Delhivery Business Case study (Dinesh Prabhu DSML 2022)

```
!gdown 1urE8XVXevyOiowQ6uKssc75mlMWaOvaq
```

```
Downloading...
From: https://drive.google.com/uc?id=1urE8XVXevyOiowQ6uKssc75mlMWaOvaq
To: /content/delhivery_data.txt
100% 55.6M/55.6M [00:00<00:00, 100MB/s]
```

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

```
Delhivery=pd.read_csv('delhivery_data.txt')
Delhivery(5)
```

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

5 rows × 24 columns

```
Delhivery.shape
```

```
(144867, 24)
```

Dropping unknown fields

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

```
df.info()
#the trip creation,od_start_time,od_end_time,cutoff time stamp, all these columns should be converted to date time type
```

```
<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
```

```
df.isnull().sum()
```

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

Observation source_name column has 293 null values and destination_name column has 261 null values

unique entries present in each column

```
for i in df.columns:
    print(f"Unique entries for column {i:<30} = {df[i].nunique()}")
```

```
Unique entries for column data                           = 2
Unique entries for column trip_creation_time             = 14817
Unique entries for column route_schedule_uuid            = 1504
Unique entries for column route_type                     = 2
Unique entries for column trip_uuid                      = 14817
Unique entries for column source_center                  = 1508
Unique entries for column source_name                    = 1498
Unique entries for column destination_center             = 1481
Unique entries for column destination_name               = 1468
Unique entries for column od_start_time                  = 26369
Unique entries for column od_end_time                    = 26369
Unique entries for column start_scan_to_end_scan         = 1915
Unique entries for column actual_distance_to_destination = 144515
Unique entries for column actual_time                    = 3182
Unique entries for column osrm_time                      = 1531
Unique entries for column osrm_distance                  = 138046
Unique entries for column segment_actual_time            = 747
Unique entries for column segment_osrm_time              = 214
Unique entries for column segment_osrm_distance          = 113799
```

Changing the data type of those columns with 2 unique entries to Category

```
df['data'] = df['data'].astype('category')
df['route_type'] = df['route_type'].astype('category')
```

```
floating_columns = ['actual_distance_to_destination', 'actual_time', 'osrm_time', 'osrm_distance',
                    'segment_actual_time', 'segment_osrm_time', 'segment_osrm_distance']
for i in floating_columns:
    print(df[i].max())
```

```
1927.4477046975032
4532.0
1686.0
2326.1991000000003
3051.0
1611.0
2191.4037000000003
```

Updatiing the data type of columns

```
for i in floating_columns:
    df[i] = df[i].astype('float32')
```

```
datetime_columns = ['trip_creation_time', 'od_start_time', 'od_end_time']
for i in datetime_columns:
    df[i] = pd.to_datetime(df[i])
```

```
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  float32
 13  actual_time                     144867 non-null  float32
 14  osrm_time                       144867 non-null  float32
 15  osrm_distance                   144867 non-null  float32
 16  segment_actual_time             144867 non-null  float32
 17  segment_osrm_time               144867 non-null  float32
 18  segment_osrm_distance           144867 non-null  float32
dtypes: category(2), datetime64[ns](3), float32(7), float64(1), object(6)
memory usage: 15.2+ MB
```

Time period for the given data

```
df['trip_creation_time'].min(), df['od_end_time'].max()
```

```
(Timestamp('2018-09-12 00:00:16.535741'),
 Timestamp('2018-10-08 03:00:24.353479'))
```

1. Basic data cleaning and exploration:

Handling missing values in the data

```
df.isnull().sum()
```

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

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

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

```
for i in missing_source_name:
    unique_source_name = df.loc[df['source_center'] == i, 'source_name'].unique()
    if pd.isna(unique_source_name):
        print("Source Center :", i, "-" * 10, "Source Name :", 'Not Found')
    else :
        print("Source Center :", i, "-" * 10, "Source Name :", unique_source_name)
```

```
Source Center : IND342902A1B ---------- Source Name : Not Found
Source Center : IND577116AAA ---------- Source Name : Not Found
Source Center : IND282002AAD ---------- Source Name : Not Found
Source Center : IND465333A1B ---------- Source Name : Not Found
Source Center : IND841301AAC ---------- Source Name : Not Found
Source Center : IND509103AAC ---------- Source Name : Not Found
Source Center : IND126116AAA ---------- Source Name : Not Found
Source Center : IND331022A1B ---------- Source Name : Not Found
Source Center : IND505326AAB ---------- Source Name : Not Found
Source Center : IND852118A1B ---------- Source Name : Not Found
```

```
for i in missing_source_name:
    unique_destination_name = df.loc[df['destination_center'] == i, 'destination_name'].unique()
    if (pd.isna(unique_source_name)) or (unique_source_name.size == 0):
        print("Destination Center :", i, "-" * 10, "Destination Name :", 'Not Found')
    else :
        print("Destination Center :", i, "-" * 10, "Destination Name :", unique_destination_name)
```

```
Destination Center : IND342902A1B ---------- Destination Name : Not Found
Destination Center : IND577116AAA ---------- Destination Name : Not Found
Destination Center : IND282002AAD ---------- Destination Name : Not Found
Destination Center : IND465333A1B ---------- Destination Name : Not Found
Destination Center : IND841301AAC ---------- Destination Name : Not Found
Destination Center : IND509103AAC ---------- Destination Name : Not Found
Destination Center : IND126116AAA ---------- Destination Name : Not Found
Destination Center : IND331022A1B ---------- Destination Name : Not Found
Destination Center : IND505326AAB ---------- Destination Name : Not Found
Destination Center : IND852118A1B ---------- Destination Name : Not Found
```

```
missing_destination_name = df.loc[df['destination_name'].isnull(), 'destination_center'].unique()
missing_destination_name
```

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

The IDs for which the source name is missing, are all those IDs for destination also missing ?

```
np.all(df.loc[df['source_name'].isnull(), 'source_center'].isin(missing_destination_name))
```

```
False
```

Treating missing destination names and source names

```
count = 1
for i in missing_destination_name:
    df.loc[df['destination_center'] == i, 'destination_name'] = df.loc[df['destination_center'] == i, 'destination_name'].replace(np.nan
    count += 1
```

```
d = {}
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_{count}']
        count += 1
d2 = {}
for idx, val in d.items():
    d2[idx] = val[0]
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
```

```
for i in missing_source_name:
    df.loc[df['source_center'] == i, 'source_name'] = df.loc[df['source_center'] == i, 'source_name'].replace(np.nan, d2[i])
```

```
df.isnull().sum()
```

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

Basic Description of the Data

```
df.describe()
```

	start_scan_to_end_scan	actual_distance_to_destination	actual_time	osr
count	144867.000000	144867.000000	144867.000000	144867.(
mean	961.262986	234.073380	416.927521	213.8
std	1037.012769	344.990021	598.103638	308.(
min	20.000000	9.000046	9.000000	6.(
25%	161.000000	23.355875	51.000000	27.(
50%	449.000000	66.126572	132.000000	64.(
75%	1634.000000	286.708878	513.000000	257.(
max	7898.000000	1927.447754	4532.000000	1686.(

```
df.describe(include = 'object')
```

	route_schedule_uuid	trip_uuid	source_center	source_name	destination_center	destination_name
count	144867	144867	144867	144867	144867	144867
unique	1504	14817	1508	1508	1481	1481
top	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	trip-153811219535896559	IND000000ACB	Gurgaon_Bilaspur_HB (Haryana)	IND000000ACB	Gurgaon_Bilaspur_HB (Haryana)
freq	1812	101	23347	23347	15192	15192

Merging of rows and aggregation of fields

```
grouping_1 = ['trip_uuid', 'source_center', 'destination_center']
df1 = df.groupby(by = grouping_1, as_index = False).agg({'data' : 'first',
                                                          'route_type' : 'first',
                                                        'trip_creation_time' : 'first',
                                                        'source_name' : 'first',
                                                        'destination_name' : 'last',
                                                        'od_start_time' : 'first',
                                                        'od_end_time' : 'first',
                                                        'start_scan_to_end_scan' : 'first',
                                                        'actual_distance_to_destination' : 'last',
                                                        'actual_time' : 'last',
                                                        'osrm_time' : 'last',
                                                        'osrm_distance' : 'last',
                                                        'segment_actual_time' : 'sum',
                                                        'segment_osrm_time' : 'sum',
                                                        'segment_osrm_distance' : 'sum'})
df1
```

	trip_uuid	source_center	destination_center	data	route_type	tri
0	trip-153671041653548748	IND209304AAA	IND000000ACB	training	FTL	
1	trip-153671041653548748	IND462022AAA	IND209304AAA	training	FTL	
2	trip-153671042288605164	IND561203AAB	IND562101AAA	training	Carting	
3	trip-153671042288605164	IND572101AAA	IND561203AAB	training	Carting	
4	trip-153671043369099517	IND000000ACB	IND160002AAC	training	FTL	
...	...	...	...	...	...	
26363	trip-153861115439069069	IND628204AAA	IND627657AAA	test	Carting	
26364	trip-153861115439069069	IND628613AAA	IND627005AAA	test	Carting	
26365	trip-153861115439069069	IND628801AAA	IND628204AAA	test	Carting	
26366	trip-153861118270144424	IND583119AAA	IND583101AAA	test	FTL	
26367	trip-153861118270144424	IND583201AAA	IND583119AAA	test	FTL	

26368 rows × 18 columns

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

```
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() / 60.0, 2))
df1['od_total_time'].head()
```

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

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

	trip_uuid	source_center	destination_center	data	route_type	tri
0	trip-153671041653548748	IND209304AAA	IND209304AAA	training	FTL	
1	trip-153671042288605164	IND561203AAB	IND561203AAB	training	Carting	
2	trip-153671043369099517	IND000000ACB	IND000000ACB	training	FTL	
3	trip-153671046011330457	IND400072AAB	IND401104AAA	training	Carting	
4	trip-153671052974046625	IND583101AAA	IND583119AAA	training	FTL	
...	...	...	...	...	...	
14812	trip-153861095625827784	IND160002AAC	IND160002AAC	test	Carting	
14813	trip-153861104386292051	IND121004AAB	IND121004AAA	test	Carting	
14814	trip-153861106442901555	IND208006AAA	IND208006AAA	test	Carting	
14815	trip-153861115439069069	IND627005AAA	IND628204AAA	test	Carting	
14816	trip-153861118270144424	IND583119AAA	IND583119AAA	test	FTL	

