Business Case: Delhivery - Feature Engineering

About Delhivery

Delhivery is the largest and fastest-growing fully integrated player in India by revenue in Fiscal 2021. They aim to build the operating system for commerce, through a combination of world-class infrastructure, logistics operations of the highest quality, and cutting-edge engineering and technology capabilities. The Data team builds intelligence and capabilities using this data that helps them to widen the gap between the quality, efficiency, and profitability of their business versus their competitor

```
# Importing the libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib as mpl
import matplotlib.pyplot as plt
import scipy.stats as spy
```

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

```
df = pd.read_csv("https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/551/original/delhivery_data.csv?1642751181")
df.head()
```

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_cent
0	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AA
1	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AA
2	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AA
3	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AA
4	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AA

5 rows × 24 columns

```
#shape of the dataset
df.shape
```

```
(144867, 24)
```

```
# columns names in dataset and their datatype
df.dtypes
```

```
data                              object
trip_creation_time                object
route_schedule_uuid               object
route_type                        object
trip_uuid                         object
source_center                     object
source_name                       object
destination_center                object
destination_name                  object
od_start_time                     object
od_end_time                       object
start_scan_to_end_scan           float64
is_cutoff                           bool
cutoff_factor                      int64
cutoff_timestamp                  object
actual_distance_to_destination   float64
actual_time                      float64
osrm_time                        float64
```

```
osrm_distance                     float64
factor                            float64
segment_actual_time               float64
segment_osrm_time                 float64
segment_osrm_distance             float64
segment_factor                    float64
dtype: object
```

```
#Basic information about the dataset
df.info()
```

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

```
#dropping the unknown columns according to the dataset
unknown_fields = ["is_cutoff", "cutoff_factor", "cutoff_timestamp", "factor", "segment_factor"]
df= df.drop(columns = unknown_fields )
```

```
#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
```

```
#For those columns where number of unique entries is 2, converting the datatype of columns 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
```

We can update the datatype to float32 since the maximum value entry is small which can help in reducing the size of dataset

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

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

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
```

Earlier the dataset was using 25.6+ MB of memory but now it has been reduced to 15.2 + MB. Around 40.63 % reduction in the memory usage.

```
#The time period for which the data is given from the time trip was created till the end of that trip
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**

1.1 Handling missing values in the dataset

```
# checking for the null values
df.isnull().sum()
```

```
data                                0
trip_creation_time                  0
route_schedule_uuid                 0
route_type                          0
trip_uuid                           0
source_center                       0
source_name                       293
destination_center                  0
destination_name                  261
od_start_time                       0
od_end_time                         0
```

```
start_scan_to_end_scan             0
actual_distance_to_destination     0
actual_time                        0
osrm_time                          0
osrm_distance                      0
segment_actual_time                0
segment_osrm_time                  0
segment_osrm_distance              0
dtype: int64
```

Source name and Destination name columns has 293 and 261 null values respectively.

```
# getting the unique source_center of those whose source_name is null
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)
```

```
# getting the unique destination_center of those whose sdestination_name is null
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)
```

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

```
False
```

The centre IDs for which the source name is missing and those all centre IDs for missing destination name are different

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
    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.isna().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
```

Now the missing values are treated.

1.2 Analyzing the structure of the data

```
#description for numerical data
df.describe()
```

	start_scan_to_end_scan	actual_distance_to_destination	actual_time	osrm_time	osrm_distance	segment_actual_time	segment_
count	144867.000000	144867.000000	144867.000000	144867.000000	144867.000000	144867.000000	144
mean	961.262986	234.073380	416.927521	213.868286	284.771301	36.196110	
std	1037.012769	344.990021	598.103638	308.011078	421.119293	53.571156	
min	20.000000	9.000046	9.000000	6.000000	9.008200	-244.000000	
25%	161.000000	23.355875	51.000000	27.000000	29.914701	20.000000	
50%	449.000000	66.126572	132.000000	64.000000	78.525803	29.000000	
75%	1634.000000	286.708878	513.000000	257.000000	343.193253	40.000000	
max	7898.000000	1927.447754	4532.000000	1686.000000	2326.199219	3051.000000	1

```
#description for numerical data
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

