delhivery-feature-engineering

July 5, 2024

#Delhivery - Business Case Study

###Introduction: Delhivery, India's leading and rapidly growing integrated player, has set its sights on creating the commerce operating system. They achieve this by utilizing world-class infrastructure, ensuring the highest quality in logistics operations, and harnessing cutting-edge engineering and technology capabilities.

####Why this case study? From Delhivery's Perspective:

- Delhivery aims to establish itself as the premier player in the logistics industry. This case study is of paramount importance as it aligns with the company's core objectives and operational excellence.
- It provides a practical framework for understanding and processing data, which is integral to their operations. By leveraging data engineering pipelines and data analysis techniques, Delhivery can achieve several critical goals.
- First, it allows them to ensure data integrity and quality by addressing missing values and structuring the dataset appropriately.
- Second, it enables the extraction of valuable features from raw data, which can be utilized for building accurate forecasting models.
- Moreover, it facilitates the identification of patterns, insights, and actionable recommendations crucial for optimizing their logistics operations.
- By conducting hypothesis testing and outlier detection, Delhivery can refine their processes and further enhance the quality of service they provide.

From Learners' Perspective:

- Learners will gain hands-on experience in data preprocessing and cleaning, which is often the most time-consuming aspect of data analysis.
- Feature engineering is a critical step in building machine learning models. In this case study, learners will understand how to extract meaningful features from raw data, including datetime manipulation and column splitting.
- The case study introduces learners to the concept of grouping data based on specific keys and then aggregating it. This is a key aspect of data analysis, especially when dealing with time-series data or data with a hierarchical structure.
- Learners will perform hypothesis testing, to validate assumptions and draw insights from data.
- The case study goes beyond data analysis by focusing on deriving actionable insights for a business. Learners will understand how data analysis can drive informed decision-making and recommendations.

###Column Profiling:

1. data - tells whether the data is testing or training data
2. trip_creation_time – Timestamp of trip creation
3. route_schedule_uuid – Unique ID for a particular route schedule
4. route_type – Transportation type

a. FTL – Full Truck Load: FTL shipments get to the destination sooner, as the truck is making no other pickups or drop-offs along the way
b. Carting: Handling system consisting of small vehicles (carts)

5. trip_uuid - Unique ID given to a particular trip (A trip may include different source and destination centers)
6. source_center - Source ID of trip origin
7. source_name - Source Name of trip origin
8. destination_cente – Destination ID
9. destination_name – Destination Name
10. od_start_time – Trip start time
11. od_end_time – Trip end time
12. start_scan_to_end_scan – Time taken to deliver from source to destination
13. is_cutoff – Unknown field
14. cutoff_factor – Unknown field
15. cutoff_timestamp – Unknown field
16. actual_distance_to_destination – Distance in kms between source and destination warehouse
17. actual_time – Actual time taken to complete the delivery (Cumulative)
18. osrm_time – An open-source routing engine time calculator which computes the shortest path between points in a given map (Includes usual traffic, distance through major and minor roads) and gives the time (Cumulative)
19. osrm_distance – An open-source routing engine which computes the shortest path between points in a given map (Includes usual traffic, distance through major and minor roads) (Cumulative)
20. factor – Unknown field
21. segment_actual_time – This is a segment time. Time taken by the subset of the package delivery
22. segment_osrm_time – This is the OSRM segment time. Time taken by the subset of the package delivery
23. segment_osrm_distance – This is the OSRM distance. Distance covered by subset of the package delivery
24. segment_factor – Unknown field

---

[256]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import␣
↪ttest_1samp,ttest_ind,ttest_rel,chi2_contingency,chisquare,f_oneway
from scipy.stats import kruskal,shapiro,levene
import warnings
warnings.filterwarnings('ignore')
```

[257]:
```
!wget https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/551/
↪original/delhivery_data.csv?1642751181 -O 'data.csv'
```

```
--2024-07-05 12:47:04--  https://d2beiqkhq929f0.cloudfront.net/public_assets/ass
ets/000/001/551/original/delhivery_data.csv?1642751181
Resolving d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)…
18.164.173.117, 18.164.173.18, 18.164.173.110, …
Connecting to d2beiqkhq929f0.cloudfront.net
(d2beiqkhq929f0.cloudfront.net)|18.164.173.117|:443… connected.
HTTP request sent, awaiting response… 200 OK
Length: 55617130 (53M) [text/plain]
Saving to: 'data.csv'

data.csv            100%[===================>]  53.04M   248MB/s    in 0.2s

2024-07-05 12:47:04 (248 MB/s) - 'data.csv' saved [55617130/55617130]
```

[258]:
```
df=pd.read_csv('data.csv')
```

####What does 'good' look like? 1. Basic data cleaning and exploration: 1. Handle missing values in the data. 2. Converting time columns into pandas datetime. 3. Analyze structure & characteristics of the dataset.

[259]:
```
df.head()
```

[259]:
```
       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]
```

[260]:
```
df=df.dropna(how='any')
```

[261]:
```
df=df.reset_index(drop=True)
```

[262]:
```
df.columns
```

[262]:
```
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'],
      dtype='object')
```

[263]:
```python
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  object
 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  object
 10  od_end_time                     144316 non-null  object
 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  object
 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), float64(10), int64(1), object(12)
memory usage: 25.5+ MB
```

[264]:
```python
df.describe()
```

[264]:
```
       start_scan_to_end_scan  cutoff_factor  actual_distance_to_destination  \
count           144316.000000  144316.000000                   144316.000000
mean               963.697698     233.561345                      234.708498
std               1038.082976     345.245823                      345.480571
min                 20.000000       9.000000                        9.000045
25%                161.000000      22.000000                       23.352027
50%                451.000000      66.000000                       66.135322
```

```
75%              1645.000000     286.000000                              286.919294
max              7898.000000    1927.000000                             1927.447705

         actual_time      osrm_time   osrm_distance         factor  \
count  144316.000000  144316.000000   144316.000000  144316.000000
mean      417.996237     214.437055      285.549785       2.120178
std       598.940065     308.448543      421.717826       1.717065
min         9.000000       6.000000        9.008200       0.144000
25%        51.000000      27.000000       29.896250       1.604545
50%       132.000000      64.000000       78.624400       1.857143
75%       516.000000     259.000000      346.305400       2.212280
max      4532.000000    1686.000000     2326.199100      77.387097

       segment_actual_time  segment_osrm_time  segment_osrm_distance  \
count        144316.000000      144316.000000          144316.000000
mean             36.175379          18.495697              22.818993
std              53.524298          14.774008              17.866367
min            -244.000000           0.000000               0.000000
25%              20.000000          11.000000              12.053975
50%              28.000000          17.000000              23.508300
75%              40.000000          22.000000              27.813325
max            3051.000000        1611.000000            2191.403700

       segment_factor
count   144316.000000
mean         2.218707
std          4.854804
min        -23.444444
25%          1.347826
50%          1.684211
75%          2.250000
max        574.250000
```

[265]:
```
df.shape
```

[265]: (144316, 24)

[266]:
```
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'],format='mixed')
```

[267]:
```
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  object
 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](3), float64(10), int64(1), object(9)
memory usage: 25.5+ MB
```

[268]:
```
df.isnull().sum()
```

[268]:
```
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
is_cutoff                         0
cutoff_factor                     0
cutoff_timestamp                  0
actual_distance_to_destination    0
actual_time                       0
```

```
osrm_time                    0
osrm_distance                0
factor                       0
segment_actual_time          0
segment_osrm_time            0
segment_osrm_distance        0
segment_factor               0
dtype: int64
```

####Try merging the rows using the hint mentioned below. Since delivery details of one package is divided into several rows (think of it as connecting flights to reach a particular destination).

1. Grouping by segment

- Create a unique identifier for different segments of a trip based on the combination of the trip_uuid, source_center, and destination_center and name it as segment_key.
- You can use inbuilt functions like groupby and aggregations like cumsum() to merge the rows in columns segment_actual_time, segment_osrm_distance, segment_osrm_time based on the segment_key.
- This way you'll get new columns named segment_actual_time_sum, segment_osrm_distance_sum, segment_osrm_time_sum.

2. Aggregating at segment level

- Create a dictionary named create_segment_dict, that defines how to aggregate and select values.

  i. You can keep the first and last values for some numeric/categorical fields if aggregating them won't make sense.

- Further group the data by segment_key because you want to perform aggregation operations for different segments of each trip based on the segment_key value.

- The aggregation functions specified in the create_segment_dict are applied to each group of rows with the same segment_key.

- Sort the resulting DataFrame segment, by two criteria:

  i. First, it sorts by segment_key to ensure that segments are ordered consistently.
  ii. Second, it sorts by od_end_time in ascending order, ensuring that segments within the same trip are ordered by their end times from earliest to latest.

[269]:
```
df['segment_key']=df['trip_uuid']+df['source_center']+df['destination_center']
df['segment_key']
```

[269]:
```
0         trip-153741093647649320IND388121AAAIND388620AAB
1         trip-153741093647649320IND388121AAAIND388620AAB
2         trip-153741093647649320IND388121AAAIND388620AAB
3         trip-153741093647649320IND388121AAAIND388620AAB
4         trip-153741093647649320IND388121AAAIND388620AAB
                                …
144311    trip-153746066843555182IND131028AABIND000000ACB
```

```
144312    trip-153746066843555182IND131028AABIND000000ACB
144313    trip-153746066843555182IND131028AABIND000000ACB
144314    trip-153746066843555182IND131028AABIND000000ACB
144315    trip-153746066843555182IND131028AABIND000000ACB
Name: segment_key, Length: 144316, dtype: object
```

[270]:
```
segment_cols = ['segment_actual_time', 'segment_osrm_distance',␣
↪'segment_osrm_time']

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

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

[270]:
```
        segment_actual_time_sum  segment_osrm_distance_sum  \
0                          14.0                    11.9653
1                          24.0                    21.7243
2                          40.0                    32.5395
3                          61.0                    45.5619
4                          67.0                    49.4772
…                           …                         …
144311                     92.0                    65.3487
144312                    118.0                    82.7212
144313                    138.0                   103.4265
144314                    155.0                   122.3150
144315                    423.0                   131.1238

        segment_osrm_time_sum
0                        11.0
1                        20.0
2                        27.0
3                        39.0
4                        44.0
…                         …
144311                   94.0
144312                  115.0
144313                  149.0
144314                  176.0
144315                  185.0

[144316 rows x 3 columns]
```

[271]:
```
create_segment_dict = {'data' : 'first',
    'trip_creation_time' : 'first', 'trip_uuid' : 'first',
    'route_schedule_uuid' : 'first', 'route_type' : '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',
    'cutoff_timestamp' : 'first', 'segment_actual_time' : 'sum',␣
↪'segment_osrm_time' : 'sum', 'segment_osrm_distance' : 'sum',
    'segment_actual_time_sum' : 'last', 'segment_osrm_distance_sum' : 'last',␣
↪'segment_osrm_time_sum' : 'last'}
```

[272]:
```
segment = df.groupby('segment_key').agg(create_segment_dict).reset_index()
segment = segment.sort_values(by=['segment_key','od_end_time'], ascending=True).
↪reset_index()
```

[273]:
```
segment
```

[273]:
```
       index                                     segment_key      data  \
0          0  trip-153671041653548748IND209304AAAIND000000ACB  training
1          1  trip-153671041653548748IND462022AAAIND209304AAA  training
2          2  trip-153671042288605164IND561203AABIND562101AAA  training
3          3  trip-153671042288605164IND572101AAAIND561203AAB  training
4          4  trip-153671043369099517IND000000ACBIND160002AAC  training
…        …                                             …       …
26217  26217  trip-153861115439069069IND628204AAAIND627657AAA      test
26218  26218  trip-153861115439069069IND628613AAAIND627005AAA      test
26219  26219  trip-153861115439069069IND628801AAAIND628204AAA      test
26220  26220  trip-153861118270144424IND583119AAAIND583101AAA      test
26221  26221  trip-153861118270144424IND583201AAAIND583119AAA      test

                trip_creation_time                trip_uuid  \
0       2018-09-12 00:00:16.535741  trip-153671041653548748
1       2018-09-12 00:00:16.535741  trip-153671041653548748
2       2018-09-12 00:00:22.886430  trip-153671042288605164
3       2018-09-12 00:00:22.886430  trip-153671042288605164
4       2018-09-12 00:00:33.691250  trip-153671043369099517
…                                …                        …
26217   2018-10-03 23:59:14.390954  trip-153861115439069069
26218   2018-10-03 23:59:14.390954  trip-153861115439069069
26219   2018-10-03 23:59:14.390954  trip-153861115439069069
26220   2018-10-03 23:59:42.701692  trip-153861118270144424
26221   2018-10-03 23:59:42.701692  trip-153861118270144424

                                     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
3       thanos::sroute:3a1b0ab2-bb0b-4c53-8c59-eb2a2c0…    Carting
4       thanos::sroute:de5e208e-7641-45e6-8100-4d9fb1e…        FTL
```

```
…                                                    …        …
26217  thanos::sroute:c5f2ba2c-8486-4940-8af6-d1d2a6a…    Carting
26218  thanos::sroute:c5f2ba2c-8486-4940-8af6-d1d2a6a…    Carting
26219  thanos::sroute:c5f2ba2c-8486-4940-8af6-d1d2a6a…    Carting
26220  thanos::sroute:412fea14-6d1f-4222-8a5f-a517042…        FTL
26221  thanos::sroute:412fea14-6d1f-4222-8a5f-a517042…        FTL

      source_center                          source_name destination_center  \
0      IND209304AAA  Kanpur_Central_H_6 (Uttar Pradesh)       IND000000ACB
1      IND462022AAA  Bhopal_Trnsport_H (Madhya Pradesh)       IND209304AAA
2      IND561203AAB   Doddablpur_ChikaDPP_D (Karnataka)       IND562101AAA
3      IND572101AAA       Tumkur_Veersagr_I (Karnataka)       IND561203AAB
4      IND000000ACB       Gurgaon_Bilaspur_HB (Haryana)       IND160002AAC
…               …                                  …                 …
26217  IND628204AAA  Tirchchndr_Shnmgprm_D (Tamil Nadu)       IND627657AAA
26218  IND628613AAA   Peikulam_SriVnktpm_D (Tamil Nadu)       IND627005AAA
26219  IND628801AAA        Eral_Busstand_D (Tamil Nadu)       IND628204AAA
26220  IND583119AAA       Sandur_WrdN1DPP_D (Karnataka)       IND583101AAA
26221  IND583201AAA                 Hospet (Karnataka)       IND583119AAA

       … actual_time osrm_time osrm_distance    cutoff_timestamp  \
0      …       732.0     329.0      446.5496 2018-09-13 12:40:43
1      …       830.0     388.0      544.8027 2018-09-12 14:56:29
2      …        47.0      26.0       28.1994 2018-09-12 02:41:24
3      …        96.0      42.0       56.9116 2018-09-12 01:39:28
4      …       611.0     212.0      281.2109 2018-09-14 16:54:36
…    …           …         …             …                   …
26217  …        51.0      41.0       42.5213 2018-10-04 03:17:33
26218  …        90.0      48.0       40.6080 2018-10-04 05:32:33
26219  …        30.0      14.0       16.0185 2018-10-04 02:05:30
26220  …       233.0      42.0       52.5303 2018-10-04 07:29:32
26221  …        42.0      26.0       28.0484 2018-10-04 03:20:29

       segment_actual_time  segment_osrm_time  segment_osrm_distance  \
0                    728.0              534.0               670.6205
1                    820.0              474.0               649.8528
2                     46.0               26.0                28.1995
3                     95.0               39.0                55.9899
4                    608.0              231.0               317.7408
…                      …                  …                     …
26217                 49.0               42.0                42.1431
26218                 89.0               77.0                78.5869
26219                 29.0               14.0                16.0184
26220                233.0               42.0                52.5303
26221                 41.0               25.0                28.0484

       segment_actual_time_sum segment_osrm_distance_sum  \
```

```
0                       728.0                  670.6205
1                       820.0                  649.8528
2                        46.0                   28.1995
3                        95.0                   55.9899
4                       608.0                  317.7408
…                         …                      …
26217                    49.0                   42.1431
26218                    89.0                   78.5869
26219                    29.0                   16.0184
26220                   233.0                   52.5303
26221                    41.0                   28.0484

       segment_osrm_time_sum
0                      534.0
1                      474.0
2                       26.0
3                       39.0
4                      231.0
…                        …
26217                   42.0
26218                   77.0
26219                   14.0
26220                   42.0
26221                   25.0

[26222 rows x 25 columns]
```

[274]:
```
segment.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26222 entries, 0 to 26221
Data columns (total 25 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  object
 4   trip_uuid                       26222 non-null  object
 5   route_schedule_uuid             26222 non-null  object
 6   route_type                      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  cutoff_timestamp                26222 non-null  datetime64[ns]
 19  segment_actual_time             26222 non-null  float64
 20  segment_osrm_time               26222 non-null  float64
 21  segment_osrm_distance           26222 non-null  float64
 22  segment_actual_time_sum         26222 non-null  float64
 23  segment_osrm_distance_sum       26222 non-null  float64
 24  segment_osrm_time_sum           26222 non-null  float64
dtypes: datetime64[ns](3), float64(11), int64(1), object(10)
memory usage: 5.0+ MB
```

[359]:
```
segment['od_total_time'] = segment['od_end_time'] - segment['od_start_time']
segment['od_total_time'] = segment['od_total_time'].apply(lambda x : round(x.
 ↪total_seconds() / 60.0, 2))
segment['od_total_time']
```

[359]:
```
0        1260.60
1         999.51
2          58.83
3         122.78
4         834.64
          …
26217      62.12
26218      91.09
26219      44.17
26220     287.47
26221      66.93
Name: od_total_time, Length: 26222, dtype: float64
```

[412]:
```
average_time_per_trip=round((segment['od_total_time'].mean())/60,2)
print(f'Average time per trip : {average_time_per_trip} hours')
```

```
Average time per trip : 4.98 hours
```

####Feature Engineering: Extract features from the below fields: 1. Calculate time taken between od_start_time and od_end_time and keep it as a feature named od_time_diff_hour. Drop the original columns, if required. 2. Destination Name: Split and extract features out of destination. City-place-code (State) 3. Source Name: Split and extract features out of destination. City-place-code (State) 4. Trip_creation_time: Extract features like month, year, day, etc.