14817 rows × 17 columns

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

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


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]


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]
```

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

```
df2['source_state'].unique()
```

```
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)
```

```
df2['source_city'] = df2['source_name'].apply(location_name_to_city)
print('No of source cities :', df2['source_city'].nunique())
df2['source_city'].unique()[:100]
```

```
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',
       'Himmatnagar', 'Jamshedpur', 'Pondicherry', 'Anand', 'Udgir',
       'Nadiad', 'Villupuram', 'Purulia', 'Bhubaneshwar', 'Bamangola',
       'Tiruppattur', 'Kotdwara', 'Medak', 'Bangalore', 'Dhrangadhra',
       'Hospet', 'Ghumarwin', 'Agra', 'Sitapur', 'Canacona', 'Bilimora',
       'SultnBthry', 'Lucknow', 'Vellore', 'Bhuj', 'Dinhata',
       'Margherita', 'Boisar', 'Vizag', 'Tezpur', 'Koduru', 'Tirupati',
       'Pen', 'Ahmedabad', 'Faizabad', 'Gandhinagar', 'Anantapur',
       'Betul', 'Panskura', 'Rasipurm', 'Sankari', 'Jorhat', 'PNQ',
       'Srikakulam', 'Dehradun', 'Jassur', 'Sawantwadi', 'Shajapur',
       'Ludhiana', 'GreaterThane'], dtype=object)
```

```
df2['source_place'] = df2['source_name'].apply(location_name_to_place)
df2['source_place'].unique()[:100]
```

```
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', 'Busstand_D', 'Central_I_1', 'IndEstat_I', 'Court_D',
       'Panchot_IP', 'Adhartal_IP', 'DumDum_DPC', 'Bomsndra_HB',
       'Swamylyt_D', 'Yadvgiri_IP', 'Old', 'Kundli_H', 'Central_I_3',
       'Vasanthm_I', 'Poonamallee_HB', 'VUNagar_DC', 'NlgaonRd_D',
       'Bnnrghta_L', 'Thirumtr_IP', 'GariDPP_D', 'Jogshwri_I',
```

```
       'KoilStrt_D', 'CotnGren_M', 'Nzbadrd_D', 'Dwaraka_D', 'Nelmngla_H',
       'NvygRDPP_D', 'Gndhichk_D', 'Central_D_3', 'Chowk_D', 'CharRsta_D',
       'Kollgpra_D', 'Peenya_IP', 'GndhiNgr_IP', 'Sanpada_I',
       'WrdN4DPP_D', 'Sakinaka_RP', 'CivilHPL_D', 'OstwlEmp_D',
       'Gajuwaka', 'Mhbhirab_D', 'MGRoad_D', 'Balajicly_I', 'BljiMrkt_D',
       'Dankuni_HB', 'Trnsport_H', 'Rakhial', 'Memnagar', 'East_I_21',
       'Mithakal_D'], dtype=object)
```

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

```
df2['destination_state'] = df2['destination_name'].apply(location_name_to_state)
df2['destination_state'].head(10)
```

```
0    Uttar Pradesh
1        Karnataka
2          Haryana
3      Maharashtra
4        Karnataka
5       Tamil Nadu
6       Tamil Nadu
7        Karnataka
8          Gujarat
9            Delhi
Name: destination_state, dtype: object
```

```
def get_fun(name):
  value = name.split("(")
  if len(value) == 1:
        return value[0]
  else:
        return value[1].replace(')', "")
```

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

```
df2['destination_name'].apply(lambda x:x.split("_")[0])
```

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

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

Trip_creation_time: Extract features like month, year and day etc

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

```
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]
```

```
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()
```

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

```
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()
```

```
0    9
1    9
2    9
```

```
3    9
4    9
Name: trip_creation_month, dtype: int8
```

```
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()
```

```
0    2018
1    2018
2    2018
3    2018
4    2018
Name: trip_creation_year, dtype: int16
```

```
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()
```

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

```
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()
```

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

Finding the structure of data after data cleaning

```
df2.shape
```

```
(14817, 28)
```

```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14817 entries, 0 to 14816
Data columns (total 28 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   trip_uuid                       14817 non-null  object
 1   source_center                   14817 non-null  object
 2   destination_center              14817 non-null  object
 3   data                            14817 non-null  category
 4   route_type                      14817 non-null  category
 5   trip_creation_time              14817 non-null  datetime64[ns]
 6   source_name                     14817 non-null  object
 7   destination_name                14817 non-null  object
 8   od_total_time                   14817 non-null  float64
 9   start_scan_to_end_scan          14817 non-null  float64
 10  actual_distance_to_destination  14817 non-null  float32
 11  actual_time                     14817 non-null  float32
 12  osrm_time                       14817 non-null  float32
 13  osrm_distance                   14817 non-null  float32
 14  segment_actual_time             14817 non-null  float32
 15  segment_osrm_time               14817 non-null  float32
 16  segment_osrm_distance           14817 non-null  float32
 17  source_state                    14817 non-null  object
 18  source_place                    14817 non-null  object
 19  source_city                     14817 non-null  object
 20  destination_state               14817 non-null  object
 21  destination_place               14817 non-null  object
 22  trip_creation_date              14817 non-null  datetime64[ns]
 23  trip_creation_day               14817 non-null  int8
 24  trip_creation_month             14817 non-null  int8
 25  trip_creation_year              14817 non-null  int16
 26  trip_creation_week              14817 non-null  int8
 27  trip_creation_hour              14817 non-null  int8
dtypes: category(2), datetime64[ns](2), float32(7), float64(2), int16(1), int8(4), object(10)
memory usage: 2.1+ MB
```

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

	count	mean	std	min	25%	50%	75%	max
od_total_time	14817.0	531.697630	658.868223	23.460000	149.930000	280.770000	638.200000	7898.550000
start_scan_to_end_scan	14817.0	530.810016	658.705957	23.000000	149.000000	280.000000	637.000000	7898.000000
actual_distance_to_destination	14817.0	164.477829	305.388153	9.002461	22.837238	48.474072	164.583206	2186.531738
actual_time	14817.0	357.143768	561.396118	9.000000	67.000000	149.000000	370.000000	6265.000000
osrm_time	14817.0	161.384018	271.360992	6.000000	29.000000	60.000000	168.000000	2032.000000
osrm_distance	14817.0	204.344711	370.395569	9.072900	30.819201	65.618805	208.475006	2840.081055
segment_actual_time	14817.0	353.892273	556.247925	9.000000	66.000000	147.000000	367.000000	6230.000000
segment_osrm_time	14817.0	180.949783	314.542053	6.000000	31.000000	65.000000	185.000000	2564.000000
segment_osrm_distance	14817.0	223.201157	416.628387	9.072900	32.654499	70.154404	218.802399	3523.632324
trip_creation_day	14817.0	18.370790	7.893275	1.000000	14.000000	19.000000	25.000000	30.000000
trip_creation_month	14817.0	9.120672	0.325757	9.000000	9.000000	9.000000	9.000000	10.000000
trip_creation_year	14817.0	2018.000000	0.000000	2018.000000	2018.000000	2018.000000	2018.000000	2018.000000
trip_creation_week	14817.0	38.295944	0.967872	37.000000	38.000000	38.000000	39.000000	40.000000
trip_creation_hour	14817.0	12.449821	7.986553	0.000000	4.000000	14.000000	20.000000	23.000000

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

	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_place	14817	761	Bilaspur_HB	1063
source_city	14817	690	Mumbai	1442
destination_state	14817	39	Maharashtra	2561
destination_place	14817	850	Bilaspur_HB	821

```
df2['trip_creation_hour'].unique()
```

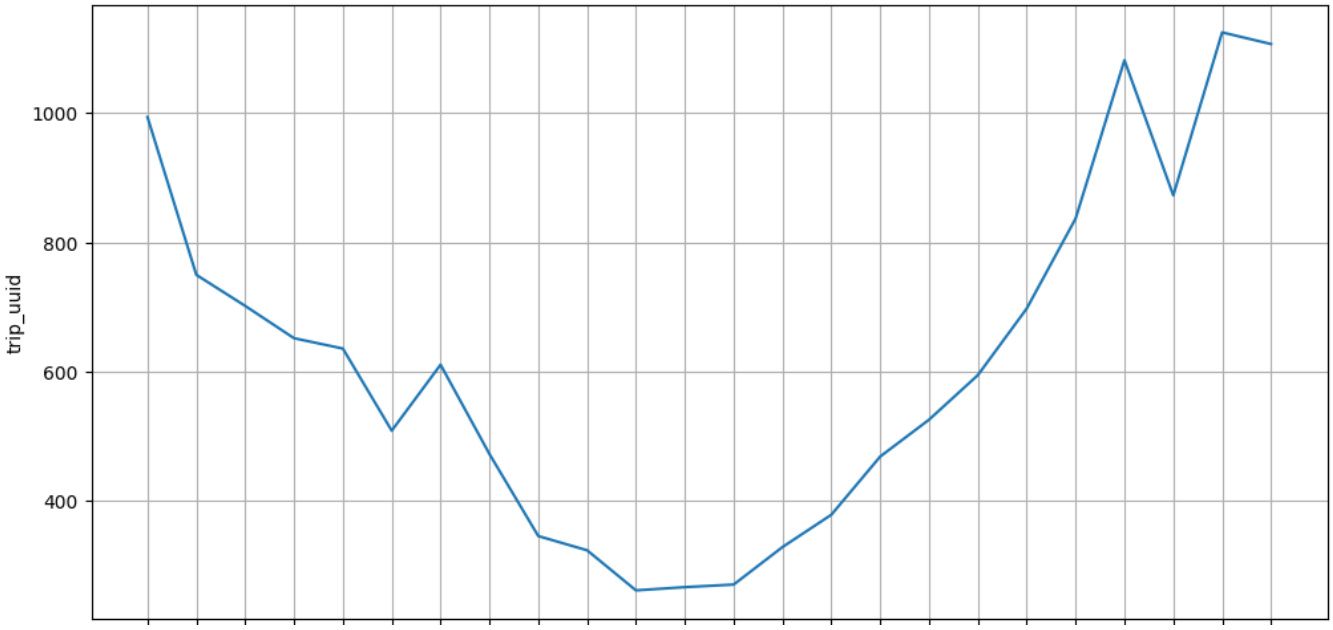
```
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
       17, 18, 19, 20, 21, 22, 23], dtype=int8)
```

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

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

