Business Case: Delhivery - Feature Engineering

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

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

How can you help here?

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

• Clean, sanitize and manipulate data to get useful features out of raw fields

• Make sense out of the raw data and help the data science team to build forecasting models on it

In [13]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

In [251…

```
import warnings
warnings.simplefilter('ignore')
```

In [62]:

```
df = pd.read_csv("delhivery_data.csv")
df.head()
```

Out[62]:

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_cei
0	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121/
1	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121/
2	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121/
3	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121/
4	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121/

5 rows × 24 columns

In [25]:

```
df.shape
```

Out[25]:

```
(144867, 24)
```

In [26]:

```
df.columns
```

Out[26]:

```
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')
```

In [27]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144867 entries, 0 to 144866
Data columns (total 24 columns):
 #   Column                          Non-Null Count   Dtype  
---  ------                          --------------   -----  
 0   data                            144867 non-null  object 
 1   trip_creation_time              144867 non-null  object 
 2   route_schedule_uuid             144867 non-null  object 
 3   route_type                      144867 non-null  object 
 4   trip_uuid                       144867 non-null  object 
 5   source_center                   144867 non-null  object 
 6   source_name                     144574 non-null  object 
 7   destination_center              144867 non-null  object 
 8   destination_name                144606 non-null  object 
 9   od_start_time                   144867 non-null  object 
 10  od_end_time                     144867 non-null  object 
 11  start_scan_to_end_scan          144867 non-null  float64
 12  is_cutoff                       144867 non-null  bool   
 13  cutoff_factor                   144867 non-null  int64  
 14  cutoff_timestamp                144867 non-null  object 
 15  actual_distance_to_destination  144867 non-null  float64
 16  actual_time                     144867 non-null  float64
 17  osrm_time                       144867 non-null  float64
 18  osrm_distance                   144867 non-null  float64
 19  factor                          144867 non-null  float64
 20  segment_actual_time             144867 non-null  float64
 21  segment_osrm_time               144867 non-null  float64
 22  segment_osrm_distance           144867 non-null  float64
 23  segment_factor                  144867 non-null  float64
dtypes: bool(1), float64(10), int64(1), object(12)
memory usage: 25.6+ MB
```

Dropping unknown fields

In [63]:
```
unknown_fields = ["is_cutoff", "cutoff_factor", "cutoff_timestamp", "factor", "segm
df = df.drop(columns = unknown_fields)
```

In [64]:
```
df.nunique()
```

Out[64]:
```
data                                   2
trip_creation_time                 14817
route_schedule_uuid                 1504
route_type                             2
trip_uuid                          14817
source_center                       1508
source_name                         1498
destination_center                  1481
destination_name                    1468
od_start_time                      26369
od_end_time                        26369
start_scan_to_end_scan              1915
actual_distance_to_destination    144515
actual_time                         3182
osrm_time                           1531
osrm_distance                     138046
segment_actual_time                  747
segment_osrm_time                    214
segment_osrm_distance             113799
dtype: int64
```

converting the datatype of column into category

In [65]:
```python
df["data"] = df["data"].astype("category")
df["route_type"] = df["route_type"].astype("category")
```

Updating the datatype of the datetime columns

In [66]:
```python
datetime_col = ["trip_creation_time", "od_start_time", "od_end_time" ]
for i in datetime_col:
    df[i] = pd.to_datetime(df[i])
```

In [67]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144867 entries, 0 to 144866
Data columns (total 19 columns):
 #   Column                          Non-Null Count   Dtype
---  ------                          --------------   -----
 0   data                            144867 non-null  category
 1   trip_creation_time              144867 non-null  datetime64[ns]
 2   route_schedule_uuid             144867 non-null  object
 3   route_type                      144867 non-null  category
 4   trip_uuid                       144867 non-null  object
 5   source_center                   144867 non-null  object
 6   source_name                     144574 non-null  object
 7   destination_center              144867 non-null  object
 8   destination_name                144606 non-null  object
 9   od_start_time                   144867 non-null  datetime64[ns]
 10  od_end_time                     144867 non-null  datetime64[ns]
 11  start_scan_to_end_scan          144867 non-null  float64
 12  actual_distance_to_destination  144867 non-null  float64
 13  actual_time                     144867 non-null  float64
 14  osrm_time                       144867 non-null  float64
 15  osrm_distance                   144867 non-null  float64
 16  segment_actual_time             144867 non-null  float64
 17  segment_osrm_time               144867 non-null  float64
 18  segment_osrm_distance           144867 non-null  float64
dtypes: category(2), datetime64[ns](3), float64(8), object(6)
memory usage: 19.1+ MB
```

Reduction in the memory usage, before it was 25.6mb and now it is 19.1mb

Basic data cleaning and exploration

Handling missing values in the data.

In [68]:
```python
df.isnull().sum()
```

Out[68]:
```
data                             0
trip_creation_time               0
route_schedule_uuid              0
route_type                       0
trip_uuid                        0
source_center                    0
source_name                    293
destination_center               0
destination_name               261
od_start_time                    0
od_end_time                      0
start_scan_to_end_scan           0
actual_distance_to_destination   0
actual_time                      0
osrm_time                        0
osrm_distance                    0
segment_actual_time              0
segment_osrm_time                0
segment_osrm_distance            0
dtype: int64
```

In [69]:
```python
missing_source_name = df.loc[df['source_name'].isnull(),'source_center'].unique()
missing_source_name
```

Out[69]:
```
array(['IND342902A1B', 'IND577116AAA', 'IND282002AAD', 'IND465333A1B',
       'IND841301AAC', 'IND509103AAC', 'IND126116AAA', 'IND331022A1B',
       'IND505326AAB', 'IND852118A1B'], dtype=object)
```

In [70]:
```python
missing_destination_name =df.loc[df['destination_name'].isnull(),'destination_cente
missing_destination_name
```

Out[70]:
```
array(['IND342902A1B', 'IND577116AAA', 'IND282002AAD', 'IND465333A1B',
       'IND841301AAC', 'IND505326AAB', 'IND852118A1B', 'IND126116AAA',
       'IND509103AAC', 'IND221005A1A', 'IND250002AAC', 'IND331001A1C',
       'IND122015AAC'], dtype=object)
```

In [271…
```python
c= 1
for i in missing_destination_name:
    mask = (df['destination_center'] == i) & (df['destination_name'].isna())
    df.loc[mask, 'destination_name'] = f'location_{c}'
    c += 1

for i in missing_source_name:
    d[i] = df.loc[df['destination_center'] == i, 'destination_name'].unique()

for idx, val in d.items():
    if len(val) == 0:
        d[idx] = [f'location_{c}']
        c += 1

d2 = {idx: val[0] for idx, val in d.items()}

for i, v in d2.items():
    print(i, v)
```

```
IND342902A1B location_1
IND577116AAA location_2
IND282002AAD location_3
IND465333A1B location_4
IND841301AAC location_5
IND509103AAC location_9
IND126116AAA location_8
IND331022A1B location_14
IND505326AAB location_6
IND852118A1B location_7
```

In [72]:
```
for i in missing_source_name:
    df.loc[df['source_center'] == i, 'source_name'] = df.loc[df['source_center'] ==
```

In [73]:
```
df.isnull().sum()
```

Out[73]:
```
data                              0
trip_creation_time                0
route_schedule_uuid               0
route_type                        0
trip_uuid                         0
source_center                     0
source_name                       0
destination_center                0
destination_name                  0
od_start_time                     0
od_end_time                       0
start_scan_to_end_scan            0
actual_distance_to_destination    0
actual_time                       0
osrm_time                         0
osrm_distance                     0
segment_actual_time               0
segment_osrm_time                 0
segment_osrm_distance             0
dtype: int64
```

Basic Description of the Data

In [74]:
```
df.describe()
```

Out[74]:

	start_scan_to_end_scan	actual_distance_to_destination	actual_time	osrm_time	osrm_c
count	144867.000000	144867.000000	144867.000000	144867.000000	144867
mean	961.262986	234.073372	416.927527	213.868272	284
std	1037.012769	344.990009	598.103621	308.011085	421
min	20.000000	9.000045	9.000000	6.000000	9
25%	161.000000	23.355874	51.000000	27.000000	29
50%	449.000000	66.126571	132.000000	64.000000	78
75%	1634.000000	286.708875	513.000000	257.000000	343
max	7898.000000	1927.447705	4532.000000	1686.000000	2326

Merging of rows and aggregation of fields

In [272…
```
group1 = ['trip_uuid', 'source_center', 'destination_center']
df1 = df.groupby(by = group1, as_index = False).agg({'data' : 'first',
                                                       'route_type' : 'first',
                                                     'trip_creation_time' : 'firs
                                                     'source_name' : 'first',
                                                     'destination_name' : 'last',
                                                     'od_start_time' : 'first',
                                                     'od_end_time' : 'first',
                                                     'start_scan_to_end_scan' : '
                                                     'actual_distance_to_destinat
                                                     'actual_time' : 'last',
                                                     'osrm_time' : 'last',
```

```
                                       'osrm_distance' : 'last',
                                       'segment_actual_time' : 'sum
                                       'segment_osrm_time' : 'sum',
                                       'segment_osrm_distance' : 's
df1.head()
```

Out[272]:

	trip_uuid	source_center	destination_center	data	route_type	trip_creation_time
0	trip-153671041653548748	IND209304AAA	IND000000ACB	training	FTL	2018-09-12 00:00:16.535741
1	trip-153671041653548748	IND462022AAA	IND209304AAA	training	FTL	2018-09-12 00:00:16.535741
2	trip-153671042288605164	IND561203AAB	IND562101AAA	training	Carting	2018-09-12 00:00:22.886430
3	trip-153671042288605164	IND572101AAA	IND561203AAB	training	Carting	2018-09-12 00:00:22.886430
4	trip-153671043369099517	IND000000ACB	IND160002AAC	training	FTL	2018-09-12 00:00:33.691250

3.1 Calculate the time taken between od_start_time and od_end_time and keep it as a feature. Drop the original columns, if required

In [274…

```
df1['od_total_time'] = df1['od_end_time'] - df1['od_start_time']
df1.drop(columns = ['od_end_time', 'od_start_time'], inplace = True)
df1['od_total_time'] = df1['od_total_time'].apply(lambda x : round(x.total_seconds(
df1['od_total_time'].head()
```

Out[274]:

```
0    1260.60
1     999.51
2      58.83
3     122.78
4     834.64
Name: od_total_time, dtype: float64
```

In [275…

```
df2 = df1.groupby(by = 'trip_uuid', as_index = False).agg({'source_center' : 'first
                                                        'destination_center' : '
                                                        'data' : 'first',
                                                        'route_type' : 'first',
                                                        'trip_creation_time' : '
                                                        'source_name' : 'first',
                                                        'destination_name' : 'la
                                                        'od_total_time' : 'sum',
                                                        'start_scan_to_end_scan'
                                                        'actual_distance_to_dest
                                                        'actual_time' : 'sum',
                                                        'osrm_time' : 'sum',
                                                        'osrm_distance' : 'sum',
                                                        'segment_actual_time' :
                                                        'segment_osrm_time' : 's
                                                        'segment_osrm_distance'
df2.head()
```

Out[275]:

	trip_uuid	source_center	destination_center	data	route_type	trip_creation_time
0	trip-153671041653548748	IND209304AAA	IND209304AAA	training	FTL	2018-09-12 00:00:16.535741
1	trip-153671042288605164	IND561203AAB	IND561203AAB	training	Carting	2018-09-12 00:00:22.886430
2	trip-153671043369099517	IND000000ACB	IND000000ACB	training	FTL	2018-09-12 00:00:33.691250
3	trip-153671046011330457	IND400072AAB	IND401104AAA	training	Carting	2018-09-12 00:01:00.113710
4	trip-153671052974046625	IND583101AAA	IND583119AAA	training	FTL	2018-09-12 00:02:09.740725

2. Build some features to prepare the data for actual analysis. Extract features from the below fields:

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

In [284…

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

In [285…

```
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]
```

In [286…

```
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]
```

In [308…

```
df2['destination_state'] = df2['destination_name'].apply(location_name_to_state)
df2['destination_state'].head()
```

Out[308]:

```
0    Uttar Pradesh
1        Karnataka
2          Haryana
3      Maharashtra
4        Karnataka
Name: destination_state, dtype: object
```

In [309…

```
df2['destination_city'] = df2['destination_name'].apply(location_name_to_city)
df2['destination_city'].head()
```

Out[309]:

```
0        Kanpur
1    Doddablpur
2       Gurgaon
3        Mumbai
4        Sandur
Name: destination_city, dtype: object
```

In [310…

```
df2['destination_place'] = df2['destination_name'].apply(location_name_to_place)
df2['destination_place'].head()
```

Out[310]:

```
0    Central_H_6
1     ChikaDPP_D
2    Bilaspur_HB
3      MiraRd_IP
4     WrdN1DPP_D
Name: destination_place, dtype: object
```

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

In [287…

```
df2['source_state'] = df2['source_name'].apply(location_name_to_state)
df2['source_state'].unique()
```

Out[287]:

```
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',
       'location_9', 'location_3', 'location_2', 'location_14',
       'location_7'], dtype=object)
```

In [288…

```
df2['source_city'] = df2['source_name'].apply(location_name_to_city)
print('No of source cities :', df2['source_city'].nunique())
```

```python
df2['source_city'].unique()[:50]
```

Out[288]:
```
No of source cities : 690
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)
```

In [289…
```python
df2['source_place'] = df2['source_name'].apply(location_name_to_place)
df2['source_place'].unique()[:50]
```

