …
26217  Thisayanvilai_UdnkdiRD_D (Tamil Nadu) 2018-10-04 02:29:04.272194
26218    Tirunelveli_VdkkuSrt_I (Tamil Nadu) 2018-10-04 04:16:39.894872
26219     Tirchchndr_Shnmgprm_D (Tamil Nadu) 2018-10-04 01:44:53.808000
26220                 Bellary_Dc (Karnataka) 2018-10-04 03:58:40.726547
26221          Sandur_WrdN1DPP_D (Karnataka) 2018-10-04 02:51:44.712656

                    od_end_time  start_scan_to_end_scan  \
0     2018-09-13 13:40:23.123744                  1260.0
1     2018-09-12 16:39:46.858469                   999.0
2     2018-09-12 03:01:59.598855                    58.0
3     2018-09-12 02:03:09.655591                   122.0
4     2018-09-14 17:34:55.442454                   834.0
…                              …                      …
26217 2018-10-04 03:31:11.183797                    62.0
26218 2018-10-04 05:47:45.162682                    91.0
26219 2018-10-04 02:29:04.272194                    44.0
```

```
26220 2018-10-04 08:46:09.166940                   287.0
26221 2018-10-04 03:58:40.726547                    66.0

       actual_distance_to_destination  actual_time  osrm_time  osrm_distance  \
0                           383.759155        732.0      329.0     446.549591
1                           440.973694        830.0      388.0     544.802673
2                            24.644020         47.0       26.0      28.199400
3                            48.542889         96.0       42.0      56.911598
4                           237.439606        611.0      212.0     281.210907
…                                  …          …        …            …
26217                        33.627182         51.0       41.0      42.521301
26218                        33.673836         90.0       48.0      40.608002
26219                        12.661944         30.0       14.0      16.018499
26220                        40.546738        233.0       42.0      52.530300
26221                        25.534794         42.0       26.0      28.048401

       segment_actual_time  segment_osrm_time  segment_osrm_distance
0                    728.0              534.0             670.620483
1                    820.0              474.0             649.852783
2                     46.0               26.0              28.199501
3                     95.0               39.0              55.989899
4                    608.0              231.0             317.740784
…                      …                …                    …
26217                 49.0               42.0              42.143101
26218                 89.0               77.0              78.586899
26219                 29.0               14.0              16.018400
26220                233.0               42.0              52.530300
26221                 41.0               25.0              28.048401

[26222 rows x 18 columns]
```

[ ]:
```python
# Time taken between od_start_time and od_end_time
df1['od_total_time'] = df1['od_end_time'] - df1['od_start_time']
df1['od_total_time'] = df1['od_total_time'].apply(lambda x : round(x.
 ↪total_seconds() / 60.0, 2))

# Dropping original columns
df1.drop(columns = ['od_end_time', 'od_start_time'], inplace = True)
```

[ ]:
```python
df2 = df1.groupby(by = 'trip_uuid', as_index = False).agg({'source_center' :␣
 ↪'first',
                                                          'destination_center'␣
 ↪: 'last',
                                                          'data' : 'first',
                                                          'route_type' :␣
 ↪'first',
```

```
                                                            'trip_creation_time'␣
↪: 'first',
                                                            'source_name' :␣
↪'first',
                                                            'destination_name' :␣
↪'last',
                                                            'od_total_time' :␣
↪'sum',
                                                           ␣
↪'start_scan_to_end_scan' : 'sum',
                                                           ␣
↪'actual_distance_to_destination' : 'sum',
                                                            'actual_time' :␣
↪'sum',
                                                            'osrm_time' : 'sum',
                                                            'osrm_distance' :␣
↪'sum',
                                                           ␣
↪'segment_actual_time' : 'sum',
                                                            'segment_osrm_time' :
↪ 'sum',
                                                           ␣
↪'segment_osrm_distance' : 'sum'})
df2
```

[ ]:

```
                     trip_uuid source_center destination_center      data  \
0      trip-153671041653548748  IND209304AAA       IND209304AAA  training
1      trip-153671042288605164  IND561203AAB       IND561203AAB  training
2      trip-153671043369099517  IND000000ACB       IND000000ACB  training
3      trip-153671046011330457  IND400072AAB       IND401104AAA  training
4      trip-153671052974046625  IND583101AAA       IND583119AAA  training
…                          …           …                  …        …
14782  trip-153861095625827784  IND160002AAC       IND160002AAC      test
14783  trip-153861104386292051  IND121004AAB       IND121004AAA      test
14784  trip-153861106442901555  IND208006AAA       IND208006AAA      test
14785  trip-153861115439069069  IND627005AAA       IND628204AAA      test
14786  trip-153861118270144424  IND583119AAA       IND583119AAA      test

      route_type         trip_creation_time  \
0            FTL 2018-09-12 00:00:16.535741
1        Carting 2018-09-12 00:00:22.886430
2            FTL 2018-09-12 00:00:33.691250
3        Carting 2018-09-12 00:01:00.113710
4            FTL 2018-09-12 00:02:09.740725
…          …                          …
14782    Carting 2018-10-03 23:55:56.258533
```

```
14783    Carting 2018-10-03 23:57:23.863155
14784    Carting 2018-10-03 23:57:44.429324
14785    Carting 2018-10-03 23:59:14.390954
14786        FTL 2018-10-03 23:59:42.701692

                              source_name  \
0       Kanpur_Central_H_6 (Uttar Pradesh)
1        Doddablpur_ChikaDPP_D (Karnataka)
2            Gurgaon_Bilaspur_HB (Haryana)
3                 Mumbai Hub (Maharashtra)
4                   Bellary_Dc (Karnataka)
…                                      …
14782      Chandigarh_Mehmdpur_H (Punjab)
14783        FBD_Balabhgarh_DPC (Haryana)
14784  Kanpur_GovndNgr_DC (Uttar Pradesh)
14785 Tirunelveli_VdkkuSrt_I (Tamil Nadu)
14786        Sandur_WrdN1DPP_D (Karnataka)

                        destination_name  od_total_time  \
0      Kanpur_Central_H_6 (Uttar Pradesh)        2260.11
1       Doddablpur_ChikaDPP_D (Karnataka)         181.61
2           Gurgaon_Bilaspur_HB (Haryana)        3934.36
3          Mumbai_MiraRd_IP (Maharashtra)         100.49
4           Sandur_WrdN1DPP_D (Karnataka)         718.34
…                                     …            …
14782      Chandigarh_Mehmdpur_H (Punjab)         258.03
14783       Faridabad_Blbgarh_DC (Haryana)          60.59
14784  Kanpur_GovndNgr_DC (Uttar Pradesh)         422.12
14785   Tirchchndr_Shnmgprm_D (Tamil Nadu)         348.52
14786        Sandur_WrdN1DPP_D (Karnataka)         354.40

       start_scan_to_end_scan  actual_distance_to_destination  actual_time  \
0                      2259.0                      824.732849       1562.0
1                       180.0                       73.186905        143.0
2                      3933.0                     1927.404297       3347.0
3                       100.0                       17.175274         59.0
4                       717.0                      127.448502        341.0
…                         …                             …          …
14782                   257.0                       57.762333         83.0
14783                    60.0                       15.513784         21.0
14784                   421.0                       38.684837        282.0
14785                   347.0                      134.723831        264.0
14786                   353.0                       66.081528        275.0

       osrm_time  osrm_distance  segment_actual_time  segment_osrm_time  \
0          717.0     991.352295               1548.0             1008.0
1           68.0      85.111000                141.0               65.0
```

```
2         1740.0    2354.066650                3308.0              1941.0
3           15.0      19.680000                  59.0                16.0
4          117.0     146.791794                 340.0               115.0
…            …             …                 …                 …
14782       62.0      73.462997                  82.0                62.0
14783       12.0      16.088200                  21.0                11.0
14784       48.0      58.903702                 281.0                88.0
14785      179.0     171.110306                 258.0               221.0
14786       68.0      80.578705                 274.0                67.0

       segment_osrm_distance
0                1320.473267
1                  84.189400
2                2545.267822
3                  19.876600
4                 146.791901
…                        …
14782              64.855103
14783              16.088299
14784             104.886597
14785             223.532394
14786              80.578705

[14787 rows x 17 columns]
```

1.5 Creating new features

[ ]:
```
def get_state(x):
  l = x.split('(')
  if len(l) == 1:
    return l[0]
  else:
    return l[1].replace(')', "")
```

[ ]:
```
def get_city(x):
  l = x.split()[0].split('_')
  if 'CCU' in x:
    return 'Kolkata'
  elif 'MAA' in x.upper():
    return 'Chennai'
  elif ('HBR' in x.upper()) or ('BLR' in x.upper()) or ('BANGALORE' in x.
↪upper()):
    return 'Bengaluru'
  elif 'FBD' in x.upper():
    return 'Faridabad'
  elif 'BOM' in x.upper():
```

```
    return 'Mumbai'
  elif 'DEL' in x.upper():
    return 'Delhi'
  elif 'OK' in x.upper():
    return 'Delhi'
  elif 'GZB' in x.upper():
    return 'Ghaziabad'
  elif 'GGN' in x.upper():
    return 'Gurgaon'
  elif 'AMD' in x.upper():
    return 'Ahmedabad'
  elif 'CJB' in x.upper():
    return 'Coimbatore'
  elif 'HYD' in x.upper():
    return 'Hyderabad'
  return l[0]
```

[ ]:
```
def get_place(x):
  l = x.split()[0].split('_', 1)
  if len(l) == 1:
    return 'unknown'
  else:
    return l[1]
```

[ ]:
```
# creating city, state, place features
df2['source_state'] = df2['source_name'].apply(get_state)
df2['source_city'] = df2['source_name'].apply(get_city)
df2['source_place'] = df2['source_name'].apply(get_place)
df2['destination_state'] = df2['destination_name'].apply(get_state)
df2['destination_city'] = df2['destination_name'].apply(get_city)
df2['destination_place'] = df2['destination_name'].apply(get_place)
df2.head()
```

[ ]:
```
                 trip_uuid source_center destination_center      data  \
0  trip-153671041653548748  IND209304AAA       IND209304AAA  training
1  trip-153671042288605164  IND561203AAB       IND561203AAB  training
2  trip-153671043369099517  IND000000ACB       IND000000ACB  training
3  trip-153671046011330457  IND400072AAB       IND401104AAA  training
4  trip-153671052974046625  IND583101AAA       IND583119AAA  training

  route_type          trip_creation_time                          source_name  \
0        FTL  2018-09-12 00:00:16.535741  Kanpur_Central_H_6 (Uttar Pradesh)
1    Carting  2018-09-12 00:00:22.886430   Doddablpur_ChikaDPP_D (Karnataka)
2        FTL  2018-09-12 00:00:33.691250      Gurgaon_Bilaspur_HB (Haryana)
3    Carting  2018-09-12 00:01:00.113710           Mumbai Hub (Maharashtra)
4        FTL  2018-09-12 00:02:09.740725             Bellary_Dc (Karnataka)
```