####In-depth analysis: 1. Grouping and Aggregating at Trip-level a. Groups the segment data by the trip_uuid column to focus on aggregating data at the trip level. b. Apply suitable aggregation functions like first, last, and sum specified in the create_trip_dict dictionary to calculate summary statistics for each trip.

[361]:
```
create_trip_dict = {

    'data' : 'first',
    'trip_creation_time' : 'first',
    'route_schedule_uuid' : 'first',
    'route_type' : 'first',
    'trip_uuid' : 'first',
    'od_total_time' : 'sum','segment_actual_time' : 'sum', 'segment_osrm_time' :
 ↪'sum', 'segment_osrm_distance' : 'sum',

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

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

    'start_scan_to_end_scan' : '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',

}
```

[362]:
```
trip = segment.groupby('trip_uuid').agg(create_trip_dict).reset_index(drop =␣
 ↪True)
```

[363]:
```
trip
```

[363]:
```
            data         trip_creation_time  \
0       training 2018-09-12 00:00:16.535741
1       training 2018-09-12 00:00:22.886430
2       training 2018-09-12 00:00:33.691250
3       training 2018-09-12 00:01:00.113710
4       training 2018-09-12 00:02:09.740725
…            …                          …
14782       test 2018-10-03 23:55:56.258533
14783       test 2018-10-03 23:57:23.863155
14784       test 2018-10-03 23:57:44.429324
14785       test 2018-10-03 23:59:14.390954
14786       test 2018-10-03 23:59:42.701692
```

```
                                   route_schedule_uuid route_type  \
0      thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6…        FTL
1      thanos::sroute:3a1b0ab2-bb0b-4c53-8c59-eb2a2c0…    Carting
2      thanos::sroute:de5e208e-7641-45e6-8100-4d9fb1e…        FTL
3      thanos::sroute:f0176492-a679-4597-8332-bbd1c7f…    Carting
4      thanos::sroute:d9f07b12-65e0-4f3b-bec8-df06134…        FTL
…                                                    …          …
14782  thanos::sroute:8a120994-f577-4491-9e4b-b7e4a14…    Carting
14783  thanos::sroute:b30e1ec3-3bfa-4bd2-a7fb-3b75769…    Carting
14784  thanos::sroute:5609c268-e436-4e0a-8180-3db4a74…    Carting
14785  thanos::sroute:c5f2ba2c-8486-4940-8af6-d1d2a6a…    Carting
14786  thanos::sroute:412fea14-6d1f-4222-8a5f-a517042…        FTL

                    trip_uuid  od_total_time  segment_actual_time  \
0      trip-153671041653548748        2260.11               1548.0
1      trip-153671042288605164         181.61                141.0
2      trip-153671043369099517        3934.36               3308.0
3      trip-153671046011330457         100.49                 59.0
4      trip-153671052974046625         718.34                340.0
…                           …             …                    …
14782  trip-153861095625827784         258.03                 82.0
14783  trip-153861104386292051          60.59                 21.0
14784  trip-153861106442901555         422.12                281.0
14785  trip-153861115439069069         348.52                258.0
14786  trip-153861118270144424         354.40                274.0

       segment_osrm_time  segment_osrm_distance source_center  …  \
0                 1008.0              1320.4733  IND209304AAA  …
1                   65.0                84.1894  IND561203AAB  …
2                 1941.0              2545.2678  IND000000ACB  …
3                   16.0                19.8766  IND400072AAB  …
4                  115.0               146.7919  IND583101AAA  …
…                    …                     …           …  …
14782               62.0                64.8551  IND160002AAC  …
14783               11.0                16.0883  IND121004AAB  …
14784               88.0               104.8866  IND208006AAA  …
14785              221.0               223.5324  IND627005AAA  …
14786               67.0                80.5787  IND583119AAA  …

      destination_center                    destination_name  \
0           IND209304AAA  Kanpur_Central_H_6 (Uttar Pradesh)
1           IND561203AAB   Doddablpur_ChikaDPP_D (Karnataka)
2           IND000000ACB       Gurgaon_Bilaspur_HB (Haryana)
3           IND401104AAA      Mumbai_MiraRd_IP (Maharashtra)
4           IND583119AAA       Sandur_WrdN1DPP_D (Karnataka)
…                    …                                   …
14782       IND160002AAC      Chandigarh_Mehmdpur_H (Punjab)
```

```
14783       IND121004AAA      Faridabad_Blbgarh_DC (Haryana)
14784       IND208006AAA  Kanpur_GovndNgr_DC (Uttar Pradesh)
14785       IND628204AAA  Tirchchndr_Shnmgprm_D (Tamil Nadu)
14786       IND583119AAA       Sandur_WrdN1DPP_D (Karnataka)

      start_scan_to_end_scan  actual_distance_to_destination  actual_time  \
0                     2259.0                      824.732854       1562.0
1                      180.0                       73.186911        143.0
2                     3933.0                     1927.404273       3347.0
3                      100.0                       17.175274         59.0
4                      717.0                      127.448500        341.0
…                        …                             …             …
14782                  257.0                       57.762332         83.0
14783                   60.0                       15.513784         21.0
14784                  421.0                       38.684839        282.0
14785                  347.0                      134.723836        264.0
14786                  353.0                       66.081533        275.0

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

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

[14787 rows x 21 columns]
```

[364]:
```
trip.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14787 entries, 0 to 14786
Data columns (total 21 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   data                            14787 non-null  object
 1   trip_creation_time              14787 non-null  object
 2   route_schedule_uuid             14787 non-null  object
 3   route_type                      14787 non-null  object
 4   trip_uuid                       14787 non-null  object
 5   od_total_time                   14787 non-null  float64
 6   segment_actual_time             14787 non-null  float64
 7   segment_osrm_time               14787 non-null  float64
 8   segment_osrm_distance           14787 non-null  float64
 9   source_center                   14787 non-null  object
 10  source_name                     14787 non-null  object
 11  destination_center              14787 non-null  object
 12  destination_name                14787 non-null  object
 13  start_scan_to_end_scan          14787 non-null  float64
 14  actual_distance_to_destination  14787 non-null  float64
 15  actual_time                     14787 non-null  float64
 16  osrm_time                       14787 non-null  float64
 17  osrm_distance                   14787 non-null  float64
 18  segment_actual_time_sum         14787 non-null  float64
 19  segment_osrm_distance_sum       14787 non-null  float64
 20  segment_osrm_time_sum           14787 non-null  float64
dtypes: float64(12), object(9)
memory usage: 2.4+ MB
```

Destination Name: Split and extract features out of destination. City-place-code (State)

Source Name: Split and extract features out of destination. City-place-code (State)

Trip_creation_time: Extract features like month, year, day, etc.

[281]:
```
def location_name_to_city(x):
  if 'location' in x:
    return 'unknown_city'
  else:
    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()):
      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]
```

[282]:
```
def location_name_to_place(x):
  if 'location' in x:
    return x
  elif 'HBR' in x:
    return 'HBR Layout PC'
  else:
    l = x.split()[0].split('_', 1)
    if len(l) == 1:
      return 'unknown_place'
    else:
      return l[1]
```

[283]:
```
def location_name_to_state(x):
  l = x.split('(')
  if len(l) == 1:
    return l[0]
  else:
    return l[1].replace(')', "")
```

[369]:
```
trip['source_state'] = trip['source_name'].apply(location_name_to_state)
print('No of source states :', trip['source_state'].nunique())
trip['source_state'].unique()
```

```
No of source states : 29
```

[369]:
```
array(['Uttar Pradesh', 'Karnataka', 'Haryana', 'Maharashtra',
       'Tamil Nadu', 'Gujarat', 'Delhi', 'Telangana', 'Rajasthan',
       'Assam', 'Madhya Pradesh', 'West Bengal', 'Andhra Pradesh',
       'Punjab', 'Chandigarh', 'Goa', 'Jharkhand', 'Pondicherry',
       'Orissa', 'Uttarakhand', 'Himachal Pradesh', 'Kerala',
```

```
       'Arunachal Pradesh', 'Bihar', 'Chhattisgarh',
       'Dadra and Nagar Haveli', 'Jammu & Kashmir', 'Mizoram', 'Nagaland'],
      dtype=object)
```

[370]:
```python
trip['source_city'] = trip['source_name'].apply(location_name_to_city)
print('No of source cities :', trip['source_city'].nunique())
trip['source_city'].unique()[:50]
```

```
No of source cities : 687
```

[370]:
```
array(['Kanpur', 'Doddablpur', 'Gurgaon', 'Mumbai', 'Bellary', 'Chennai',
       'Bengaluru', 'Surat', 'Delhi', 'Pune', 'Faridabad', 'Shirala',
       'Hyderabad', 'Thirumalagiri', 'Gulbarga', 'Jaipur', 'Allahabad',
       'Guwahati', 'Narsinghpur', 'Shrirampur', 'Madakasira', 'Sonari',
       'Dindigul', 'Jalandhar', 'Chandigarh', 'Deoli', 'Pandharpur',
       'Kolkata', 'Bhandara', 'Kurnool', 'Bhiwandi', 'Bhatinda',
       'RoopNagar', 'Bantwal', 'Lalru', 'Kadi', 'Shahdol', 'Gangakher',
       'Durgapur', 'Vapi', 'Jamjodhpur', 'Jetpur', 'Mehsana', 'Jabalpur',
       'Junagadh', 'Gundlupet', 'Mysore', 'Goa', 'Bhopal', 'Sonipat'],
      dtype=object)
```

[371]:
```python
trip['source_place'] = trip['source_name'].apply(location_name_to_place)
print('No of source places :', trip['source_place'].nunique())
trip['source_place'].unique()[:50]
```

```
No of source places : 755
```

[371]:
```
array(['Central_H_6', 'ChikaDPP_D', 'Bilaspur_HB', 'unknown_place', 'Dc',
       'Poonamallee', 'Chrompet_DPC', 'HBR Layout PC', 'Central_D_12',
       'Lajpat_IP', 'North_D_3', 'Balabhgarh_DPC', 'Central_DPP_3',
       'Shamshbd_H', 'Xroad_D', 'Nehrugnj_I', 'Central_I_7',
       'Central_H_1', 'Nangli_IP', 'North', 'KndliDPP_D', 'Central_D_9',
       'DavkharRd_D', 'Bandel_D', 'RTCStand_D', 'Central_DPP_1',
       'KGAirprt_HB', 'North_D_2', 'Central_D_1', 'DC', 'Mthurard_L',
       'Mullanpr_DC', 'Central_DPP_2', 'RajCmplx_D', 'Beliaghata_DPC',
       'RjnaiDPP_D', 'AbbasNgr_I', 'Mankoli_HB', 'DPC', 'Airport_H',
       'Hub', 'Gateway_HB', 'Tathawde_H', 'ChotiHvl_DC', 'Trmltmpl_D',
       'OnkarDPP_D', 'Mehmdpur_H', 'KaranNGR_D', 'Sohagpur_D',
       'Chrompet_L'], dtype=object)
```

[372]:
```python
trip['destination_state'] = trip['destination_name'].
 ↪apply(location_name_to_state)
print('No of destination states :', trip['destination_state'].nunique())
trip['destination_state'].unique()
```

```
No of destination states : 31
```

[372]:
```
array(['Uttar Pradesh', 'Karnataka', 'Haryana', 'Maharashtra',
       'Tamil Nadu', 'Gujarat', 'Delhi', 'Telangana', 'Rajasthan',
       'Madhya Pradesh', 'Assam', 'West Bengal', 'Andhra Pradesh',
       'Punjab', 'Chandigarh', 'Dadra and Nagar Haveli', 'Orissa',
       'Bihar', 'Jharkhand', 'Goa', 'Uttarakhand', 'Himachal Pradesh',
       'Kerala', 'Arunachal Pradesh', 'Mizoram', 'Chhattisgarh',
       'Jammu & Kashmir', 'Nagaland', 'Meghalaya', 'Tripura',
       'Daman & Diu'], dtype=object)
```

[373]:
```
trip['destination_city'] = trip['destination_name'].apply(location_name_to_city)
print('No of destination cities :', trip['destination_city'].nunique())
trip['destination_city'].unique()[:50]
```

```
No of destination cities : 805
```

[373]:
```
array(['Kanpur', 'Doddablpur', 'Gurgaon', 'Mumbai', 'Sandur', 'Chennai',
       'Bengaluru', 'Surat', 'Delhi', 'PNQ', 'Faridabad', 'Ratnagiri',
       'Bangalore', 'Hyderabad', 'Aland', 'Jaipur', 'Satna', 'Guwahati',
       'Bareli', 'Nashik', 'Hooghly', 'Sivasagar', 'Palani', 'Jalandhar',
       'Chandigarh', 'Yavatmal', 'Sangola', 'Kolkata', 'Savner',
       'Kurnool', 'Bhatinda', 'Bhiwandi', 'Barnala', 'Murbad', 'Kadaba',
       'Gulbarga', 'Naraingarh', 'Ludhiana', 'Kadi', 'Jabalpur',
       'Gangakher', 'Bankura', 'Silvassa', 'Porbandar', 'Jetpur',
       'Khammam', 'Mehsana', 'Katni', 'Una', 'Malavalli'], dtype=object)
```

[374]:
```
trip['destination_place'] = trip['destination_name'].
 ↪apply(location_name_to_place)
print('No of destination places :', trip['destination_place'].nunique())
trip['destination_place'].unique()[:50]
```

```
No of destination places : 843
```

[374]:
```
array(['Central_H_6', 'ChikaDPP_D', 'Bilaspur_HB', 'MiraRd_IP',
       'WrdN1DPP_D', 'Poonamallee', 'Vandalur_Dc', 'HBR Layout PC',
       'Central_D_3', 'Bhogal', 'unknown_place', 'MjgaonRd_D',
       'Nelmngla_H', 'Uppal_I', 'RazaviRd_D', 'Central_I_7',
       'Central_I_2', 'Hub', 'SourvDPP_D', 'Varachha_DC', 'TgrniaRD_I',
       'DC', 'Gokulam_D', 'Babupaty_D', 'Bomsndra_HB', 'Alwal_I',
       'RjndraRd_D', 'Mehmdpur_H', 'Sanpada_I', 'JajuDPP_D',
       'Central_DPP_2', 'Dankuni_HB', 'Wagodha_D', 'AbbasNgr_I',
       'Balabhgarh_DPC', 'DPC', 'Mankoli_HB', 'Shamshbd_H', 'SnkunDPP_D',
       'Kharar_DC', 'AnugrDPP_D', 'Nehrugnj_I', 'Ward2DPP_D',
       'MilrGanj_HB', 'KaranNGR_D', 'Adhartal_IP', 'Poonamallee_HB',
       'Busstand_D', 'BhowmDPP_D', 'Samrvrni_D'], dtype=object)
```