Out[289]:
```
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)
```

Trip_creation_time: Extract features like month, year and day etc

In [99]:
```python
df2['trip_creation_date'] = pd.to_datetime(df2['trip_creation_time'].dt.date)
df2['trip_creation_date'].head()
```

Out[99]:
```
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]
```

In [102…
```python
df2['trip_creation_year'] = df2['trip_creation_time'].dt.year
df2['trip_creation_year'] = df2['trip_creation_year'].astype('int16')
df2['trip_creation_year'].head()
```

Out[102]:
```
0    2018
1    2018
2    2018
3    2018
4    2018
Name: trip_creation_year, dtype: int16
```

In [101…
```python
df2['trip_creation_month'] = df2['trip_creation_time'].dt.month
df2['trip_creation_month'] = df2['trip_creation_month'].astype('int8')
df2['trip_creation_month'].head()
```

Out[101]:
```
0    9
1    9
2    9
3    9
4    9
Name: trip_creation_month, dtype: int8
```

In [103…

```python
df2['trip_creation_week'] = df2['trip_creation_time'].dt.isocalendar().week
df2['trip_creation_week'] = df2['trip_creation_week'].astype('int8')
df2['trip_creation_week'].head()
```

Out[103]:

```
0    37
1    37
2    37
3    37
4    37
Name: trip_creation_week, dtype: int8
```

In [100…

```python
df2['trip_creation_day'] = df2['trip_creation_time'].dt.day
df2['trip_creation_day'] = df2['trip_creation_day'].astype('int8')
df2['trip_creation_day'].head()
```

Out[100]:

```
0    12
1    12
2    12
3    12
4    12
Name: trip_creation_day, dtype: int8
```

In [104…

```python
df2['trip_creation_hour'] = df2['trip_creation_time'].dt.hour
df2['trip_creation_hour'] = df2['trip_creation_hour'].astype('int8')
df2['trip_creation_hour'].head()
```

Out[104]:

```
0    0
1    0
2    0
3    0
4    0
Name: trip_creation_hour, dtype: int8
```

In [107…

```python
df2.describe().T
```

Out[107]:

	count	mean	std	min	25%	
od_total_time	14817.0	531.697630	658.868223	23.460000	149.930000	280.77
start_scan_to_end_scan	14817.0	530.810016	658.705957	23.000000	149.000000	280.00
actual_distance_to_destination	14817.0	164.477838	305.388147	9.002461	22.837239	48.47
actual_time	14817.0	357.143754	561.396157	9.000000	67.000000	149.00
osrm_time	14817.0	161.384018	271.360995	6.000000	29.000000	60.00
osrm_distance	14817.0	204.344689	370.395573	9.072900	30.819200	65.61
segment_actual_time	14817.0	353.892286	556.247965	9.000000	66.000000	147.00
segment_osrm_time	14817.0	180.949787	314.542047	6.000000	31.000000	65.00
segment_osrm_distance	14817.0	223.201161	416.628374	9.072900	32.654500	70.15
trip_creation_day	14817.0	18.370790	7.893275	1.000000	14.000000	19.00
trip_creation_month	14817.0	9.120672	0.325757	9.000000	9.000000	9.00
trip_creation_year	14817.0	2018.000000	0.000000	2018.000000	2018.000000	2018.00
trip_creation_week	14817.0	38.295944	0.967872	37.000000	38.000000	38.00
trip_creation_hour	14817.0	12.449821	7.986553	0.000000	4.000000	14.00

In [108…

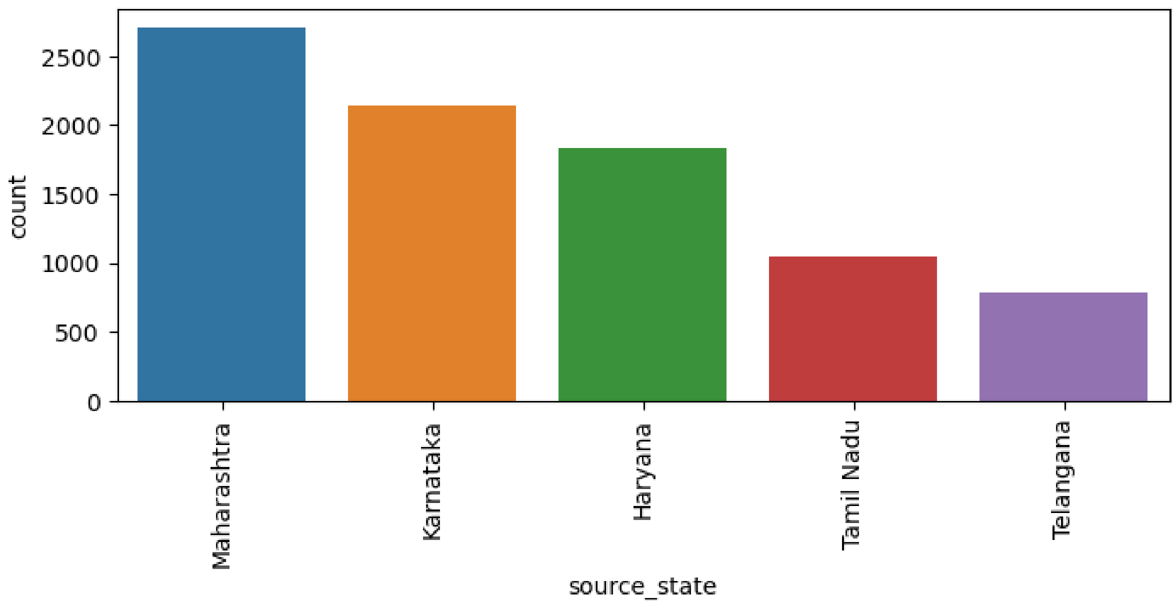
```
df2.describe(include=object).T
```

Out[108]:

	count	unique	top	freq
trip_uuid	14817	14817	trip-153671041653548748	1
source_center	14817	938	IND000000ACB	1063
destination_center	14817	1042	IND000000ACB	821
source_name	14817	938	Gurgaon_Bilaspur_HB (Haryana)	1063
destination_name	14817	1042	Gurgaon_Bilaspur_HB (Haryana)	821
source_state	14817	34	Maharashtra	2714
source_city	14817	690	Mumbai	1442
source_place	14817	761	Bilaspur_HB	1063
destination_state	14817	39	Maharashtra	2561
destination_city	14817	806	Mumbai	1548
destination_place	14817	850	Bilaspur_HB	821

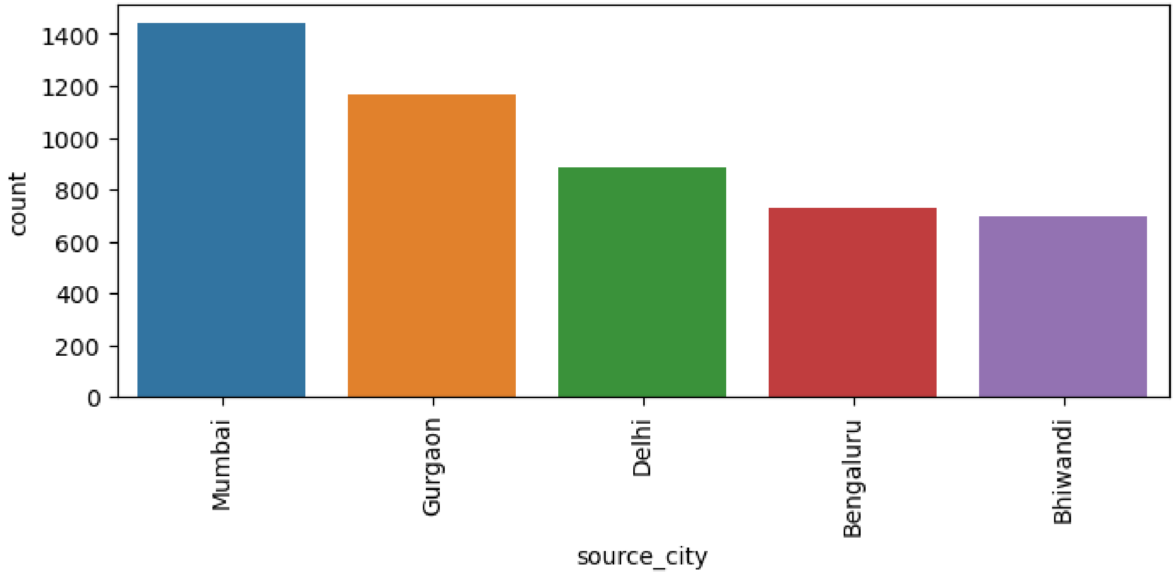
In [298…

```
df_city=df2['source_state'].value_counts()[:5].reset_index()
plt.figure(figsize=(8,3))
ax=sns.barplot(data=df_city,x=df_city['index'],y=df_city['source_state'])
plt.xticks(rotation=90)
plt.xlabel("source_state")
plt.ylabel("count")
plt.show()
```



In [297…

```
df_city=df2['source_city'].value_counts()[:5].reset_index()
plt.figure(figsize=(8,3))
ax=sns.barplot(data=df_city,x=df_city['index'],y=df_city['source_city'])
plt.xticks(rotation=90)
plt.xlabel("source_city")
plt.ylabel("count")
plt.show()
```



Trips on the hourly basis

In [109…

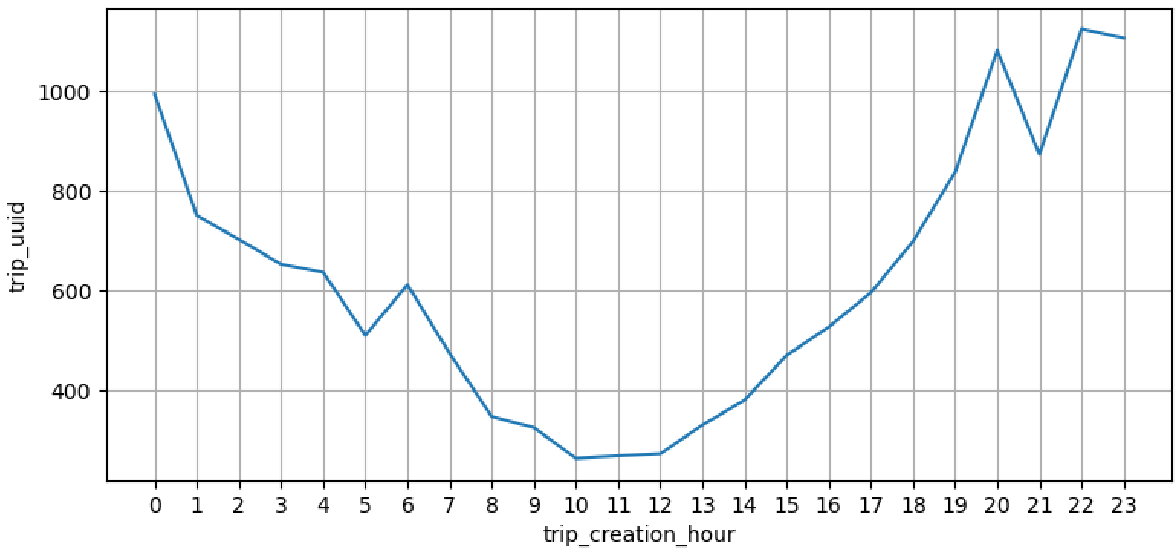
```
df_hour = df2.groupby('trip_creation_hour')['trip_uuid'].count().to_frame().reset_i
df_hour.head()
```

Out[109]:

	trip_creation_hour	trip_uuid
0	0	994
1	1	750
2	2	702
3	3	652
4	4	636

In [119…

```
plt.figure(figsize = (9, 4))
sns.lineplot(data = df_hour, x = df_hour['trip_creation_hour'], y = df_hour['trip_u
plt.xticks(np.arange(0,24))
plt.grid('x')
plt.show()
```



The plot suggests that the number of trips begins to rise after noon, peaks at 10 P.M., and subsequently declines.