```
plt.figure(figsize = (12, 6))
sns.lineplot(data = df_hour,
             x = df_hour['trip_creation_hour'],
             y = df_hour['trip_uuid'],
             markers = '*')
plt.xticks(np.arange(0,24))
plt.grid('both')
plt.plot()
```

[]



It can be inferred from the above plot that the number of trips start increasing after the noon, becomes maximum at 10 P.M and then start decreasing.

trips that are created for different days of the month

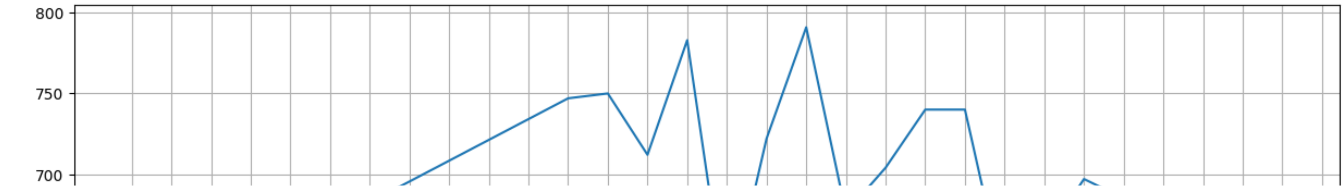
```
df2['trip_creation_day'].unique()
```

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

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

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

[]



1:It can be inferred from the above plot that most of the trips are created in the mid of the month.

2:That means customers usually make more orders in the mid of the month.

```
df2['trip_creation_week'].unique()
```

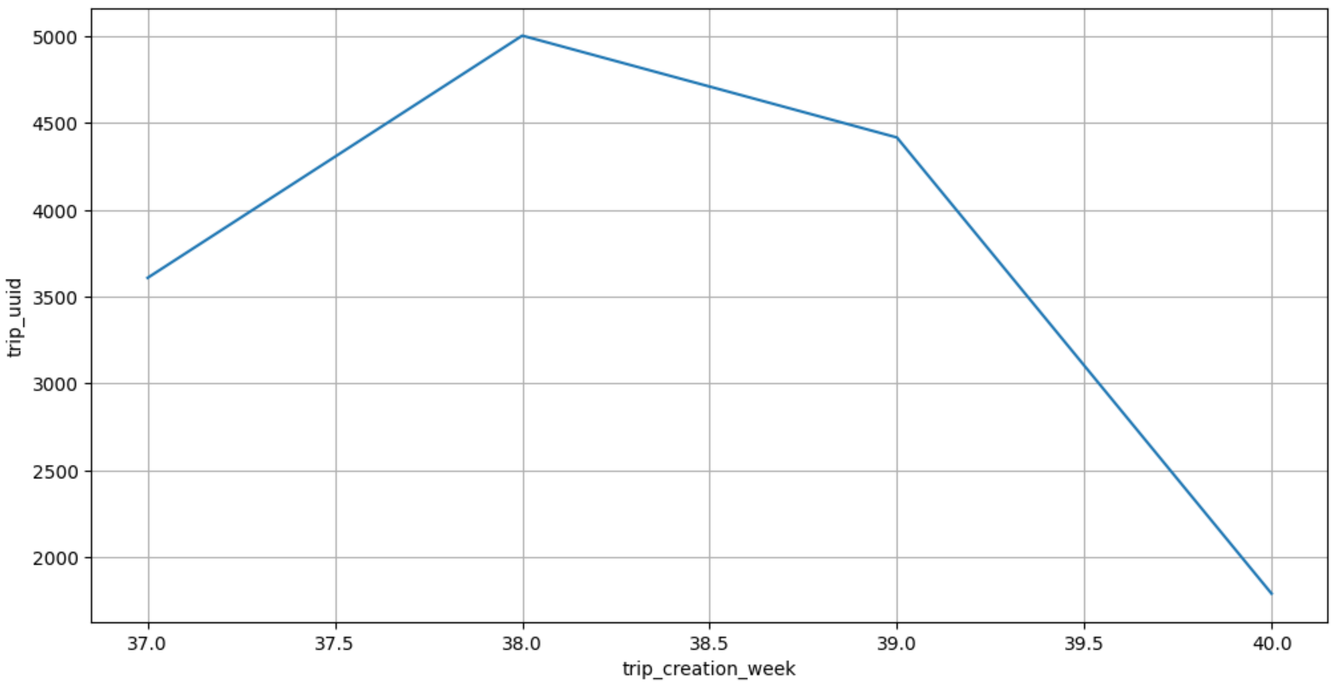
    array([37, 38, 39, 40], dtype=int8)

```
df_week = df2.groupby(by = 'trip_creation_week')['trip_uuid'].count().to_frame().reset_index()
df_week.head()
```

	trip_creation_week	trip_uuid
0	37	3608
1	38	5004
2	39	4417
3	40	1788

```
plt.figure(figsize = (12, 6))
sns.lineplot(data = df_week,
             x = df_week['trip_creation_week'],
             y = df_week['trip_uuid'],
             markers = 'o')
plt.grid('both')
plt.plot()
```

[]



It can be inferred from the above plot that most of the trips are created in the 38th week.

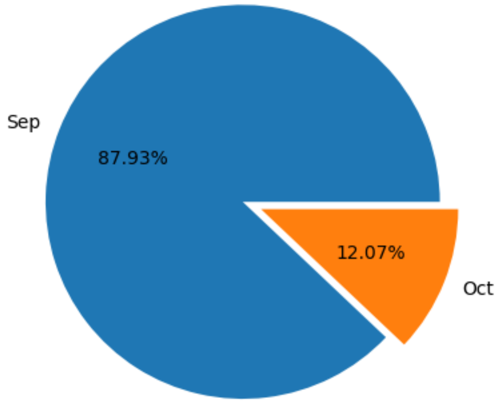
trips created in the given two months

```
df_month = df2.groupby(by = 'trip_creation_month')['trip_uuid'].count().to_frame().reset_index()
df_month['perc'] = np.round(df_month['trip_uuid'] * 100/ df_month['trip_uuid'].sum(), 2)
df_month.head()
```

	trip_creation_month	trip_uuid	perc
0	9	13029	87.93

```
plt.pie(x = df_month['trip_uuid'],
        labels = ['Sep', 'Oct'],
        explode = [0, 0.1],
       autopct = '%.2f%%')
plt.plot()
```

```
[]
```



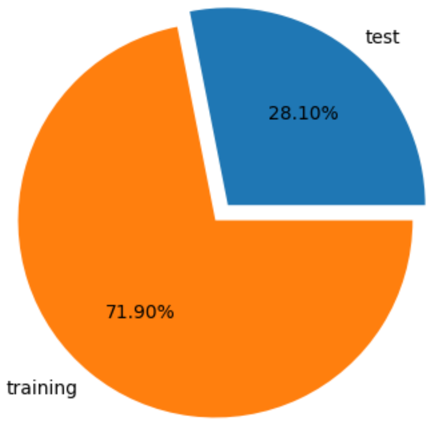
the distribution of trip data for the orders

```
df_data = df2.groupby(by = 'data')['trip_uuid'].count().to_frame().reset_index()
df_data['perc'] = np.round(df_data['trip_uuid'] * 100/ df_data['trip_uuid'].sum(), 2)
df_data.head()
```

	data	trip_uuid	perc
0	test	4163	28.1
1	training	10654	71.9

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

```
[]
```



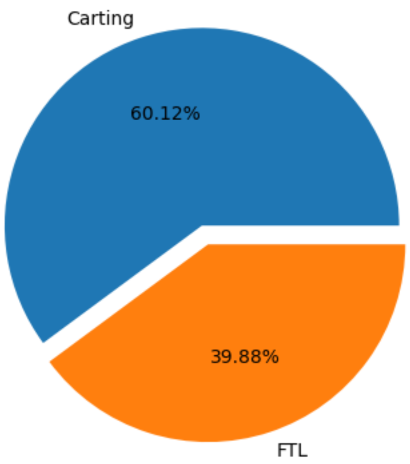
distribution of route types for the orders

```
df_route = df2.groupby(by = 'route_type')['trip_uuid'].count().to_frame().reset_index()
df_route['perc'] = np.round(df_route['trip_uuid'] * 100/ df_route['trip_uuid'].sum(), 2)
df_route.head()
```

	route_type	trip_uuid	perc
0	Carting	8908	60.12
1	FTL	5909	39.88