[290]:
```
trip['trip_creation_time']=pd.to_datetime(trip['trip_creation_time'])
```

[291]:
```python
trip['trip_creation_date'] = pd.to_datetime(trip['trip_creation_time'].dt.date)
trip['trip_creation_date'].head()
```

[291]:
```
0   2018-09-12
1   2018-09-12
2   2018-09-12
3   2018-09-12
4   2018-09-12
Name: trip_creation_date, dtype: datetime64[ns]
```

[292]:
```python
trip['trip_creation_day'] = trip['trip_creation_time'].dt.day
trip['trip_creation_day'].unique()
```

[292]:
```
array([12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28,
       29, 30,  1,  2,  3], dtype=int32)
```

[293]:
```python
trip['trip_creation_month'] = trip['trip_creation_time'].dt.month
trip['trip_creation_month'].unique()
```

[293]:
```
array([ 9, 10], dtype=int32)
```

[294]:
```python
trip['trip_creation_year'] = trip['trip_creation_time'].dt.year
trip['trip_creation_year'].unique()
```

[294]:
```
array([2018], dtype=int32)
```

[295]:
```python
trip['trip_creation_week'] = trip['trip_creation_time'].dt.isocalendar().week
trip['trip_creation_week'].head()
```

[295]:
```
0    37
1    37
2    37
3    37
4    37
Name: trip_creation_week, dtype: UInt32
```

[296]:
```python
trip['trip_creation_hour'] = trip['trip_creation_time'].dt.hour
trip['trip_creation_hour'].unique()
```

[296]:
```
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
       17, 18, 19, 20, 21, 22, 23], dtype=int32)
```

[297]:
```python
trip.shape
```

[297]:
```
(14787, 34)
```

[365]:
```python
trip.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14787 entries, 0 to 14786
Data columns (total 21 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   data                            14787 non-null  object 
 1   trip_creation_time              14787 non-null  object 
 2   route_schedule_uuid             14787 non-null  object 
 3   route_type                      14787 non-null  object 
 4   trip_uuid                       14787 non-null  object 
 5   od_total_time                   14787 non-null  float64
 6   segment_actual_time             14787 non-null  float64
 7   segment_osrm_time               14787 non-null  float64
 8   segment_osrm_distance           14787 non-null  float64
 9   source_center                   14787 non-null  object 
 10  source_name                     14787 non-null  object 
 11  destination_center              14787 non-null  object 
 12  destination_name                14787 non-null  object 
 13  start_scan_to_end_scan          14787 non-null  float64
 14  actual_distance_to_destination  14787 non-null  float64
 15  actual_time                     14787 non-null  float64
 16  osrm_time                       14787 non-null  float64
 17  osrm_distance                   14787 non-null  float64
 18  segment_actual_time_sum         14787 non-null  float64
 19  segment_osrm_distance_sum       14787 non-null  float64
 20  segment_osrm_time_sum           14787 non-null  float64
dtypes: float64(12), object(9)
memory usage: 2.4+ MB
```

[375]:
```
trip.columns
```

[375]:
```
Index(['data', 'trip_creation_time', 'route_schedule_uuid', 'route_type',
       'trip_uuid', 'od_total_time', 'segment_actual_time',
       'segment_osrm_time', 'segment_osrm_distance', 'source_center',
       'source_name', 'destination_center', 'destination_name',
       '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', 'source_state',
       'source_city', 'source_place', 'destination_state', 'destination_city',
       'destination_place'],
      dtype='object')
```

[366]:
```
trip.describe(include='object').T
```

[366]:
```
                     count unique  \
data                 14787      2
trip_creation_time   14787  14787
```

```
route_schedule_uuid  14787   1497
route_type           14787      2
trip_uuid            14787  14787
source_center        14787    930
source_name          14787    930
destination_center   14787   1035
destination_name     14787   1035

                                                                       top   freq
data                                                              training  10645
trip_creation_time                              2018-09-12 00:00:16.535741      1
route_schedule_uuid  thanos::sroute:a16bfa03-3462-4bce-9c82-5784c7d…          53
route_type                                                         Carting   8906
trip_uuid                                            trip-153671041653548748      1
source_center                                                  IND000000ACB   1052
source_name                                   Gurgaon_Bilaspur_HB (Haryana)   1052
destination_center                                             IND000000ACB    821
destination_name                              Gurgaon_Bilaspur_HB (Haryana)    821
```

[367]:
```
trip.describe().T
```

[367]:
```
                                  count        mean         std        min  \
od_total_time                   14787.0  530.313468  658.415416  23.460000
segment_actual_time             14787.0  353.059174  556.365911   9.000000
segment_osrm_time               14787.0  180.511598  314.679279   6.000000
segment_osrm_distance           14787.0  222.705466  416.846279   9.072900
start_scan_to_end_scan          14787.0  529.429025  658.254936  23.000000
actual_distance_to_destination  14787.0  164.090196  305.502982   9.002461
actual_time                     14787.0  356.306012  561.517936   9.000000
osrm_time                       14787.0  160.990938  271.459495   6.000000
osrm_distance                   14787.0  203.887411  370.565564   9.072900
segment_actual_time_sum         14787.0  353.059174  556.365911   9.000000
segment_osrm_distance_sum       14787.0  222.705466  416.846279   9.072900
segment_osrm_time_sum           14787.0  180.511598  314.679279   6.000000

                                       25%         50%         75%  \
od_total_time                   149.695000  279.710000  633.535000
segment_actual_time              66.000000  147.000000  364.000000
segment_osrm_time                30.000000   65.000000  184.000000
segment_osrm_distance            32.578850   69.784200  216.560600
start_scan_to_end_scan          149.000000  279.000000  632.000000
actual_distance_to_destination   22.777099   48.287894  163.591258
actual_time                      67.000000  148.000000  367.000000
osrm_time                        29.000000   60.000000  168.000000
osrm_distance                    30.756900   65.302800  206.644200
segment_actual_time_sum          66.000000  147.000000  364.000000
segment_osrm_distance_sum        32.578850   69.784200  216.560600
```

```
segment_osrm_time_sum            30.000000   65.000000  184.000000

                                        max
od_total_time                   7898.550000
segment_actual_time             6230.000000
segment_osrm_time               2564.000000
segment_osrm_distance           3523.632400
start_scan_to_end_scan          7898.000000
actual_distance_to_destination  2186.531787
actual_time                     6265.000000
osrm_time                       2032.000000
osrm_distance                   2840.081000
segment_actual_time_sum         6230.000000
segment_osrm_distance_sum       3523.632400
segment_osrm_time_sum           2564.000000
```

###Bi-variate and Multi-variate Analysis

[301]:
```
trip['trip_creation_hour'].unique()
```

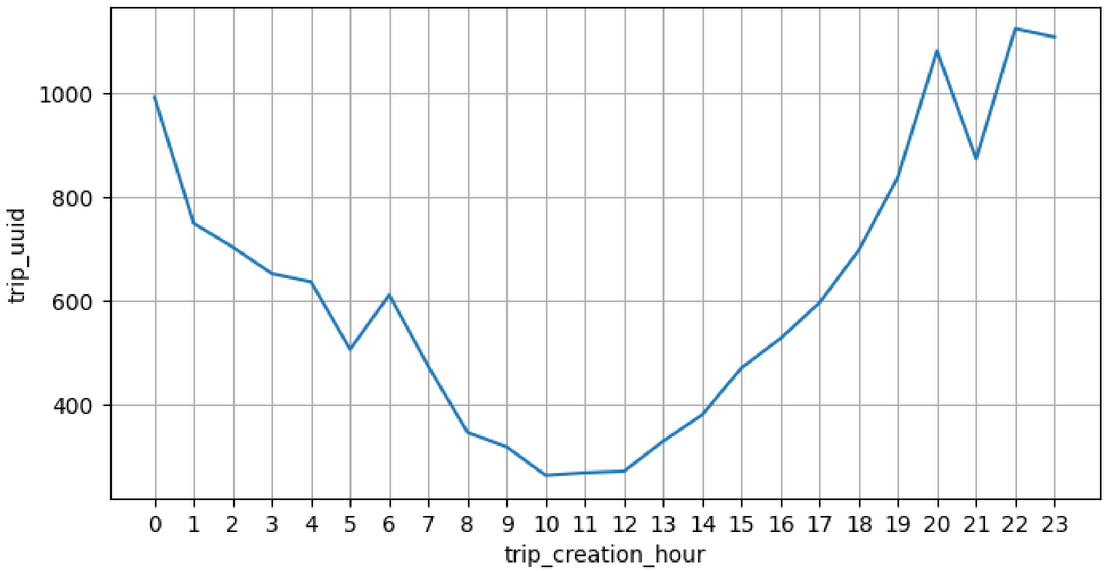
[301]:
```
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
       17, 18, 19, 20, 21, 22, 23], dtype=int32)
```

[302]:
```
trip_hour = trip.groupby(by = 'trip_creation_hour')['trip_uuid'].count().
 ↪to_frame().reset_index()
trip_hour.head()
```

[302]:
```
   trip_creation_hour  trip_uuid
0                   0        991
1                   1        748
2                   2        702
3                   3        651
4                   4        635
```

[303]:
```
plt.figure(figsize = (8, 4))
sns.lineplot(data = trip_hour, x = trip_hour['trip_creation_hour'], y =␣
 ↪trip_hour['trip_uuid'])
plt.xticks(np.arange(0,24))
plt.grid('both')
plt.plot()
```

[303]: []



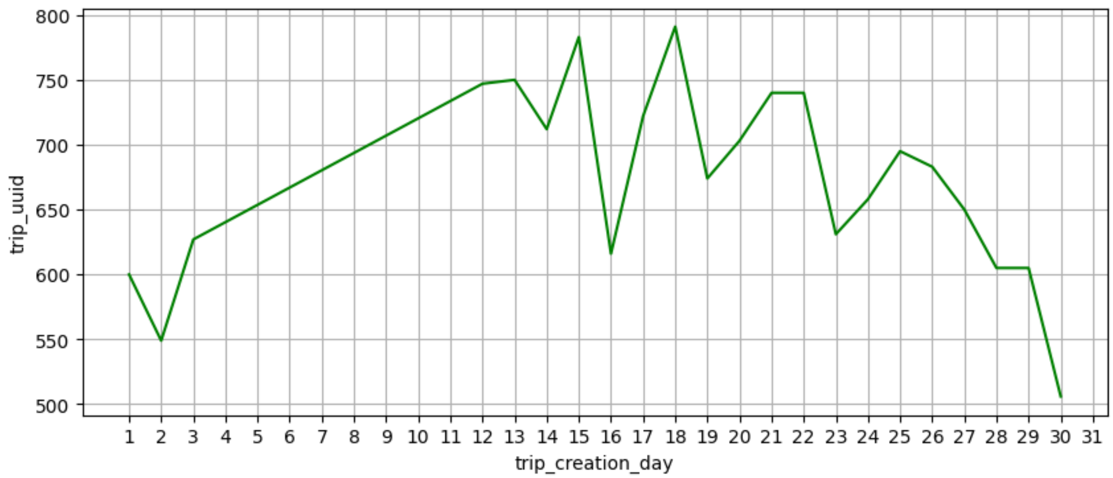
[304]:
```
trip_day = trip.groupby(by = 'trip_creation_day')['trip_uuid'].count().
    ↪to_frame().reset_index()
trip_day.head()
```

[304]:

	trip_creation_day	trip_uuid
0	1	600
1	2	549
2	3	627
3	12	747
4	13	750

[305]:
```
plt.figure(figsize = (10, 4))
sns.lineplot(data = trip_day, x = trip_day['trip_creation_day'], y =␣
    ↪trip_day['trip_uuid'],color='green')
plt.xticks(np.arange(1,32))
plt.grid('both')
plt.plot()
```

[305]: []



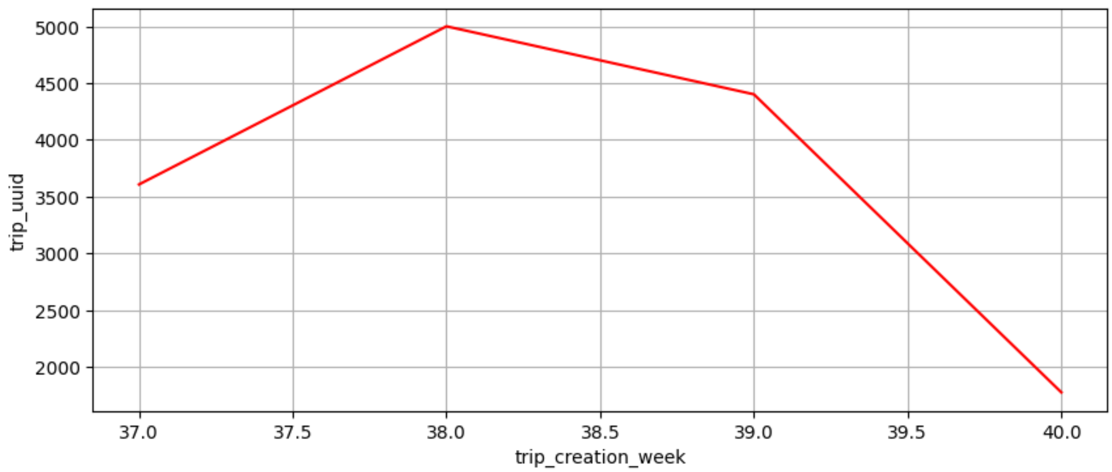
[306]:
```
trip_week = trip.groupby(by = 'trip_creation_week')['trip_uuid'].count().
    ↪to_frame().reset_index()
trip_week.head()
```

[306]:

	trip_creation_week	trip_uuid
0	37	3608
1	38	5001
2	39	4402
3	40	1776

[307]:
```
plt.figure(figsize = (10, 4))
sns.lineplot(data = trip_week, x = trip_week['trip_creation_week'], y =␣
    ↪trip_week['trip_uuid'],color='red')
plt.grid('both')
plt.plot()
```

[307]: []



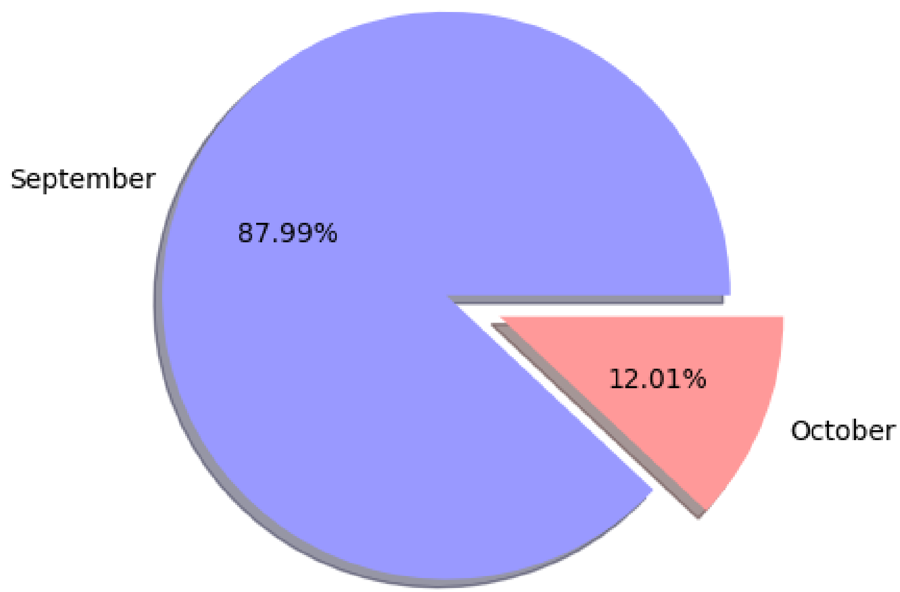
[308]:
```
trip_month = trip.groupby('trip_creation_month')['trip_uuid'].count().
    ↪to_frame().reset_index()
trip_month['percentage'] = np.round(trip_month['trip_uuid'] * 100/
    ↪trip_month['trip_uuid'].sum(), 2)
trip_month.head()
```