Trips for the different days of the month

In [116…

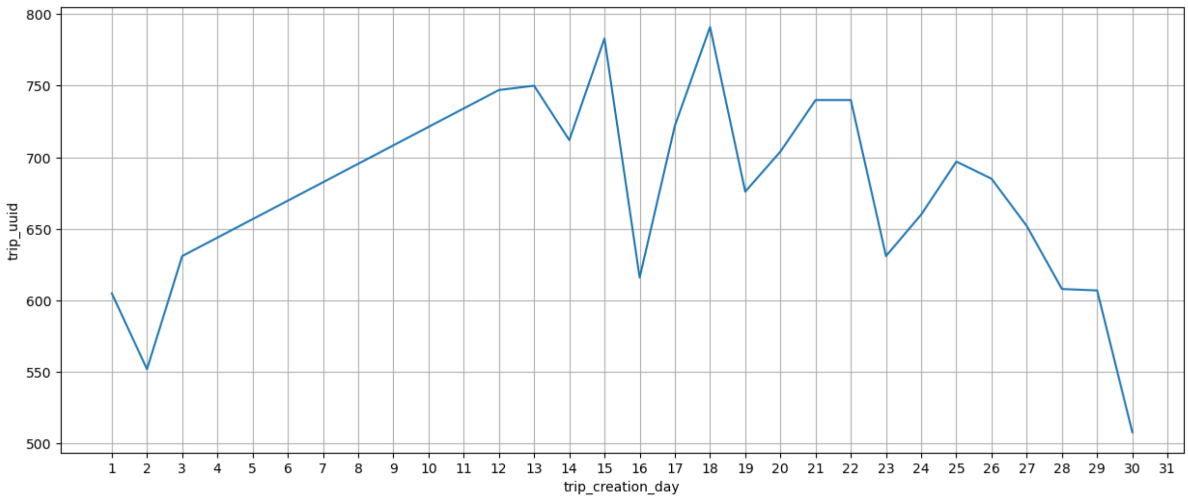
```
df_day = df2.groupby('trip_creation_day')['trip_uuid'].count().to_frame().reset_inc
df_day.head()
```

Out[116]:

	trip_creation_day	trip_uuid
0	1	605
1	2	552
2	3	631
3	12	747
4	13	750

In [120…

```
plt.figure(figsize = (15, 6))
sns.lineplot(data = df_day, x = df_day['trip_creation_day'], y = df_day['trip_uuid'
plt.xticks(np.arange(1, 32))
plt.grid('x')
plt.show()
```

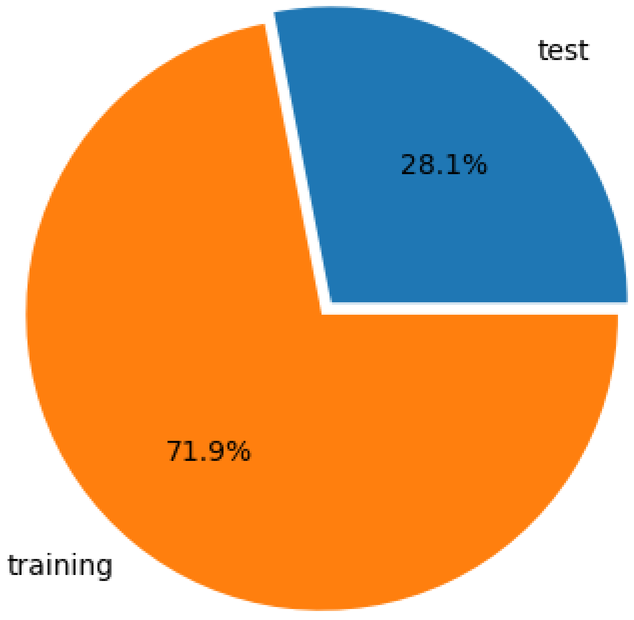


The plot indicates that the majority of trips are generated in the middle of the month, suggesting that customers tend to place more orders during that time frame.

Distribution of trip data for the orders

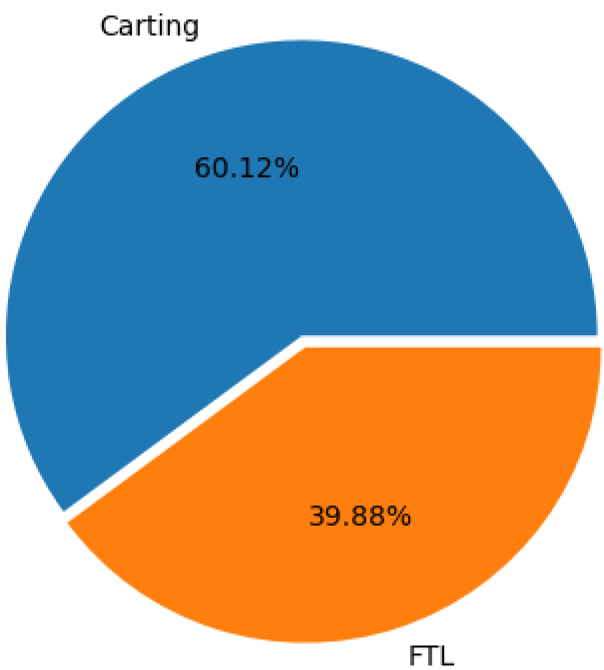
In [125…

```
df_data = df2.groupby('data')['trip_uuid'].count().to_frame().reset_index()
df_data['percentage'] = np.round(df_data['trip_uuid'] * 100/ df_data['trip_uuid'].s
plt.pie(x = df_data['trip_uuid'],labels = df_data['data'], explode = [0, 0.05], aut
plt.show()
```



Distribution of route types for the orders

```
In [131…
df_route = df2.groupby('route_type')['trip_uuid'].count().to_frame().reset_index()
df_route['percentage'] = np.round(df_route['trip_uuid'] * 100/ df_route['trip_uuid'
plt.pie(x = df_route['trip_uuid'], labels = ['Carting', 'FTL'],explode = [0, 0.04],
plt.show()
```



Distribution of number of trips created from different states

```
In [134…
df_source_state = df2.groupby('source_state')['trip_uuid'].count().to_frame().reset
df_source_state['percentage'] = np.round(df_source_state['trip_uuid'] * 100/ df_sou
```

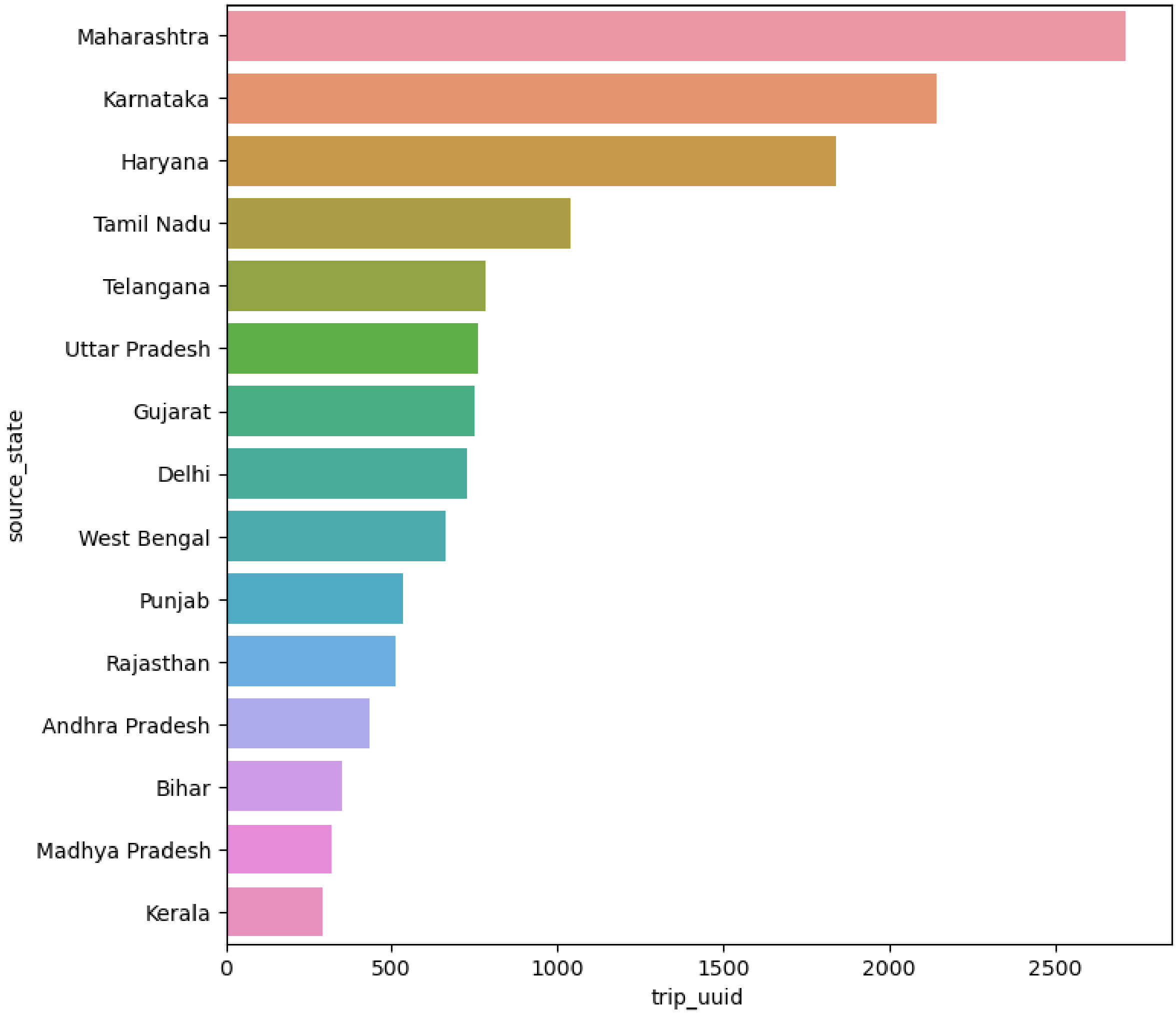
```
df_source_state = df_source_state.sort_values(by = 'trip_uuid', ascending = False)
df_source_state.head()
```

Out[134]:

	source_state	trip_uuid	percentage
17	Maharashtra	2714	18.32
14	Karnataka	2143	14.46
10	Haryana	1838	12.40
24	Tamil Nadu	1039	7.01
25	Telangana	781	5.27

In [302…

```
plt.figure(figsize = (8, 8))
sns.barplot(data = df_source_state, x = df_source_state['trip_uuid'], y = df_source
plt.show()
```



The plot reveals that Maharashtra has the highest number of originated trips, followed by Karnataka and Haryana. This suggests a robust seller presence in these states.

20 cities based on the number of trips created from different cities

In [303…

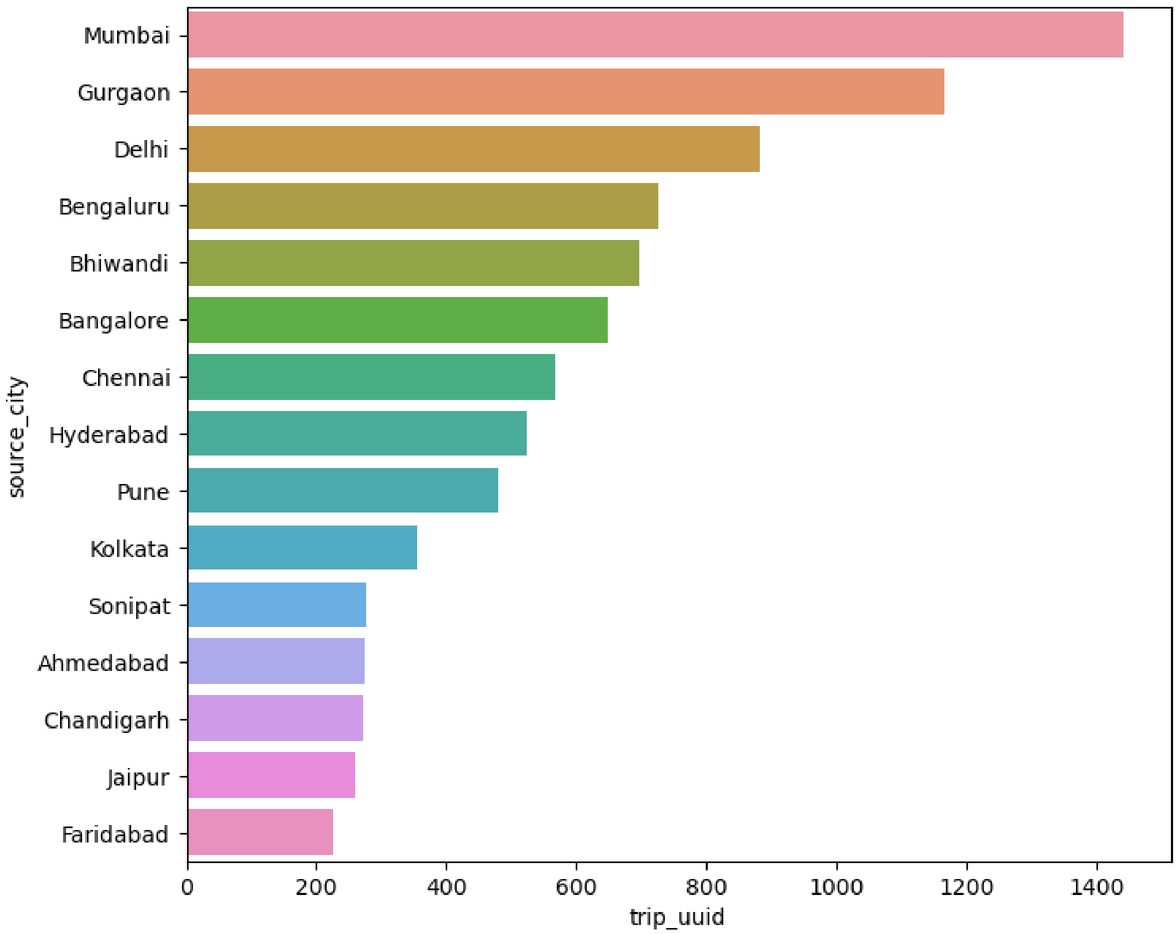
```
df_source_city = df2.groupby('source_city')['trip_uuid'].count().to_frame().reset_i
df_source_city['percentage'] = np.round(df_source_city['trip_uuid'] * 100/ df_sourc
df_source_city = df_source_city.sort_values('trip_uuid', ascending = False)[:20]
df_source_city.head(10)
```

Out[303]:

	source_city	trip_uuid	percentage
439	Mumbai	1442	9.73
237	Gurgaon	1165	7.86
169	Delhi	883	5.96
79	Bengaluru	726	4.90
100	Bhiwandi	697	4.70
58	Bangalore	648	4.37
136	Chennai	568	3.83
264	Hyderabad	524	3.54
516	Pune	480	3.24
357	Kolkata	356	2.40

In [304…

```
plt.figure(figsize = (8, 7))
sns.barplot(data = df_source_city, x = df_source_city['trip_uuid'], y = df_source_c
plt.show()
```