```
plt.pie(x = df_route['trip_uuid'],
        labels = ['Carting', 'FTL'],
        explode = [0, 0.1],
        autopct = '%.2f%%')
plt.plot()
```

[]



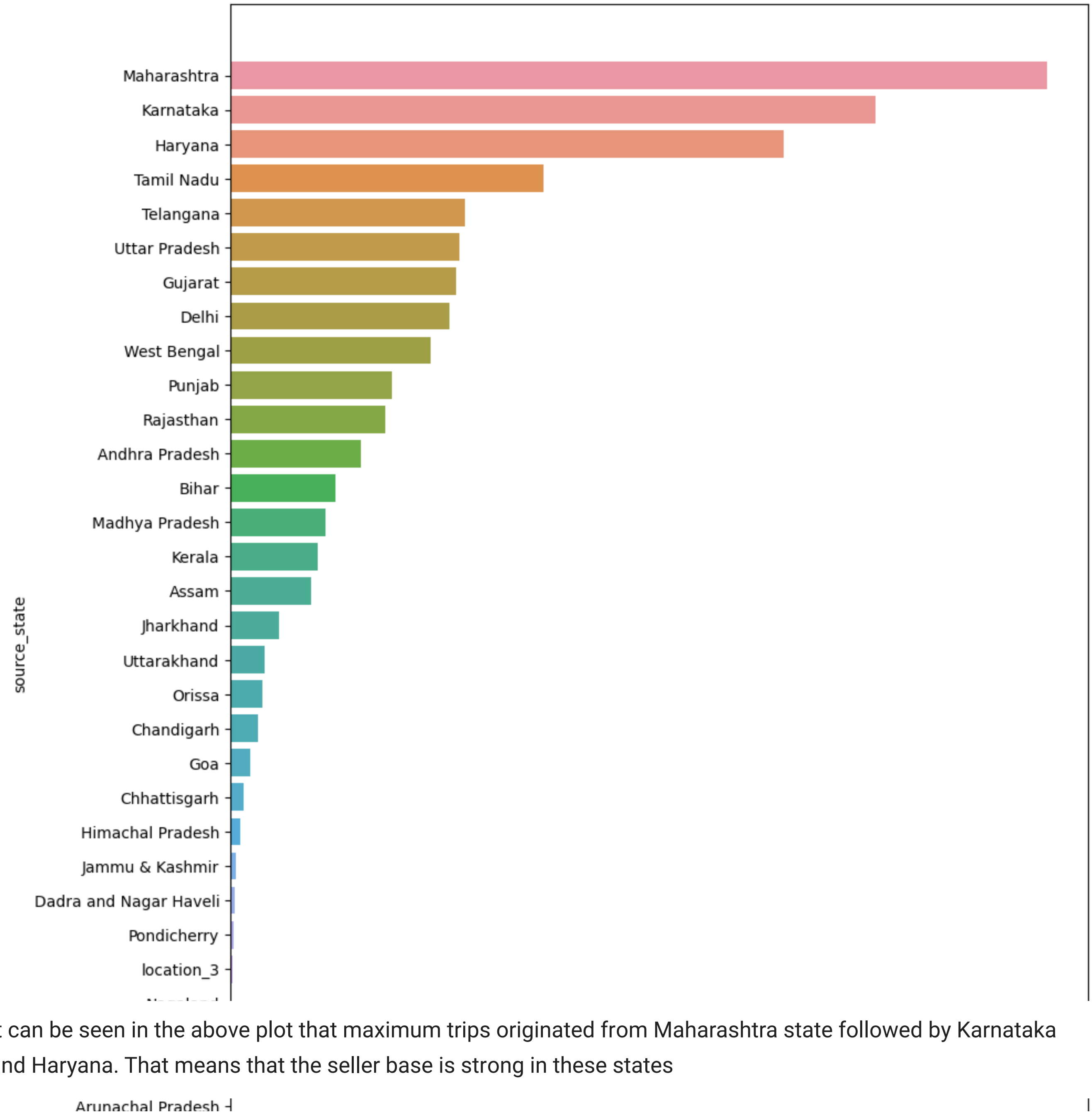
the distribution of number of trips created from different states

```
df_source_state = df2.groupby(by = 'source_state')['trip_uuid'].count().to_frame().reset_index()
df_source_state['perc'] = np.round(df_source_state['trip_uuid'] * 100/ df_source_state['trip_uuid'].sum(), 2)
df_source_state = df_source_state.sort_values(by = 'trip_uuid', ascending = False)
df_source_state.head()
```

	source_state	trip_uuid	perc
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

```
plt.figure(figsize = (10, 15))
sns.barplot(data = df_source_state,
            x = df_source_state['trip_uuid'],
            y = df_source_state['source_state'])
plt.plot()
```

[ ]



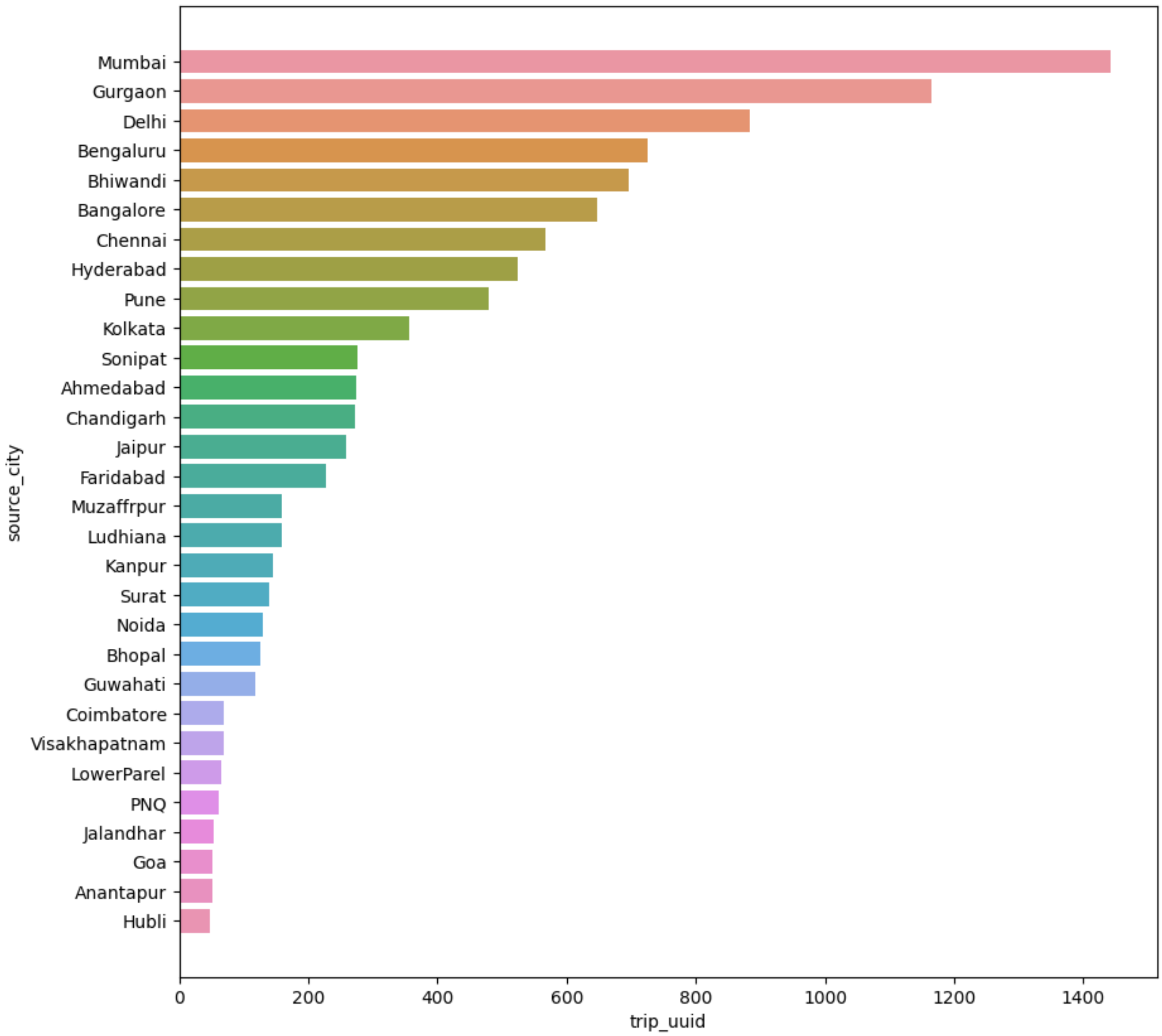
It can be seen in the above plot that maximum trips originated from Maharashtra state followed by Karnataka and Haryana. That means that the seller base is strong in these states

```
df_source_city = df2.groupby(by = 'source_city')['trip_uuid'].count().to_frame().reset_index()
df_source_city['perc'] = np.round(df_source_city['trip_uuid'] * 100/ df_source_city['trip_uuid'].sum(), 2)
df_source_city = df_source_city.sort_values(by = 'trip_uuid', ascending = False)[:30]
df_source_city
```

	source_city	trip_uuid	perc
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
610	Sonipat	276	1.86
2	Ahmedabad	274	1.85
133	Chandigarh	273	1.84
270	Jaipur	259	1.75
201	Faridabad	227	1.53
447	Muzaffrpur	159	1.07
382	Ludhiana	158	1.07

```
plt.figure(figsize = (10, 10))
sns.barplot(data = df_source_city,
            x = df_source_city['trip_uuid'],
            y = df_source_city['source_city'])
plt.plot()
```

```
[]
```



It can be seen in the above plot that maximum trips originated from Mumbai city followed by Gurgaon Delhi, Bengaluru and Bhiwandi. That means that the seller base is strong in these cities.

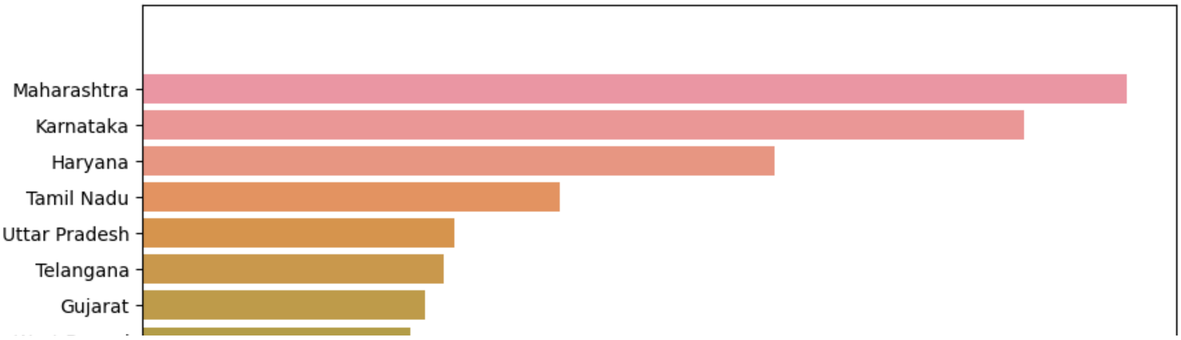
the distribution of number of trips which ended in different states

```
df_destination_state = df2.groupby(by = 'destination_state')['trip_uuid'].count().to_frame().reset_index()
df_destination_state['perc'] = np.round(df_destination_state['trip_uuid'] * 100/ df_destination_state['trip_uuid'].sum(), 2)
df_destination_state = df_destination_state.sort_values(by = 'trip_uuid', ascending = False)
df_destination_state.head()
```

	destination_state	trip_uuid	perc
18	Maharashtra	2561	17.28
15	Karnataka	2294	15.48
11	Haryana	1643	11.09
25	Tamil Nadu	1084	7.32
28	Uttar Pradesh	811	5.47