[308]:

	trip_creation_month	trip_uuid	percentage
0	9	13011	87.99
1	10	1776	12.01

[309]:
```
plt.pie(x = trip_month['trip_uuid'], labels = ['September', 'October'], explode
    ↪= [0.1, 0.1],shadow=True, autopct = '%.2f%%',colors=['#9999ff','#ff9999'])
plt.plot()
```

[309]: []



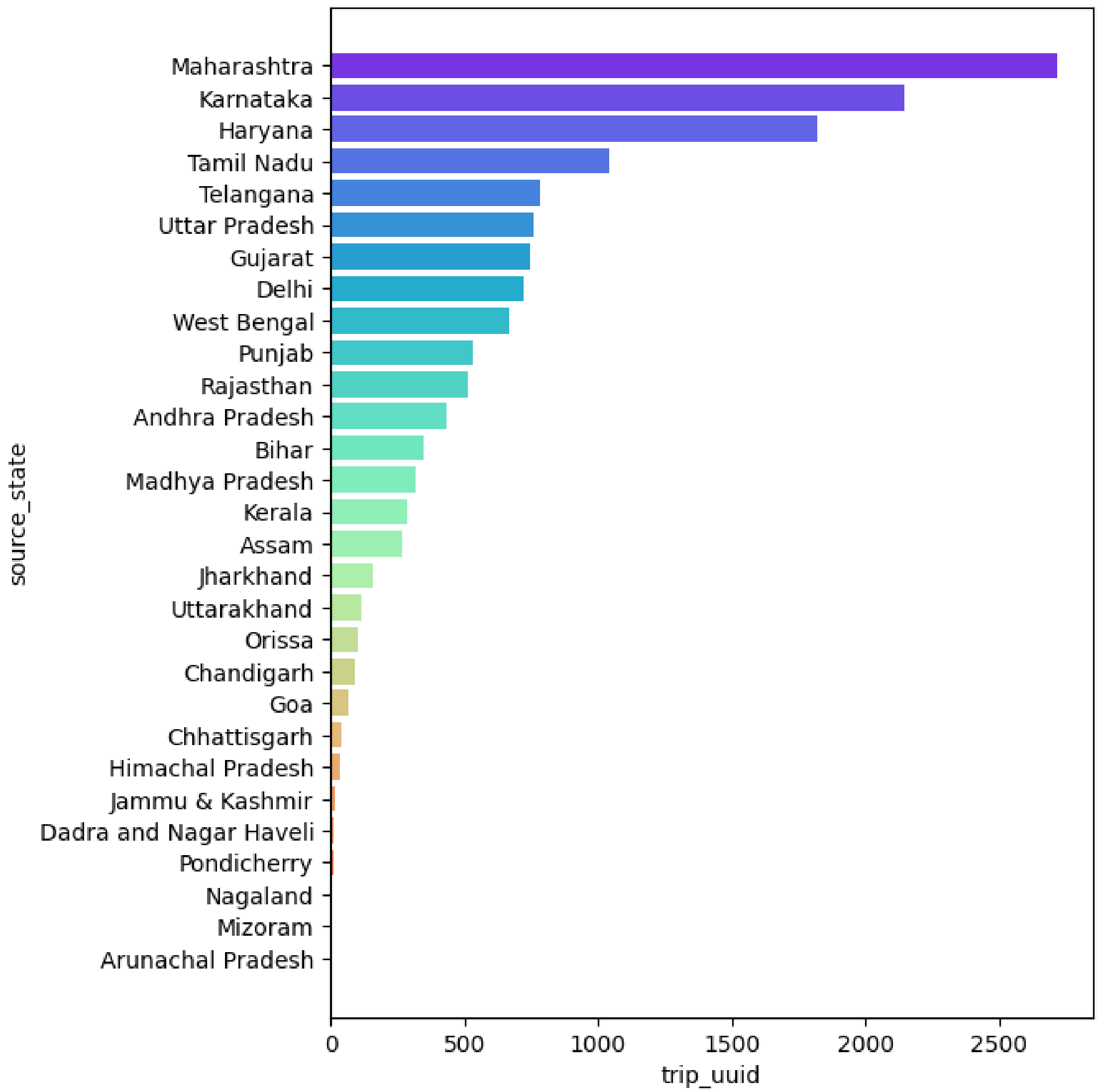
[310]:
```
trip_source_state = trip.groupby(by = 'source_state')['trip_uuid'].count().
 ↪to_frame().reset_index()
trip_source_state['percentage'] = np.round(trip_source_state['trip_uuid'] * 100/
 ↪ trip_source_state['trip_uuid'].sum(), 2)
trip_source_state = trip_source_state.sort_values(by = 'trip_uuid', ascending =␣
 ↪False)
trip_source_state.head()
```

[310]:

	source_state	trip_uuid	percentage
17	Maharashtra	2714	18.35
14	Karnataka	2143	14.49
10	Haryana	1823	12.33
24	Tamil Nadu	1039	7.03
25	Telangana	784	5.30

[311]:
```
plt.figure(figsize = (6, 8))
sns.barplot(data = trip_source_state, x = trip_source_state['trip_uuid'], y =␣
 ↪trip_source_state['source_state'],palette='rainbow')
plt.plot()
```

[311]: []



[376]:
```
trip_destination_state = trip.groupby(by = 'destination_state')['trip_uuid'].
↪count().to_frame().reset_index()
trip_destination_state['percentage'] = np.
↪round(trip_destination_state['trip_uuid'] * 100/␣
↪trip_destination_state['trip_uuid'].sum(), 2)
trip_destination_state = trip_destination_state.sort_values(by = 'trip_uuid',␣
↪ascending = False)
trip_destination_state.head()
```

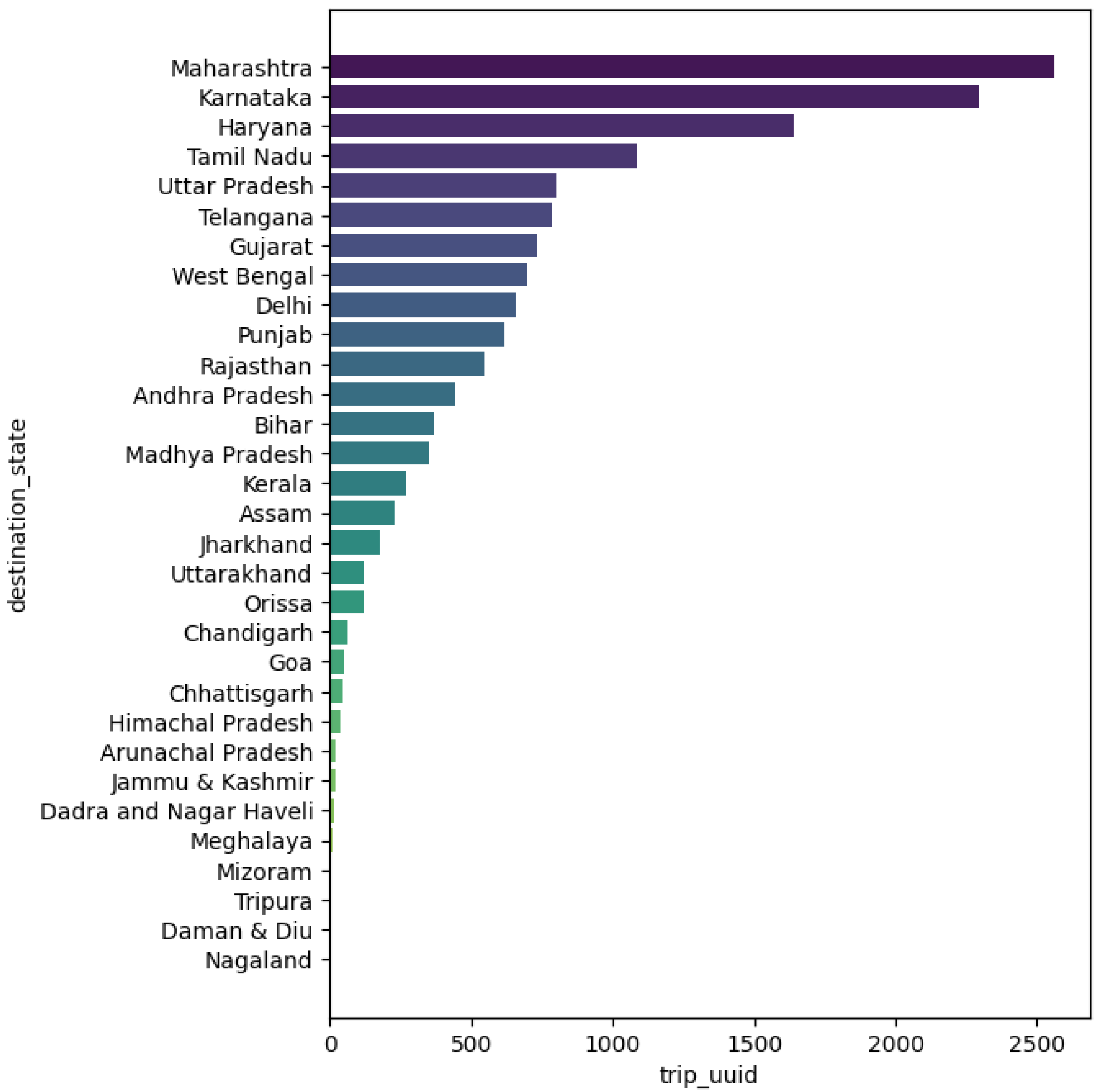
[376]:

	destination_state	trip_uuid	percentage
18	Maharashtra	2561	17.32
15	Karnataka	2294	15.51
11	Haryana	1640	11.09

```
25        Tamil Nadu       1084        7.33
28     Uttar Pradesh        805        5.44
```

[399]:
```
plt.figure(figsize = (6, 8))
sns.barplot(data = trip_destination_state, x =␣
↪trip_destination_state['trip_uuid'], y =␣
↪trip_destination_state['destination_state'],palette='viridis')
plt.plot()
```

[399]: []



[387]:
```
trip_source_city = trip.groupby('source_city')['trip_uuid'].count().to_frame().
↪reset_index()
```

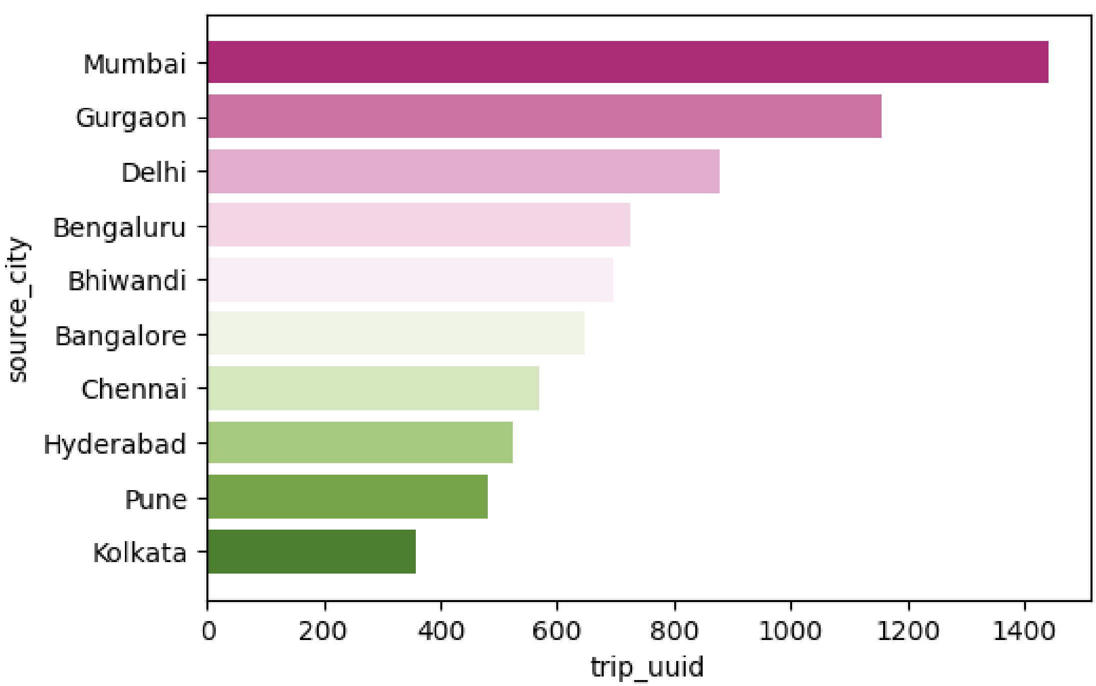
```
trip_source_city['percentage'] = np.round(trip_source_city['trip_uuid'] * 100/␣
↪trip_source_city['trip_uuid'].sum(), 2)
trip_source_city = trip_source_city.sort_values(by = 'trip_uuid', ascending =␣
↪False)[:10]
trip_source_city
```

[387]:

	source_city	trip_uuid	percentage
436	Mumbai	1442	9.75
235	Gurgaon	1154	7.80
167	Delhi	880	5.95
77	Bengaluru	726	4.91
98	Bhiwandi	697	4.71
56	Bangalore	648	4.38
134	Chennai	568	3.84
262	Hyderabad	524	3.54
514	Pune	480	3.25
354	Kolkata	356	2.41

[390]:
```
plt.figure(figsize = (6, 4))
sns.barplot(data = trip_source_city, x = trip_source_city['trip_uuid'], y =␣
↪trip_source_city['source_city'],palette='PiYG')
plt.plot()
```

[390]: []



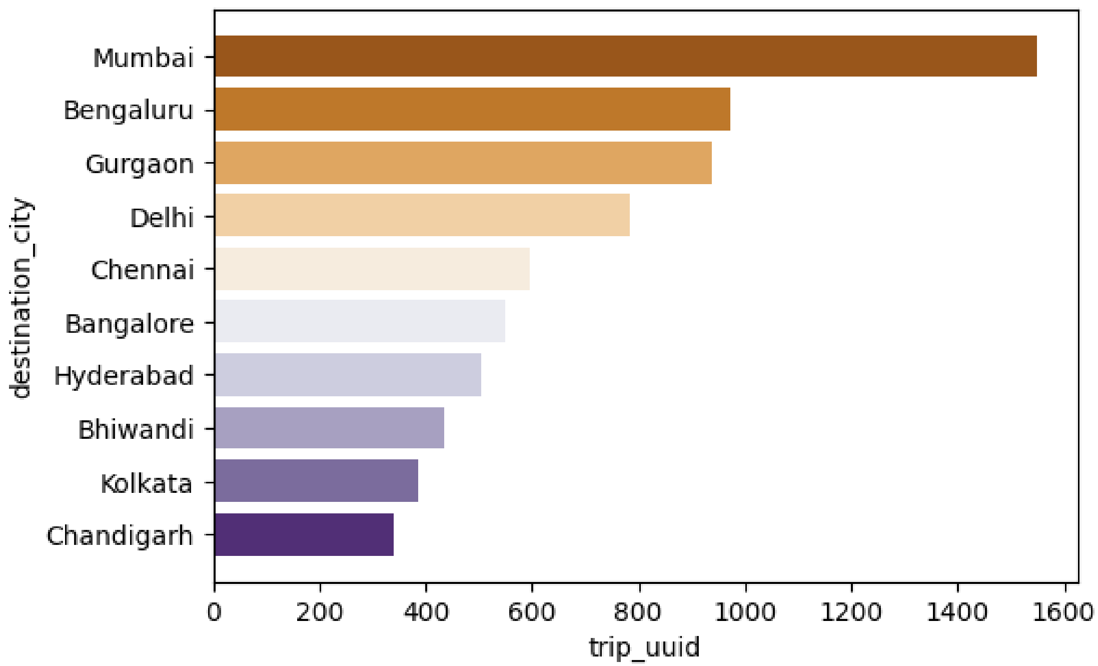
[388]:
```
trip_destination_city = trip.groupby('destination_city')['trip_uuid'].count().
    ↪to_frame().reset_index()
trip_destination_city['percentage'] = np.
    ↪round(trip_destination_city['trip_uuid'] * 100/␣
    ↪trip_destination_city['trip_uuid'].sum(), 2)
trip_destination_city = trip_destination_city.sort_values(by = 'trip_uuid',␣
    ↪ascending = False)[:10]
trip_destination_city
```

[388]:

	destination_city	trip_uuid	percentage
513	Mumbai	1548	10.47
96	Bengaluru	974	6.59
280	Gurgaon	936	6.33
199	Delhi	783	5.30
163	Chennai	595	4.02
72	Bangalore	551	3.73
305	Hyderabad	503	3.40
115	Bhiwandi	434	2.94
417	Kolkata	384	2.60
158	Chandigarh	339	2.29

[392]:
```
plt.figure(figsize = (6, 4))
sns.barplot(data = trip_destination_city, x =␣
    ↪trip_destination_city['trip_uuid'], y =␣
    ↪trip_destination_city['destination_city'],palette='PuOr')
plt.plot()
```

[392]: []



####Hypothesis Testing: 1. Perform hypothesis testing / visual analysis between :

```
a. actual_time aggregated value and OSRM time aggregated value.

b. actual_time aggregated value and segment actual time aggregated value.

c. OSRM distance aggregated value and segment OSRM distance aggregated value.

d. OSRM time aggregated value and segment OSRM time aggregated value.
```

Note: Aggregated values are the values you'll get after merging the rows on the basis of trip_uuid.