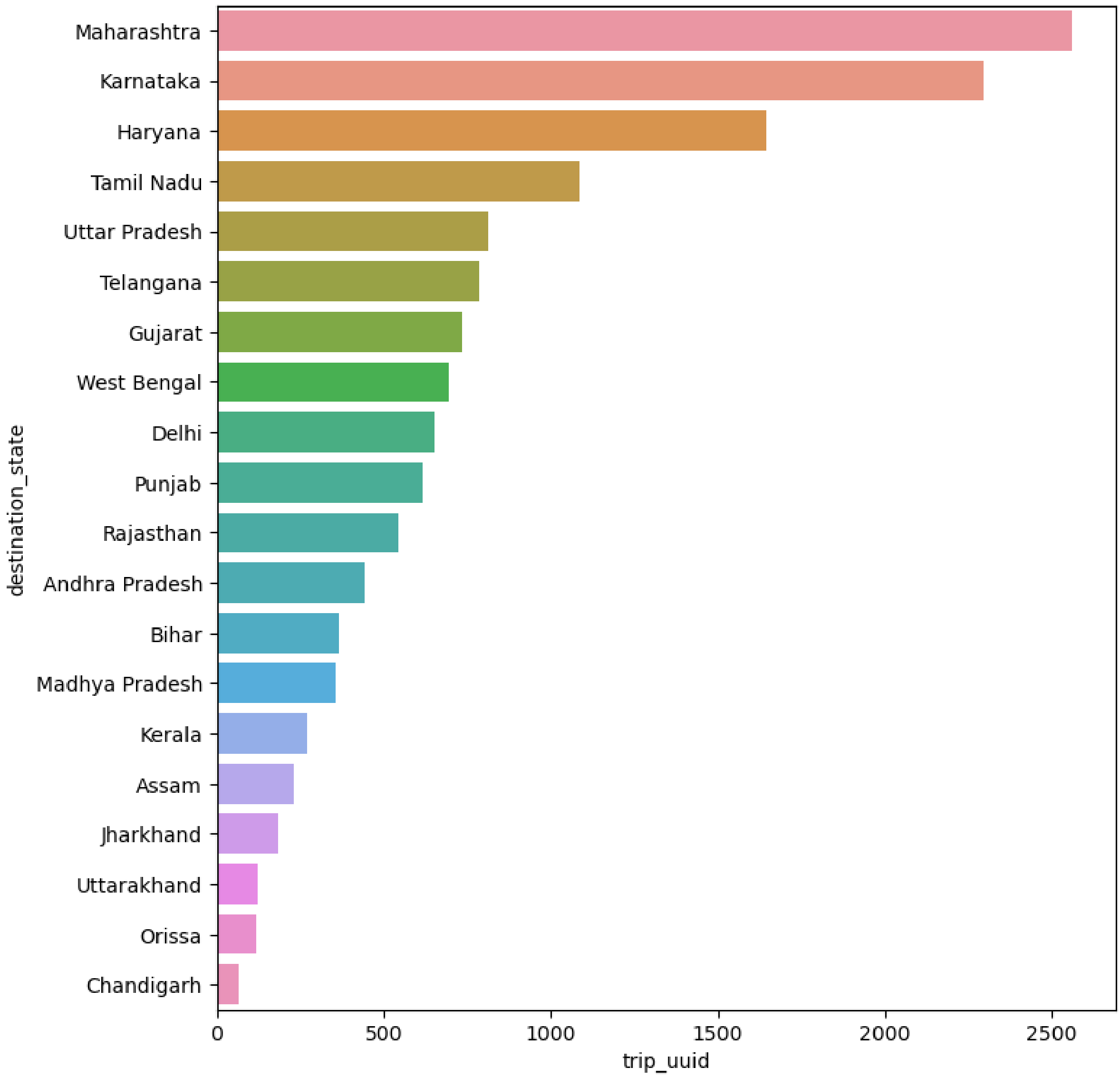


-The plot illustrates that Mumbai has the highest number of originated trips, followed by Gurgaon, Delhi, Bengaluru, and Bhiwandi. This indicates a strong seller presence in these cities.

Distribution of number of trips which ended in different states

In [312…

```
df_destination_state = df2.groupby('destination_state')['trip_uuid'].count().to_fra
df_destination_state['perc'] = np.round(df_destination_state['trip_uuid'] * 100/ df
df_destination_state = df_destination_state.sort_values('trip_uuid', ascending = Fa

plt.figure(figsize = (8, 9))
sns.barplot(data = df_destination_state, x = df_destination_state['trip_uuid'], y =
plt.show()
```



- highest number of trips ended in Maharashtra, followed by Karnataka, Haryana, Tamil Nadu, and Uttar Pradesh.

In [148…

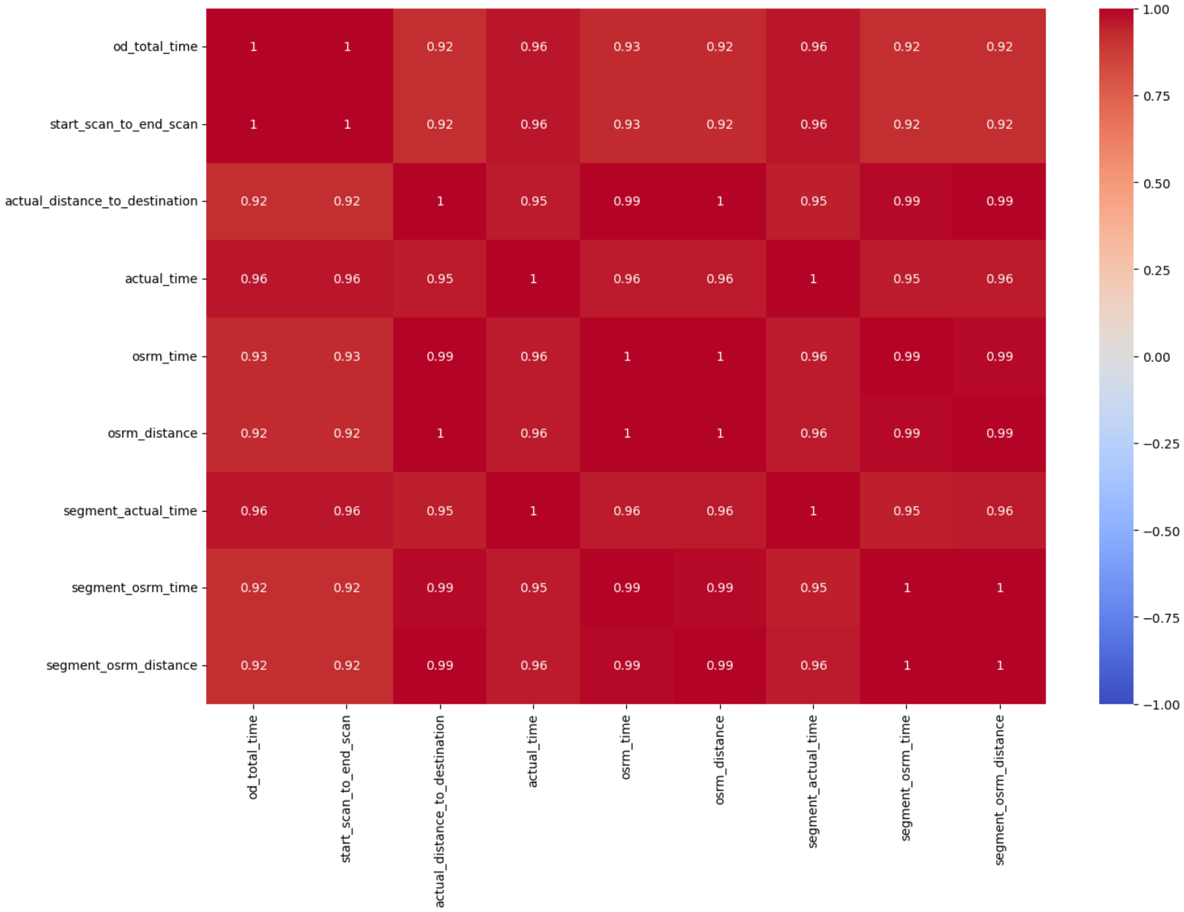
```
num_columns = ['od_total_time', 'start_scan_to_end_scan', 'actual_distance_to_desti
               'actual_time', 'osrm_time', 'osrm_distance', 'segment_actual_ti
               'segment_osrm_time', 'segment_osrm_distance']

df_corr = df2[num_columns].corr()
df_corr
```

Out[148]:

	od_total_time	start_scan_to_end_scan	actual_distance_to_destination
od_total_time	1.000000	0.999999	0.918222
start_scan_to_end_scan	0.999999	1.000000	0.918308
actual_distance_to_destination	0.918222	0.918308	1.000000
actual_time	0.961094	0.961147	0.953757
osrm_time	0.926516	0.926571	0.993561
osrm_distance	0.924219	0.924299	0.997264
segment_actual_time	0.961119	0.961171	0.952821
segment_osrm_time	0.918490	0.918561	0.987538
segment_osrm_distance	0.919199	0.919291	0.993061

In [151…

```
plt.figure(figsize = (15, 10))
sns.heatmap(data=df_corr, vmin=-1, vmax=1, annot=True, cmap='coolwarm')
plt.show()
```



- There is a strong correlation (> 0.9) among the specified numerical columns.

3. In-depth analysis and feature engineering:

3.2 Compare the difference between Point a. and start_scan_to_end_scan. Do hypothesis testing/ Visual analysis to check.

STEP-1 : Set up Null Hypothesis

- **Null Hypothesis (H0)** - Total Trip Time and Expected total trip time are same.

- **Alternate Hypothesis (HA)** - Total Trip Time and Expected total trip time are different.

STEP-2 : Checking for basic assumpitons for the hypothesis

- Distribution check using **QQ Plot**
- Homogeneity of Variances using **Lavenes test**

STEP-3: Define Test statistics

- If the assumptions of the T-Test are satisfied, we can proceed with conducting the T-Test for independent samples. Otherwise, we will resort to performing the non-parametric equivalent of the T-Test for independent samples, namely the Mann-Whitney U rank test for two independent samples.

STEP-4: Compute the p-value and fix value of alpha.

- We set our ***alpha to be 0.05***

STEP-5: Compare p-value and alpha.

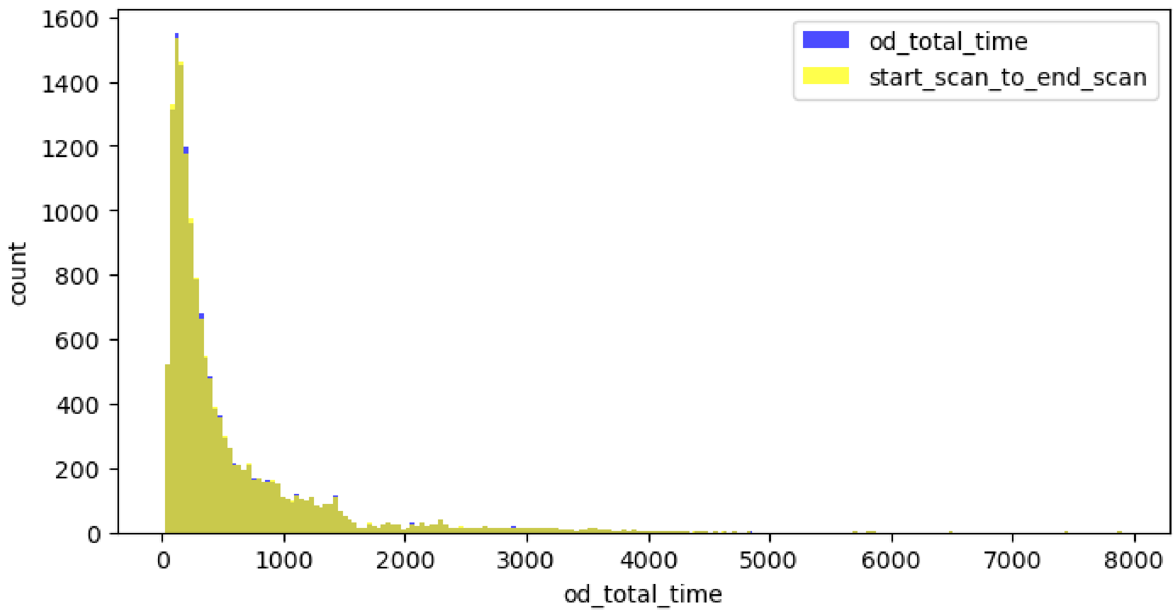
- Based on p-value, we will accept or reject H0.