1.3.Merging of rows and aggregation of fields

```
# 1) Mergig rows on bases of Trip_uuid, Source ID and Destination
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	trip_creation_time	source_name	desti
0	trip-153671041653548748	IND209304AAA	IND000000ACB	training	FTL	2018-09-12 00:00:16.535741	Kanpur_Central_H_6 (Uttar Pradesh)	Gurgaor
1	trip-153671041653548748	IND462022AAA	IND209304AAA	training	FTL	2018-09-12 00:00:16.535741	Bhopal_Trnsport_H (Madhya Pradesh)	Kanpur_Cent
2	trip-153671042288605164	IND561203AAB	IND562101AAA	training	Carting	2018-09-12 00:00:22.886430	Doddablpur_ChikaDPP_D (Karnataka)	Chikblapu
3	trip-153671042288605164	IND572101AAA	IND561203AAB	training	Carting	2018-09-12 00:00:22.886430	Tumkur_Veersagr_I (Karnataka)	Doddablpur_
4	trip-153671043369099517	IND000000ACB	IND160002AAC	training	FTL	2018-09-12 00:00:33.691250	Gurgaon_Bilaspur_HB (Haryana)	Chandigarh_
...	...	...	...	...	...	...	...	
26363	trip-153861115439069069	IND628204AAA	IND627657AAA	test	Carting	2018-10-03 23:59:14.390954	Tirchchndr_Shnmgprm_D (Tamil Nadu)	Thisayanvilai
26364	trip-153861115439069069	IND628613AAA	IND627005AAA	test	Carting	2018-10-03 23:59:14.390954	Peikulam_SriVnktpm_D (Tamil Nadu)	Tirunelv
26365	trip-153861115439069069	IND628801AAA	IND628204AAA	test	Carting	2018-10-03 23:59:14.390954	Eral_Busstand_D (Tamil Nadu)	Tirchchndr_
26366	trip-153861118270144424	IND583119AAA	IND583101AAA	test	FTL	2018-10-03 23:59:42.701692	Sandur_WrdN1DPP_D (Karnataka)	Bellary_D
26367	trip-153861118270144424	IND583201AAA	IND583119AAA	test	FTL	2018-10-03 23:59:42.701692	Hospet (Karnataka)	Sandur_

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)

#Syntax: total_seconds()
#Parameters: This function does not accept any parameter.
#Return values: This function returns the total number of seconds covered for the specified duration of time instance.
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
```

```
# 2) Aggregate on the basis of just Trip_uuid
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'})
```

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

```
# A function to extact the state name by spliting the source name
def location_name_to_state(x):
  l= x.split("(")
  if len(l)== 1:
    return l[0]
  else:
    return l[1].replace(')',"")
```

```
# A function to extract city name from source name
def location_name_to_city(x):
    if 'location' in x: #those with null values in source name are returned as unknown city
        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]
```

```
# A function to extract place name from source name
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]
```

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

```
# destination state column
df2['destination_state'] = df2['destination_name'].apply(location_name_to_state)
print('Number of destination states :', df2['destination_state'].nunique())
df2['destination_state'].unique()
```

```
Number of destination states : 39
array(['Uttar Pradesh', 'Karnataka', 'Haryana', 'Maharashtra',
       'Tamil Nadu', 'Gujarat', 'Delhi', 'Telangana', 'Rajasthan',
```

```
       'Madhya Pradesh', 'Assam', 'West Bengal', 'Andhra Pradesh',
       'Punjab', 'Chandigarh', 'Dadra and Nagar Haveli', 'Orissa',
       'Bihar', 'Jharkhand', 'Goa', 'Uttarakhand', 'Himachal Pradesh',
       'Kerala', 'Arunachal Pradesh', 'Mizoram', 'Chhattisgarh',
       'Jammu & Kashmir', 'Nagaland', 'Meghalaya', 'Tripura',
       'location_13', 'location_6', 'location_2', 'location_7',
       'location_3', 'location_5', 'location_12', 'location_11',
       'Daman & Diu'], dtype=object)
```

```
# Destination city column
df2['destination_city'] = df2['destination_name'].apply(location_name_to_city)
print('Number of destination cities :', df2['destination_city'].nunique())
df2['destination_city'].unique()[:20]
```

```
Number of destination cities : 806
array(['Kanpur', 'Doddablpur', 'Gurgaon', 'Mumbai', 'Sandur', 'Chennai',
       'Bengaluru', 'Surat', 'Delhi', 'PNQ', 'Faridabad', 'Ratnagiri',
       'Bangalore', 'Hyderabad', 'Aland', 'Jaipur', 'Satna', 'Guwahati',
       'Bareli', 'Nashik'], dtype=object)
```

```
# Destination place column
df2['destination_place'] = df2['destination_name'].apply(location_name_to_place)
print('Number of destination places :', df2['destination_place'].nunique())
df2['destination_place'].unique()[:20]
```

```
Number of destination places : 850
array(['Central_H_6', 'ChikaDPP_D', 'Bilaspur_HB', 'MiraRd_IP',
       'WrdN1DPP_D', 'Poonamallee', 'Vandalur_Dc', 'HBR Layout PC',
       'Central_D_3', 'Bhogal', 'unknown_place', 'MjgaonRd_D',
       'Nelmngla_H', 'Uppal_I', 'RazaviRd_D', 'Central_I_7',
       'Central_I_2', 'Hub', 'SourvDPP_D', 'Varachha_DC'], dtype=object)
```

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

```
# Source state column
df2['source_state'] = df2['source_name'].apply(location_name_to_state)
print('Number of source states :', df2['source_state'].nunique())
df2['source_state'].unique()
```

```
Number of source states : 34
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)
```

```
# Source city column
df2['source_city'] = df2['source_name'].apply(location_name_to_city)
print('Number of source cities :', df2['source_city'].nunique())
df2['source_city'].unique()[:20]
```

```
Number 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'], dtype=object)
```

```
# Source place column
df2['source_place'] = df2['source_name'].apply(location_name_to_place)
print('Number of source place :', df2['source_place'].nunique())
df2['source_place'].unique()[:20]
```

```
Number of source place : 761
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'], dtype=object)
```