```
                     destination_name  od_total_time  start_scan_to_end_scan  \
0  Kanpur_Central_H_6 (Uttar Pradesh)        2260.11                  2259.0
1   Doddablpur_ChikaDPP_D (Karnataka)         181.61                   180.0
2       Gurgaon_Bilaspur_HB (Haryana)        3934.36                  3933.0
3      Mumbai_MiraRd_IP (Maharashtra)         100.49                   100.0
4       Sandur_WrdN1DPP_D (Karnataka)         718.34                   717.0

   …  source_place  destination_state  destination_city  destination_place  \
0  …    Central_H_6     Uttar Pradesh            Kanpur        Central_H_6
1  …     ChikaDPP_D         Karnataka        Doddablpur         ChikaDPP_D
2  …    Bilaspur_HB           Haryana           Gurgaon        Bilaspur_HB
3  …        unknown       Maharashtra            Mumbai          MiraRd_IP
4  …             Dc         Karnataka            Sandur        WrdN1DPP_D

   trip_creation_date  trip_creation_day  trip_creation_month  \
0          2018-09-12                 12                    9
1          2018-09-12                 12                    9
2          2018-09-12                 12                    9
3          2018-09-12                 12                    9
4          2018-09-12                 12                    9

  trip_creation_year trip_creation_hour trip_creation_week
0               2018                  0                 37
1               2018                  0                 37
2               2018                  0                 37
3               2018                  0                 37
4               2018                  0                 37

[5 rows x 29 columns]
```

[ ]:

```
# creating features based on time
df2['trip_creation_date'] = pd.to_datetime(df2['trip_creation_time'].dt.date)
df2['trip_creation_day'] = df2['trip_creation_time'].dt.day
df2['trip_creation_month'] = df2['trip_creation_time'].dt.month
df2['trip_creation_year'] = df2['trip_creation_time'].dt.year
df2['trip_creation_hour'] = df2['trip_creation_time'].dt.hour
df2['trip_creation_week'] = df2['trip_creation_time'].dt.isocalendar().week

# reducing memory size
df2['trip_creation_hour'] = df2['trip_creation_hour'].astype('int8')
df2['trip_creation_week'] = df2['trip_creation_week'].astype('int8')
df2['trip_creation_year'] = df2['trip_creation_year'].astype('int16')
df2['trip_creation_month'] = df2['trip_creation_month'].astype('int8')
df2['trip_creation_day'] = df2['trip_creation_day'].astype('int8')

df2.head()
```

[ ]:
```
                  trip_uuid source_center destination_center      data  \
0  trip-153671041653548748  IND209304AAA       IND209304AAA  training
1  trip-153671042288605164  IND561203AAB       IND561203AAB  training
2  trip-153671043369099517  IND000000ACB       IND000000ACB  training
3  trip-153671046011330457  IND400072AAB       IND401104AAA  training
4  trip-153671052974046625  IND583101AAA       IND583119AAA  training

  route_type         trip_creation_time                         source_name  \
0        FTL 2018-09-12 00:00:16.535741  Kanpur_Central_H_6 (Uttar Pradesh)
1    Carting 2018-09-12 00:00:22.886430   Doddablpur_ChikaDPP_D (Karnataka)
2        FTL 2018-09-12 00:00:33.691250       Gurgaon_Bilaspur_HB (Haryana)
3    Carting 2018-09-12 00:01:00.113710            Mumbai Hub (Maharashtra)
4        FTL 2018-09-12 00:02:09.740725              Bellary_Dc (Karnataka)

                   destination_name  od_total_time  start_scan_to_end_scan  \
0  Kanpur_Central_H_6 (Uttar Pradesh)        2260.11                  2259.0
1   Doddablpur_ChikaDPP_D (Karnataka)         181.61                   180.0
2       Gurgaon_Bilaspur_HB (Haryana)        3934.36                  3933.0
3      Mumbai_MiraRd_IP (Maharashtra)         100.49                   100.0
4       Sandur_WrdN1DPP_D (Karnataka)         718.34                   717.0

   …  source_place  destination_state  destination_city  destination_place  \
0  …    Central_H_6      Uttar Pradesh            Kanpur        Central_H_6
1  …     ChikaDPP_D          Karnataka        Doddablpur         ChikaDPP_D
2  …    Bilaspur_HB            Haryana           Gurgaon        Bilaspur_HB
3  …        unknown        Maharashtra            Mumbai          MiraRd_IP
4  …             Dc          Karnataka            Sandur         WrdN1DPP_D

   trip_creation_date  trip_creation_day  trip_creation_month  \
0          2018-09-12                 12                    9
1          2018-09-12                 12                    9
2          2018-09-12                 12                    9
3          2018-09-12                 12                    9
4          2018-09-12                 12                    9

  trip_creation_year trip_creation_hour trip_creation_week
0               2018                  0                 37
1               2018                  0                 37
2               2018                  0                 37
3               2018                  0                 37
4               2018                  0                 37

[5 rows x 29 columns]
```

[ ]:
```
df2.shape
```

[ ]:
```
(14787, 29)
```

[ ]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14787 entries, 0 to 14786
Data columns (total 29 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   trip_uuid                       14787 non-null  object
 1   source_center                   14787 non-null  object
 2   destination_center              14787 non-null  object
 3   data                            14787 non-null  category
 4   route_type                      14787 non-null  category
 5   trip_creation_time              14787 non-null  datetime64[ns]
 6   source_name                     14787 non-null  object
 7   destination_name                14787 non-null  object
 8   od_total_time                   14787 non-null  float64
 9   start_scan_to_end_scan          14787 non-null  float32
 10  actual_distance_to_destination  14787 non-null  float32
 11  actual_time                     14787 non-null  float32
 12  osrm_time                       14787 non-null  float32
 13  osrm_distance                   14787 non-null  float32
 14  segment_actual_time             14787 non-null  float32
 15  segment_osrm_time               14787 non-null  float32
 16  segment_osrm_distance           14787 non-null  float32
 17  source_state                    14787 non-null  object
 18  source_city                     14787 non-null  object
 19  source_place                    14787 non-null  object
 20  destination_state               14787 non-null  object
 21  destination_city                14787 non-null  object
 22  destination_place               14787 non-null  object
 23  trip_creation_date              14787 non-null  datetime64[ns]
 24  trip_creation_day               14787 non-null  int8
 25  trip_creation_month             14787 non-null  int8
 26  trip_creation_year              14787 non-null  int16
 27  trip_creation_hour              14787 non-null  int8
 28  trip_creation_week              14787 non-null  int8
dtypes: category(2), datetime64[ns](2), float32(8), float64(1), int16(1),
int8(4), object(11)
memory usage: 2.1+ MB
```

1.6 Descriptive Statistics

[ ]:
```
df2.describe().T
```

[ ]:
```
                                 count                           mean  \
trip_creation_time               14787  2018-09-22 12:26:28.269885696
od_total_time                  14787.0                     530.313468
```

```
start_scan_to_end_scan         14787.0                       529.429016
actual_distance_to_destination 14787.0                       164.090195
actual_time                    14787.0                          356.306
osrm_time                      14787.0                       160.990936
osrm_distance                  14787.0                       203.887405
segment_actual_time            14787.0                       353.059174
segment_osrm_time              14787.0                       180.511597
segment_osrm_distance          14787.0                       222.705444
trip_creation_date               14787  2018-09-21 23:28:44.406573568
trip_creation_day              14787.0                        18.375127
trip_creation_month            14787.0                         9.120105
trip_creation_year             14787.0                           2018.0
trip_creation_hour             14787.0                        12.456212
trip_creation_week             14787.0                        38.293907

                                                      min  \
trip_creation_time             2018-09-12 00:00:16.535741
od_total_time                                       23.46
start_scan_to_end_scan                               23.0
actual_distance_to_destination                   9.002461
actual_time                                           9.0
osrm_time                                             6.0
osrm_distance                                      9.0729
segment_actual_time                                   9.0
segment_osrm_time                                     6.0
segment_osrm_distance                              9.0729
trip_creation_date                    2018-09-12 00:00:00
trip_creation_day                                     1.0
trip_creation_month                                   9.0
trip_creation_year                                 2018.0
trip_creation_hour                                    0.0
trip_creation_week                                   37.0

                                                         25%  \
trip_creation_time             2018-09-17 02:38:18.128431872
od_total_time                                        149.695
start_scan_to_end_scan                                 149.0
actual_distance_to_destination                     22.777099
actual_time                                             67.0
osrm_time                                               29.0
osrm_distance                                        30.7569
segment_actual_time                                     66.0
segment_osrm_time                                       30.0
segment_osrm_distance                               32.57885
trip_creation_date                       2018-09-17 00:00:00
trip_creation_day                                       14.0
trip_creation_month                                      9.0
```

```
trip_creation_year                                   2018.0
trip_creation_hour                                      4.0
trip_creation_week                                     38.0

                                                        50%  \
trip_creation_time              2018-09-22 03:39:19.609193984
od_total_time                                        279.71
start_scan_to_end_scan                                279.0
actual_distance_to_destination                    48.287895
actual_time                                           148.0
osrm_time                                              60.0
osrm_distance                                     65.302795
segment_actual_time                                   147.0
segment_osrm_time                                      65.0
segment_osrm_distance                             69.784203
trip_creation_date                      2018-09-22 00:00:00
trip_creation_day                                      19.0
trip_creation_month                                     9.0
trip_creation_year                                   2018.0
trip_creation_hour                                     14.0
trip_creation_week                                     38.0

                                                        75%  \
trip_creation_time              2018-09-27 19:23:14.074359552
od_total_time                                       633.535
start_scan_to_end_scan                                632.0
actual_distance_to_destination                   163.591255
actual_time                                           367.0
osrm_time                                             168.0
osrm_distance                                    206.644203
segment_actual_time                                   364.0
segment_osrm_time                                     184.0
segment_osrm_distance                            216.560608
trip_creation_date                      2018-09-27 00:00:00
trip_creation_day                                      25.0
trip_creation_month                                     9.0
trip_creation_year                                   2018.0
trip_creation_hour                                     20.0
trip_creation_week                                     39.0

                                                     max         std
trip_creation_time              2018-10-03 23:59:42.701692         NaN
od_total_time                                      7898.55  658.415416
start_scan_to_end_scan                              7898.0  658.254944
actual_distance_to_destination                 2186.531738  305.502991
actual_time                                         6265.0  561.517944
osrm_time                                           2032.0  271.459503
```

```
osrm_distance                                        2840.081055  370.565552
segment_actual_time                                       6230.0  556.365906
segment_osrm_time                                         2564.0  314.679291
segment_osrm_distance                                3523.632324  416.846283
trip_creation_date                           2018-10-03 00:00:00         NaN
trip_creation_day                                           30.0    7.882198
trip_creation_month                                         10.0    0.325096
trip_creation_year                                        2018.0         0.0
trip_creation_hour                                          23.0    7.987387
trip_creation_week                                          40.0    0.967366
```