1. **p-val > alpha** : Accept H0
2. **p-val < alpha** : Reject H0

- Visual Tests to know if the samples follow normal distribution

In [164…

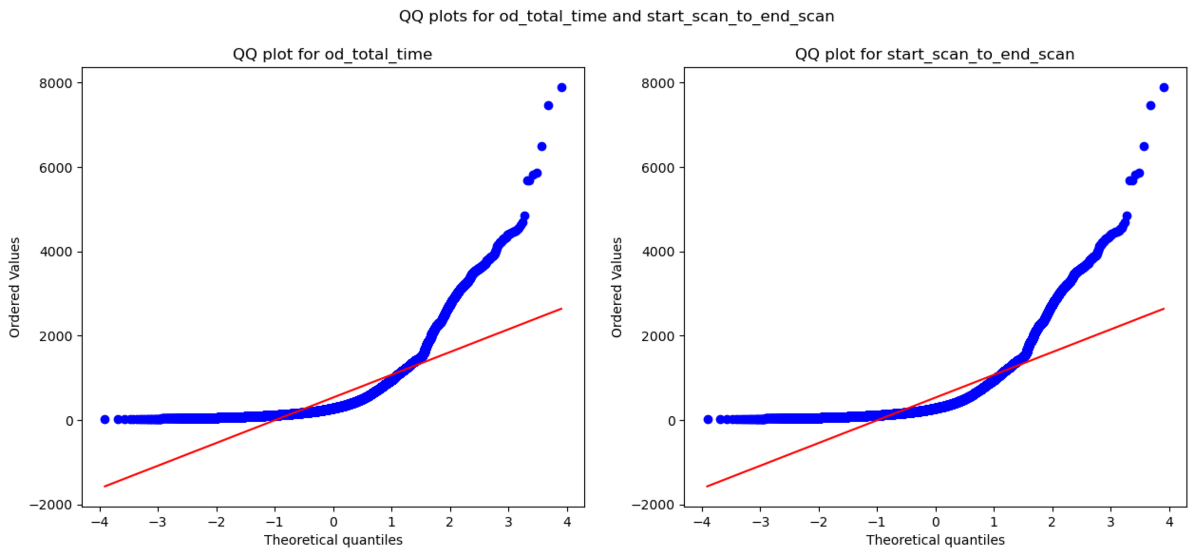
```
plt.figure(figsize=(8, 4))
plt.hist(df2['od_total_time'], bins='auto', color='blue', alpha=0.7, label='od_tota
plt.hist(df2['start_scan_to_end_scan'], bins='auto', color='yellow', alpha=0.7, lab
plt.legend()
plt.xlabel('od_total_time')
plt.ylabel('count')
plt.show()
```



- Distribution check using QQ Plot

In [165…

```
from scipy.stats import probplot

plt.figure(figsize=(15, 6))
plt.subplot(1, 2, 1)
plt.suptitle('QQ plots for od_total_time and start_scan_to_end_scan')
probplot(df2['od_total_time'], plot=plt.subplot(1, 2, 1), dist='norm', fit=True)
plt.title('QQ plot for od_total_time')
plt.subplot(1, 2, 2)
probplot(df2['start_scan_to_end_scan'], plot=plt.subplot(1, 2, 2), dist='norm', fit
plt.title('QQ plot for start_scan_to_end_scan')
plt.show()
```



From the above plot it seems sample doesn't follow normal distribution

Shapiro-Wilk test for normality

In [168…

```
import scipy.stats as spy

test_stat, p_value = spy.shapiro(df2['od_total_time'].sample(3000))
print('p-value', p_value)
if p_value < 0.05:
```

```
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 0.0
The sample does not follow normal distribution
```

Homogeneity of Variances using Lavene's test

In [169…

```
test_stat, p_value = spy.levene(df2['od_total_time'], df2['start_scan_to_end_scan']
print('p-value', p_value)
if p_value < 0.05:
    print('The samples do not have  Homogenous Variance')
else:
    print('The samples have Homogenous Variance ')
```

```
p-value 0.9668007217581142
The samples have Homogenous Variance
```

- As the samples do not exhibit a normal distribution, the application of the T-Test is not suitable in this context. Instead, we can utilize its non-parametric equivalent, namely the Mann-Whitney U rank test, for comparing two independent samples.

In [170…

```
test_stat, p_value = spy.mannwhitneyu(df2['od_total_time'], df2['start_scan_to_end_
print('P-value :',p_value)
```

```
P-value : 0.7815123224221716
```

Since p-value > alpha therfore it can be concluded that od_total_time and start_scan_to_end_scan are similar

3.3 Do hypothesis testing/ visual analysis between actual_time aggregated value and OSRM time aggregated value (aggregated values are the values you'll get after merging the rows on the basis of trip_uuid)

In [172…

```
df2[['actual_time', 'osrm_time']].describe()
```

Out[172]:

	actual_time	osrm_time
count	14817.000000	14817.000000
mean	357.143754	161.384018
std	561.396157	271.360995
min	9.000000	6.000000
25%	67.000000	29.000000
50%	149.000000	60.000000
75%	370.000000	168.000000
max	6265.000000	2032.000000

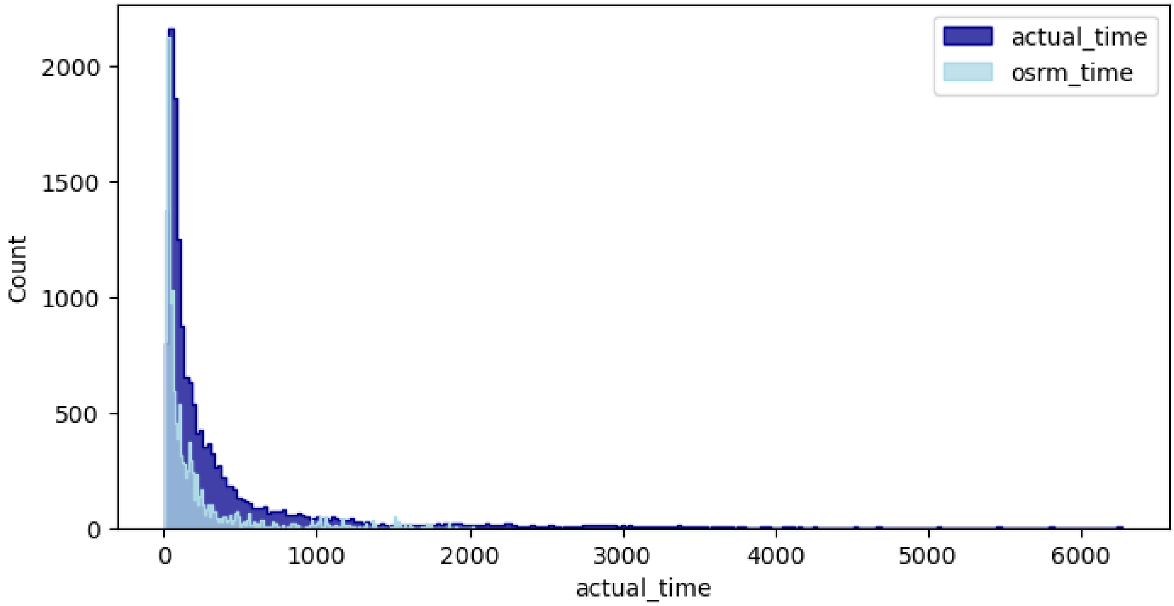
Null Hypothesis - There is no difference between actual_time and osrm_time.

Alternative Hypothesis - There is significant difference between actual_time and osrm_time

Checking the sample if it follows the normal distribution

In [176…

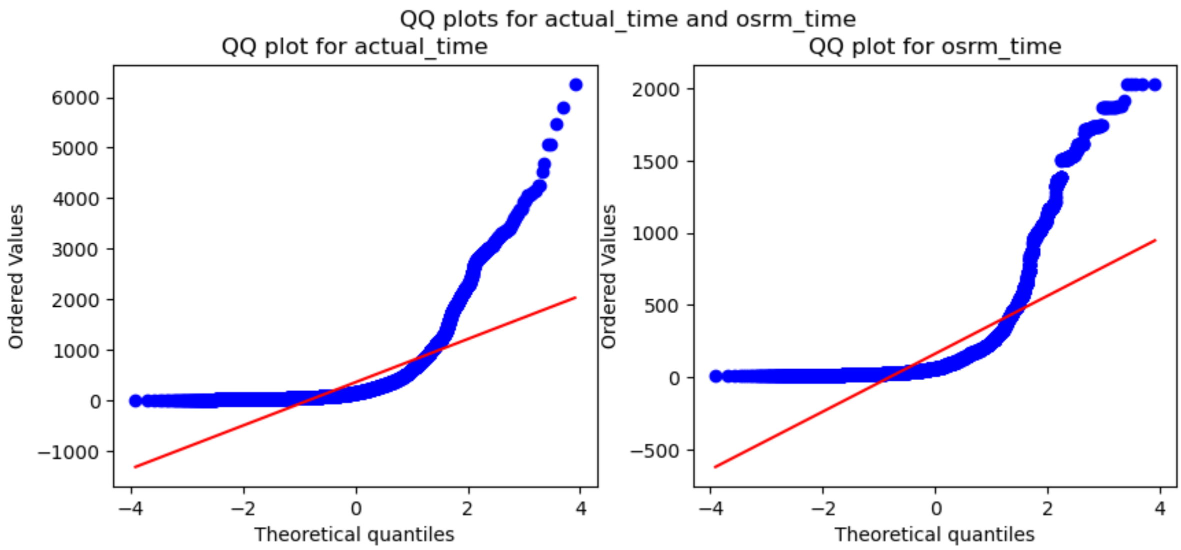
```
plt.figure(figsize = (8, 4))
sns.histplot(df2['actual_time'], element = 'step', color = 'darkblue')
sns.histplot(df2['osrm_time'], element = 'step', color = 'lightblue')
plt.legend(['actual_time', 'osrm_time'])
plt.show()
```



Distribution check using QQ Plot

In [179…

```
plt.figure(figsize=(10, 4))
plt.subplot(1, 2, 1)
plt.suptitle('QQ plots for actual_time and osrm_time')
probplot(df2['actual_time'], plot=plt.subplot(1, 2, 1), dist='norm', fit=True)
plt.title('QQ plot for actual_time')
plt.subplot(1, 2, 2)
probplot(df2['osrm_time'], plot=plt.subplot(1, 2, 2), dist='norm', fit=True)
plt.title('QQ plot for osrm_time')
plt.show()
```



samples do not follow normal distribution

- Apply Shapiro-Wilk test

H_0 : The sample **follows normal distribution** H_1 : The sample **does not follow normal distribution**

alpha = 0.05

Test Statistics : **Shapiro-Wilk test for normality**

In [181...

```
test_stat, p_value = spy.shapiro(df2['actual_time'].sample(3000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 0.0
The sample does not follow normal distribution
```

In [182...

```
test_stat, p_value = spy.shapiro(df2['osrm_time'].sample(5000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 0.0
The sample does not follow normal distribution
```

Homogeneity of Variances using Lavene's test

In [183...

```
test_stat, p_value = spy.levene(df2['actual_time'], df2['osrm_time'])
print('p-value', p_value)
if p_value < 0.05:
    print('The samples do not have  Homogenous Variance')
else:
    print('The samples have Homogenous Variance ')
```

```
p-value 1.871297993683208e-220
The samples do not have  Homogenous Variance
```

- As the samples do not exhibit a normal distribution, the application of the T-Test is not suitable in this context. Instead, we can utilize its non-parametric equivalent, namely the Mann-Whitney U rank test, for comparing two independent samples.

In [184...

```
test_stat, p_value = spy.mannwhitneyu(df2['actual_time'], df2['osrm_time'])
print('p-value', p_value)
if p_value < 0.05:
    print('The samples are not similar')
else:
    print('The samples are similar ')
```

```
p-value 0.0
The samples are not similar
```

Since p-value < alpha therfore it can be concluded that actual_time and osrm_time are not similar.

3.4 Do hypothesis testing/ visual analysis between actual_time aggregated value and segment actual time aggregated value

(aggregated values are the values you'll get after merging the rows on the basis of trip_uuid)

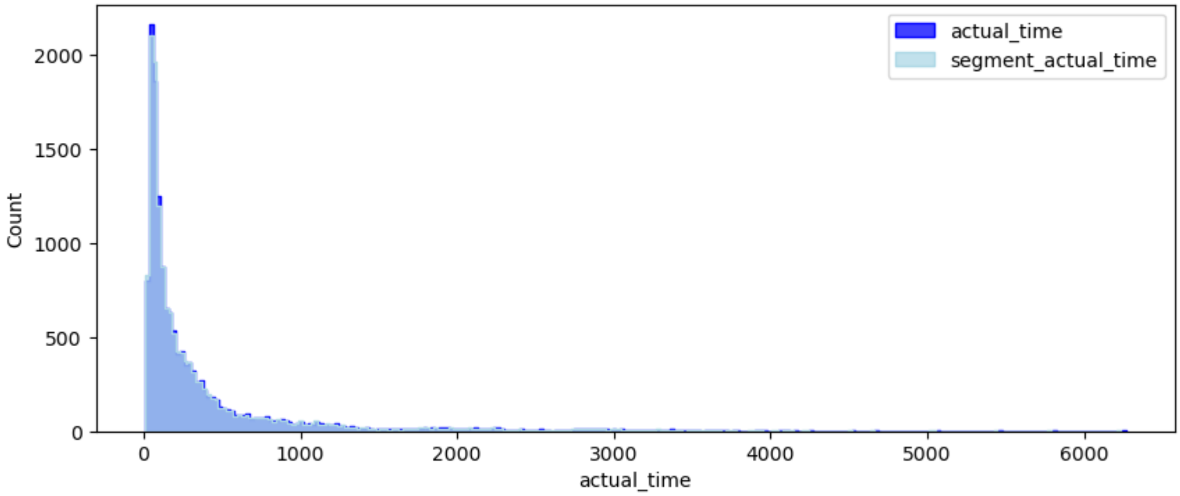
Null Hypothesis - There is no difference between actual_time and segment_actual_time.