[312]:
```
trip[['actual_time', 'osrm_time']].describe()
```

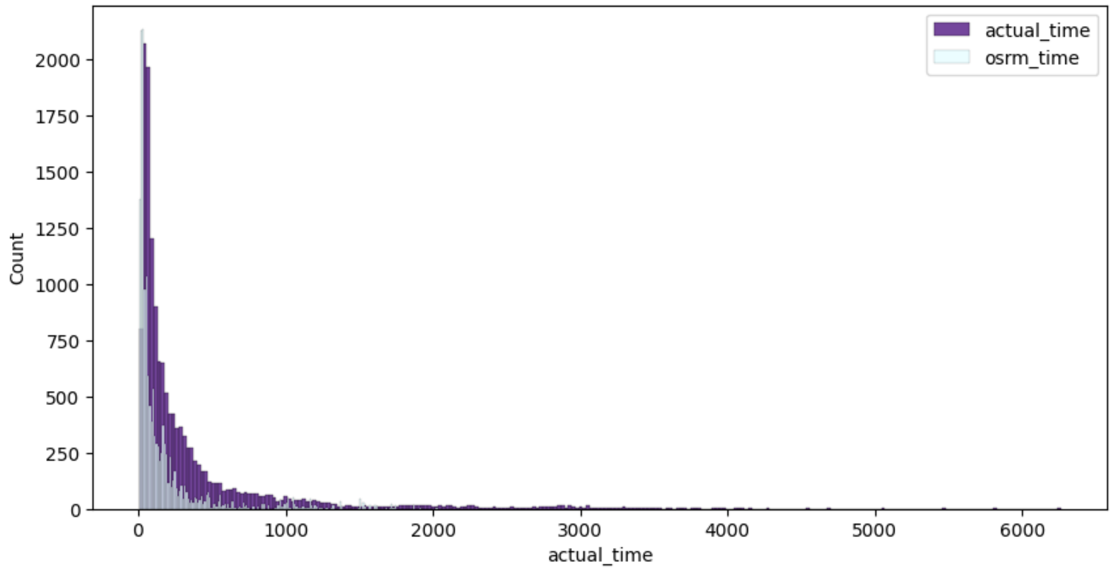
[312]:

	actual_time	osrm_time
count	14787.000000	14787.000000
mean	356.306012	160.990938
std	561.517936	271.459495
min	9.000000	6.000000
25%	67.000000	29.000000
50%	148.000000	60.000000
75%	367.000000	168.000000
max	6265.000000	2032.000000

[400]:
```
plt.figure(figsize = (10, 5))
sns.histplot(trip['actual_time'], color = '#45087b')
```

```
sns.histplot(trip['osrm_time'], color = '#e5fdff')
plt.legend(['actual_time', 'osrm_time'])
plt.plot()
```

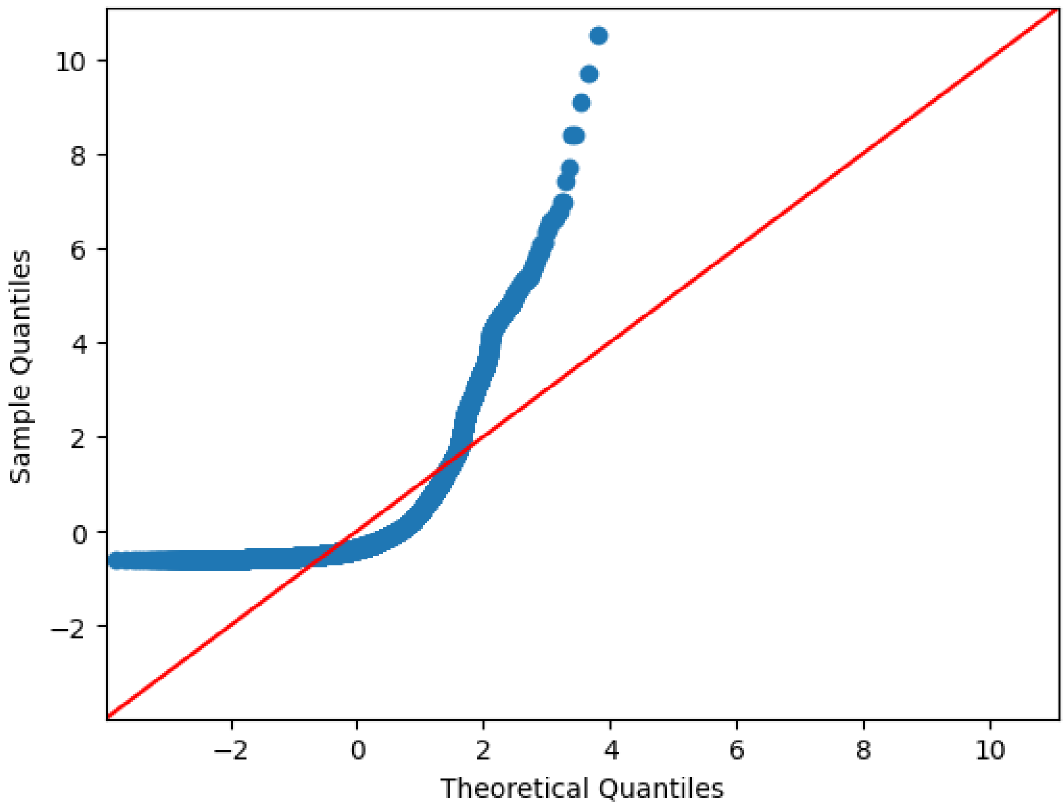
[400]: []



[314]:
```
import statsmodels.api as sm
```

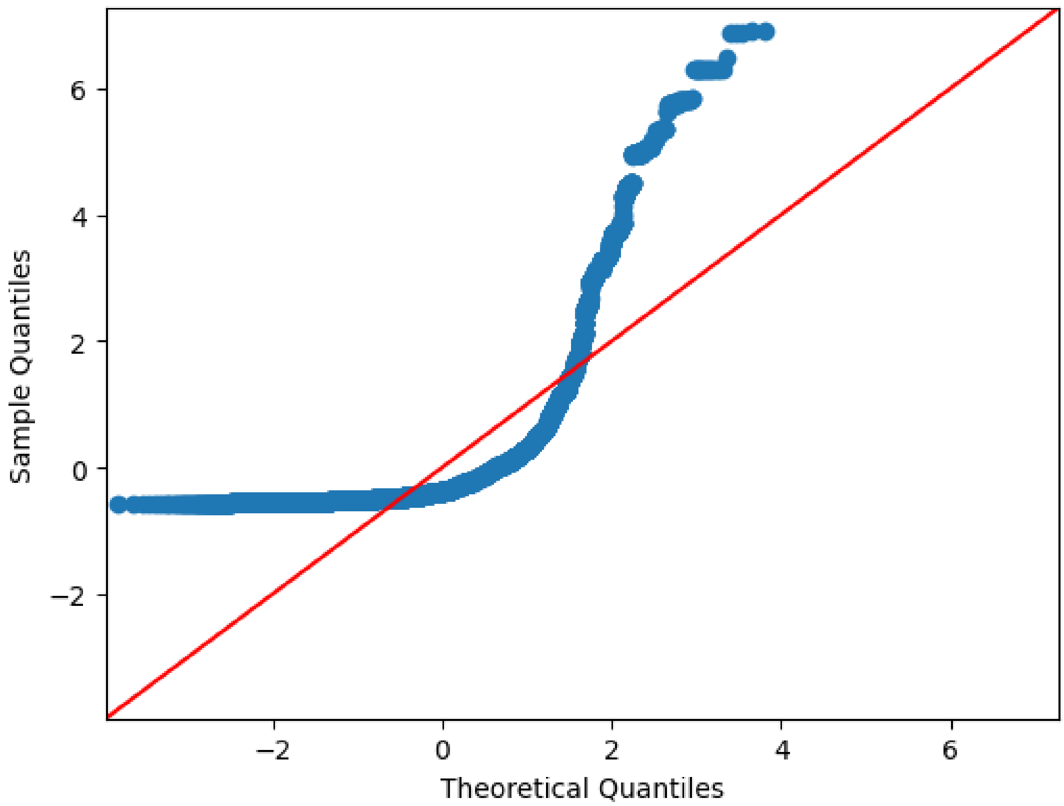
[315]:
```
plt.figure(figsize = (2, 2))
sm.qqplot(trip['actual_time'],fit=True,line='45')
plt.show()
```

```
<Figure size 200x200 with 0 Axes>
```



[316]:
```
plt.figure(figsize = (2, 2))
sm.qqplot(trip['osrm_time'],fit=True,line='45')
plt.show()
```

<Figure size 200x200 with 0 Axes>



Shapiro Test: (at alpha=0.05)

H0: Actual time follows Normal Distribution

Ha: Actual time does not follow Normal Distribution

[317]:
```
tstat,pval=shapiro(trip['actual_time'])
if pval<0.05:
  print("P-value : " ,pval)
  print("Actual time does not follow Normal Distribution")
else:
  print("Actual time follows Normal Distribution")
```

```
P-value :  0.0
Actual time does not follow Normal Distribution
```

H0: osrm time follows Normal Distribution

Ha: osrm time does not follow Normal Distribution

[318]:
```
tstat,pval=shapiro(trip['osrm_time'])
if pval<0.05:
  print("P-value : " ,pval)
  print("osrm time does not follow Normal Distribution")
```

```
else:
  print("osrm time follows Normal Distribution")
```

```
P-value :  0.0
osrm time does not follow Normal Distribution
```

Levene's test for checking homogeneity:

H0: Actual time and osrm time have homogenous variances

Ha: Actual time and osrm time do not have homogenous variances

[319]:
```
tstat,pval=levene(trip['actual_time'],trip['osrm_time'])
if pval<0.05:
  print("P-value : " ,pval)
  print("Actual time and osrm time do not have homogenous variances")
else:
  print("Actual time and osrm time have homogenous variances")
```

```
P-value :  8.743536461316657e-219
Actual time and osrm time do not have homogenous variances
```

Since the data columns do not follow normal distribution, non-parametric test is needed to be used. Using Kruskal Wallis Test to check if actual time and osrm time are similar.

[320]:
```
tstat,pval=kruskal(trip['actual_time'],trip['osrm_time'])
if pval<0.05:
  print("P-value : " ,pval)
  print("Actual time and osrm time are significantly different")
else:
  print("Actual time and osrm time are similar")
```

```
P-value :  0.0
Actual time and osrm time are significantly different
```

[321]:
```
trip[['actual_time', 'segment_actual_time']].describe()
```

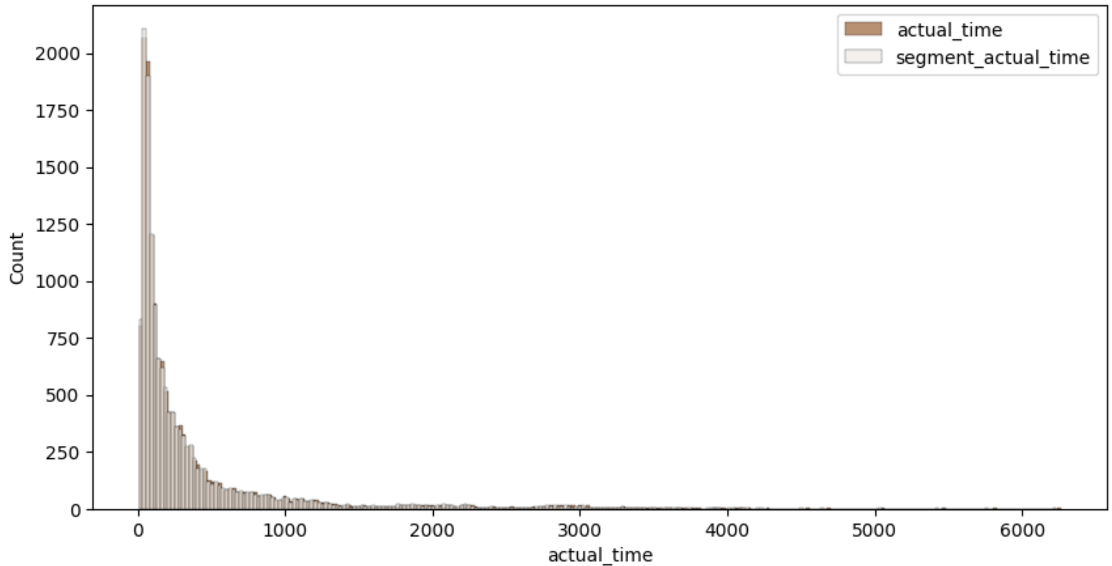
[321]:

	actual_time	segment_actual_time
count	14787.000000	14787.000000
mean	356.306012	353.059174
std	561.517936	556.365911
min	9.000000	9.000000
25%	67.000000	66.000000
50%	148.000000	147.000000
75%	367.000000	364.000000
max	6265.000000	6230.000000

[401]:
```
plt.figure(figsize = (10, 5))
sns.histplot(trip['actual_time'], color = '#a16b43')
sns.histplot(trip['segment_actual_time'], color = '#f0ece7')
```

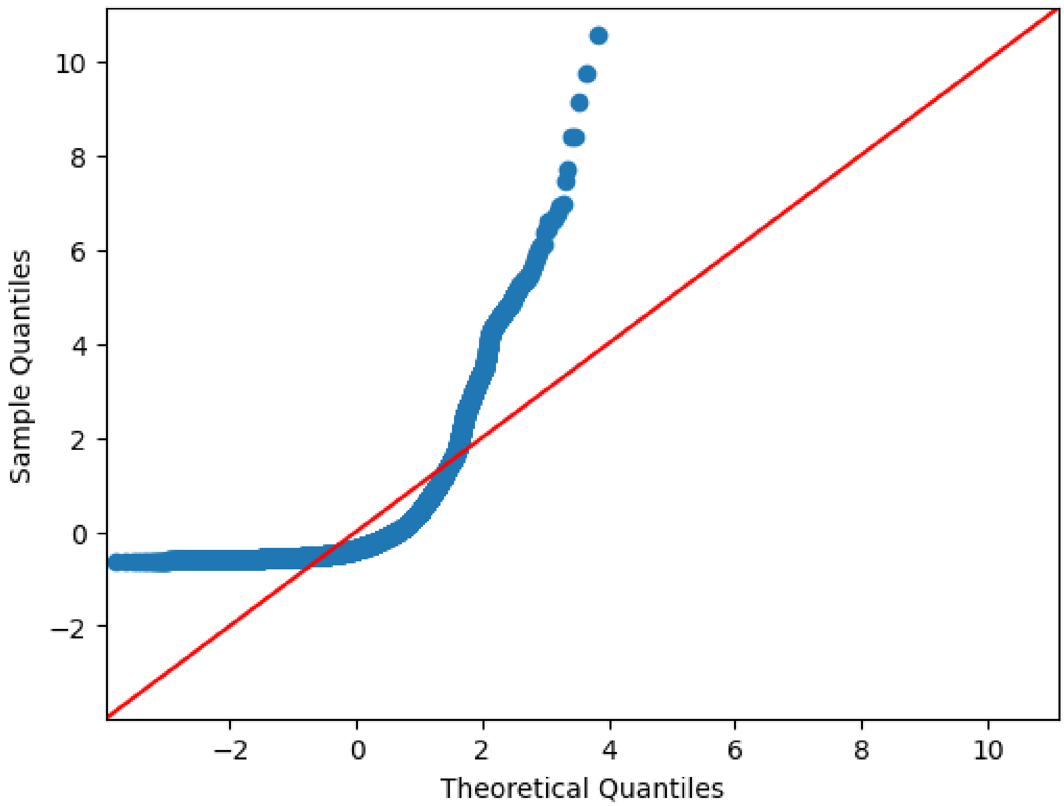
```
plt.legend(['actual_time', 'segment_actual_time'])
plt.plot()
```

[401]: []



[403]:
```
plt.figure(figsize = (2, 2))
sm.qqplot(trip['segment_actual_time'],fit=True,line='45')
plt.show()
```

<Figure size 200x200 with 0 Axes>



Shapiro Test: (at alpha=0.05)

H0: Segment Actual time follows Normal Distribution

Ha: Segment Actual time does not follow Normal Distribution

[324]:
```
tstat,pval=shapiro(trip['segment_actual_time'])
if pval<0.05:
  print("P-value : " ,pval)
  print("Segment Actual time does not follow Normal Distribution")
else:
  print("Segment Actual time follows Normal Distribution")
```

```
P-value :  0.0
Segment Actual time does not follow Normal Distribution
```

Levene's test for checking homogeneity:

H0: Actual time and Segment Actual time have homogenous variances

Ha: Actual time and Segment Actual time do not have homogenous variances

[325]:
```
tstat,pval=levene(trip['actual_time'],trip['segment_actual_time'])
if pval<0.05:
```

```
  print("P-value : " ,pval)
  print("Actual time and Segment Actual time do not have homogenous variances")
else:
  print("Actual time and Segment Actual time have homogenous variances")
```

```
Actual time and Segment Actual time have homogenous variances
```

Since the data columns do not follow normal distribution, non-parametric test is needed to be used. Using Kruskal Wallis Test to check if actual time and segment actual time are similar.