[ ]:

```
df2.describe(include='object').T
```

[ ]:

	count	unique	top	freq
trip_uuid	14787	14787	trip-153671041653548748	1
source_center	14787	930	IND000000ACB	1052
destination_center	14787	1035	IND000000ACB	821
source_name	14787	930	Gurgaon_Bilaspur_HB (Haryana)	1052
destination_name	14787	1035	Gurgaon_Bilaspur_HB (Haryana)	821
source_state	14787	29	Maharashtra	2714
source_city	14787	686	Mumbai	1442
source_place	14787	754	Bilaspur_HB	1052
destination_state	14787	31	Maharashtra	2561
destination_city	14787	804	Mumbai	1548
destination_place	14787	842	Bilaspur_HB	821

- Top source and destination center is Gurgaon_Bilaspur_HB (Haryana).
- Source of most of the orders is Mumbai and destination is also Mumbai.

1.7 Exploratory Data Analysis

1.7.1 Training vs Testing data

[ ]:

```
df2['data'].value_counts()
```

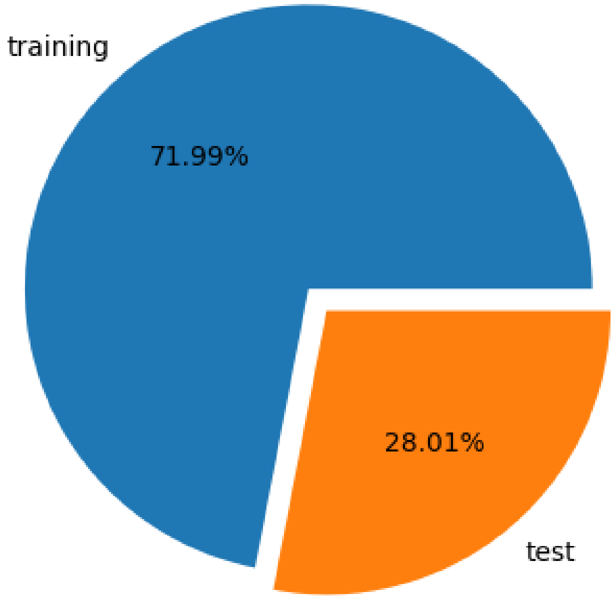
[ ]:

```
data
training    10645
test         4142
Name: count, dtype: int64
```

[ ]:

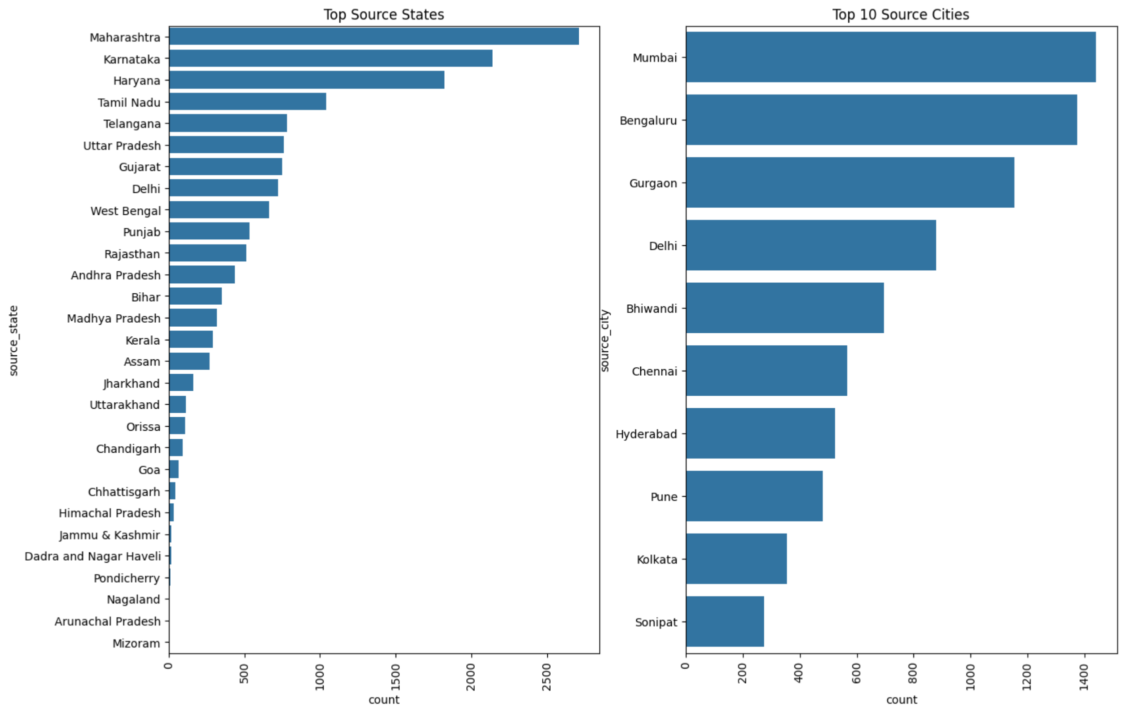
```
plt.pie(x = df2['data'].value_counts(),
        labels = df2['data'].value_counts().index,
        explode = [0, 0.1],
        autopct = '%.2f%%')
plt.plot()
```

[ ]: []



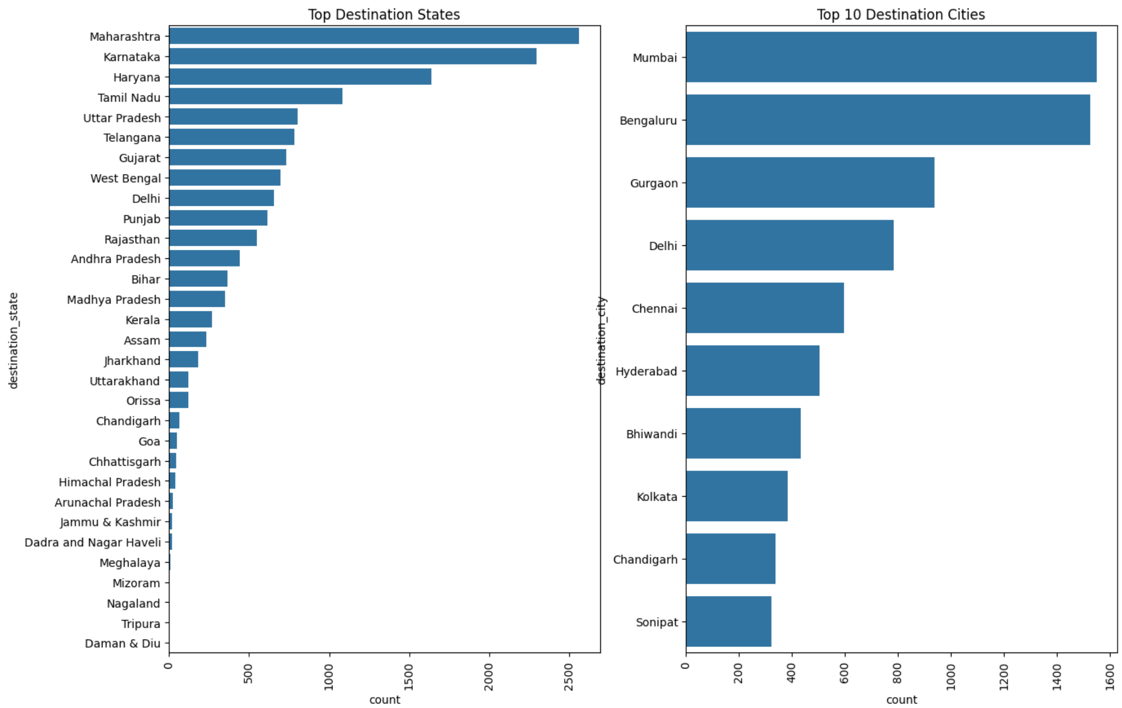
1.7.2 Source Analysis

[ ]:
```
fig = plt.figure(figsize = (15,10))

plt.subplot(1,2,1)
plt.title('Top Source States')
sns.countplot(y = 'source_state', data = df2, order = df2['source_state'].
  ↪value_counts().index)
plt.xticks(rotation = 90)

plt.subplot(1,2,2)
plt.title('Top 10 Source Cities')
sns.countplot(y = 'source_city', data = df2, order = df2['source_city'].
  ↪value_counts().head(10).index)
plt.xticks(rotation = 90)

plt.show()
```