Alternative Hypothesis - There is significant difference between actual_time and segment_actual_time

- Visual Tests to know if the samples follow normal distribution

In [190…

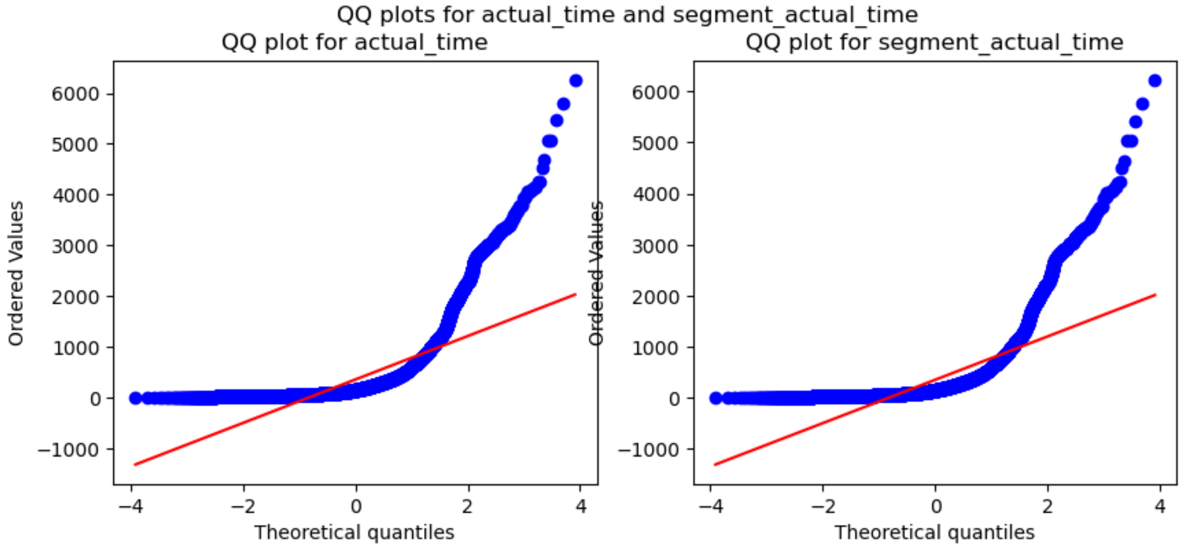
```
plt.figure(figsize = (10, 4))
sns.histplot(df2['actual_time'], element = 'step', color = 'blue')
sns.histplot(df2['segment_actual_time'], element = 'step', color = 'lightblue')
plt.legend(['actual_time', 'segment_actual_time'])
plt.show()
```



Distribution check using QQ Plot

In [193…

```
plt.figure(figsize = (10, 4))
plt.subplot(1, 2, 1)
plt.suptitle('QQ plots for actual_time and segment_actual_time')
probplot(df2['actual_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for actual_time')
plt.subplot(1, 2, 2)
probplot(df2['segment_actual_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for segment_actual_time')
plt.show()
```



samples do not follow normal distribution

Applying Shapiro-Wilk test for normality

In [194...

```
test_stat, p_value = spy.shapiro(df2['actual_time'].sample(3000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 0.0
The sample does not follow normal distribution
```

In [196...

```
test_stat, p_value = spy.shapiro(df2['segment_actual_time'].sample(3000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 0.0
The sample does not follow normal distribution
```

Homogeneity of Variances using Lavene's test

In [197...

```
test_stat, p_value = spy.levene(df2['actual_time'], df2['segment_actual_time'])
print('p-value', p_value)

if p_value < 0.05:
    print('The samples do not have Homogenous Variance')
else:
    print('The samples have Homogenous Variance ')
```

```
p-value 0.6955022668700895
The samples have Homogenous Variance
```

Since the samples do not come from normal distribution T-Test cannot be applied here, we can perform its non parametric equivalent test i.e., Mann-Whitney U rank test for two independent samples.

In [198...

```
test_stat, p_value = spy.mannwhitneyu(df2['actual_time'], df2['segment_actual_time'
print('p-value', p_value)
if p_value < 0.05:
```

```
    print('The samples are not similar')
else:
    print('The samples are similar ')
```

```
p-value 0.4164235159622476
The samples are similar
```

Since p-value > alpha therfore it can be concluded that actual_time and segment_actual_time are similar

3.5 Do hypothesis testing/ visual analysis between osrm distance aggregated value and segment osrm distance aggregated value

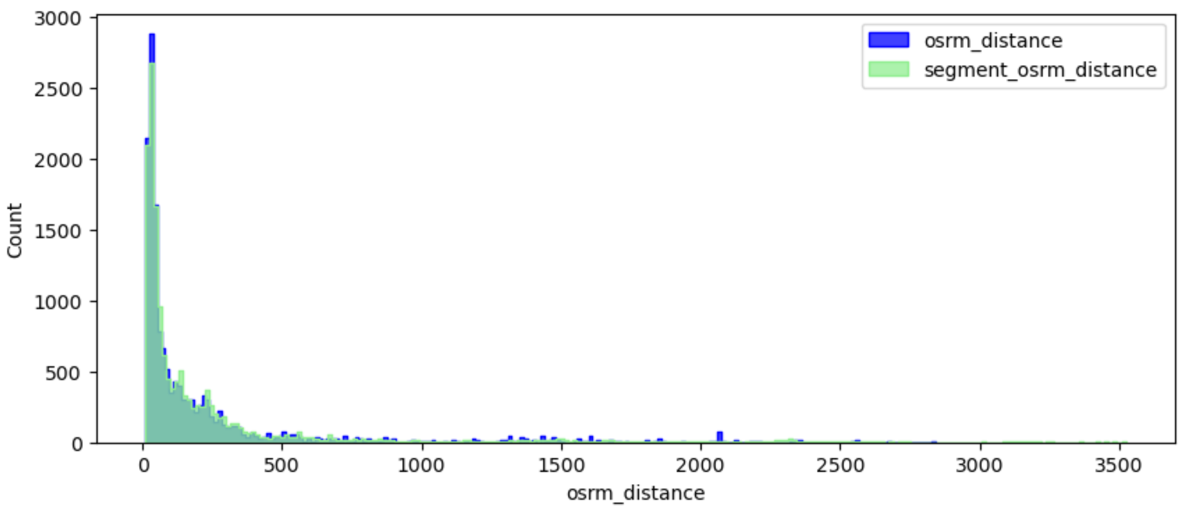
Null Hypothesis - There is no difference between osrm distance and segment_osrm distance.

Alternative Hypothesis - There is significant difference between osrm distance and segment_osrm distance.

Visual Tests to know if the samples follow normal distribution

In [201…

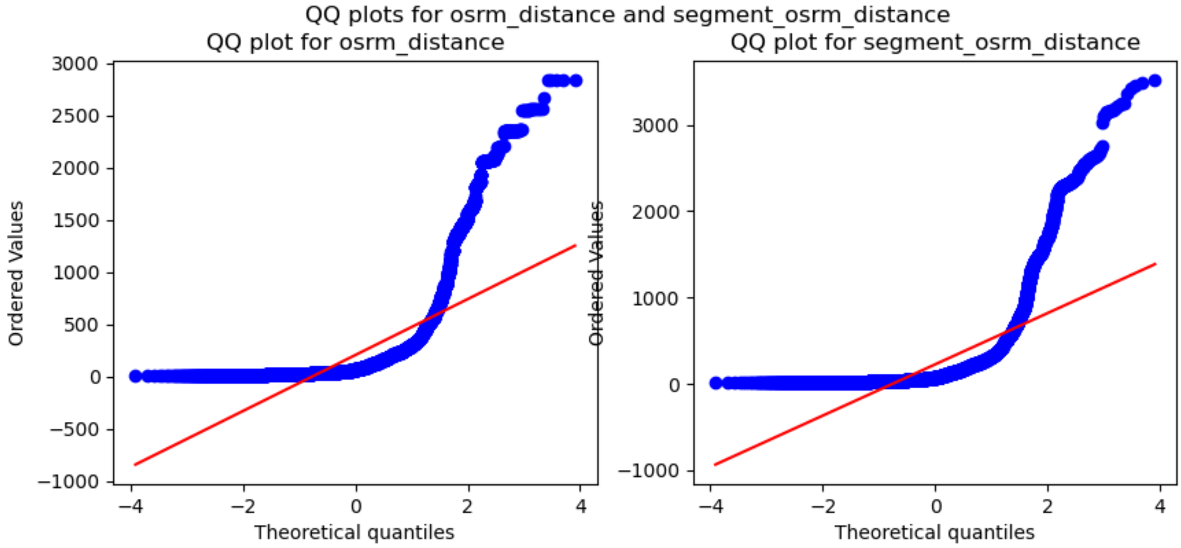
```
plt.figure(figsize = (10, 4))
sns.histplot(df2['osrm_distance'], element = 'step', color = 'blue')
sns.histplot(df2['segment_osrm_distance'], element = 'step', color = 'lightgreen')
plt.legend(['osrm_distance', 'segment_osrm_distance'])
plt.show()
```



Distribution check using QQ Plot

In [202…

```
plt.figure(figsize = (10, 4))
plt.subplot(1, 2, 1)
plt.suptitle('QQ plots for osrm_distance and segment_osrm_distance')
probplot(df2['osrm_distance'], plot = plt, dist = 'norm')
plt.title('QQ plot for osrm_distance')
plt.subplot(1, 2, 2)
probplot(df2['segment_osrm_distance'], plot = plt, dist = 'norm')
plt.title('QQ plot for segment_osrm_distance')
plt.show()
```



- Samples do not follow normal distribution

Applying Shapiro-Wilk test for normality

H_0 : The sample **follows normal distribution** H_1 : The sample **does not follow normal distribution**

alpha = 0.05

Test Statistics : **Shapiro-Wilk test for normality**

In [203...

```
test_stat, p_value = spy.shapiro(df2['osrm_distance'].sample(3000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 0.0
The sample does not follow normal distribution
```

In [204...

```
test_stat, p_value = spy.shapiro(df2['segment_osrm_distance'].sample(3000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 0.0
The sample does not follow normal distribution
```

Homogeneity of Variances using Lavene's test

In [206...

```
test_stat, p_value = spy.levene(df2['osrm_distance'], df2['segment_osrm_distance'])
print('p-value', p_value)

if p_value < 0.05:
    print('The samples do not have Homogenous Variance')
else:
    print('The samples have Homogenous Variance ')
```

```
p-value 0.00020976354422600578
The samples do not have Homogenous Variance
```

Since the samples do not follow any of the assumptions, T-Test cannot be applied here. We can perform its non parametric equivalent test i.e., Mann-Whitney U rank test for two independent samples.

In [207…
```
test_stat, p_value = spy.mannwhitneyu(df2['osrm_distance'], df2['segment_osrm_dista
print('p-value', p_value)
if p_value < 0.05:
    print('The samples are not similar')
else:
    print('The samples are similar ')
```

```
p-value 9.511383588276373e-07
The samples are not similar
```

Since p-value < alpha therfore it can be concluded that osrm_distance and segment_osrm_distance are not similar.

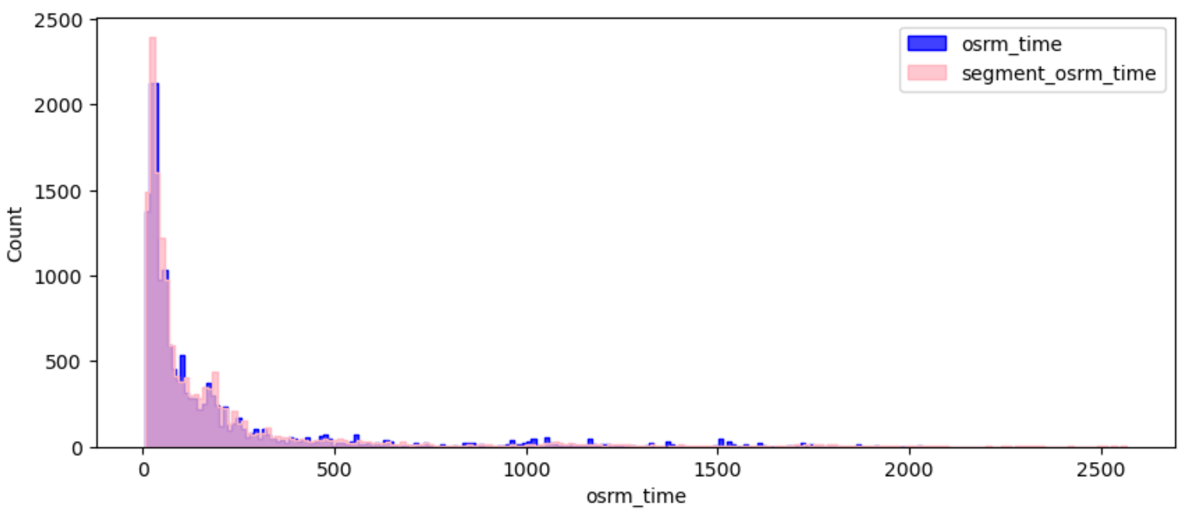
3.6 Do hypothesis testing/ visual analysis between osrm time aggregated value and segment osrm time aggregated value

Null Hypothesis - There is no difference between osrm time and segment_osrm time.

Alternative Hypothesis - There is significant difference between osrm time and segment_osrm time.