2.3 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'].value_counts()
```

```
2018-09-18    791
2018-09-15    783
2018-09-13    750
2018-09-12    747
2018-09-21    740
2018-09-22    740
2018-09-17    722
2018-09-14    712
2018-09-20    704
2018-09-25    697
2018-09-26    685
2018-09-19    676
2018-09-24    660
2018-09-27    652
2018-09-23    631
2018-10-03    631
2018-09-16    616
2018-09-28    608
2018-09-29    607
2018-10-01    605
2018-10-02    552
2018-09-30    508
Name: trip_creation_date, dtype: int64
```

Maximum no of trips are created on 18th September followed by 15th September and least trips were created on 30th October

```
df2['trip_creation_day'] = df2['trip_creation_time'].dt.day
df2['trip_creation_day'] = df2['trip_creation_day'].astype('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'].value_counts()
```

```
9     13029
10     1788
Name: trip_creation_month, dtype: int64
```

September has a total of 13029 trips compared to October with 1788 trips

```
df2['trip_creation_year'] = df2['trip_creation_time'].dt.year
df2['trip_creation_year'] = df2['trip_creation_year'].astype('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_hour'] = df2['trip_creation_time'].dt.hour
df2['trip_creation_hour'] = df2['trip_creation_hour'].astype('int8')
```

Structure of data after data cleaning

```
df2.shape
```

```
(14817, 29)
```

```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14817 entries, 0 to 14816
Data columns (total 29 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  destination_state               14817 non-null  object
 18  destination_city                14817 non-null  object
 19  destination_place               14817 non-null  object
 20  source_state                    14817 non-null  object
 21  source_city                     14817 non-null  object
 22  source_place                    14817 non-null  object
 23  trip_creation_date              14817 non-null  datetime64[ns]
 24  trip_creation_day               14817 non-null  int8
 25  trip_creation_month             14817 non-null  int8
 26  trip_creation_year              14817 non-null  int16
 27  trip_creation_week              14817 non-null  int8
 28  trip_creation_hour              14817 non-null  int8
dtypes: category(2), datetime64[ns](2), float32(7), float64(2), int16(1), int8(4), object(11)
memory usage: 2.2+ 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
destination_state	14817	39	Maharashtra	2561
destination_city	14817	806	Mumbai	1548
destination_place	14817	850	Bilaspur_HB	821
source_state	14817	34	Maharashtra	2714
source_city	14817	690	Mumbai	1442
source_place	14817	761	Bilaspur_HB	1063

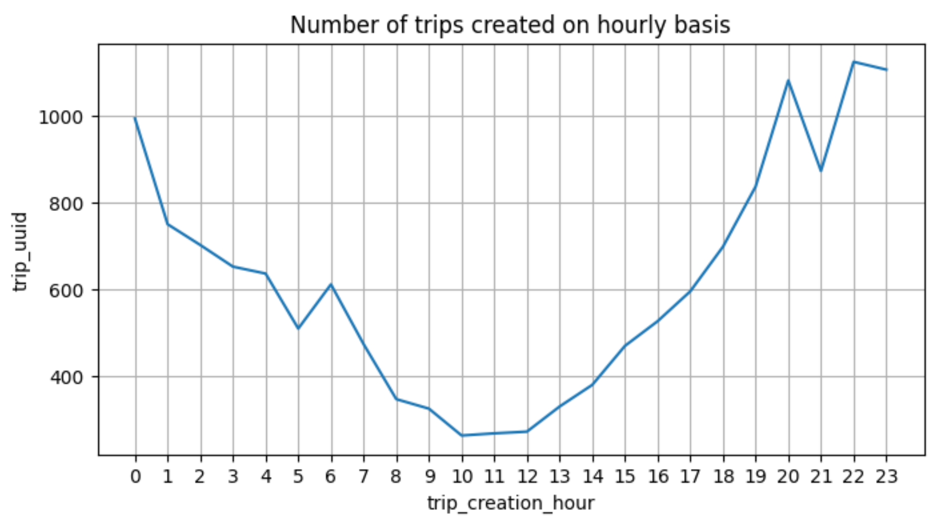
***Visual Analysis of newly created features ***

1) Trips are created on the hourly basis

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

plt.figure(figsize = (8, 4))
sns.lineplot(data = df_hour,
             x = df_hour['trip_creation_hour'],
             y = df_hour['trip_uuid'],
             markers = '*')
plt.xticks(np.arange(0,24)) # to get all 24 hours in x-axis
plt.title("Number of trips created on hourly basis")
plt.grid('both')
plt.plot()
```

[]

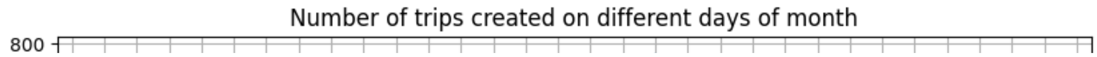


From the above plot we can notice that trips gets increased after noon and reaches its peak at 10.00 pm and the start decreasing again

2) Trips created on different days of the month