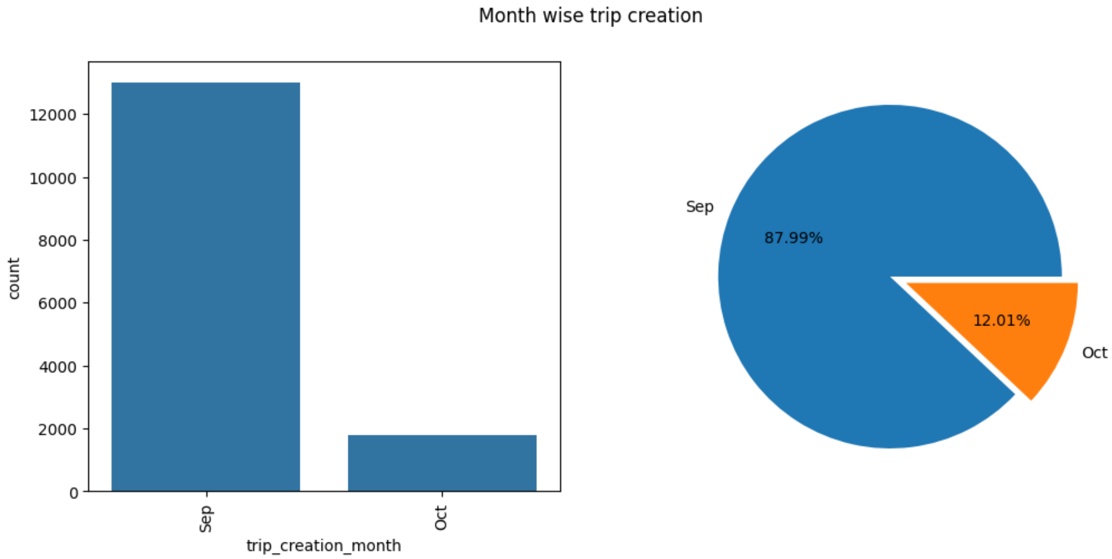
1.7.3 Destination Analysis

[ ]:
```
fig = plt.figure(figsize = (15,10))

plt.subplot(1,2,1)
plt.title('Top Destination States')
sns.countplot(y = 'destination_state', data = df2, order =␣
↪df2['destination_state'].value_counts().index)
plt.xticks(rotation = 90)

plt.subplot(1,2,2)
plt.title('Top 10 Destination Cities')
sns.countplot(y = 'destination_city', data = df2, order =␣
↪df2['destination_city'].value_counts().head(10).index)
plt.xticks(rotation = 90)

plt.show()
```



1.7.4 Month wise analysis

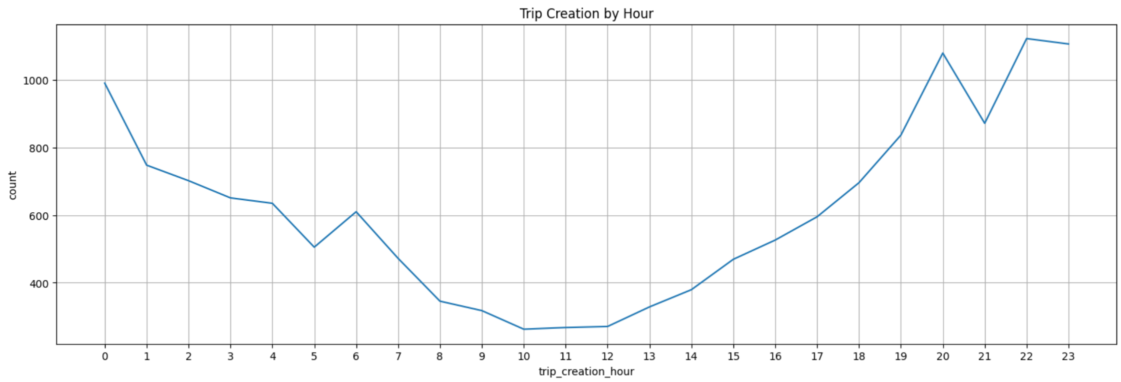
[ ]:
```
fig = plt.figure(figsize = (12,5)).suptitle('Month wise trip creation')

plt.subplot(1,2,1)
sns.countplot(x = 'trip_creation_month', data = df2)
plt.xticks(rotation = 90, ticks=[0,1], labels = ['Sep', 'Oct'])

plt.subplot(1,2,2)
plt.pie(x = df2['trip_creation_month'].value_counts(),
        labels = ['Sep', 'Oct'],
        explode = [0, 0.1],
       autopct = '%.2f%%')

plt.show()
```

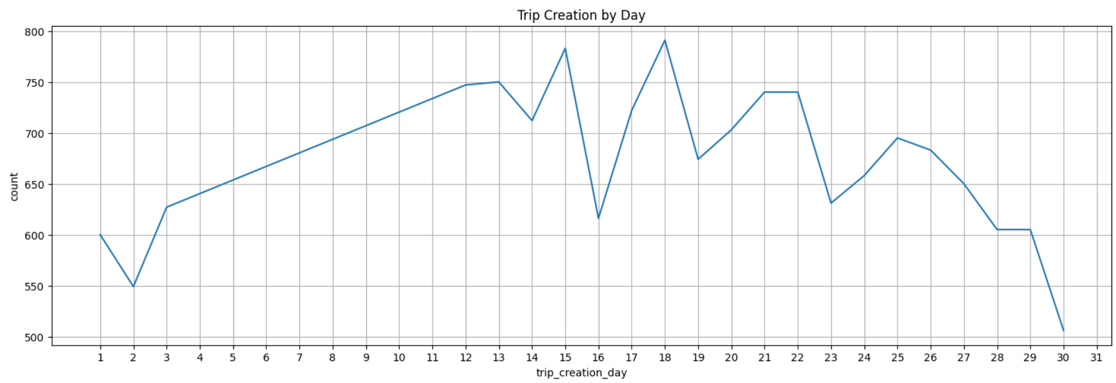


1.7.5 Trip Creation by Hour and Day

[ ]:
```
fig = plt.figure(figsize = (18, 12))

plt.subplot(2,1,1)
plt.title('Trip Creation by Hour')
sns.lineplot(data = df2['trip_creation_hour'].value_counts().reset_index().
 ↪sort_values(by = 'trip_creation_hour'),
             x ='trip_creation_hour',
             y = 'count')
plt.xticks(np.arange(0,24))
plt.grid('both')

plt.subplot(2,1,2)
plt.title('Trip Creation by Day')
sns.lineplot(data = df2['trip_creation_day'].value_counts().reset_index().
 ↪sort_values(by = 'trip_creation_day'),
             x ='trip_creation_day',
             y = 'count')
plt.xticks(np.arange(1,32))
plt.grid('both')

plt.plot()
```

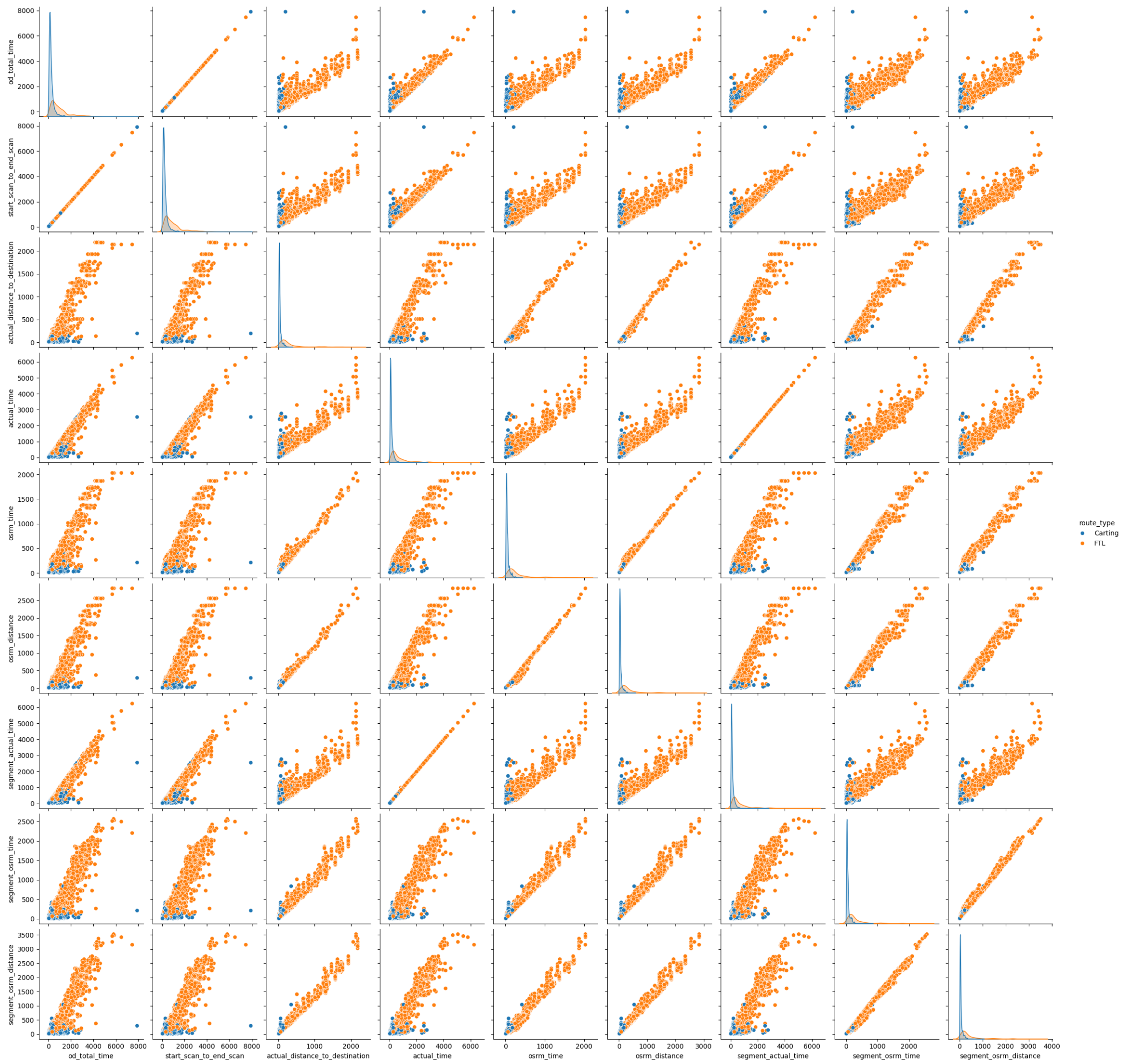
[ ]: []





1.7.6 Pair Plot

[ ]:
```
numerical_columns = ['od_total_time', 'start_scan_to_end_scan',␣
↪'actual_distance_to_destination',
                     'actual_time', 'osrm_time', 'osrm_distance',␣
↪'segment_actual_time',
                     'segment_osrm_time', 'segment_osrm_distance']

sns.pairplot(data = df2, vars = numerical_columns, hue = 'route_type')
plt.show()
```