[326]:
```
tstat,pval=kruskal(trip['actual_time'],trip['segment_actual_time'])
if pval<0.05:
  print("P-value : " ,pval)
  print("Actual time and Segment Actual time are significantly different")
else:
  print("Actual time and Segment Actual time are similar")
```

```
Actual time and Segment Actual time are similar
```

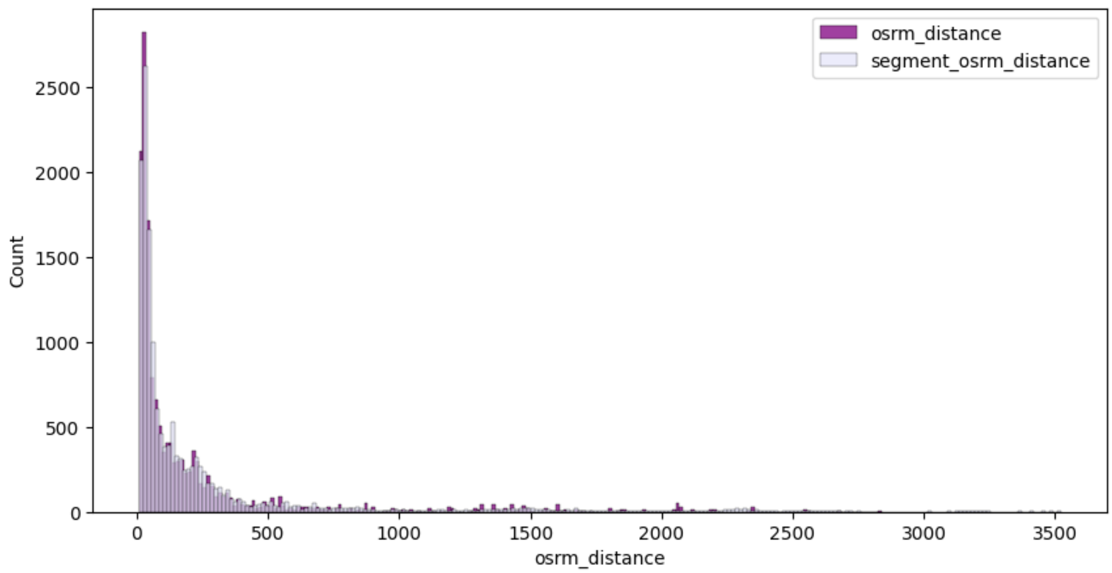
[327]:
```
trip[['osrm_distance', 'segment_osrm_distance']].describe()
```

[327]:

	osrm_distance	segment_osrm_distance
count	14787.000000	14787.000000
mean	203.887411	222.705466
std	370.565564	416.846279
min	9.072900	9.072900
25%	30.756900	32.578850
50%	65.302800	69.784200
75%	206.644200	216.560600
max	2840.081000	3523.632400

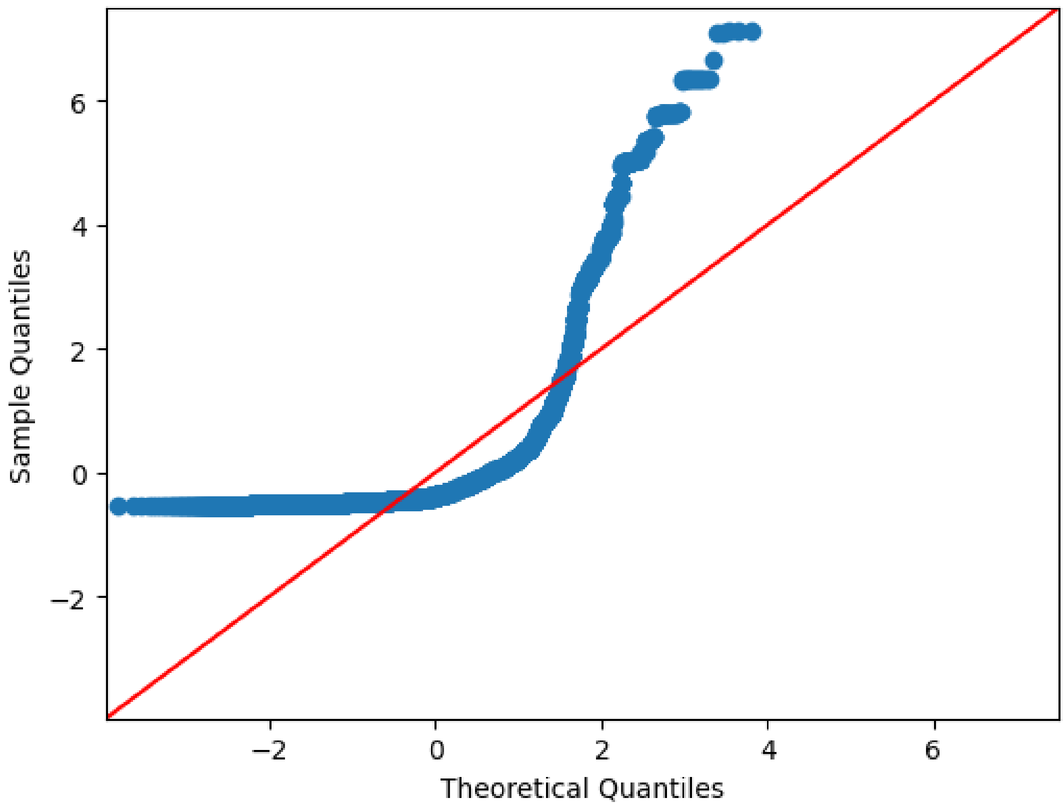
[404]:
```
plt.figure(figsize = (10, 5))
sns.histplot(trip['osrm_distance'], color = '#800080')
sns.histplot(trip['segment_osrm_distance'], color = '#e6e6fa')
plt.legend(['osrm_distance', 'segment_osrm_distance'])
plt.plot()
```

[404]: []



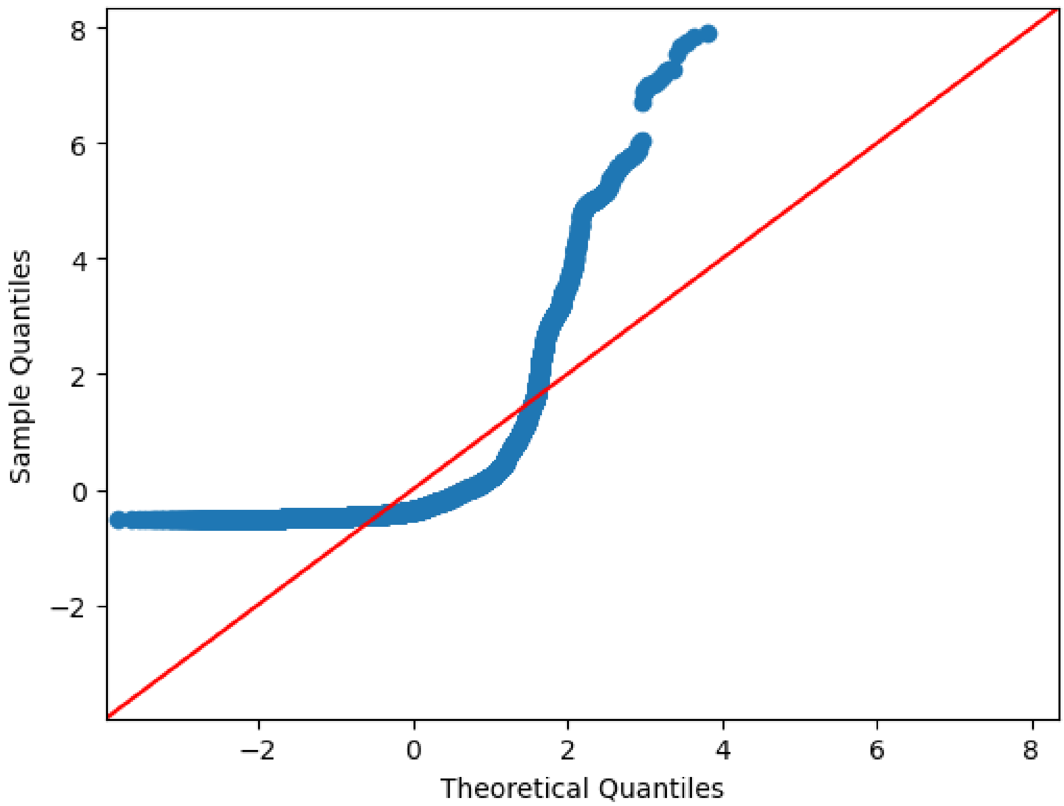
[329]:
```
plt.figure(figsize = (2, 2))
sm.qqplot(trip['osrm_distance'],fit=True,line='45')
plt.show()
```

```
<Figure size 200x200 with 0 Axes>
```



[330]:
```
plt.figure(figsize = (2, 2))
sm.qqplot(trip['segment_osrm_distance'],fit=True,line='45')
plt.show()
```

```
<Figure size 200x200 with 0 Axes>
```



Shapiro Test: (at alpha=0.05)

H0: osrm distance follows Normal Distribution

Ha: osrm distance does not follow Normal Distribution

[331]:
```
tstat,pval=shapiro(trip['osrm_distance'])
if pval<0.05:
  print("P-value : " ,pval)
  print("osrm distance does not follow Normal Distribution")
else:
  print("osrm distance follows Normal Distribution")
```

```
P-value :  0.0
osrm distance does not follow Normal Distribution
```

Shapiro Test: (at alpha=0.05)

H0: segment osrm distance follows Normal Distribution

Ha: segment osrm distance does not follow Normal Distribution

[332]:
```
tstat,pval=shapiro(trip['segment_osrm_distance'])
if pval<0.05:
```

```
    print("P-value : " ,pval)
    print("Segment osrm distance does not follow Normal Distribution")
else:
    print("Segment osrm distance follows Normal Distribution")
```

```
P-value :  0.0
Segment osrm distance does not follow Normal Distribution
```

Levene's test for checking homogeneity:

H0: osrm distance and segment osrm distance have homogenous variances

Ha: osrm distance and segment osrm distance do not have homogenous variances

[333]:
```
tstat,pval=levene(trip['osrm_distance'],trip['segment_osrm_distance'])
if pval<0.05:
    print("P-value : " ,pval)
    print("osrm distance and segment osrm distance do not have homogenous␣
 ↪variances")
else:
    print("osrm distance and segment osrm distance have homogenous variances")
```

```
P-value :  0.00022171213513990103
osrm distance and segment osrm distance do not have homogenous variances
```

Since the data columns do not follow normal distribution, non-parametric test is needed to be used. Using Kruskal Wallis Test to check if osrm distance and segment osrm distance are similar.

[334]:
```
tstat,pval=kruskal(trip['osrm_distance'],trip['segment_osrm_distance'])
if pval<0.05:
    print("P-value : " ,pval)
    print("osrm distance and segment osrm distance are significantly different")
else:
    print("osrm distance and segment osrm distance are similar")
```

```
P-value :  1.00010530431339998e-06
osrm distance and segment osrm distance are significantly different
```

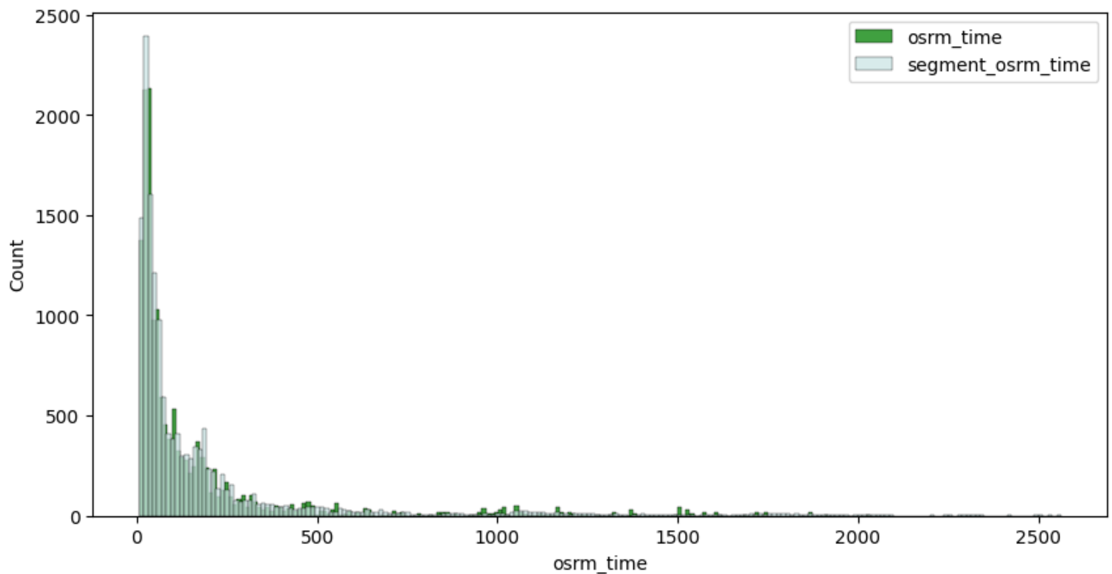
[335]:
```
trip[['osrm_time', 'segment_osrm_time']].describe()
```

[335]:

	osrm_time	segment_osrm_time
count	14787.000000	14787.000000
mean	160.990938	180.511598
std	271.459495	314.679279
min	6.000000	6.000000
25%	29.000000	30.000000
50%	60.000000	65.000000
75%	168.000000	184.000000
max	2032.000000	2564.000000