```
df_day = df2.groupby(by = 'trip_creation_day')['trip_uuid'].count().to_frame().reset_index()
plt.figure(figsize = (10, 4))
sns.lineplot(data = df_day,
             x = df_day['trip_creation_day'],
             y = df_day['trip_uuid'],
             markers = 'o')
plt.xticks(np.arange(0,32)) # to get all 32 daysin x-axis
plt.title("Number of trips created on different days of month")
plt.grid('both')
plt.plot()
```

[]

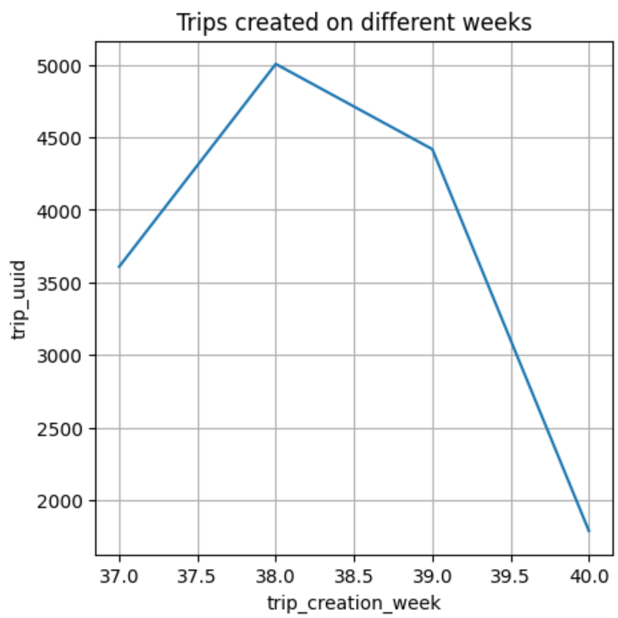


It can be inferred from the above plot that most of the trips are created in the mid of the month i.e most of customers places orders in mid of the month and least orders are placed at the end of the month i.e 30th of the month.

3) Trips created on different weeks

```
df_week = df2.groupby(by = 'trip_creation_week')['trip_uuid'].count().to_frame().reset_index()
plt.figure(figsize = (5, 5))
sns.lineplot(data = df_week,
             x = df_week['trip_creation_week'],
             y = df_week['trip_uuid'])
plt.title("Trips created on different weeks")
plt.grid('both')
plt.plot()
```

[]



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

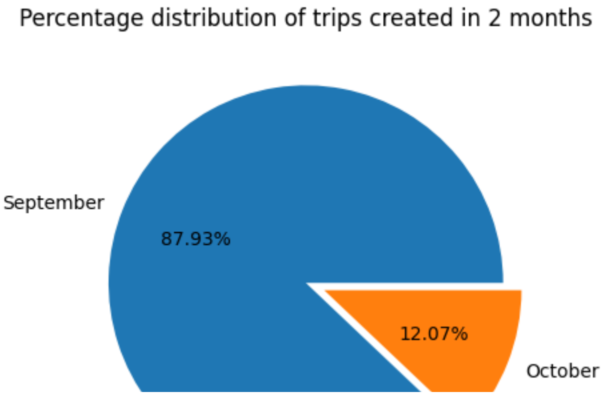
4) Number of trips are created in the given two months

```
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
1	10	1788	12.07

```
plt.pie(x = df_month['trip_uuid'], labels = ['September', 'October'],
        explode = [0, 0.1], autopct = '%.2f%%')
plt.title("Percentage distribution of trips created in 2 months")
plt.plot()
# autopct : allows us to display the percent value using string formatting
# explode : The exploded slices look as if they were cut out from the pie
# and moved slightly outward from its center
```

[]



Around 87.93% of trips i.e 13029 trips were created in September and 12% in the month of October

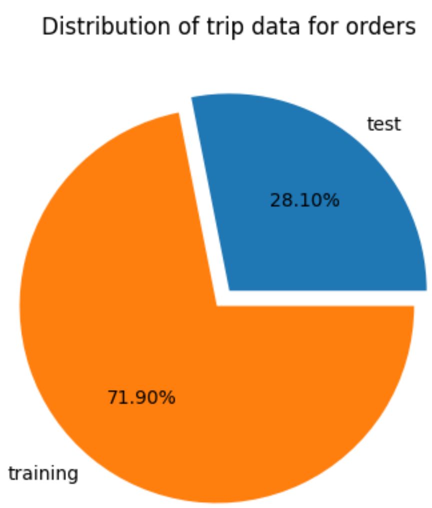
5) Distribution of trip data for the orders

```
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
```

	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.title("Distribution of trip data for orders")
plt.plot()
```

[]



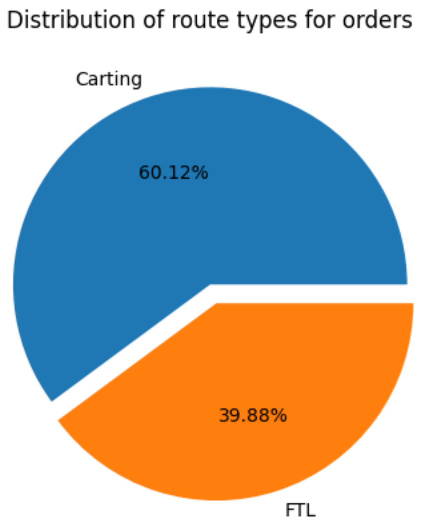
6) Distribution of route types for the orders