1.7.7 Heat map

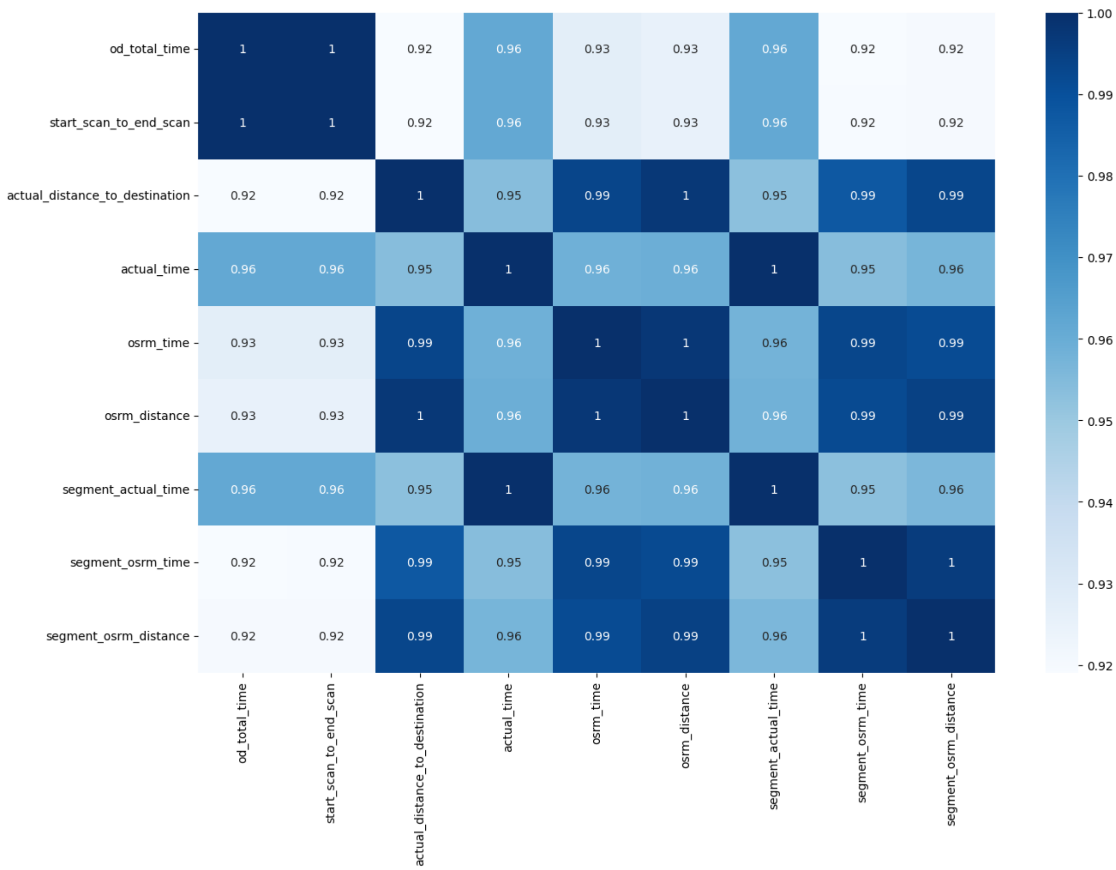
[ ]:
```
corr_df = df2[numerical_columns].corr()
corr_df
```

[ ]:
```
                                od_total_time  start_scan_to_end_scan  \
od_total_time                        1.000000                0.999999
start_scan_to_end_scan               0.999999                1.000000
actual_distance_to_destination       0.919074                0.919159
actual_time                          0.961560                0.961612
osrm_time                            0.927416                0.927471
osrm_distance                        0.925126                0.925205
segment_actual_time                  0.961582                0.961634
segment_osrm_time                    0.919358                0.919429
```

```
segment_osrm_distance                0.920099               0.920191

                                actual_distance_to_destination  actual_time  \
od_total_time                                         0.919074     0.961560
start_scan_to_end_scan                                0.919159     0.961612
actual_distance_to_destination                        1.000000     0.953920
actual_time                                           0.953920     1.000000
osrm_time                                             0.993568     0.958781
osrm_distance                                         0.997268     0.959398
segment_actual_time                                   0.952987     0.999989
segment_osrm_time                                     0.987542     0.954044
segment_osrm_distance                                 0.993068     0.957151

                                osrm_time  osrm_distance  segment_actual_time  \
od_total_time                    0.927416       0.925126             0.961582
start_scan_to_end_scan           0.927471       0.925205             0.961634
actual_distance_to_destination   0.993568       0.997268             0.952987
actual_time                      0.958781       0.959398             0.999989
osrm_time                        1.000000       0.997588             0.957955
osrm_distance                    0.997588       1.000000             0.958540
segment_actual_time              0.957955       0.958540             1.000000
segment_osrm_time                0.993263       0.991802             0.953214
segment_osrm_distance            0.991624       0.994712             0.956293

                                segment_osrm_time  segment_osrm_distance
od_total_time                            0.919358               0.920099
start_scan_to_end_scan                   0.919429               0.920191
actual_distance_to_destination           0.987542               0.993068
actual_time                              0.954044               0.957151
osrm_time                                0.993263               0.991624
osrm_distance                            0.991802               0.994712
segment_actual_time                      0.953214               0.956293
segment_osrm_time                        1.000000               0.996098
segment_osrm_distance                    0.996098               1.000000
```

[ ]:
```
plt.figure(figsize = (15, 10))
sns.heatmap(data = corr_df, annot = True, cmap='Blues')
plt.plot()
```

[ ]: []



1.8 Hypothesis Testing

1.8.1 Does the route_type affect the actual travel time (actual_time)?

[ ]:
```
df2.groupby(by = 'route_type')['actual_time'].mean()
```

[ ]:
```
route_type
Carting    125.776443
FTL        705.412659
Name: actual_time, dtype: float32
```

Since this is categorical vs numerical having only 2 categorical fields, we can use 2 sample T-test

Null Hypothesis: There is no significant difference in actual travel time across different route types.

Alternative Hypothesis: There is a significant difference in actual travel time across different route types.

[ ]:
```
H0 = 'There is no significant difference in actual travel time across different␣
↪route types'
```

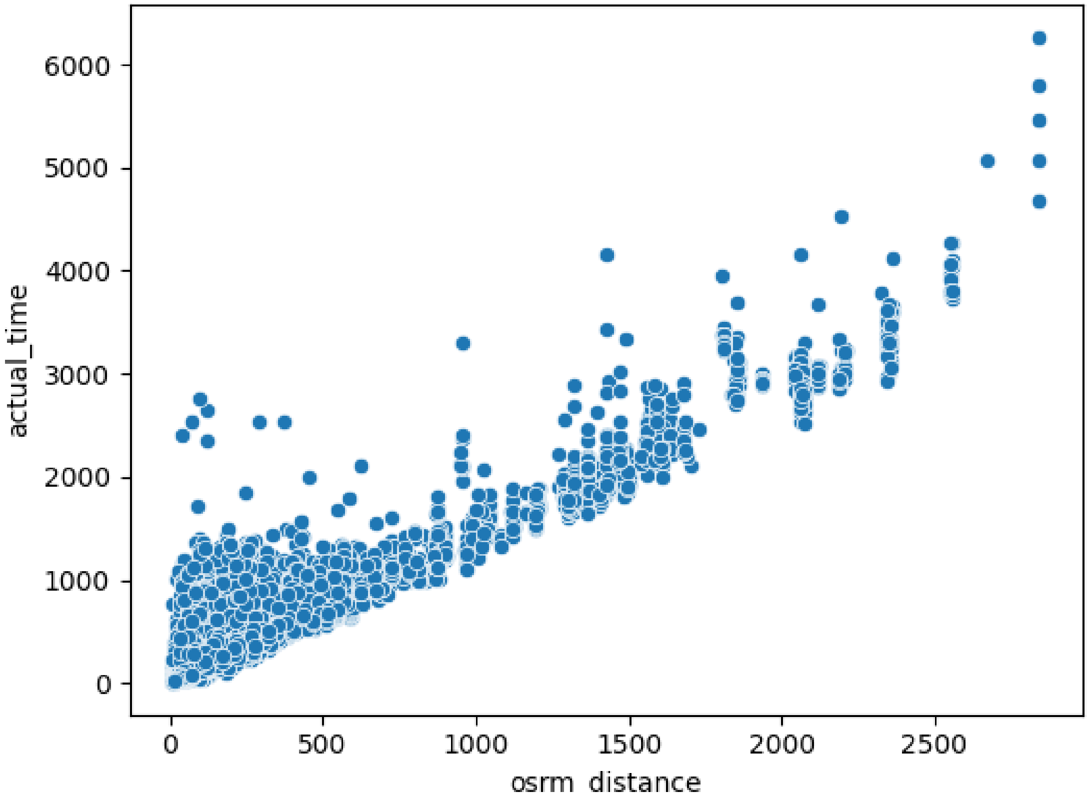
```
Ha = 'There is a significant difference in actual travel time across different␣
 ↪route types'
alpha = 0.05

#2 sample ttest
t_stat, p_val = stats.ttest_ind(df2[df2['route_type'] ==␣
 ↪'Carting']['actual_time'],
                                df2[df2['route_type'] == 'FTL']['actual_time'],
                                alternative='two-sided')

print(f't-statistic: {t_stat}')
print(f'p-value: {p_val}')
print(f'alpha: {alpha}\n')
if p_val < alpha:
  print('Result: Reject Null Hypothesis')
  print(Ha)
else:
  print('Result: Failed to reject Null Hypothesis')
  print(H0)
```

```
t-statistic: -71.18729076027243
p-value: 0.0
alpha: 0.05

Result: Reject Null Hypothesis
There is a significant difference in actual travel time across different route
types
```

1.8.2 Is there a relationship between the distance (osrm_distance) and actual travel time (actual_time)?

Since both the columns are numerical, we have to choose between Pearson and Spearman Correlation based on relation

[ ]:
```
sns.scatterplot(data = df2, x = 'osrm_distance', y = 'actual_time')
plt.show()
```



As this is monotonic, we can use spearman correlation

Null Hypothesis: There is no correlation between osrm_distance and actual_time.

Alternative Hypothesis: There is a correlation between osrm_distance and actual_time.