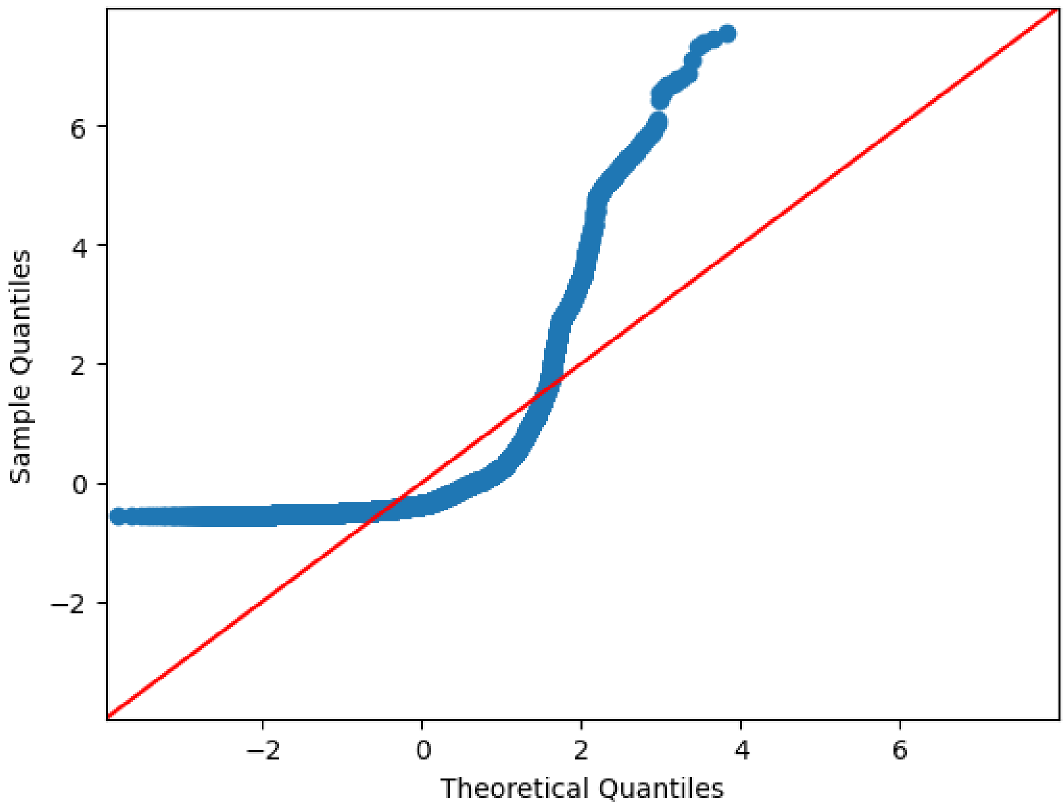
[405]:
```
plt.figure(figsize = (10, 5))
sns.histplot(trip['osrm_time'], color = 'green')
sns.histplot(trip['segment_osrm_time'], color = '#cce5e5')
plt.legend(['osrm_time', 'segment_osrm_time'])
plt.plot()
```

[405]: []



[337]:
```
plt.figure(figsize = (2, 2))
sm.qqplot(trip['segment_osrm_time'],fit=True,line='45')
plt.show()
```

<Figure size 200x200 with 0 Axes>



Shapiro Test: (at alpha=0.05)

H0: segment osrm time follows Normal Distribution

Ha: segment osrm time does not follow Normal Distribution

[338]:
```
tstat,pval=shapiro(trip['segment_osrm_time'])
if pval<0.05:
  print("P-value : " ,pval)
  print("Segment osrm time does not follow Normal Distribution")
else:
  print("Segment osrm time follows Normal Distribution")
```

```
P-value :  0.0
Segment osrm time does not follow Normal Distribution
```

Levene's test for checking homogeneity:

H0: osrm time and segment osrm time have homogenous variances

Ha: osrm time and segment osrm time do not have homogenous variances

[339]:
```
tstat,pval=levene(trip['osrm_time'],trip['segment_osrm_time'])
if pval<0.05:
```

```
  print("P-value : " ,pval)
  print("osrm time and segment osrm time do not have homogenous variances")
else:
  print("osrm time and segment osrm time have homogenous variances")
```

```
P-value :  9.250556006347759e-08
osrm time and segment osrm time do not have homogenous variances
```

Since the data columns do not follow normal distribution, non-parametric test is needed to be used. Using Kruskal Wallis Test to check if osrm time and segment osrm time are similar.

[340]:
```
tstat,pval=kruskal(trip['osrm_time'],trip['segment_osrm_time'])
if pval<0.05:
  print("P-value : " ,pval)
  print("osrm time and segment osrm time are significantly different")
else:
  print("osrm time and segment osrm time are similar")
```

```
P-value :  2.48934342075211e-08
osrm time and segment osrm time are significantly different
```

[341]:
```
numerical_columns = ['od_total_time','segment_actual_time',␣
 ↪'segment_osrm_time', 'segment_osrm_distance','start_scan_to_end_scan',␣
 ↪'actual_distance_to_destination', 'actual_time', 'osrm_time',␣
 ↪'osrm_distance']
trip[numerical_columns].describe().T
```

[341]:

	count	mean	std	min
od_total_time	14787.0	530.313468	658.415416	23.460000
segment_actual_time	14787.0	353.059174	556.365911	9.000000
segment_osrm_time	14787.0	180.511598	314.679279	6.000000
segment_osrm_distance	14787.0	222.705466	416.846279	9.072900
start_scan_to_end_scan	14787.0	529.429025	658.254936	23.000000
actual_distance_to_destination	14787.0	164.090196	305.502982	9.002461
actual_time	14787.0	356.306012	561.517936	9.000000
osrm_time	14787.0	160.990938	271.459495	6.000000
osrm_distance	14787.0	203.887411	370.565564	9.072900

	25%	50%	75%
od_total_time	149.695000	279.710000	633.535000
segment_actual_time	66.000000	147.000000	364.000000
segment_osrm_time	30.000000	65.000000	184.000000
segment_osrm_distance	32.578850	69.784200	216.560600
start_scan_to_end_scan	149.000000	279.000000	632.000000
actual_distance_to_destination	22.777099	48.287894	163.591258
actual_time	67.000000	148.000000	367.000000
osrm_time	29.000000	60.000000	168.000000
osrm_distance	30.756900	65.302800	206.644200

```
                                         max
od_total_time                    7898.550000
segment_actual_time              6230.000000
segment_osrm_time                2564.000000
segment_osrm_distance            3523.632400
start_scan_to_end_scan           7898.000000
actual_distance_to_destination   2186.531787
actual_time                      6265.000000
osrm_time                        2032.000000
osrm_distance                    2840.081000
```

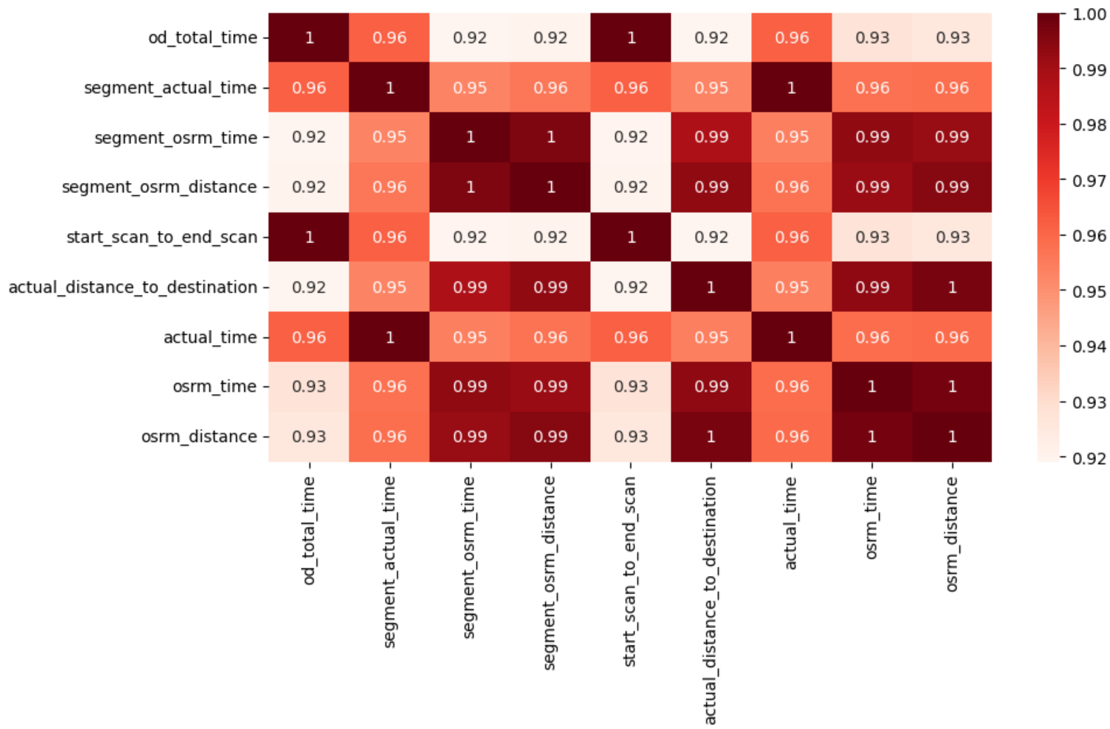
[393]:
```python
trip_corr = trip[numerical_columns].corr()
trip_corr
```

[393]:
```
                                od_total_time  segment_actual_time  \
od_total_time                        1.000000             0.961582
segment_actual_time                  0.961582             1.000000
segment_osrm_time                    0.919358             0.953214
segment_osrm_distance                0.920099             0.956293
start_scan_to_end_scan               0.999999             0.961634
actual_distance_to_destination       0.919074             0.952987
actual_time                          0.961560             0.999989
osrm_time                            0.927416             0.957955
osrm_distance                        0.925126             0.958540

                                segment_osrm_time  segment_osrm_distance  \
od_total_time                            0.919358               0.920099
segment_actual_time                      0.953214               0.956293
segment_osrm_time                        1.000000               0.996098
segment_osrm_distance                    0.996098               1.000000
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

                                start_scan_to_end_scan  \
od_total_time                                 0.999999
segment_actual_time                           0.961634
segment_osrm_time                             0.919429
segment_osrm_distance                         0.920191
start_scan_to_end_scan                        1.000000
actual_distance_to_destination                0.919159
actual_time                                   0.961612
osrm_time                                     0.927471
osrm_distance                                 0.925205
```

```
                                 actual_distance_to_destination  actual_time  \
od_total_time                                          0.919074     0.961560
segment_actual_time                                    0.952987     0.999989
segment_osrm_time                                      0.987542     0.954044
segment_osrm_distance                                  0.993068     0.957151
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

                                 osrm_time  osrm_distance
od_total_time                     0.927416       0.925126
segment_actual_time               0.957955       0.958540
segment_osrm_time                 0.993263       0.991802
segment_osrm_distance             0.991624       0.994712
start_scan_to_end_scan            0.927471       0.925205
actual_distance_to_destination    0.993568       0.997268
actual_time                       0.958781       0.959398
osrm_time                         1.000000       0.997588
osrm_distance                     0.997588       1.000000
```

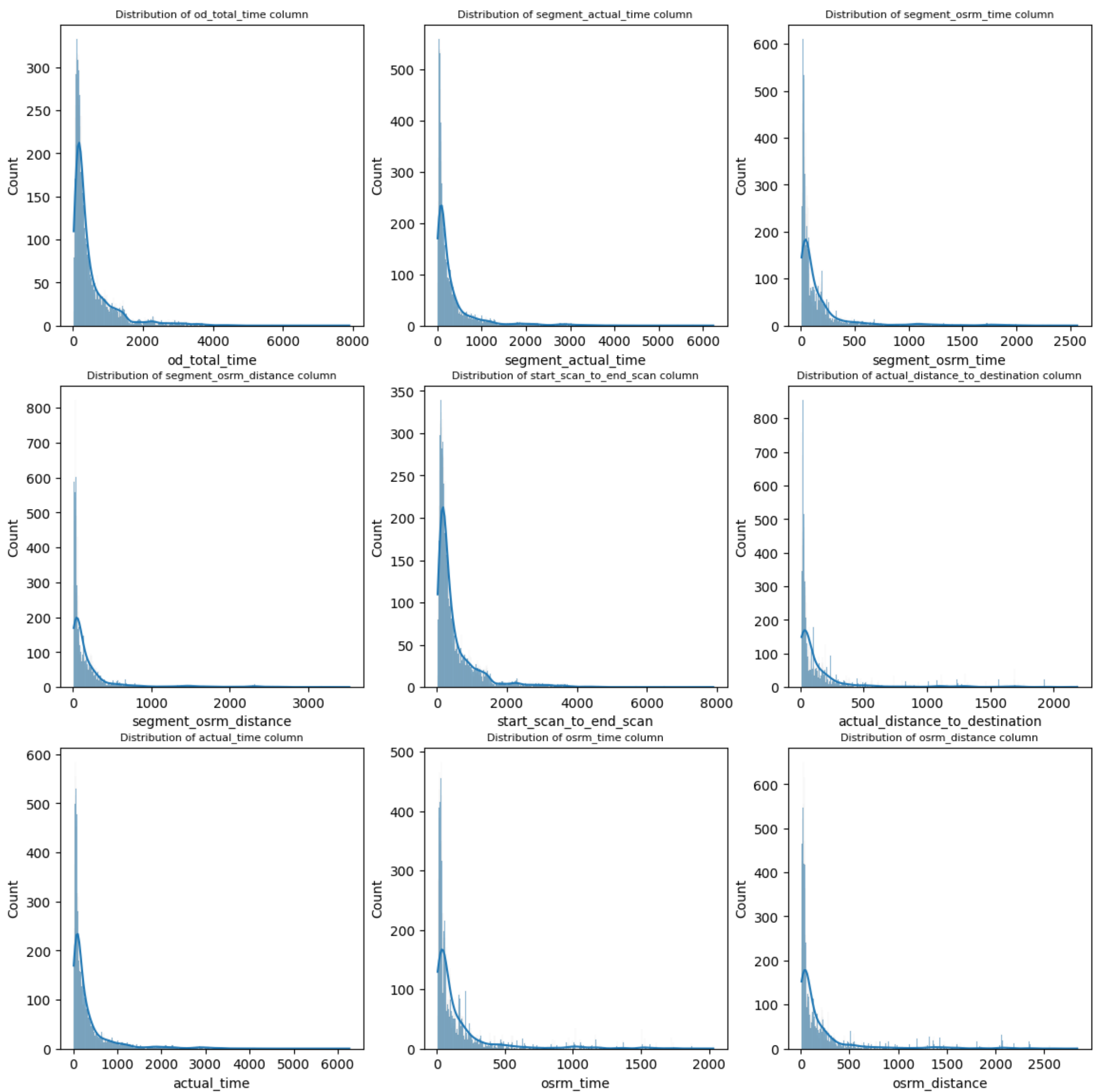
[398]:
```
plt.figure(figsize = (10, 5))
sns.heatmap(data = trip_corr, annot = True,cmap='Reds')
plt.plot()
```

[398]: []



[406]:

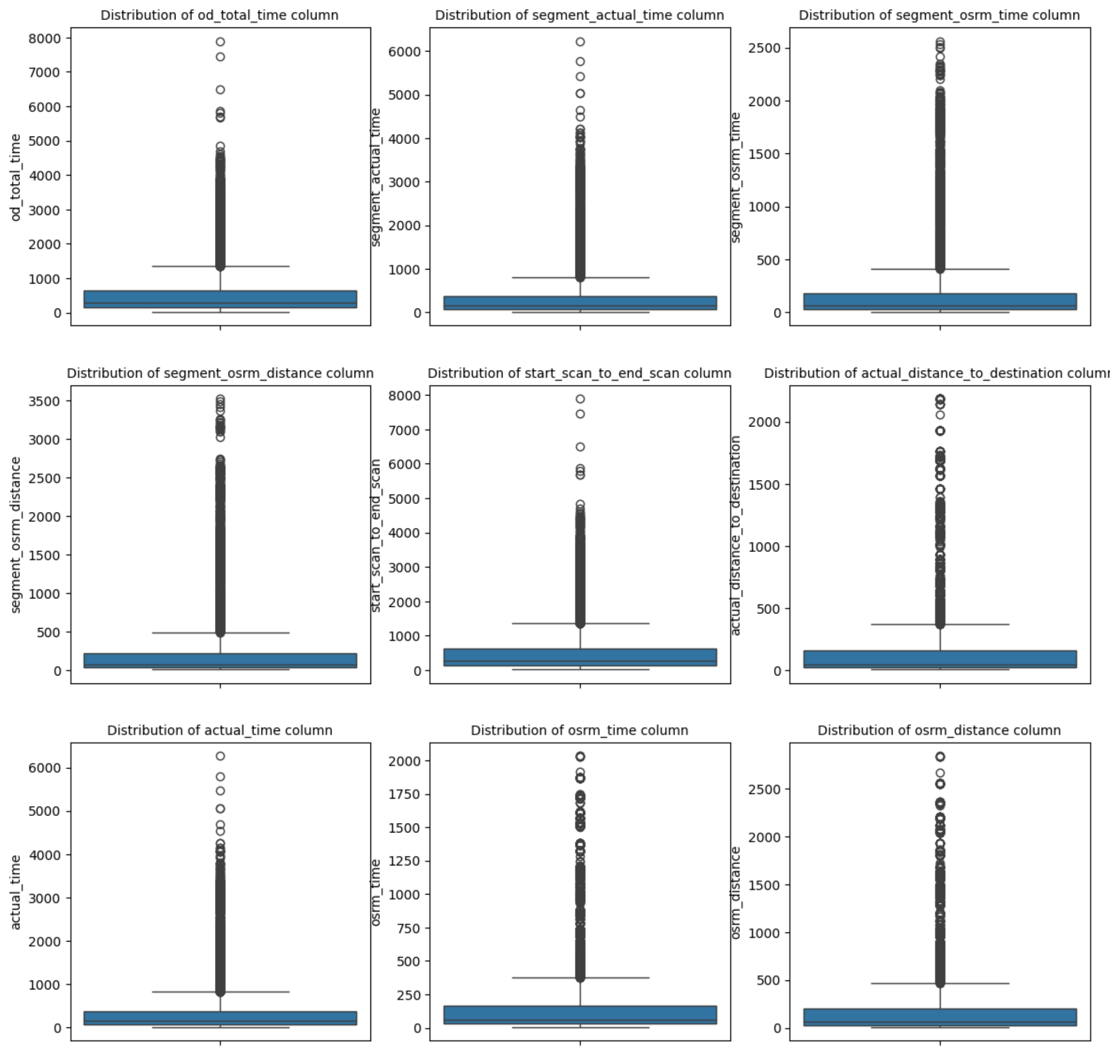
```
plt.figure(figsize = (14, 14))
for i in range(len(numerical_columns)):
 plt.subplot(3, 3, i + 1)
 sns.histplot(trip[numerical_columns[i]], bins = 1000, kde = True)
 plt.title(f"Distribution of {numerical_columns[i]} column",fontsize=8)
 plt.plot()
```



####Outlier Detection & Treatment

1. Find any existing outliers in numerical features.
2. Visualize the outlier values using Boxplot.
3. Handle the outliers using the IQR method.