```
plt.figure(figsize = (10, 15))
sns.barplot(data = df_destination_state,
            x = df_destination_state['trip_uuid'],
            y = df_destination_state['destination_state'])
plt.plot()
```

[]



It can be seen in the above plot that maximum trips ended in Maharashtra state followed by Karnataka, Haryana, Tamil Nadu and Uttar Pradesh. That means that the number of orders placed in these states is significantly high in these states.

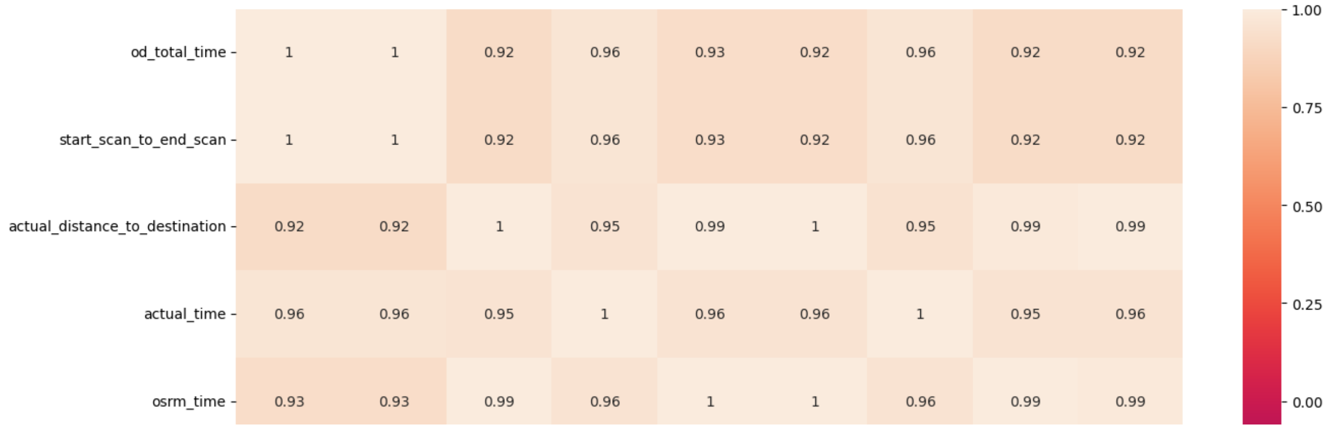
```
df_corr = df2[numerical_columns].corr()
df_corr
```

	od_total_time	start_scan_to_end_scan	actual_distance_to_destination	actual_time	osrm_time	osrm_di
od_total_time	1.000000	0.999999	0.918222	0.961094	0.926516	0.9
start_scan_to_end_scan	0.999999	1.000000	0.918308	0.961147	0.926571	0.9
actual_distance_to_destination	0.918222	0.918308	1.000000	0.953757	0.993561	0.9
actual_time	0.961094	0.961147	0.953757	1.000000	0.958593	0.9
osrm_time	0.926516	0.926571	0.993561	0.958593	1.000000	0.9
osrm_distance	0.924219	0.924299	0.997264	0.959214	0.997580	1.0
segment_actual_time	0.961119	0.961171	0.952821	0.999989	0.957765	0.9
segment_osrm_time	0.918490	0.918561	0.987538	0.953872	0.993259	0.9
segment_osrm_distance	0.919199	0.919291	0.993061	0.956967	0.991608	0.9

Meghalaya

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

[ ]



Very High Correlation (> 0.9) exists between columns all the numerical columns specified above

3. In-depth analysis and feature engineering:

STEP-1 : Set up Null Hypothesis

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

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

STEP-2 : Checking for basic assumpitons for the hypothesis

1:Distribution check using QQ Plot

2:Homogeneity of Variances using Lavene's test

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

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

p-val > alpha : Accept H0

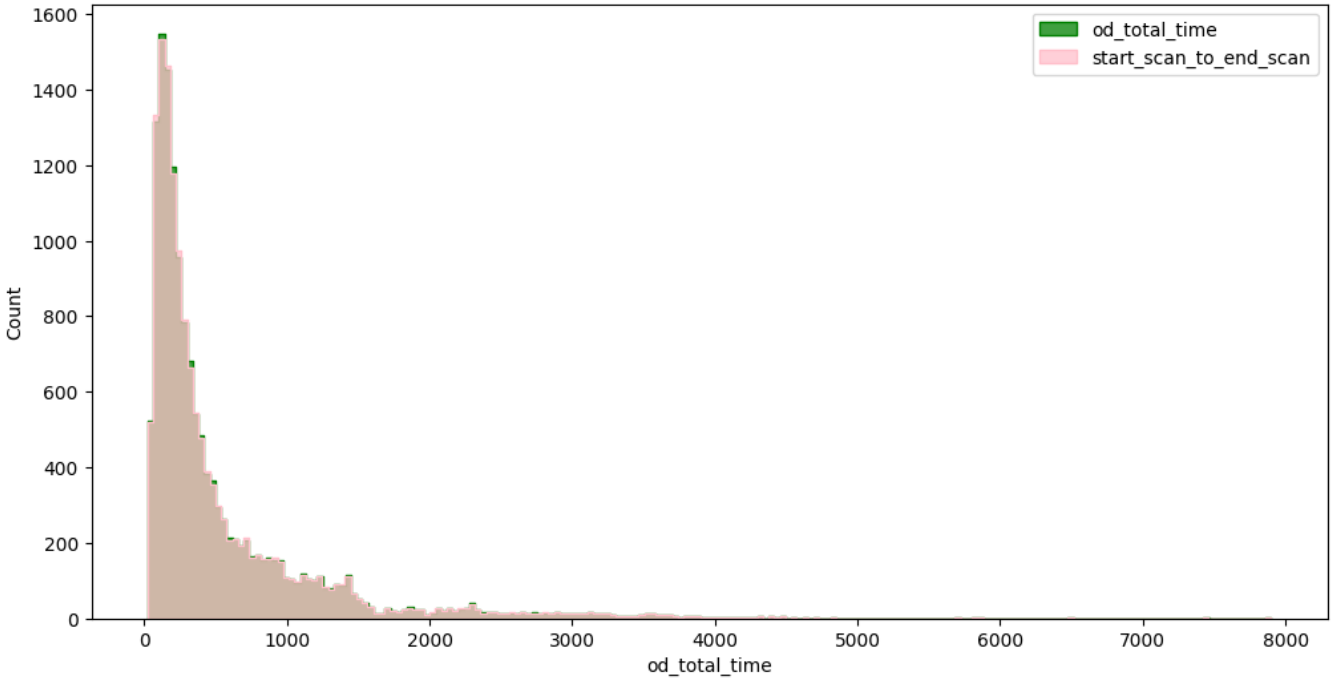
p-val < alpha : Reject H0

```
df2[['od_total_time', 'start_scan_to_end_scan']].describe()
```

	od_total_time	start_scan_to_end_scan
count	14817.000000	14817.000000
mean	531.697630	530.810016
std	658.868223	658.705957
min	23.460000	23.000000
25%	149.930000	149.000000
50%	280.770000	280.000000
75%	638.200000	637.000000
max	7898.550000	7898.000000

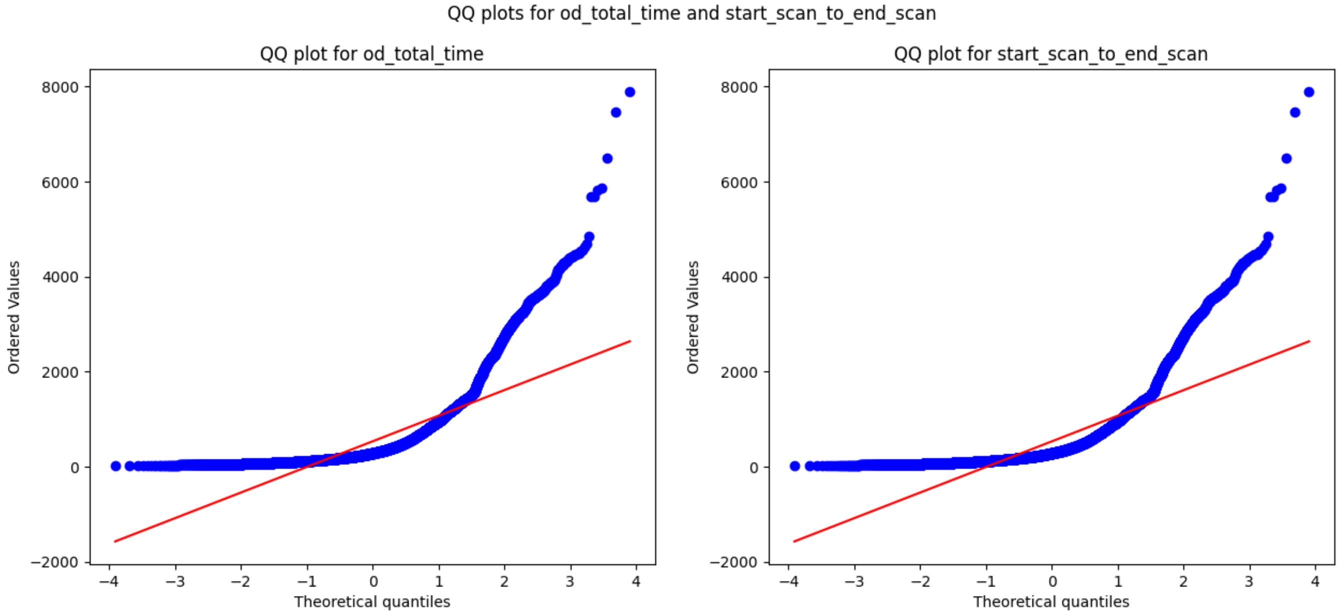
```
plt.figure(figsize = (12, 6))
sns.histplot(df2['od_total_time'], element = 'step', color = 'green')
sns.histplot(df2['start_scan_to_end_scan'], element = 'step', color = 'pink')
plt.legend(['od_total_time', 'start_scan_to_end_scan'])
plt.plot()
```

[]




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

[]



It can be seen from the above plots that the samples do not come from normal distribution.

Applying Shapiro test for normality

$H0$: The sample follows normal distribution $H1$

Ha : The sample does not follow normal distribution

alpha = 0.05

Test Statistics : Shapiro-Wilk test for normality

```
test_stat, p_value = spy.shapiro(df2['od_total_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
```

```
test_stat, p_value = spy.shapiro(df2['start_scan_to_end_scan'].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
```

Transforming the data using boxcox transformation to check if the transformed data follows normal distribution.