[ ]:
```
H0 = 'There is no correlation between osrm_distance and actual_times'
Ha = 'There is a correlation between osrm_distance and actual_time'
alpha = 0.05

# spearman rank correlation test
spearman_corr, p_val = stats.spearmanr(df['osrm_distance'], df['actual_time'])

print(f'spearman_corr: {spearman_corr}')
print(f'p-value: {p_val}')
print(f'alpha: {alpha}\n')
if p_val < alpha:
  print('Result: Reject Null Hypothesis')
  print(Ha)
else:
  print('Result: Failed to reject Null Hypothesis')
  print(H0)
```

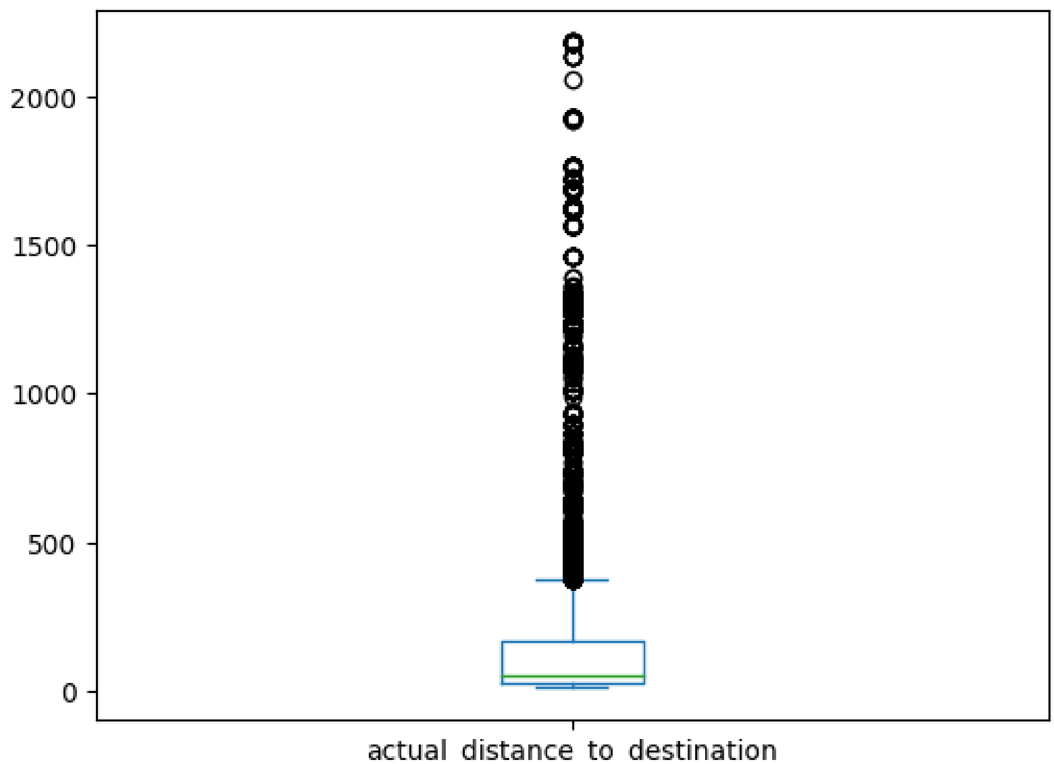
```
spearman_corr: 0.958806732006333
p-value: 0.0
alpha: 0.05

Result: Reject Null Hypothesis
There is a correlation between osrm_distance and actual_time
```

1.8.3 Are the trip creation times (trip_creation_hour) associated with a significant change in travel duration (actual_time)?

For finding relation between trip_creation_hour and actual_time, we need to consider another factor i.e., distance between source and destination (actual_distance_to_destination).

[ ]:
```
df2['actual_distance_to_destination'].plot(kind='box')
```

[ ]:
```
<Axes: >
```



As distance increases, duration also increases. So we should not consider outliers

[ ]:
```
df2['actual_distance_to_destination'].describe()
```

[ ]:
```
count    14787.000000
mean       164.090195
```

```
std         305.502991
min           9.002461
25%          22.777099
50%          48.287895
75%         163.591255
max        2186.531738
Name: actual_distance_to_destination, dtype: float64
```

Lets take the range from lower whisker to upper whisker

[ ]:
```
df_dtd = df2[(df2['actual_distance_to_destination'] > 22) &␣
 ↪(df2['actual_distance_to_destination']< 164)]
df_dtd.groupby(by = 'trip_creation_hour')['actual_time'].mean()
```

[ ]:
```
trip_creation_hour
0     182.624313
1     197.616867
2     200.162018
3     209.062881
4     164.062500
5     258.405701
6     208.511627
7     161.760178
8     172.307693
9     251.712570
10    237.580414
11    261.007629
12    193.917648
13    187.073166
14    150.457443
15    133.880661
16    164.046616
17    150.409088
18    139.362457
19    166.330978
20    170.555176
21    197.729782
22    208.001495
23    187.723770
Name: actual_time, dtype: float32
```

As this is the categorical vs numerical having more than 2 categorical variables, we have to use ANOVA (if satisfies assumptions of anova) or Kruskal Wallis test

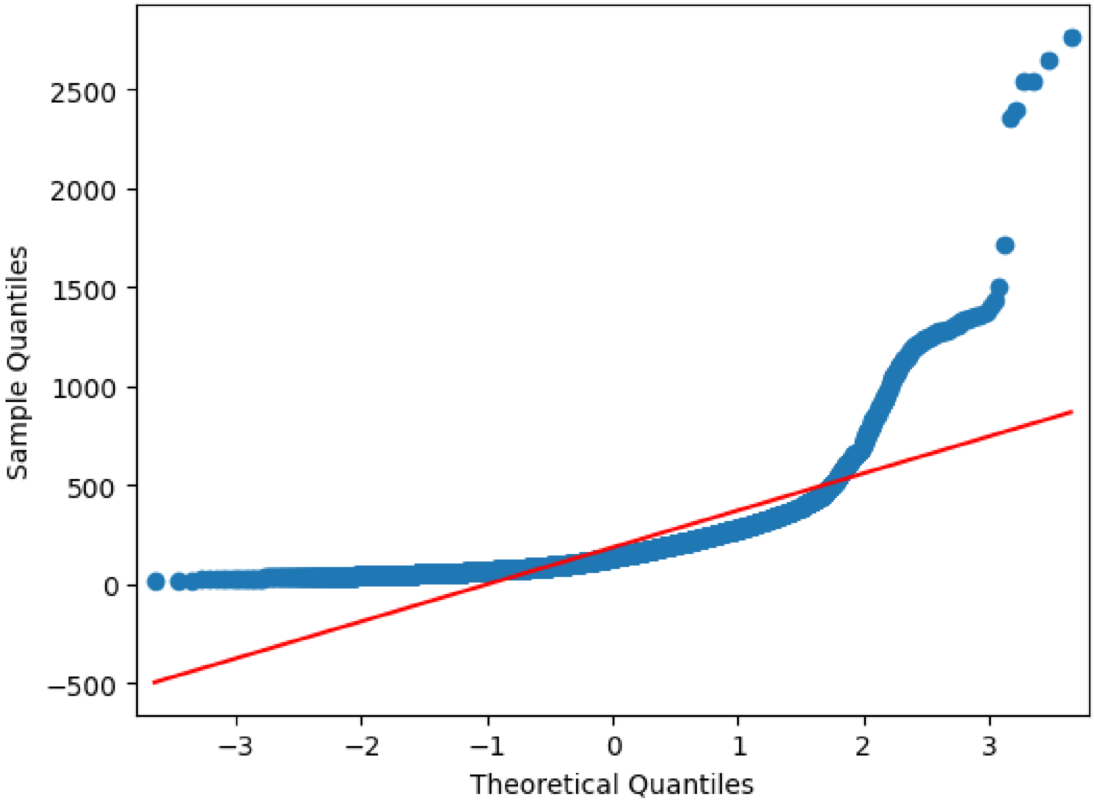
Checking assumptions of ANOVA **Assumptions of ANOVA:** 1. Data should be normally distributed *(QQ plot and shapiro test)* 2. Data should be independent across each record 3. Equal variance in different groups *(levene test)*

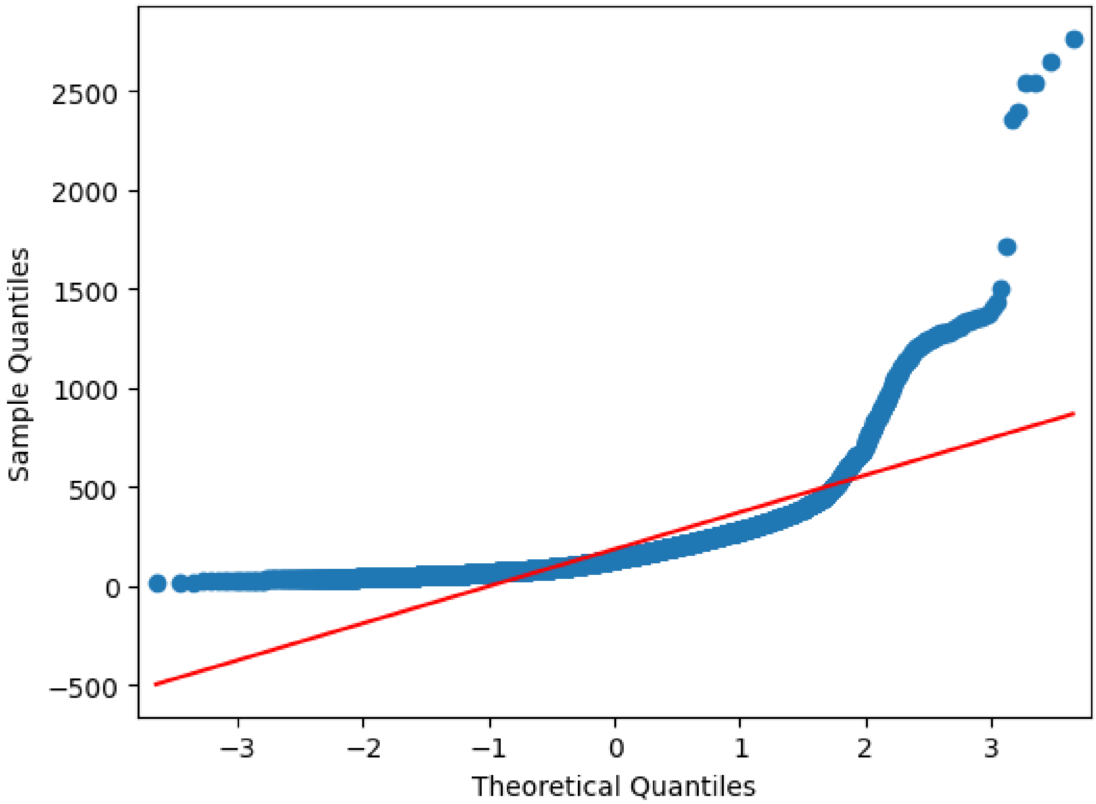
As data is independent, we can check for normality and equal variance

QQ Plot for checking Normality

[ ]:
```
import statsmodels.api as sm
sm.qqplot(df_dtd['actual_time'], line ='s')
```

[ ]:





Shapiro test for checking Normality

```
[ ]: test_stat, p_value = stats.shapiro(df_dtd['actual_time'].sample(5000))
     print('p-value', p_value)
     if p_value < 0.05:
         print('The sample does not follow normal distribution')
     else:
         print('The sample follows normal distribution')
```

```
p-value 2.5485733900473127e-73
The sample does not follow normal distribution
```

Levene's Test for checking Equal Variance

```
[ ]: hour_groups = [df_dtd[df_dtd['trip_creation_hour'] == hour]['actual_time'] for␣
      ↪hour in df_dtd['trip_creation_hour'].unique()]
```

```
[ ]: test_stat, p_value = stats.levene(*hour_groups)
     print('p-value', p_value)
     if p_value < 0.05:
         print('The samples do not have Homogenous Variance')
     else:
```

```
    print('The samples have Homogenous Variance ')
```

```
p-value 3.309649679336099e-20
The samples do not have Homogenous Variance
```

We can say that data is not normally distributed and do not have equal variance. So we can use Kruskal Wallis Test

Kruskal Wallis test **Null Hypothesis:** There is no significant difference in actual_time between different hours of the day.