```
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.title("Distribution of route types for orders")
plt.plot()
```

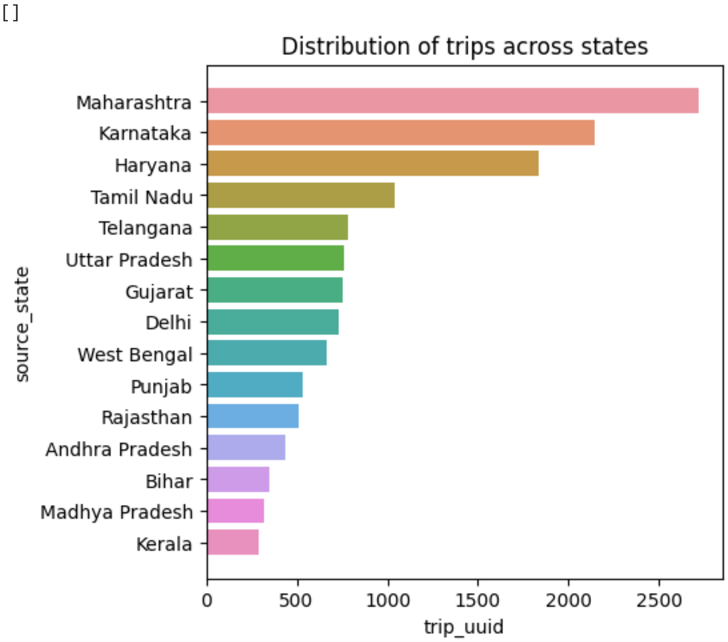
[]



7) 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['perc'] = np.round(df_source_state['trip_uuid'] * 100/ df_source_state['trip_uuid'].sum(), 2) #sorting in descending
df_source_state = df_source_state.sort_values(by = 'trip_uuid', ascending = False)[:15]
plt.figure(figsize = (5, 5))
sns.barplot(data = df_source_state,x = df_source_state['trip_uuid'],
            y = df_source_state['source_state'])
plt.title("Distribution of trips across states")
plt.plot()
```

[]

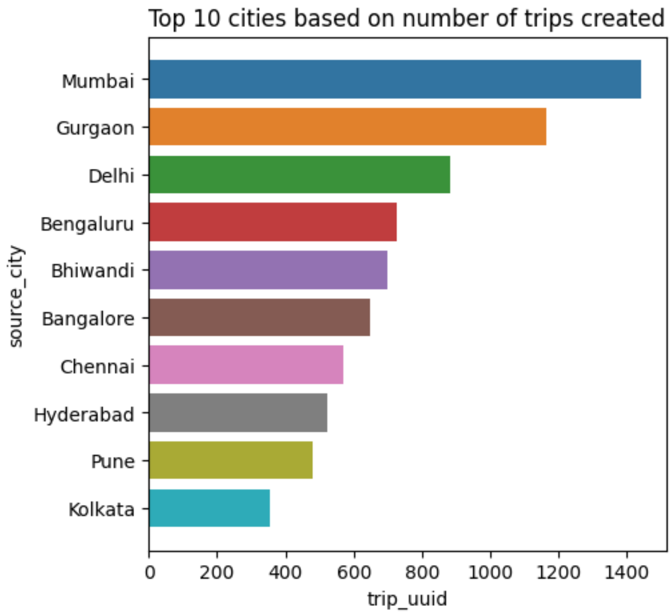


From the above plot we can infere that maximum trips originated from Maharashtra state followed by Karnataka and Haryana. That means that the seller base is strong in these states

8) Top 10 cities based on the number of trips created from different cities

```
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)[:10]
plt.figure(figsize = (5, 5))
sns.barplot(data = df_source_city,
            x = df_source_city['trip_uuid'],
            y = df_source_city['source_city'])
plt.title("Top 10 cities based on number of trips created")
plt.plot()
```

```
[]
```



Maximum trips originated from Mumbai city followed by Gurgaon Delhi, Bengaluru and Bhiwandi. That means that the seller base is strong in these cities

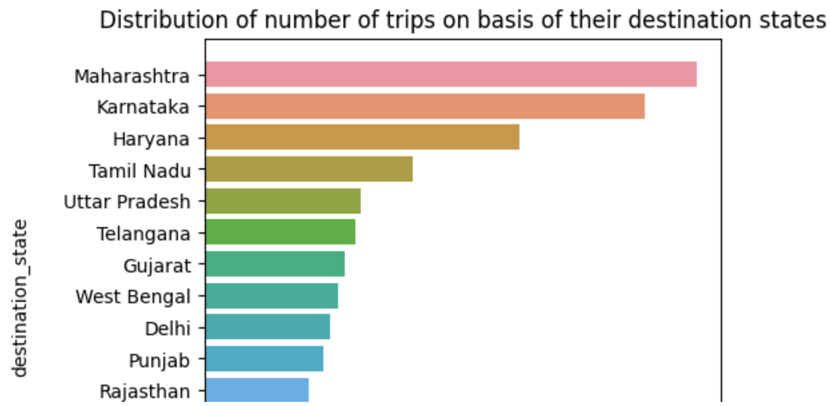
9) Distribution of number of trips on basis of their destination states

```
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)[:15]
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 = (5, 5))
sns.barplot(data = df_destination_state,
            x = df_destination_state['trip_uuid'],
            y = df_destination_state['destination_state'])
plt.title("Distribution of number of trips on basis of their destination states")
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 state

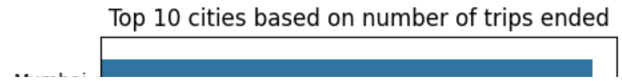
10) Top 10 cities based on the number of trips ended in different cities