```
transformed_od_total_time = spy.boxcox(df2['od_total_time'])[0]
test_stat, p_value = spy.shapiro(transformed_od_total_time)
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 7.172770042757021e-25
The sample does not follow normal distribution
/usr/local/lib/python3.10/dist-packages/scipy/stats/_morestats.py:1882: UserWarning: p-value may not be accurate for N > 5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

```
transformed_start_scan_to_end_scan = spy.boxcox(df2['start_scan_to_end_scan'])[0]
test_stat, p_value = spy.shapiro(transformed_start_scan_to_end_scan)
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 1.0471322892609475e-24
The sample does not follow normal distribution
```

Even after applying the boxcox transformation on each of the "od_total_time" and "start_scan_to_end_scan" columns, the distributions do not follow normal distribution.

```
# Homogeneity of Variances using Lavene's test

# Null Hypothesis(H0) - Homogenous Variance

# Alternate Hypothesis(HA) - Non Homogenous Variance

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
```

Since the samples are not normally distributed, 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.

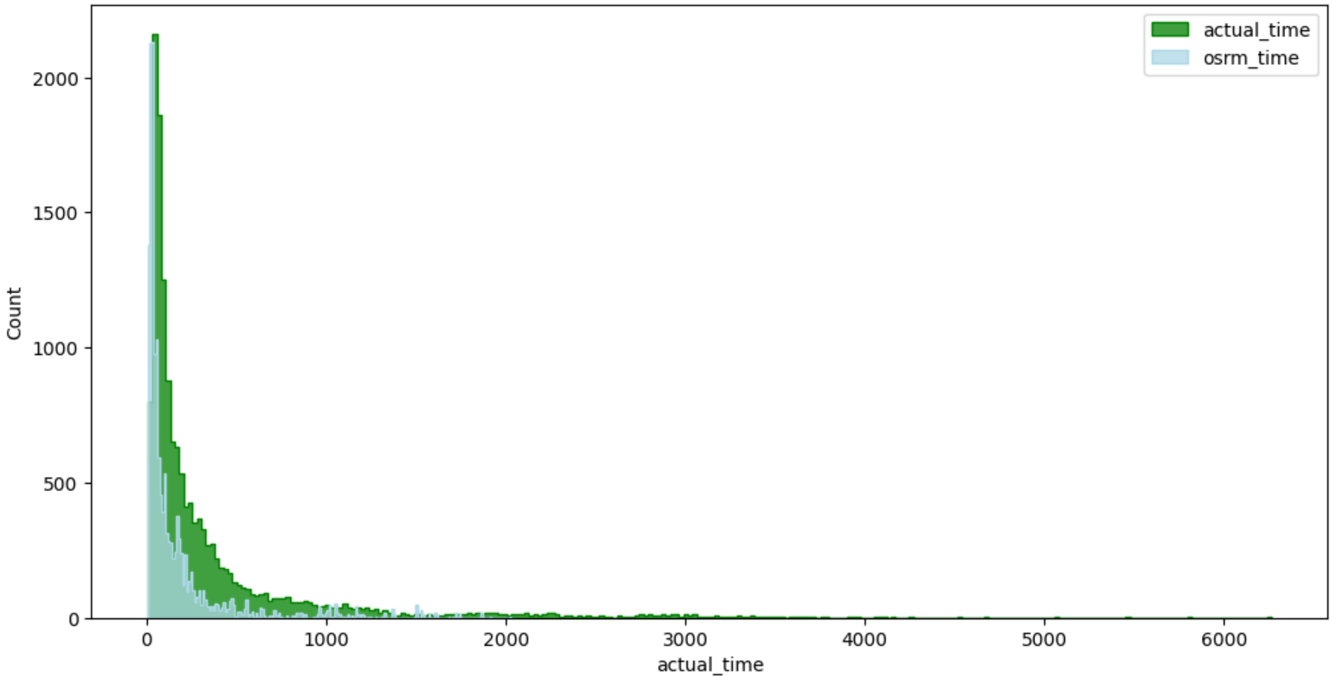
Do hypothesis testing / visual analysis between actual_time aggregated value and OSRM time aggregated value (aggregated values are the values you'll get after merging the rows on the basis of trip_uuid)

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

	actual_time	osrm_time
count	14817.000000	14817.000000
mean	357.143768	161.384018
std	561.396118	271.360992
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

```
# Visual Tests to know if the samples follow normal distribution
plt.figure(figsize = (12, 6))
sns.histplot(df2['actual_time'], element = 'step', color = 'green')
sns.histplot(df2['osrm_time'], element = 'step', color = 'lightblue')
plt.legend(['actual_time', 'osrm_time'])
plt.plot()
```

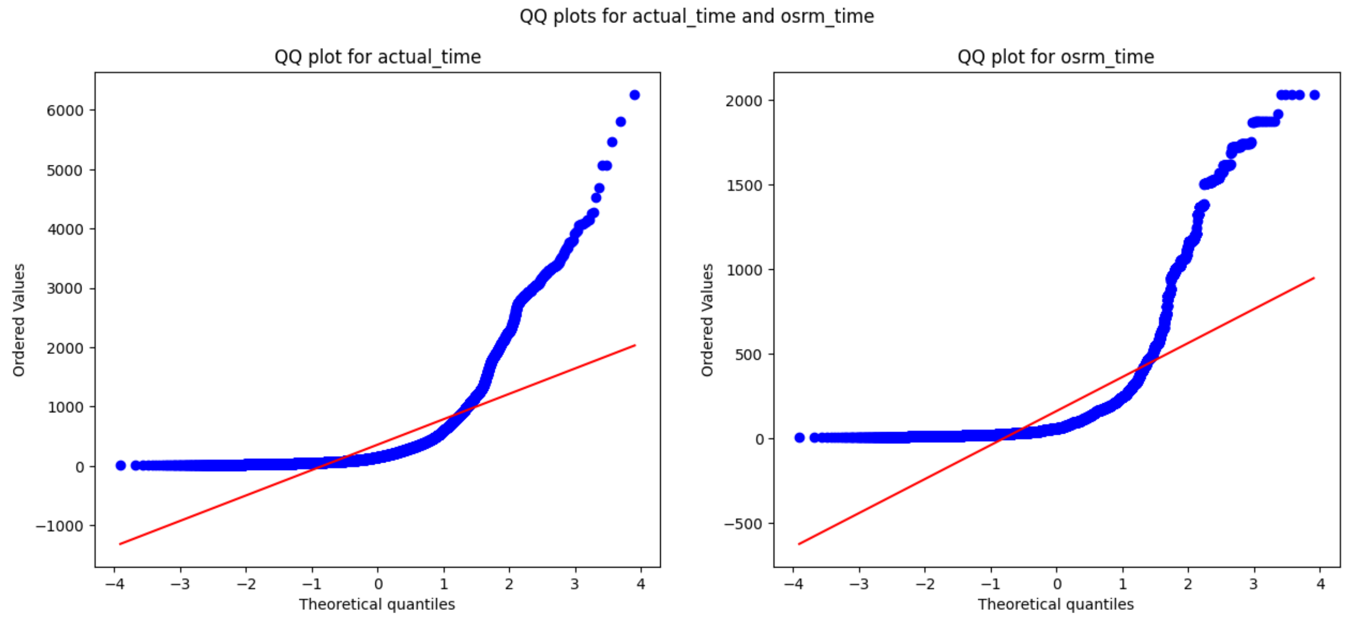
[]



Distribution check using QQ Plot

```
plt.figure(figsize = (15, 6))
plt.subplot(1, 2, 1)
plt.suptitle('QQ plots for actual_time and osrm_time')
spy.probplot(df2['actual_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for actual_time')
plt.subplot(1, 2, 2)
spy.probplot(df2['osrm_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for osrm_time')
plt.plot()
```

[]




```
# It can be seen from the above plots that the samples do not come from normal distribution.
# Applying Shapiro-Wilk test for normality
# H0 : The sample follows normal distribution H1
#  H1: The sample does not follow normal distribution

# alpha = 0.05

# Test Statistics : Shapiro-Wilk test for normality

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

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

```
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

```
# Null Hypothesis(H0) - Homogenous Variance

# Alternate Hypothesis(HA) - Non Homogenous Variance

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 1.871098057987424e-220
The samples do not have  Homogenous Variance
```

we are applying ttest sample sample same or not

h0 :sample are same

ha: sample are diffent

```
actual_time_50 =df2['actual_time'].sample(50)
osrm_time_50 =df2['osrm_time'].sample(50)
statistic,pvalue=spy.ttest_rel(actual_time_50,osrm_time_50)
print(pvalue)
if p_value < 0.05:
    print('The samples are not similar')
else:
    print('The samples are similar ')
```

```
0.09252181445605037
The samples are not similar
```