Visual Tests to know if the samples follow normal distribution

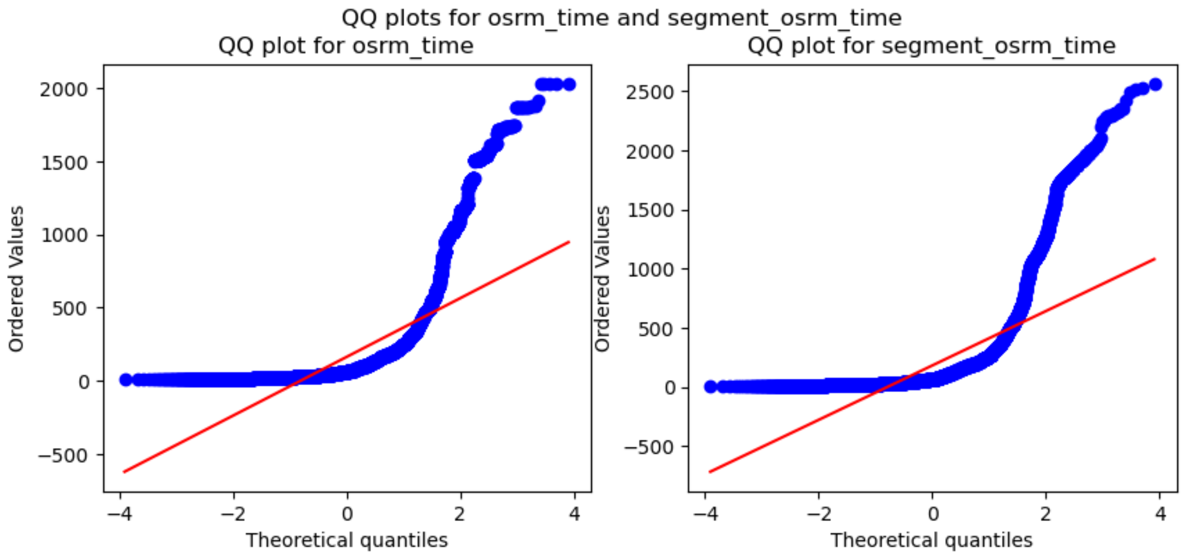
In [209…
```
plt.figure(figsize = (10, 4))
sns.histplot(df2['osrm_time'], element = 'step', color = 'blue')
sns.histplot(df2['segment_osrm_time'], element = 'step', color = 'lightpink')
plt.legend(['osrm_time', 'segment_osrm_time'])
plt.show()
```



Distribution check using QQ Plot

In [210…
```
plt.figure(figsize = (10, 4))
plt.subplot(1, 2, 1)
plt.suptitle('QQ plots for osrm_time and segment_osrm_time')
probplot(df2['osrm_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for osrm_time')
plt.subplot(1, 2, 2)
```

```
probplot(df2['segment_osrm_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for segment_osrm_time')
plt.show()
```



samples do not follow normal distribution

Applying Shapiro-Wilk test for normality

H_0 : The sample **follows normal distribution** H_1 : The sample **does not follow normal distribution**

alpha = 0.05

Test Statistics : **Shapiro-Wilk test for normality**

In [211…

```
test_stat, p_value = spy.shapiro(df2['osrm_time'].sample(3000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 0.0
The sample does not follow normal distribution
```

In [212…

```
test_stat, p_value = spy.shapiro(df2['segment_osrm_time'].sample(3000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 0.0
The sample does not follow normal distribution
```

Homogeneity of Variances using Lavene's test

In [213…

```
test_stat, p_value = spy.levene(df2['osrm_time'], df2['segment_osrm_time'])
print('p-value', p_value)

if p_value < 0.05:
    print('The samples do not have Homogenous Variance')
else:
    print('The samples have Homogenous Variance ')
```

```
p-value 8.349482669010088e-08
The samples do not have Homogenous Variance
```

Since the samples do not follow any of the assumptions, T-Test cannot be applied here. We can perform its non parametric equivalent test i.e., Mann-Whitney U rank test for two independent samples

In [214…

```
test_stat, p_value = spy.mannwhitneyu(df2['osrm_time'], df2['segment_osrm_time'])
print('p-value', p_value)
if p_value < 0.05:
    print('The samples are not similar')
else:
    print('The samples are similar ')
```

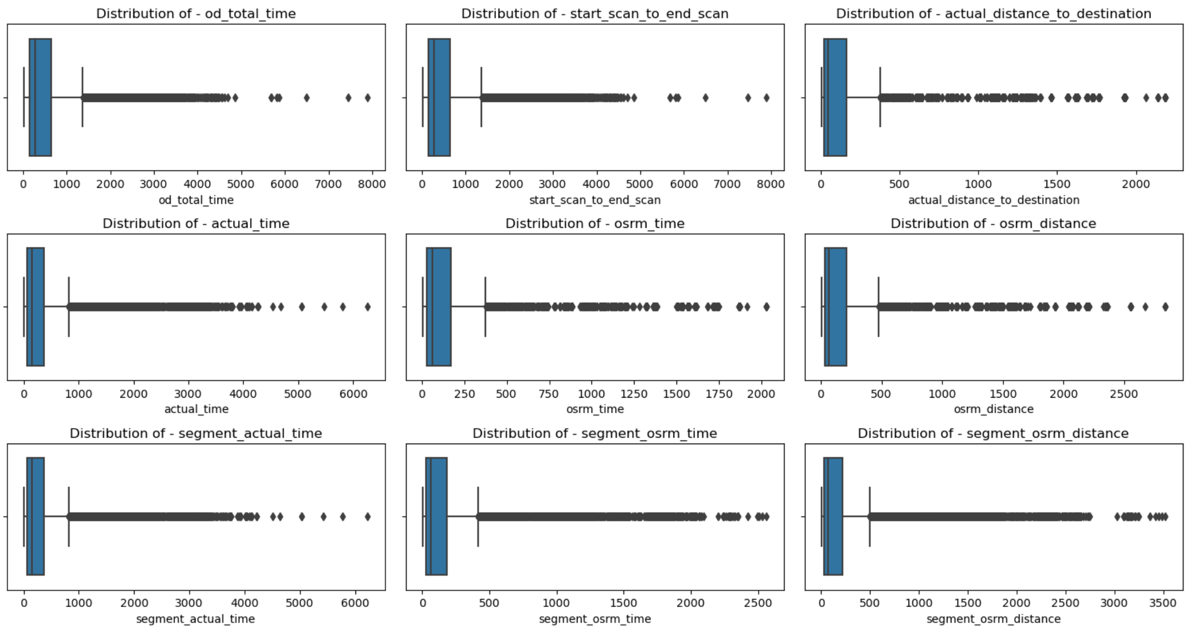
```
p-value 2.2995370859748865e-08
The samples are not similar
```

Since p-value < alpha therfore it can be concluded that osrm_time and segment_osrm_time are not similar

3.7 Find outliers in the numerical variables

In [216…

```
numerical_columns = ['od_total_time', 'start_scan_to_end_scan', 'actual_distance_to
                     'actual_time', 'osrm_time', 'osrm_distance', 'segment_actual_ti
                     'segment_osrm_time', 'segment_osrm_distance']
plt.figure(figsize=(15, 8))

for i, column in enumerate(numerical_columns, 1):
    plt.subplot(3, 3, i)
    sns.boxplot(x=df2[column])
    plt.title(f'Distribution of - {column}')

plt.tight_layout()
plt.show()
```



In [218…

```
#Detecting outliers
for i in numerical_columns:
    Q1 = np.quantile(df2[i], 0.25)
    Q3 = np.quantile(df2[i], 0.75)
    IQR = Q3 - Q1
```

```
    LB = Q1 - 1.5 * IQR
    UB = Q3 + 1.5 * IQR
    outliers = df2.loc[(df2[i] < LB) | (df2[i] > UB)]
    print('Column :', i)
    print(f'Q1 : {Q1}')
    print(f'Q3 : {Q3}')
    print(f'IQR : {IQR}')
    print(f'LB : {LB}')
    print(f'UB : {UB}')
    print(f'Number of outliers : {outliers.shape[0]}')
    print('----------------------------------')
```

```
Column : od_total_time
Q1 : 149.93
Q3 : 638.2
IQR : 488.27000000000004
LB : -582.4750000000001
UB : 1370.605
Number of outliers : 1266
----------------------------------
Column : start_scan_to_end_scan
Q1 : 149.0
Q3 : 637.0
IQR : 488.0
LB : -583.0
UB : 1369.0
Number of outliers : 1267
----------------------------------
Column : actual_distance_to_destination
Q1 : 22.83723905859321
Q3 : 164.58320763841138
IQR : 141.74596857981817
LB : -189.78171381113404
UB : 377.2021605081386
Number of outliers : 1449
----------------------------------
Column : actual_time
Q1 : 67.0
Q3 : 370.0
IQR : 303.0
LB : -387.5
UB : 824.5
Number of outliers : 1643
----------------------------------
Column : osrm_time
Q1 : 29.0
Q3 : 168.0
IQR : 139.0
LB : -179.5
UB : 376.5
Number of outliers : 1517
----------------------------------
Column : osrm_distance
Q1 : 30.8192
Q3 : 208.475
IQR : 177.6558
LB : -235.6645
UB : 474.9587
Number of outliers : 1524
----------------------------------
Column : segment_actual_time
Q1 : 66.0
Q3 : 367.0
IQR : 301.0
LB : -385.5
UB : 818.5
Number of outliers : 1643
----------------------------------
Column : segment_osrm_time
Q1 : 31.0
Q3 : 185.0
IQR : 154.0
LB : -200.0
UB : 416.0
Number of outliers : 1492
----------------------------------
```

```
Column : segment_osrm_distance
Q1 : 32.6545
Q3 : 218.8024
IQR : 186.1479
LB : -246.56735000000003
UB : 498.02425000000005
Number of outliers : 1548
----------------------------------
```

Do one-hot encoding of categorical variables

In [219…

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144867 entries, 0 to 144866
Data columns (total 19 columns):
 #   Column                          Non-Null Count   Dtype
---  ------                          --------------   -----
 0   data                            144867 non-null  category
 1   trip_creation_time              144867 non-null  datetime64[ns]
 2   route_schedule_uuid             144867 non-null  object
 3   route_type                      144867 non-null  category
 4   trip_uuid                       144867 non-null  object
 5   source_center                   144867 non-null  object
 6   source_name                     144867 non-null  object
 7   destination_center              144867 non-null  object
 8   destination_name                144867 non-null  object
 9   od_start_time                   144867 non-null  datetime64[ns]
 10  od_end_time                     144867 non-null  datetime64[ns]
 11  start_scan_to_end_scan          144867 non-null  float64
 12  actual_distance_to_destination  144867 non-null  float64
 13  actual_time                     144867 non-null  float64
 14  osrm_time                       144867 non-null  float64
 15  osrm_distance                   144867 non-null  float64
 16  segment_actual_time             144867 non-null  float64
 17  segment_osrm_time               144867 non-null  float64
 18  segment_osrm_distance           144867 non-null  float64
dtypes: category(2), datetime64[ns](3), float64(8), object(6)
memory usage: 19.1+ MB
```

In [221…

```
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()
df2['route_type'] = label_encoder.fit_transform(df2['route_type'])
df2['data'] = label_encoder.fit_transform(df2['data'])
```

In [223…

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

Out[223]:

```
0    8908
1    5909
Name: route_type, dtype: int64
```

In [224…

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

Out[224]:

```
1    10654
0     4163
Name: data, dtype: int64
```

In [241…

```
df2[['route_type', 'data']].head(10)
```

Out[241]:

	route_type	data
0	1	1
1	0	1
2	1	1
3	0	1
4	1	1
5	0	1
6	0	1
7	0	1
8	0	1
9	0	1

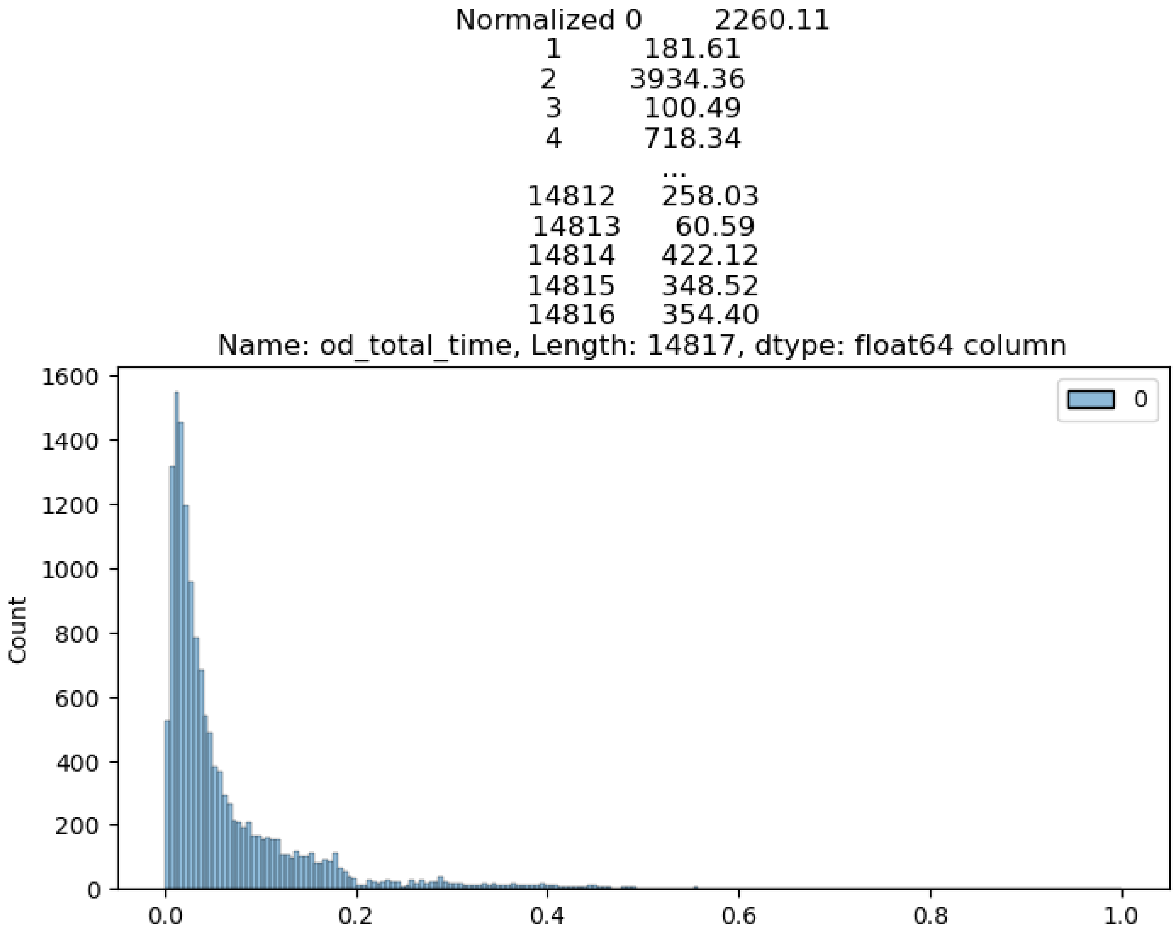
Normalize/ Standardize the numerical features using MinMaxScaler or StandardScaler.

In [266…