```
df_destination_city = df2.groupby(by = 'destination_city')['trip_uuid'].count().to_frame().reset_index()
df_destination_city['perc'] = np.round(df_destination_city['trip_uuid'] * 100/ df_destination_city['trip_uuid'].sum(), 2)
df_destination_city = df_destination_city.sort_values(by = 'trip_uuid', ascending = False)[:10]
df_destination_city
```

	destination_city	trip_uuid	perc
515	Mumbai	1548	10.45
96	Bengaluru	975	6.58
282	Gurgaon	936	6.32
200	Delhi	778	5.25
163	Chennai	595	4.02
72	Bangalore	551	3.72
308	Hyderabad	503	3.39
115	Bhiwandi	434	2.93
418	Kolkata	384	2.59
158	Chandigarh	339	2.29

```
plt.figure(figsize = (5, 5))
sns.barplot(data = df_destination_city, x = df_destination_city['trip_uuid'],
            y = df_destination_city['destination_city'])
plt.title("Top 10 cities based on number of trips ended")
plt.plot()
```

[]



Maximum number of trips ended in Mumbai city followed by Bengaluru, Gurgaon, Delhi and Chennai. That means that the number of orders placed in these cities is significantly high which are some of major metropolitian cities of India

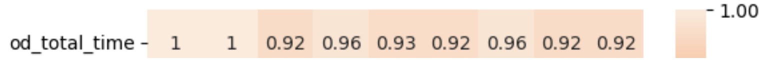
11) Understanding the Correlation between numerical columns using a heat map

```
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']
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_distanc
od_total_time	1.000000	0.999999	0.918222	0.961094	0.926516	0.92421
start_scan_to_end_scan	0.999999	1.000000	0.918308	0.961147	0.926571	0.92429
actual_distance_to_destination	0.918222	0.918308	1.000000	0.953757	0.993561	0.99726
actual_time	0.961094	0.961147	0.953757	1.000000	0.958593	0.95921
osrm_time	0.926516	0.926571	0.993561	0.958593	1.000000	0.99758
osrm_distance	0.924219	0.924299	0.997264	0.959214	0.997580	1.00000
segment_actual_time	0.961119	0.961171	0.952821	0.999989	0.957765	0.95835
segment_osrm_time	0.918490	0.918561	0.987538	0.953872	0.993259	0.99179
segment_osrm_distance	0.919199	0.919291	0.993061	0.956967	0.991608	0.99471

```
plt.figure(figsize = (6, 6))
sns.heatmap(data = df_corr, vmin = -1, vmax = 1, annot = True)
plt.plot()
```

```
[]
```



As we can see the correlation between numerical columns is above 0.9 i.e there exist a very high correlation between all the 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.

Set up Null Hypothesis and Alternative hypothesis

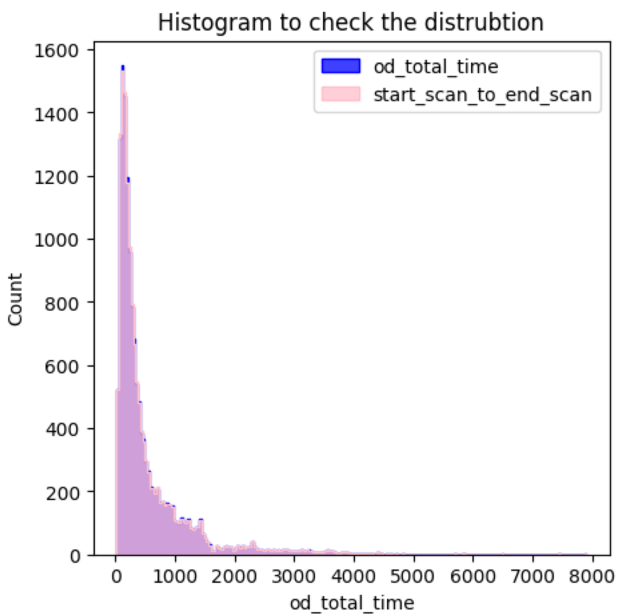
H0 : od_total_time (Total Trip Time) and start_scan_to_end_scan (Expected total trip time) are same.