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

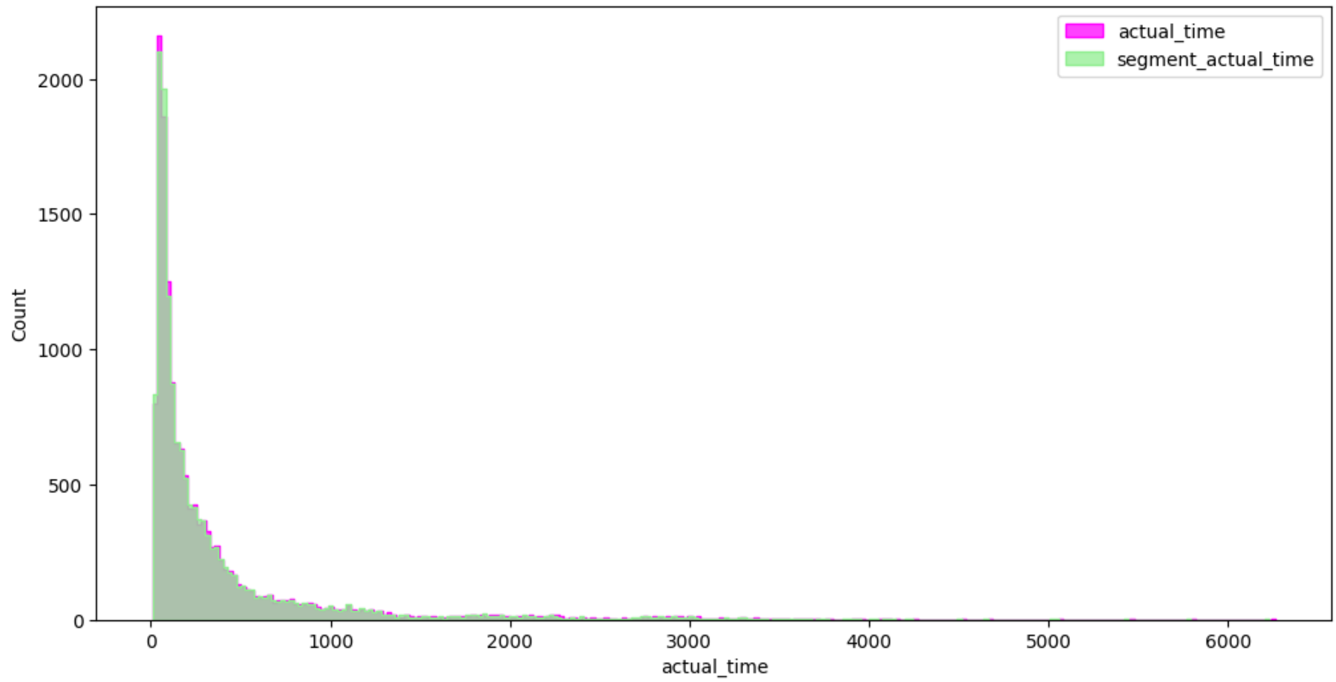
Do hypothesis testing/ visual analysis between actual_time aggregated value and segment actual time aggregated value (aggregated values are the values you'll get after merging the rows on the basis of trip_uuid)

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

	actual_time	segment_actual_time
count	14817.000000	14817.000000
mean	357.143768	353.892273
std	561.396118	556.247925
min	9.000000	9.000000
25%	67.000000	66.000000
50%	149.000000	147.000000
75%	370.000000	367.000000
max	6265.000000	6230.000000

```
plt.figure(figsize = (12, 6))
sns.histplot(df2['actual_time'], element = 'step', color = 'magenta')
sns.histplot(df2['segment_actual_time'], element = 'step', color = 'lightgreen')
plt.legend(['actual_time', 'segment_actual_time'])
plt.plot()
```

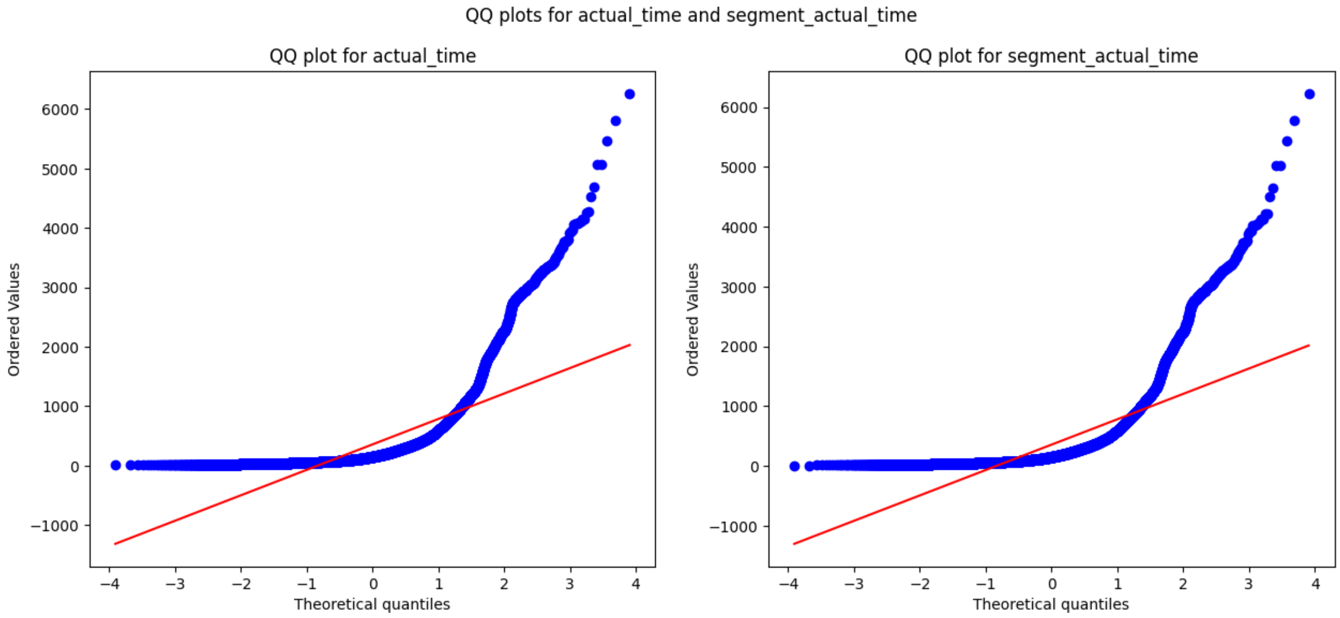
```
[]
```



Distribution check using QQ Plot

```
plt.figure(figsize = (15, 6))
plt.subplot(1, 2, 1)
plt.suptitle('QQ plots for actual_time and segment_actual_time')
spy.probplot(df2['actual_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for actual_time')
plt.subplot(1, 2, 2)
spy.probplot(df2['segment_actual_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for segment_actual_time')
plt.plot()
```

```
[]
```




```
# It can be seen from the above plots that the samples do not come from normal distribution.
# Applying Shapiro-Wilk test for normality
# H0 : The sample follows normal distribution H1
#  Ha: The sample does not follow normal distribution

# alpha = 0.05

# Test Statistics : Shapiro-Wilk test for normality

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

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

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

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

Homogeneity of Variances using Lavene's test

```
# Null Hypothesis(H0) - Homogenous Variance

# Alternate Hypothesis(HA) - Non Homogenous Variance

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 0.695502241317651
The samples have Homogenous Variance
```

```
# we are applying spy.ttest_rel test

actual_time_50 =df2['actual_time'].sample(50)
segment_actual_time_50 =df2['segment_actual_time'].sample(50)
statistic,pvalue=spy.ttest_rel(actual_time_50,segment_actual_time_50)
print(pvalue)
if p_value < 0.05:
    print('The samples are not similar')
else:
    print('The samples are similar ')
```

```
0.07112610180776827
The samples are similar
```

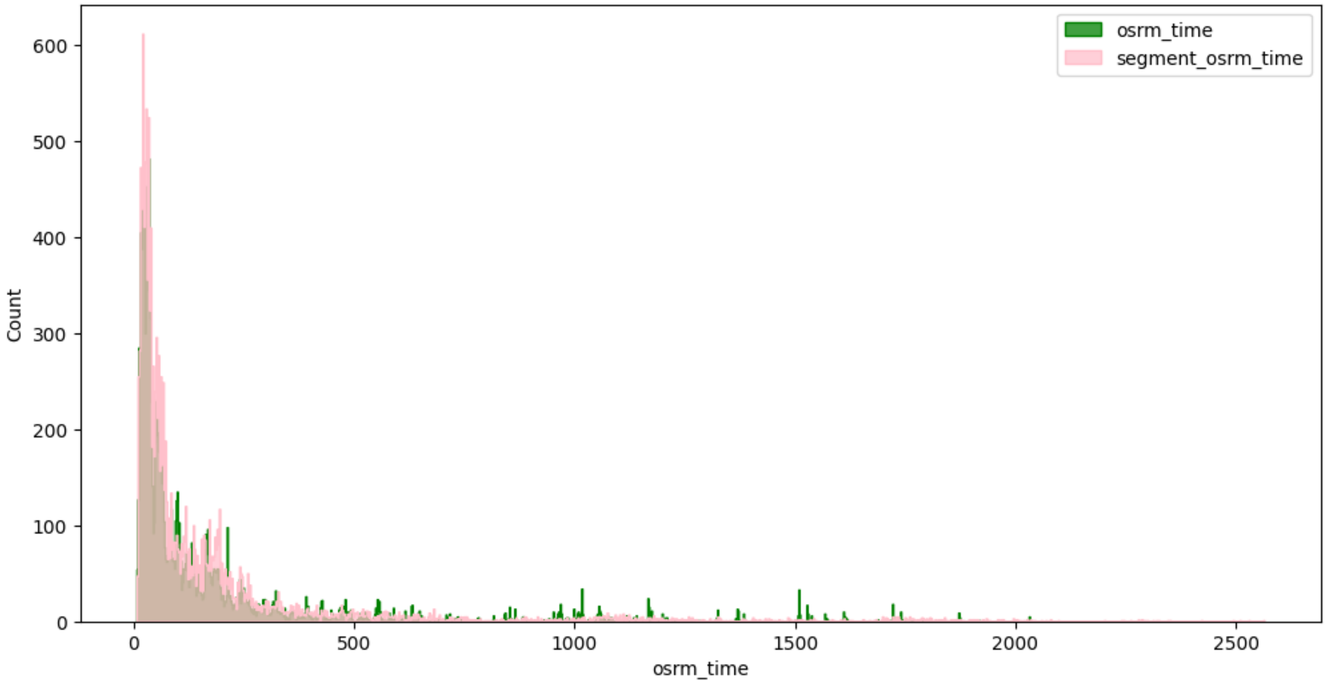
```
df2[['osrm_time', 'segment_osrm_time']].describe().T
```

	count	mean	std	min	25%	50%	75%	max
osrm_time	14817.0	161.384018	271.360992	6.0	29.0	60.0	168.0	2032.0
segment_osrm_time	14817.0	180.949783	314.542053	6.0	31.0	65.0	185.0	2564.0

Visual Tests to know if the samples follow normal distribution

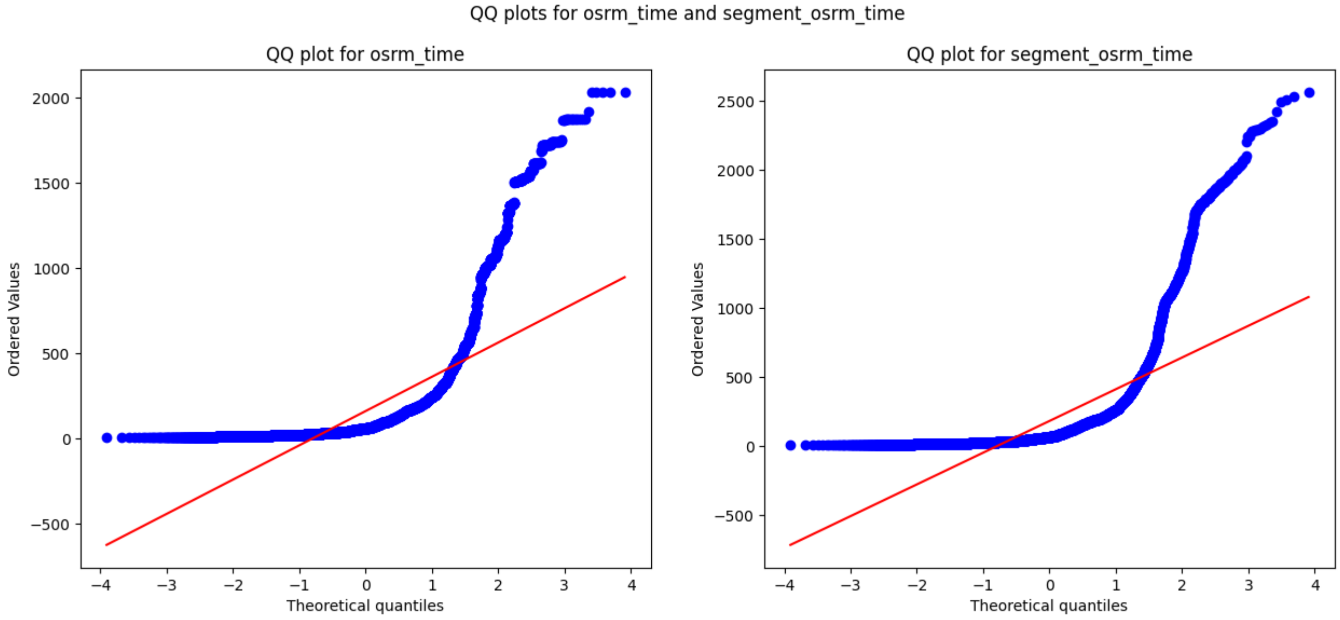
```
plt.figure(figsize = (12, 6))
sns.histplot(df2['osrm_time'], element = 'step', color = 'green', bins = 1000)
sns.histplot(df2['segment_osrm_time'], element = 'step', color = 'pink', bins = 1000)
plt.legend(['osrm_time', 'segment_osrm_time'])
plt.plot()
```