Alternative Hypothesis: There is a significant difference in actual_time between different hours of the day.

[ ]:
```
H0 = 'There is no significant difference in actual_time between different hours␣
 ↪of the day'
Ha = 'There is a significant difference in actual_time between different hours␣
 ↪of the day'
alpha = 0.05

# kruskal wallis test
h_stat, p_val = stats.kruskal(*hour_groups)

print(f'h_stat: {h_stat}')
print(f'p-value: {p_val}')
print(f'alpha: {alpha}\n')
if p_val < alpha:
  print('Result: Reject Null Hypothesis')
  print(Ha)
else:
  print('Result: Failed to reject Null Hypothesis')
  print(H0)
```

```
h_stat: 247.5250631117618
p-value: 1.5326050640314032e-39
alpha: 0.05

Result: Reject Null Hypothesis
There is a significant difference in actual_time between different hours of the
day
```

1.9 Feature Encoding

[ ]:
```
df2.head()
```

[ ]:
```
                  trip_uuid source_center destination_center      data  \
0  trip-153671041653548748  IND209304AAA       IND209304AAA  training
1  trip-153671042288605164  IND561203AAB       IND561203AAB  training
```

```
2  trip-153671043369099517  IND000000ACB       IND000000ACB  training
3  trip-153671046011330457  IND400072AAB       IND401104AAA  training
4  trip-153671052974046625  IND583101AAA       IND583119AAA  training

  route_type         trip_creation_time                          source_name  \
0        FTL 2018-09-12 00:00:16.535741  Kanpur_Central_H_6 (Uttar Pradesh)
1    Carting 2018-09-12 00:00:22.886430   Doddablpur_ChikaDPP_D (Karnataka)
2        FTL 2018-09-12 00:00:33.691250      Gurgaon_Bilaspur_HB (Haryana)
3    Carting 2018-09-12 00:01:00.113710           Mumbai Hub (Maharashtra)
4        FTL 2018-09-12 00:02:09.740725             Bellary_Dc (Karnataka)

                     destination_name  od_total_time  start_scan_to_end_scan  \
0  Kanpur_Central_H_6 (Uttar Pradesh)        2260.11                  2259.0
1   Doddablpur_ChikaDPP_D (Karnataka)         181.61                   180.0
2       Gurgaon_Bilaspur_HB (Haryana)        3934.36                  3933.0
3      Mumbai_MiraRd_IP (Maharashtra)         100.49                   100.0
4       Sandur_WrdN1DPP_D (Karnataka)         718.34                   717.0

   …  source_place  destination_state  destination_city  destination_place  \
0  …    Central_H_6      Uttar Pradesh            Kanpur        Central_H_6
1  …     ChikaDPP_D          Karnataka        Doddablpur         ChikaDPP_D
2  …    Bilaspur_HB            Haryana           Gurgaon        Bilaspur_HB
3  …        unknown        Maharashtra            Mumbai          MiraRd_IP
4  …             Dc          Karnataka            Sandur         WrdN1DPP_D

   trip_creation_date  trip_creation_day  trip_creation_month  \
0          2018-09-12                 12                    9
1          2018-09-12                 12                    9
2          2018-09-12                 12                    9
3          2018-09-12                 12                    9
4          2018-09-12                 12                    9

  trip_creation_year trip_creation_hour trip_creation_week
0               2018                  0                 37
1               2018                  0                 37
2               2018                  0                 37
3               2018                  0                 37
4               2018                  0                 37

[5 rows x 29 columns]
```

[ ]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14787 entries, 0 to 14786
Data columns (total 29 columns):
 #   Column                          Non-Null Count  Dtype
```

```
---  ------                         --------------  -----
 0   trip_uuid                      14787 non-null  object
 1   source_center                  14787 non-null  object
 2   destination_center             14787 non-null  object
 3   data                           14787 non-null  category
 4   route_type                     14787 non-null  category
 5   trip_creation_time             14787 non-null  datetime64[ns]
 6   source_name                    14787 non-null  object
 7   destination_name               14787 non-null  object
 8   od_total_time                  14787 non-null  float64
 9   start_scan_to_end_scan         14787 non-null  float32
 10  actual_distance_to_destination 14787 non-null  float32
 11  actual_time                    14787 non-null  float32
 12  osrm_time                      14787 non-null  float32
 13  osrm_distance                  14787 non-null  float32
 14  segment_actual_time            14787 non-null  float32
 15  segment_osrm_time              14787 non-null  float32
 16  segment_osrm_distance          14787 non-null  float32
 17  source_state                   14787 non-null  object
 18  source_city                    14787 non-null  object
 19  source_place                   14787 non-null  object
 20  destination_state              14787 non-null  object
 21  destination_city               14787 non-null  object
 22  destination_place              14787 non-null  object
 23  trip_creation_date             14787 non-null  datetime64[ns]
 24  trip_creation_day              14787 non-null  int8
 25  trip_creation_month            14787 non-null  int8
 26  trip_creation_year             14787 non-null  int16
 27  trip_creation_hour             14787 non-null  int8
 28  trip_creation_week             14787 non-null  int8
dtypes: category(2), datetime64[ns](2), float32(8), float64(1), int16(1),
int8(4), object(11)
memory usage: 2.1+ MB
```

We can remove columns like trip_uuid, trip_creation_time and trip_creation_date for feature encoding as they are redundant

[ ]:
```
df_encoded = df2.copy()
df_encoded.drop(columns = ['trip_uuid', 'trip_creation_time',␣
 ↪'trip_creation_date'], inplace = True)
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14787 entries, 0 to 14786
Data columns (total 26 columns):
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
```

```
 0   source_center                   14787 non-null  object
 1   destination_center              14787 non-null  object
 2   data                            14787 non-null  category
 3   route_type                      14787 non-null  category
 4   source_name                     14787 non-null  object
 5   destination_name                14787 non-null  object
 6   od_total_time                   14787 non-null  float64
 7   start_scan_to_end_scan          14787 non-null  float32
 8   actual_distance_to_destination  14787 non-null  float32
 9   actual_time                     14787 non-null  float32
 10  osrm_time                       14787 non-null  float32
 11  osrm_distance                   14787 non-null  float32
 12  segment_actual_time             14787 non-null  float32
 13  segment_osrm_time               14787 non-null  float32
 14  segment_osrm_distance           14787 non-null  float32
 15  source_state                    14787 non-null  object
 16  source_city                     14787 non-null  object
 17  source_place                    14787 non-null  object
 18  destination_state               14787 non-null  object
 19  destination_city                14787 non-null  object
 20  destination_place               14787 non-null  object
 21  trip_creation_day               14787 non-null  int8
 22  trip_creation_month             14787 non-null  int8
 23  trip_creation_year              14787 non-null  int16
 24  trip_creation_hour              14787 non-null  int8
 25  trip_creation_week              14787 non-null  int8
dtypes: category(2), float32(8), float64(1), int16(1), int8(4), object(10)
memory usage: 1.8+ MB
```

[ ]:
```
cat_cols = df_encoded.select_dtypes(include='category').columns
obj_cols = df_encoded.select_dtypes(include='object').columns
num_cols = df_encoded.
↪select_dtypes(include=['float64','float32','int8','int16']).columns
```

1.9.1 Label Encoding for Categorical columns having 2 unique values

[ ]:
```
for i in cat_cols:
  print(df_encoded[i].value_counts())
```