```
from sklearn.preprocessing import MinMaxScaler, StandardScaler
```

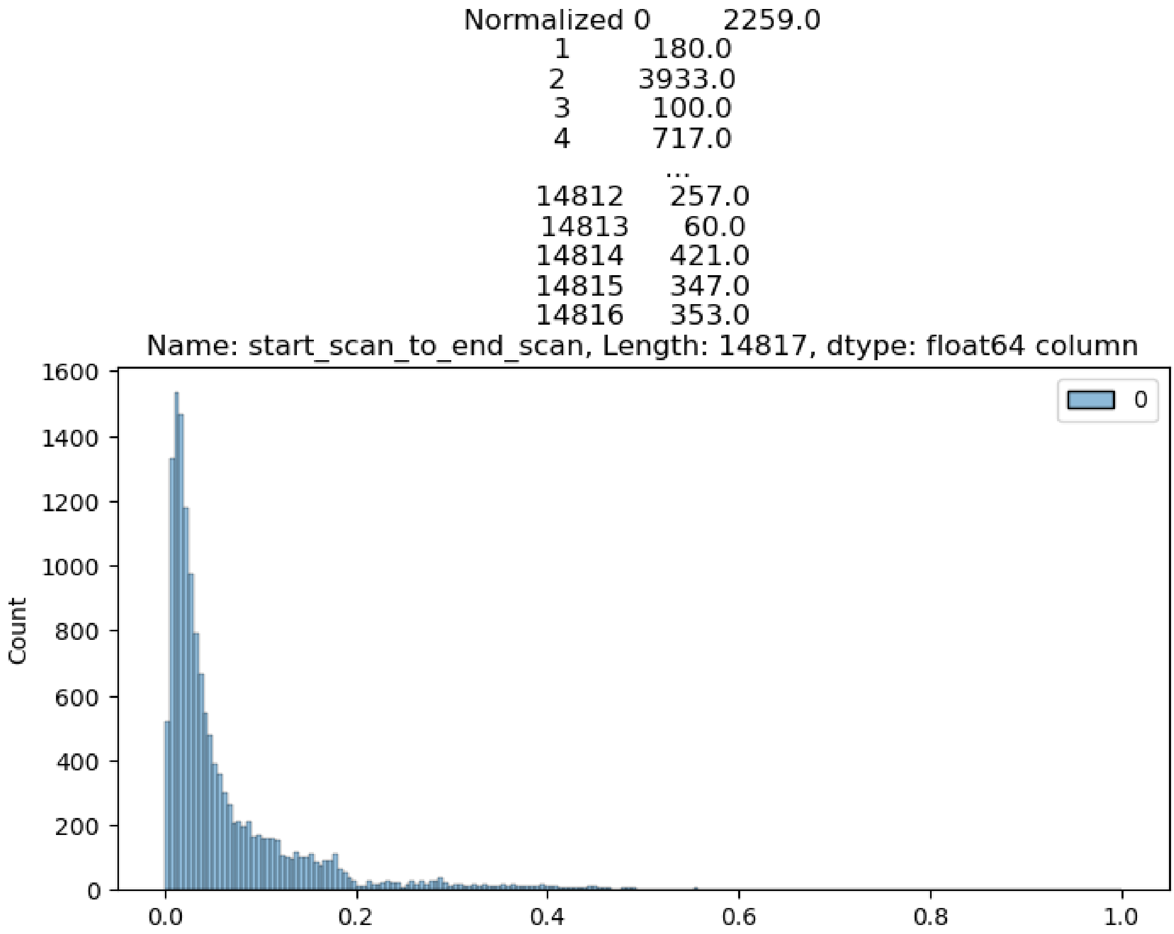
In [263…

```
#Normalization

plt.figure(figsize = (8, 4))
scaler = MinMaxScaler()
scaled = scaler.fit_transform(df2['od_total_time'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Normalized {df2['od_total_time']} column")
plt.show()
```



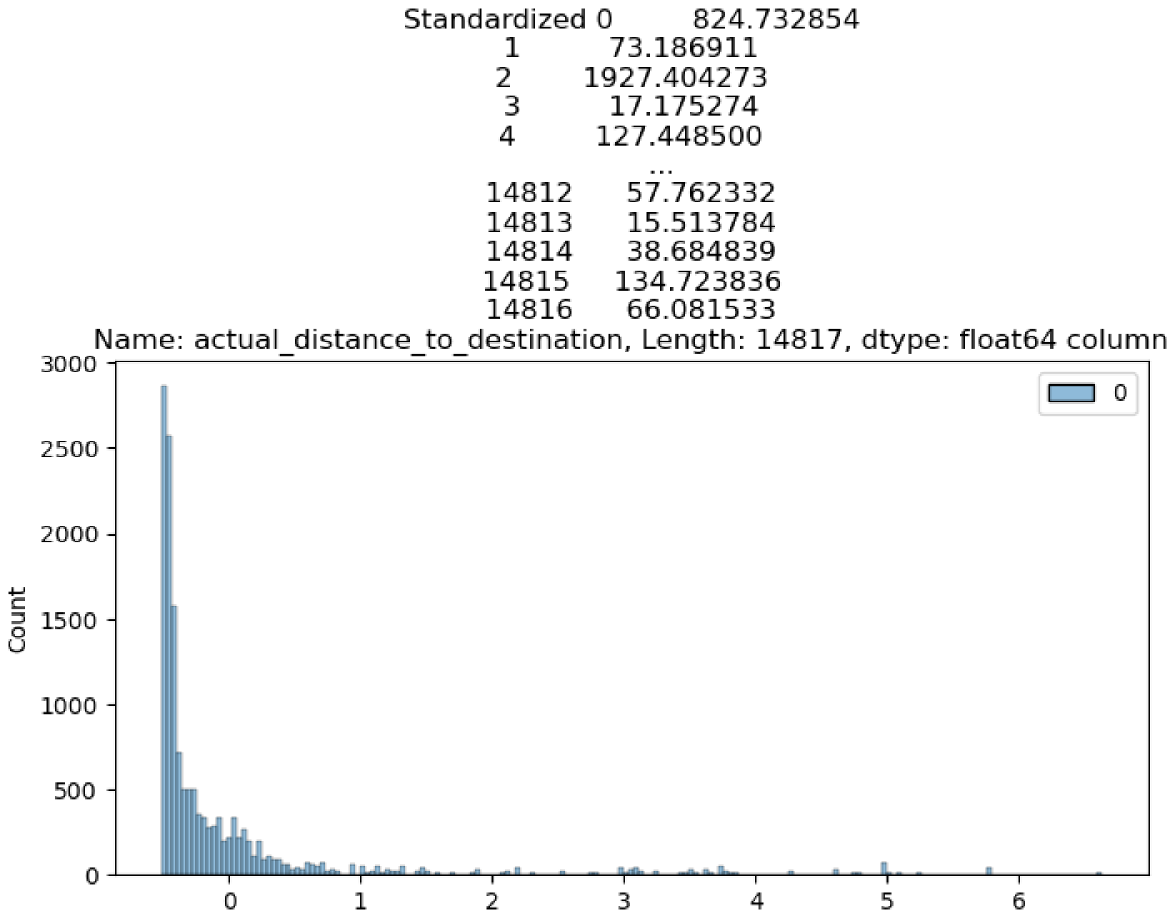
In [265…

```
plt.figure(figsize = (8, 4))
scaler = MinMaxScaler()
scaled = scaler.fit_transform(df2['start_scan_to_end_scan'].to_numpy().reshape(-1,
sns.histplot(scaled)
plt.title(f"Normalized {df2['start_scan_to_end_scan']} column")
plt.show()
```



In [267…

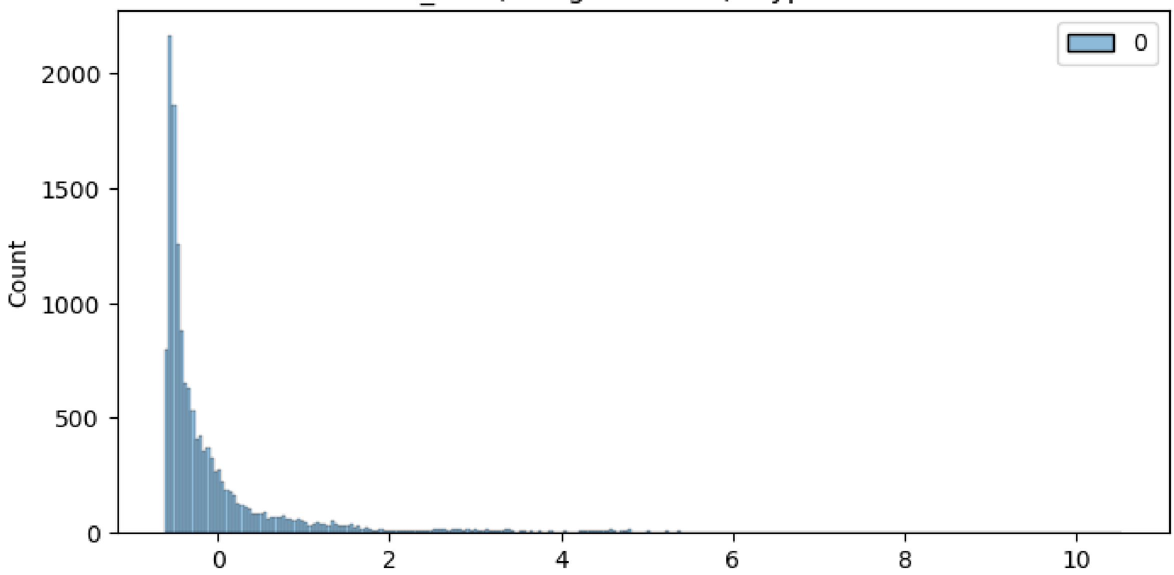
```
#Standardization

plt.figure(figsize = (8, 4))
scaler = StandardScaler()
scaled = scaler.fit_transform(df2['actual_distance_to_destination'].to_numpy().resh
sns.histplot(scaled)
plt.title(f"Standardized {df2['actual_distance_to_destination']} column")
plt.show()
```



In [268…

```
plt.figure(figsize = (8, 4))
scaler = StandardScaler()
scaled = scaler.fit_transform(df2['actual_time'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Standardized {df2['actual_time']} column")
plt.show()
```

```
Standardized 0        1562.0
1         143.0
2        3347.0
3          59.0
4         341.0
         ...
14812      83.0
14813      21.0
14814     282.0
14815     264.0
14816     275.0
Name: actual_time, Length: 14817, dtype: float64 column
```



Business Insights

- The data spans from '2018-09-12 00:00:16' to '2018-10-08 03:00:24', involving 14,817 unique trip IDs, 1,508 unique source centers, 1,481 unique destination centers, 690 unique source cities, and 806 unique destination cities. Testing data predominates over training data.
- Most of the data is for testing than for training, Most common route type is Carting.
- The names of 14 unique location ids are missing in the data.
- Trip count increases post-noon, peaks at 10 P.M., and then decreases. Maximum trips occurred in the 38th week.
- Trips primarily originate from states such as Maharashtra, Karnataka, Haryana, Tamil Nadu, and Telangana.
- Mumbai has the highest number of originated trips, followed by Gurgaon Delhi, Bengaluru, and Bhiwandi, indicating a strong seller base in these cities.
- A majority of orders are placed mid-month, indicating customer preferences for ordering during this period.
- Most destination orders come from cities like Bengaluru, Mumbai, Gurgaon, Bangalore, and Delhi.
- The features actual_time and osrm_time are statistically different.
- The features osrm_distance and segment_osrm_distance are statistically different from each other.

Recommendations

- A significant number of orders originate from or are destined for states like Maharashtra, Karnataka, Haryana, and Tamil Nadu. Optimizing existing corridors can enhance service penetration in these areas.
- Conducting customer profiling for those in Maharashtra, Karnataka, Haryana, Tamil Nadu, and Uttar Pradesh is essential. Understanding why major orders come from these states will help improve the overall buying and delivery experience for customers.
- Considering state-specific factors like heavy traffic and challenging terrain conditions is crucial for planning and meeting demand, particularly during peak festival seasons.
- The OSRM trip planning system requires enhancements to address discrepancies, especially for transporters relying on the routing engine for optimal results.
- There's a noticeable difference between osrm_time and actual_time. It's crucial for the team to minimize this gap to improve delivery time predictions, ensuring a more accurate estimate for customers.