```
[]
```



```
plt.figure(figsize = (15, 6))
plt.subplot(1, 2, 1)
plt.suptitle('QQ plots for osrm_time and segment_osrm_time')
spy.probplot(df2['osrm_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for osrm_time')
plt.subplot(1, 2, 2)
spy.probplot(df2['segment_osrm_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for segment_osrm_time')
plt.plot()
```

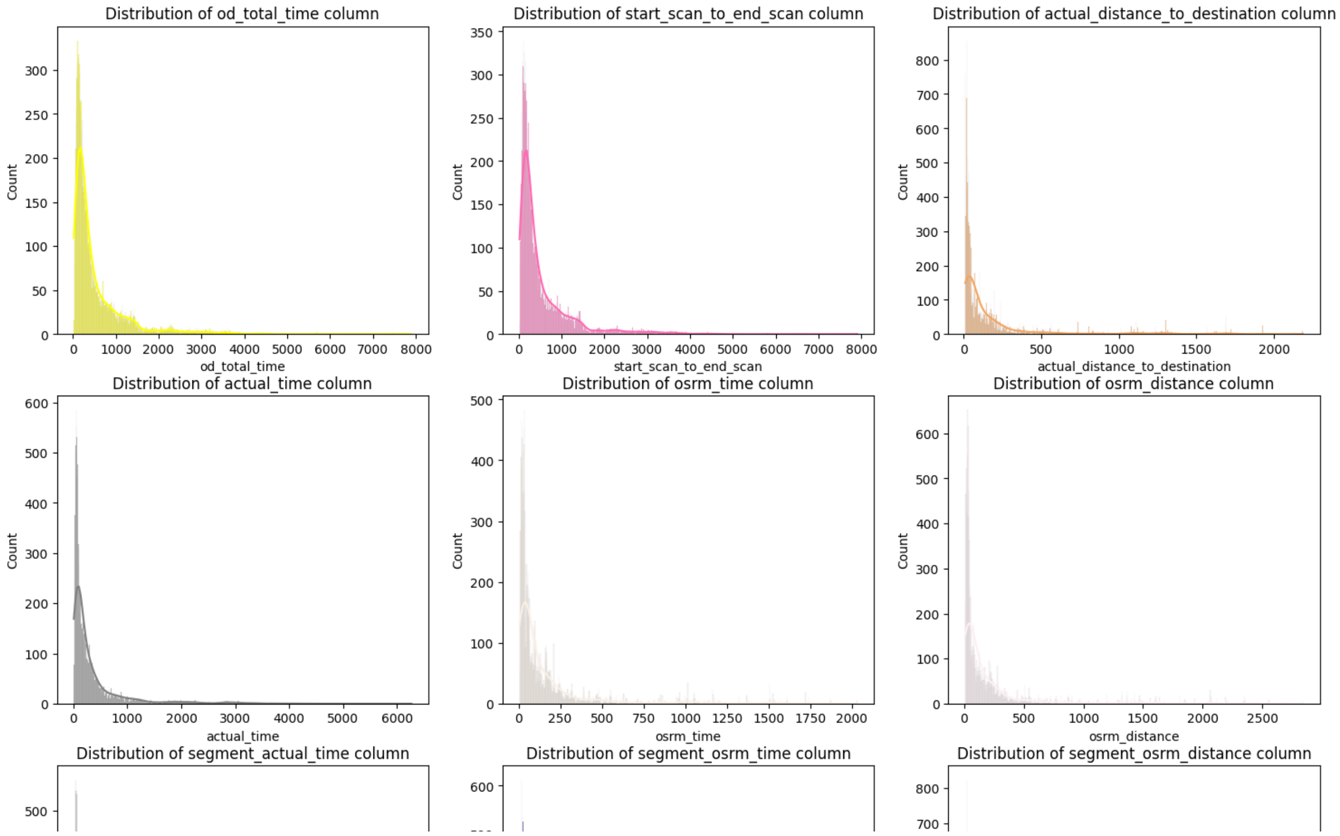
[]



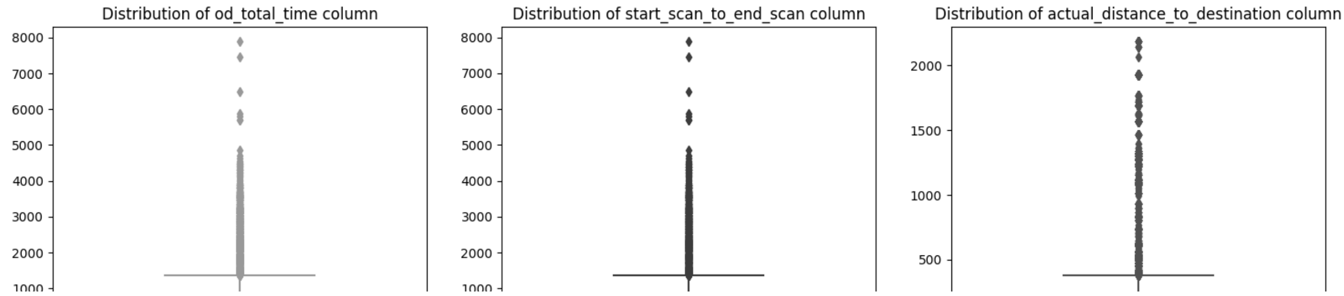
Find outliers in the numerical variables (you might find outliers in almost all the variables), and check it using visual analysis

```
numerical_columns = ['od_total_time', 'start_scan_to_end_scan', 'actual_distance_to_destination',
                     'actual_time', 'osrm_time', 'osrm_distance', 'segment_actual_time',
                     'segment_osrm_time', 'segment_osrm_distance']
df2[numerical_columns].describe().T
```

```
import matplotlib as mpl
plt.figure(figsize = (18, 15))
for i in range(len(numerical_columns)):
    plt.subplot(3, 3, i + 1)
    clr = np.random.choice(list(mpl.colors.cnames))
    sns.histplot(df2[numerical_columns[i]], bins = 1000, kde = True, color = clr)
    plt.title(f"Distribution of {numerical_columns[i]} column")
    plt.plot()
```




```
plt.figure(figsize = (18, 15))
for i in range(len(numerical_columns)):
    plt.subplot(3, 3, i + 1)
    clr = np.random.choice(list(mpl.colors.cnames))
    sns.boxplot(df2[numerical_columns[i]], color = clr)
    plt.title(f"Distribution of {numerical_columns[i]} column")
    plt.plot()
```



It can be clearly seen in the above plots that there are outliers in all the numerical columns that need to be treated.

```
# 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 : 22.837238311767578
Q3 : 164.5832061767578
IQR : 141.74596786499023
LB : -189.78171348571777
UB : 377.20215797424316
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 : 30.81920051574707
Q3 : 208.47500610351562
IQR : 177.65580558776855
LB : -235.66450786590576
UB : 474.95871448516846
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
```

The outliers present in our sample data can be the true outliers. It's best to remove outliers only when there is a sound reason for doing so. Some outliers represent natural variations in the population, and they should be left as is in the dataset.

```
# Do one-hot encoding of categorical variables (like route_type)

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

```
Carting    8908
FTL        5909
Name: route_type, dtype: int64
```

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

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

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

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

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

```
label_encoder = LabelEncoder()
df2['data'] = label_encoder.fit_transform(df2['data'])
```

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

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

Business Insights

1.The data is given from the period '2018-09-12 00:00:16' to '2018-10-08 03:00:24'.

2 .There are about 14817 unique trip IDs, 1508 unique source centers, 1481 unique destination_centers, 690 unique source cities, 806 unique destination cities.

3 .Most of the data is for testing than for training.

Most common route type is Carting. 5.The names of 14 unique location ids are missing in the data.

6.The number of trips start increasing after the noon, becomes maximum at 10 P.M and then start decreasing.

Maximum trips are created in the 38th week.