```
data
training    10645
test         4142
Name: count, dtype: int64
route_type
Carting    8906
FTL        5881
Name: count, dtype: int64
```

[ ]:
```
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()
for i in cat_cols:
  df_encoded[i] = label_encoder.fit_transform(df_encoded[i])
```

[ ]:
```
df_encoded[cat_cols].head()
```

[ ]:

	data	route_type
0	1	1
1	1	0
2	1	1
3	1	0
4	1	1

1.9.2 Frequency Encoding for Categorical columns having more than 2 fields

As there is no target variable, we are using frequency encoding instead of Target Encoding.

[ ]:
```
for i in obj_cols:
  freq_mapping = df_encoded[i].value_counts(normalize=True)
  df_encoded[i] = df_encoded[i].map(freq_mapping)
```

[ ]:
```
df_encoded[obj_cols].head()
```

[ ]:

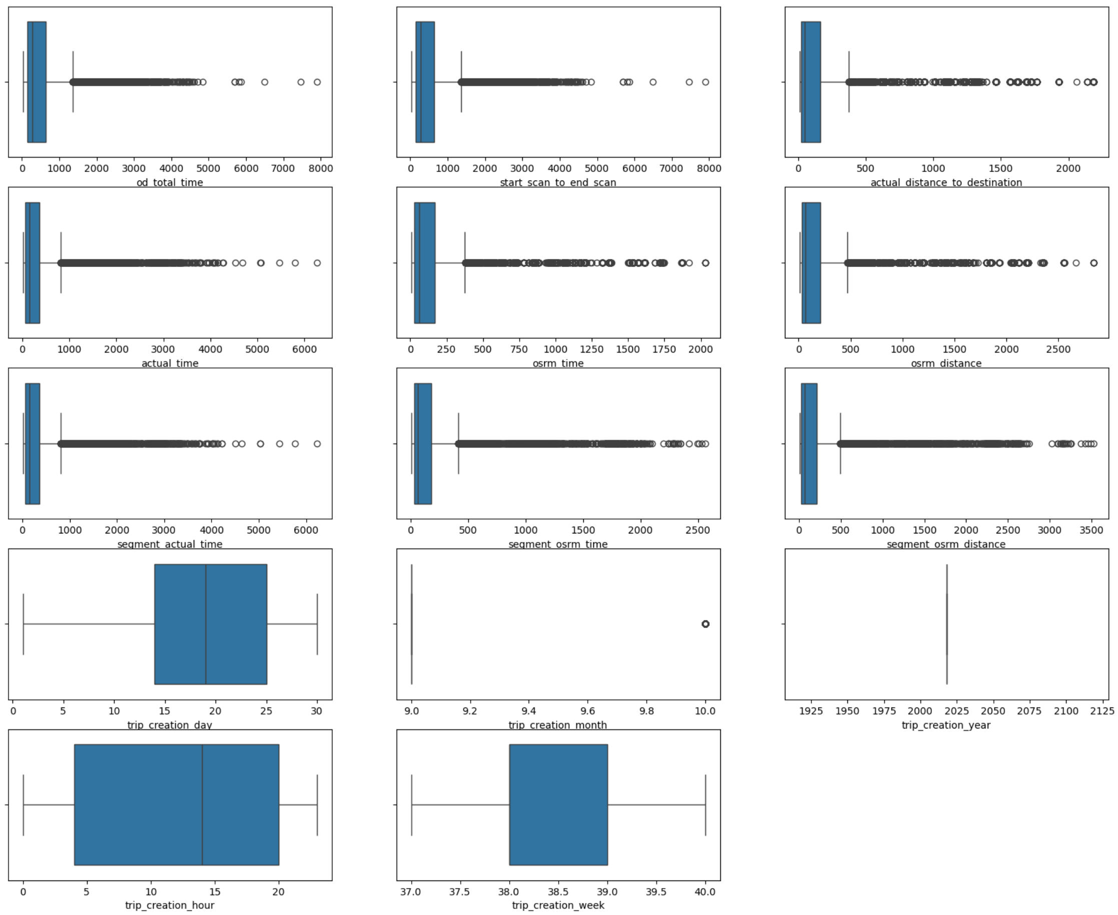
	source_center	destination_center	source_name	destination_name	\
0	0.007912	0.006425	0.007912	0.006425	
1	0.000812	0.000812	0.000812	0.000812	
2	0.071144	0.055522	0.071144	0.055522	
3	0.020288	0.012511	0.020288	0.012511	
4	0.001217	0.000609	0.001217	0.000609	

	source_state	source_city	source_place	destination_state	\
0	0.051396	0.009806	0.007912	0.054440	
1	0.144925	0.000812	0.000812	0.155136	
2	0.123284	0.078042	0.071144	0.110908	
3	0.183540	0.097518	0.043552	0.173193	
4	0.144925	0.001217	0.002435	0.155136	

	destination_city	destination_place
0	0.010009	0.006425
1	0.000812	0.000812
2	0.063299	0.055522
3	0.104687	0.012511
4	0.000609	0.000609

1.9.3 Scaling for Number Columns

[ ]:
```
fig = plt.figure(figsize = (20,16))
for i in num_cols:
  plt.subplot(5,3,num_cols.tolist().index(i)+1)
  sns.boxplot(x = df_encoded[i])
```



- As there are no outliers for segment_actual_time, segment_osrm_distance, trip_creation_day, trip_creation_month, we can use min max scaler for these.
- We can use standard scaler for the rest as they have outliers.

[ ]:
```
from sklearn.preprocessing import MinMaxScaler
min_max_cols = ['segment_actual_time', 'segment_osrm_distance',␣
 ↪'trip_creation_day', 'trip_creation_month']
scaler = MinMaxScaler()
df_encoded[min_max_cols] = scaler.fit_transform(df_encoded[min_max_cols])
```

[ ]:
```
df_encoded[min_max_cols].head()
```

[ ]:

	segment_actual_time	segment_osrm_distance	trip_creation_day
0	0.247388	0.373134	0.37931
1	0.021218	0.021373	0.37931
2	0.530301	0.721625	0.37931
3	0.008037	0.003074	0.37931
4	0.053207	0.039185	0.37931

	trip_creation_month
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0

[ ]:
```
from sklearn.preprocessing import StandardScaler
standard_scaler = StandardScaler()
cols = list(set(num_cols) - set(min_max_cols))
df_encoded[cols] = standard_scaler.fit_transform(df_encoded[cols])
```

[ ]:
```
df_encoded[cols].head()
```

[ ]:

	actual_time	actual_distance_to_destination	segment_osrm_time
0	2.147277	2.162548	2.629714
1	-0.379887	-0.297563	-0.367090
2	5.326268	5.772034	5.594737
3	-0.529486	-0.480911	-0.522809
4	-0.027259	-0.119943	-0.208192

	trip_creation_hour	osrm_time	trip_creation_week	trip_creation_year
0	-1.559538	2.048290	-1.337602	0.0
1	-1.559538	-0.342571	-1.337602	0.0
2	-1.559538	5.816936	-1.337602	0.0
3	-1.559538	-0.537818	-1.337602	0.0
4	-1.559538	-0.162059	-1.337602	0.0

	od_total_time	osrm_distance	start_scan_to_end_scan
0	2.627300	2.125107	2.627598
1	-0.529628	-0.320538	-0.530859
2	5.170234	5.802622	5.170772
3	-0.652837	-0.497115	-0.652397
4	0.285584	-0.154082	0.284962

[ ]:
```
# Final Encoded data
df_encoded.head()
```

[ ]:

	source_center	destination_center	data	route_type	source_name
0	0.007912	0.006425	1	1	0.007912

```
1      0.000812          0.000812    1          0     0.000812
2      0.071144          0.055522    1          1     0.071144
3      0.020288          0.012511    1          0     0.020288
4      0.001217          0.000609    1          1     0.001217

   destination_name  od_total_time  start_scan_to_end_scan  \
0          0.006425       2.627300                2.627598
1          0.000812      -0.529628               -0.530859
2          0.055522       5.170234                5.170772
3          0.012511      -0.652837               -0.652397
4          0.000609       0.285584                0.284962

   actual_distance_to_destination  actual_time  …  source_city  \
0                        2.162548     2.147277  …     0.009806
1                       -0.297563    -0.379887  …     0.000812
2                        5.772034     5.326268  …     0.078042
3                       -0.480911    -0.529486  …     0.097518
4                       -0.119943    -0.027259  …     0.001217

   source_place  destination_state  destination_city  destination_place  \
0      0.007912           0.054440          0.010009           0.006425
1      0.000812           0.155136          0.000812           0.000812
2      0.071144           0.110908          0.063299           0.055522
3      0.043552           0.173193          0.104687           0.012511
4      0.002435           0.155136          0.000609           0.000609

   trip_creation_day  trip_creation_month  trip_creation_year  \
0            0.37931                  0.0                 0.0
1            0.37931                  0.0                 0.0
2            0.37931                  0.0                 0.0
3            0.37931                  0.0                 0.0
4            0.37931                  0.0                 0.0

   trip_creation_hour  trip_creation_week
0           -1.559538           -1.337602
1           -1.559538           -1.337602
2           -1.559538           -1.337602
3           -1.559538           -1.337602
4           -1.559538           -1.337602

[5 rows x 26 columns]
```

2 Insights

- The data spans from September 12, 2018, 00:00:16 to October 8, 2018, 03:00:24.
- There are approximately 14,817 unique trip IDs, 1,508 unique source centers, 1,481 unique

destination centers, 690 unique source cities, and 806 unique destination cities.

- The most common route type is Carting.
- The number of trips starts to increase after noon, peaks around 10 P.M., and then declines afterward.
- Most orders are sourced from states like Maharashtra, Karnataka, Haryana, Tamil Nadu, and Telangana.
- The highest number of trips originated from Mumbai and Bengaluru, followed by Gurgaon, Delhi, and Bhiwandi, suggesting a strong seller base in these cities.
- The majority of trips concluded in Maharashtra, followed by Karnataka, Haryana, Tamil Nadu, and Uttar Pradesh, indicating a high volume of orders in these states.
- Cities with the highest number of completed trips include Mumbai and Bengaluru, followed by Gurgaon, Delhi, and Chennai, reflecting significant order placement in these cities.
- In terms of destination cities, Bengaluru, Mumbai, Gurgaon, Bangalore, and Delhi see the most orders.
- There is a significant variation in actual travel time across different route types.
- A strong correlation exists between OSRM distance and actual travel time.
- There is a significant difference in actual travel time depending on the time of day.

3 Recommendations

- **Optimize Peak Time Operations:** Since trips surge after noon, peaking at 10 P.M., Delhivery should allocate additional resources, such as drivers, vehicles, and support staff, during these times to handle the increased demand effectively.
- **Enhance Carting Route Efficiency:** Given that Carting is the most common route type, Delhivery should focus on improving Carting-specific resources, such as vehicle optimization and increasing fleet availability for this route to boost operational efficiency.
- **Expand Infrastructure in Key Sourcing Regions:** As most orders originate from Maharashtra, Karnataka, Haryana, Tamil Nadu, and Telangana, Delhivery should invest in expanding regional hubs and warehousing capacity in these states to streamline logistics and reduce supply chain bottlenecks.
- **Strengthen Seller Relations in Major Cities:** With strong trip origin bases in Mumbai, Bengaluru, Gurgaon, Delhi, and Bhiwandi, Delhivery should enhance seller engagement by providing faster pickups, tailored fulfillment solutions, and better support services to boost collaboration.
- **Improve Last-Mile Logistics in High-Demand Cities:** To handle the high volume of trips ending in cities like Mumbai, Bengaluru, Gurgaon, Delhi, and Chennai, Delhivery should establish micro-fulfillment centers and utilize local delivery networks to shorten last-mile delivery times. Implementing electric vehicles for urban logistics can further reduce costs and improve sustainability.

- **Leverage AI for Dynamic Route Optimization:** Using AI-powered tools, Delhivery can dynamically adjust routes based on factors like traffic, order density, and time of day, minimizing delays and improving delivery efficiency.
- **Offer Time-Sensitive Delivery Slots:** With travel times varying by time of day, Delhivery can introduce customer-specific delivery slots and promote off-peak delivery options to reduce congestion during high-demand periods while ensuring timely deliveries in lower-traffic hours.
- **Implement Predictive Maintenance and Driver Management:** To maintain fleet efficiency and prevent breakdowns during peak times, Delhivery should adopt predictive maintenance strategies for vehicles. Additionally, implementing driver fatigue management programs will ensure optimal driver performance during long or high-demand shifts.