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

Visual Tests to know if the samples follow normal distribution using hist plot

```
plt.figure(figsize = (5, 5))
sns.histplot(df2['od_total_time'], element = 'step', color = 'blue')
sns.histplot(df2['start_scan_to_end_scan'], element = 'step', color = 'pink')
plt.legend(['od_total_time', 'start_scan_to_end_scan'])
plt.title("Histogram to check the distrubtion")
plt.plot()
```

```
[]
```



Shapiro-Wilk test for normality:

H0 : The sample follows normal distribution

H1 : The sample does not follow normal distribution

```
# Test for normality for start_scan_to_end_scan column
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
```

```
# Test for normality for od_total_time column
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
```

Both the sample do not follow normal distribution therefore transforming the data using boxcox transformation to check if the transformed data follows normal distribution

```
#Box-cox transformation for od_total_time
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
```

```
#Box-cox transformation for start_scan_to_end_scan
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

H0 - Same Variance

H1 - 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.

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

```
P-value : 0.7815123224221716
```

Conclusion : As we can see p_value > 0.05 we can accept the null hypothesis 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)

Set up Null Hypothesis and Alternative hypothesis

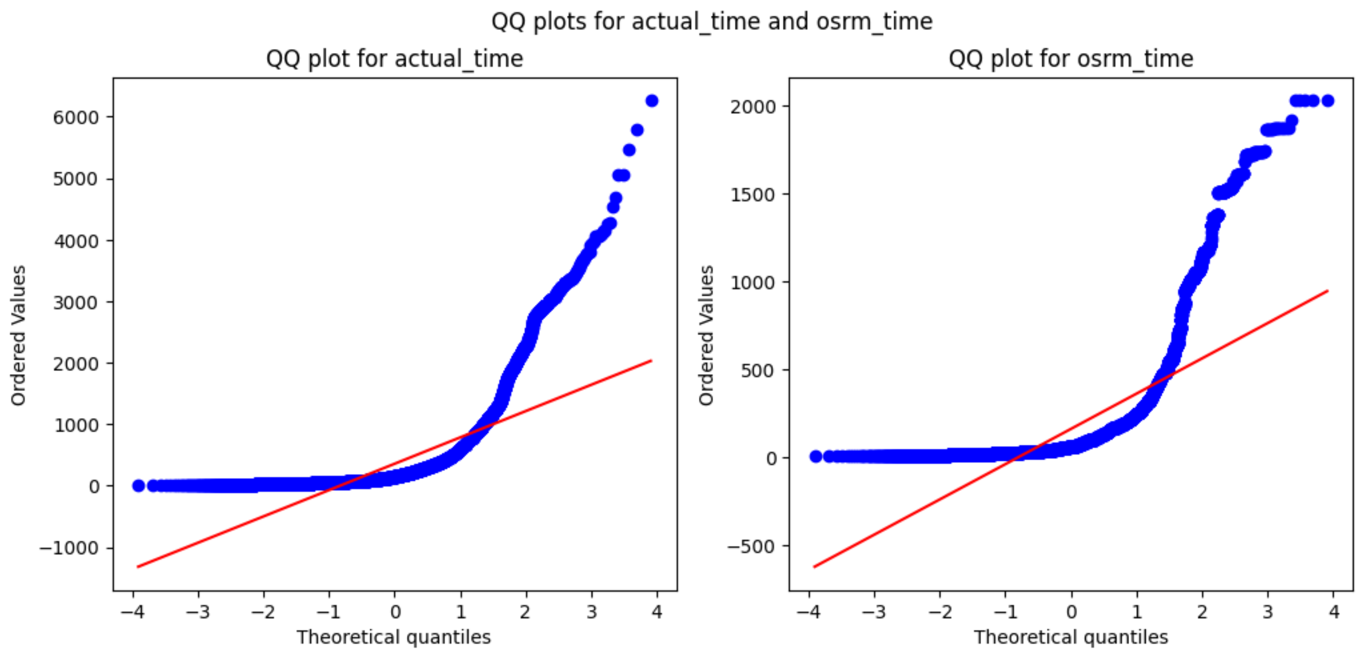
H0 : actual_time and orsm_time are same.

HA : actual_time and orsm_time are different.

Visual Analysis of distribution using QQ Plot

```
plt.figure(figsize = (12, 5))
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()
```

```
[]
```



As we can infer distribution does not follow normal distribution

Shapiro-Wilk test for normality with alpha 0.05:

H0 : The sample follows normal distribution

H1 : The sample does not follow normal distribution

```
# Test for normality for actual_time column
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 for normality for orsm_time column
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
```

Both the sample do not follow normal distribution therefore transforming the data using boxcox transformation to check if the transformed data follows normal distribution

```
#Box-cox transformation for actual_time
transformed_actual_time = spy.boxcox(df2['actual_time'])[0]
test_stat, p_value = spy.shapiro(transformed_actual_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 1.020620453603145e-28
The sample does not follow normal distribution
```

```
#Box-cox transformation for orsm_time
transformed_osrm_time = spy.boxcox(df2['osrm_time'])[0]
test_stat, p_value = spy.shapiro(transformed_osrm_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 3.5882550510138333e-35
The sample does not follow normal distribution
```

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

Homogeneity of Variances using Lavene's test

H0 - Same Variance

H1 - 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
```

Since the samples are not normally distributed, and donot follow any assumptions of 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

```
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
```

Conclusion : As we can see p_value > 0.05 we can accept the null hypothesis 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 will get after merging the rows on the basis of trip_uuid)

Set up Null Hypothesis and Alternative hypothesis

H0 : actual_time and segment_actual_time are same.