[343]:
```
plt.figure(figsize = (14, 14))
for i in range(len(numerical_columns)):
 plt.subplot(3, 3, i + 1)
 sns.boxplot(trip[numerical_columns[i]])
 plt.title(f"Distribution of {numerical_columns[i]} column",fontsize=10)
 plt.plot()
```



[344]:
```
for i in numerical_columns:
  Q1 = np.quantile(trip[i], 0.25)
  Q3 = np.quantile(trip[i], 0.75)
  IQR = Q3 - Q1
  LB = Q1 - 1.5 * IQR
  UB = Q3 + 1.5 * IQR
  outliers = trip.loc[(trip[i] < LB) | (trip[i] > UB)]
  print('Column :', i)
  print(f'Q1 : {Q1}')
  print(f'Q3 : {Q3}')
  print(f'IQR : {IQR}')
  print(f'Lower Boundary : {LB}')
  print(f'Upper Boundary : {UB}')
  print(f'Outlier Count : {outliers.shape[0]}')
  print('*'*100)
```

```
Column : od_total_time
Q1 : 149.695
Q3 : 633.535
IQR : 483.84
Lower Boundary : -576.065
Upper Boundary : 1359.295
Outlier Count : 1275
********************************************************************************
********************
Column : segment_actual_time
Q1 : 66.0
Q3 : 364.0
IQR : 298.0
Lower Boundary : -381.0
Upper Boundary : 811.0
Outlier Count : 1644
********************************************************************************
********************
Column : segment_osrm_time
Q1 : 30.0
Q3 : 184.0
IQR : 154.0
Lower Boundary : -201.0
Upper Boundary : 415.0
Outlier Count : 1485
********************************************************************************
********************
Column : segment_osrm_distance
Q1 : 32.57885
Q3 : 216.5606
IQR : 183.98174999999998
Lower Boundary : -243.393775
Upper Boundary : 492.533225
Outlier Count : 1550
********************************************************************************
********************
Column : start_scan_to_end_scan
Q1 : 149.0
Q3 : 632.0
IQR : 483.0
Lower Boundary : -575.5
Upper Boundary : 1356.5
Outlier Count : 1282
********************************************************************************
********************
Column : actual_distance_to_destination
Q1 : 22.777098943155323
Q3 : 163.5912581579725
```

```
IQR : 140.81415921481718
Lower Boundary : -188.44413987907043
Upper Boundary : 374.81249698019826
Outlier Count : 1452
********************************************************************************
********************
Column : actual_time
Q1 : 67.0
Q3 : 367.0
IQR : 300.0
Lower Boundary : -383.0
Upper Boundary : 817.0
Outlier Count : 1646
********************************************************************************
********************
Column : osrm_time
Q1 : 29.0
Q3 : 168.0
IQR : 139.0
Lower Boundary : -179.5
Upper Boundary : 376.5
Outlier Count : 1506
********************************************************************************
********************
Column : osrm_distance
Q1 : 30.7569
Q3 : 206.6442
IQR : 175.8873
Lower Boundary : -233.07405000000003
Upper Boundary : 470.47515000000004
Outlier Count : 1522
********************************************************************************
********************
```

[345]:

```
trip = trip[~((trip[numerical_columns] < LB) | (trip[numerical_columns] > UB)).
 ↪any(axis=1)]
trip = trip.reset_index(drop=True)
```

[346]:

```
trip
```

[346]:

```
          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 00:02:34.161600
3     training 2018-09-12 00:04:22.011653
4     training 2018-09-12 00:04:28.263977
…        …                         …
```

```
9986      test 2018-10-03 23:55:56.258533
9987      test 2018-10-03 23:57:23.863155
9988      test 2018-10-03 23:57:44.429324
9989      test 2018-10-03 23:59:14.390954
9990      test 2018-10-03 23:59:42.701692

                                    route_schedule_uuid route_type  \
0     thanos::sroute:3a1b0ab2-bb0b-4c53-8c59-eb2a2c0…    Carting
1     thanos::sroute:f0176492-a679-4597-8332-bbd1c7f…    Carting
2     thanos::sroute:9bf03170-d0a2-4a3f-aa4d-9aaab3d…    Carting
3     thanos::sroute:a97698cc-846e-41a7-916b-88b1741…    Carting
4     thanos::sroute:d5b71ae9-a11a-4f52-bcb7-274b65e…    Carting
…                                                  …         …
9986  thanos::sroute:8a120994-f577-4491-9e4b-b7e4a14…    Carting
9987  thanos::sroute:b30e1ec3-3bfa-4bd2-a7fb-3b75769…    Carting
9988  thanos::sroute:5609c268-e436-4e0a-8180-3db4a74…    Carting
9989  thanos::sroute:c5f2ba2c-8486-4940-8af6-d1d2a6a…    Carting
9990  thanos::sroute:412fea14-6d1f-4222-8a5f-a517042…        FTL

                   trip_uuid  od_total_time  segment_actual_time  \
0     trip-153671042288605164         181.61                141.0
1     trip-153671046011330457         100.49                 59.0
2     trip-153671055416136166         190.49                 60.0
3     trip-153671066201138152          98.01                 24.0
4     trip-153671066826362165         146.84                 64.0
…                         …            …                  …
9986  trip-153861095625827784         258.03                 82.0
9987  trip-153861104386292051          60.59                 21.0
9988  trip-153861106442901555         422.12                281.0
9989  trip-153861115439069069         348.52                258.0
9990  trip-153861118270144424         354.40                274.0

      segment_osrm_time  segment_osrm_distance source_center  …  \
0                  65.0                84.1894  IND561203AAB  …
1                  16.0                19.8766  IND400072AAB  …
2                  23.0                28.0647  IND600056AAA  …
3                  13.0                12.0184  IND600044AAD  …
4                  34.0                28.9203  IND560043AAC  …
…                   …                    …            …   …
9986               62.0                64.8551  IND160002AAC  …
9987               11.0                16.0883  IND121004AAB  …
9988               88.0               104.8866  IND208006AAA  …
9989              221.0               223.5324  IND627005AAA  …
9990               67.0                80.5787  IND583119AAA  …

        source_place destination_state destination_city  destination_place  \
0         ChikaDPP_D         Karnataka       Doddablpur         ChikaDPP_D
```

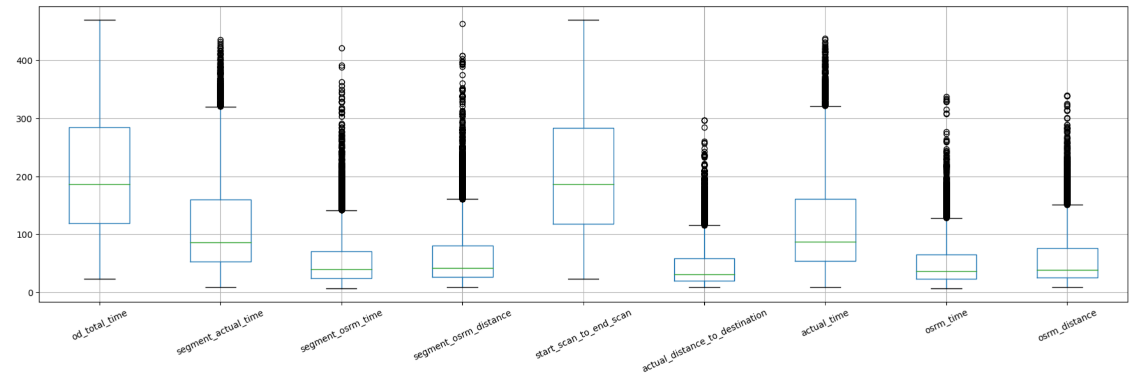
```
1       unknown_place       Maharashtra          Mumbai          MiraRd_IP
2          Poonamallee       Tamil Nadu         Chennai        Poonamallee
3         Chrompet_DPC       Tamil Nadu         Chennai        Vandalur_Dc
4        HBR Layout PC        Karnataka       Bengaluru      HBR Layout PC
…                  …              …              …                  …
9986        Mehmdpur_H           Punjab      Chandigarh         Mehmdpur_H
9987     Balabhgarh_DPC          Haryana       Faridabad         Blbgarh_DC
9988        GovndNgr_DC   Uttar Pradesh          Kanpur        GovndNgr_DC
9989         VdkkuSrt_I       Tamil Nadu      Tirchchndr         Shnmgprm_D
9990        WrdN1DPP_D        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
…                    …                 …                  …
9986          2018-10-03                  3                   10
9987          2018-10-03                  3                   10
9988          2018-10-03                  3                   10
9989          2018-10-03                  3                   10
9990          2018-10-03                  3                   10

      trip_creation_year  trip_creation_week  trip_creation_hour
0                   2018                  37                   0
1                   2018                  37                   0
2                   2018                  37                   0
3                   2018                  37                   0
4                   2018                  37                   0
…                    …                  …                  …
9986                2018                  40                  23
9987                2018                  40                  23
9988                2018                  40                  23
9989                2018                  40                  23
9990                2018                  40                  23

[9991 rows x 34 columns]
```

[347]:
```
trip.shape
```

[347]: (9991, 34)

[348]:
```
#Post Outlier treatment through IQR method:
trip[numerical_columns].boxplot(rot=25, figsize=(22,6))
```

[348]: <Axes: >



####Perform one-hot encoding on categorical features.

There are 2 columns- route_type and data upon which one hot encoding can be done since there are only two unique values within these columns.

[349]:
```
trip['route_type'].value_counts()
```

[349]:
```
route_type
Carting    8010
FTL        1981
Name: count, dtype: int64
```

[350]:
```
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()
trip['route_type']= label_encoder.fit_transform(trip['route_type'])
```

[351]:
```
trip['route_type'].value_counts()
```

[351]:
```
route_type
0    8010
1    1981
Name: count, dtype: int64
```

[352]:
```
trip['data'].value_counts()
```

[352]:
```
data
training    7129
test        2862
Name: count, dtype: int64
```

[353]:
```
trip['data']= label_encoder.fit_transform(trip['data'])
```

[354]:
```
trip['data'].value_counts()
```

[354]: data
```
1    7129
0    2862
Name: count, dtype: int64
```

####Normalize/ Standardize the numerical features using MinMaxScaler or StandardScaler.

[355]:
```python
from sklearn.preprocessing import MinMaxScaler,StandardScaler
```

[356]:
```python
standard_scaler = StandardScaler()
standard_scaler.fit(trip[numerical_columns])
```

[356]: StandardScaler()

[357]:
```python
trip[numerical_columns] = standard_scaler.transform(trip[numerical_columns])
```

[358]:
```python
trip[numerical_columns]
```

[358]:
```
      od_total_time  segment_actual_time  segment_osrm_time  \
0         -0.239762             0.312631           0.130461
1         -0.978060            -0.676196          -0.845370
2         -0.158942            -0.664137          -0.705966
3         -1.000631            -1.098256          -0.905115
4         -0.556214            -0.615901          -0.486902
…             …                   …                  …
9986       0.455760            -0.398842           0.070716
9987      -1.341202            -1.134433          -0.944945
9988       1.949194             2.000872           0.588504
9989       1.279338             1.723519           3.237187
9990       1.332854             1.916460           0.170290

      segment_osrm_distance  start_scan_to_end_scan  \
0                  0.350348               -0.248540
1                 -0.776738               -0.977741
2                 -0.633241               -0.166504
3                 -0.914454               -0.995971
4                 -0.618247               -0.558450
…                     …                     …
9986               0.011513                0.453317
9987              -0.843128               -1.342341
9988               0.713068                1.948179
9989               2.792344                1.273668
9990               0.287070                1.328358

      actual_distance_to_destination  actual_time  osrm_time  osrm_distance
0                           0.641634     0.319121   0.366589       0.511736
1                          -0.699577    -0.685137  -0.883338      -0.768664
```

```
2                                -0.521861    -0.661226  -0.694669      -0.604586
3                                -0.892929    -1.103578  -0.930505      -0.918592
4                                -0.573890    -0.625360  -0.435251      -0.587843
…                                        …          …        …            …
9986                              0.272289    -0.398206   0.225088       0.283800
9987                             -0.739361    -1.139445  -0.954088      -0.838951
9988                             -0.184525     1.980930  -0.105081      -0.001107
9989                              2.115149     1.765732   2.984360       2.194631
9990                              0.471494     1.897242   0.366589       0.423045

[9991 rows x 9 columns]
```

####Business Insights & Recommendations * Patterns observed in the data along with what you can infer from them. * Check from where most orders are coming from (State, Corridor, etc.) * Busiest corridor, avg distance between them, avg time taken, etc. * Actionable items for the business.

Business Insights:

1. There are approximately 14787 unique trip IDs given in the dataset which comprises of just 2 months worth data.
2. Carting is the top route type used.
3. Top 5 Source states from where the trip is created are : Maharashtra, Karnataka, Haryana, Tamil nadu, Telangana. This means that the sellers are majorly based in these states.
4. Bottom source and destination states are majorly from North-East (Arunachal Pradesh, Mizoram etc.)
5. Top 5 destination states where the trip ended are : Maharashtra, Karnataka, Haryana, Tamil nadu, Uttar Pradesh. This means that the customers ordering are majorly based in these states.
6. Top cities sourcing and collecting the orders are Mumbai, Bangalore and NCR regions.
7. Actual time and Segment actual time are similar to each other in the dataset.
8. Actual time and OSRM time are significantly different.
9. OSRM distance and Segment OSRM distance are significantly different.
10. OSRM time and Segment OSRM time are significantly different.
11. Average time taken for each trip to complete is around 5 hours (4.98 hours precisely).

Actionable Items: 1. Central, Easterna nd North-Eastern corridors have significantly less traffic, with very less trips. Delhivery can improve their business and logistics in these areas. 2. Maharashtra and Karnataka have the highest trips, Delhivery can introduce loyalty programs for customer retention. Also, improve the speed of deliveries in these segments since it greatly impacts the revenue of the company. 3. Actual time and OSRM (Open Source Routing Machine) said time are most of the times not matching and are statistically different. The OSRM planning certainly needs improvement. 4. Delhivery agents need to follow OSRM distance which is the most economic instead of deflecting from it that increases the distance as well as time taken.