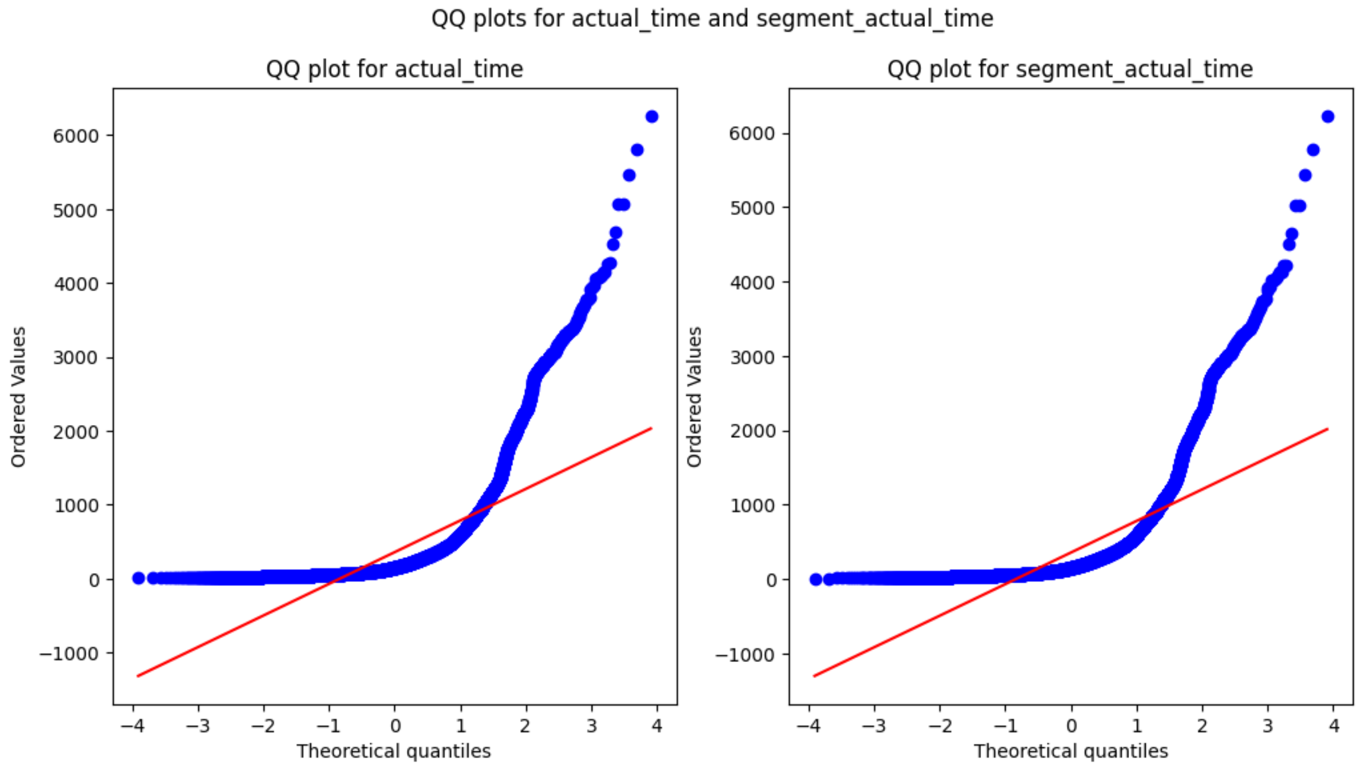
HA : actual_time and segment_actual_time are different.

Visual Analysis of distribution using QQ Plot

```
plt.figure(figsize = (12, 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()
```

```
[]
```



As we can infer distribution does not follow normal distribution

Shapiro-Wilk test for normality with alpha 0.05:

H0 : The sample follows normal distribution

H1 : The sample does not follow normal distribution

```
# Test for normality for  column actual_time
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 for normality for  column segment_actual_time
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
```

Both the sample do not follow normal distribution therefore transforming the data using boxcox transformation to check if the transformed data follows normal distribution

```
#Box-cox transformation for actual_time
transformed_actual_time = spy.boxcox(df2['actual_time'])[0]
test_stat, p_value = spy.shapiro(transformed_actual_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 1.020620453603145e-28
The sample does not follow normal distribution
```

```
#Box-cox transformation for segment_actual_time
transformed_segment_actual_time = spy.boxcox(df2['segment_actual_time'])[0]
test_stat, p_value = spy.shapiro(transformed_segment_actual_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 5.700074948787037e-29
The sample does not follow normal distribution
```

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

Homogeneity of Variances using Lavene's test

H0 - Same Variance

H1 - 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
```

As 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

```
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
```

Conclusion : As p_value > 0.05 we can conclude 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 (aggregated values are the values you will get after merging the rows on the basis of trip_uuid)

Set up Null Hypothesis and Alternative hypothesis

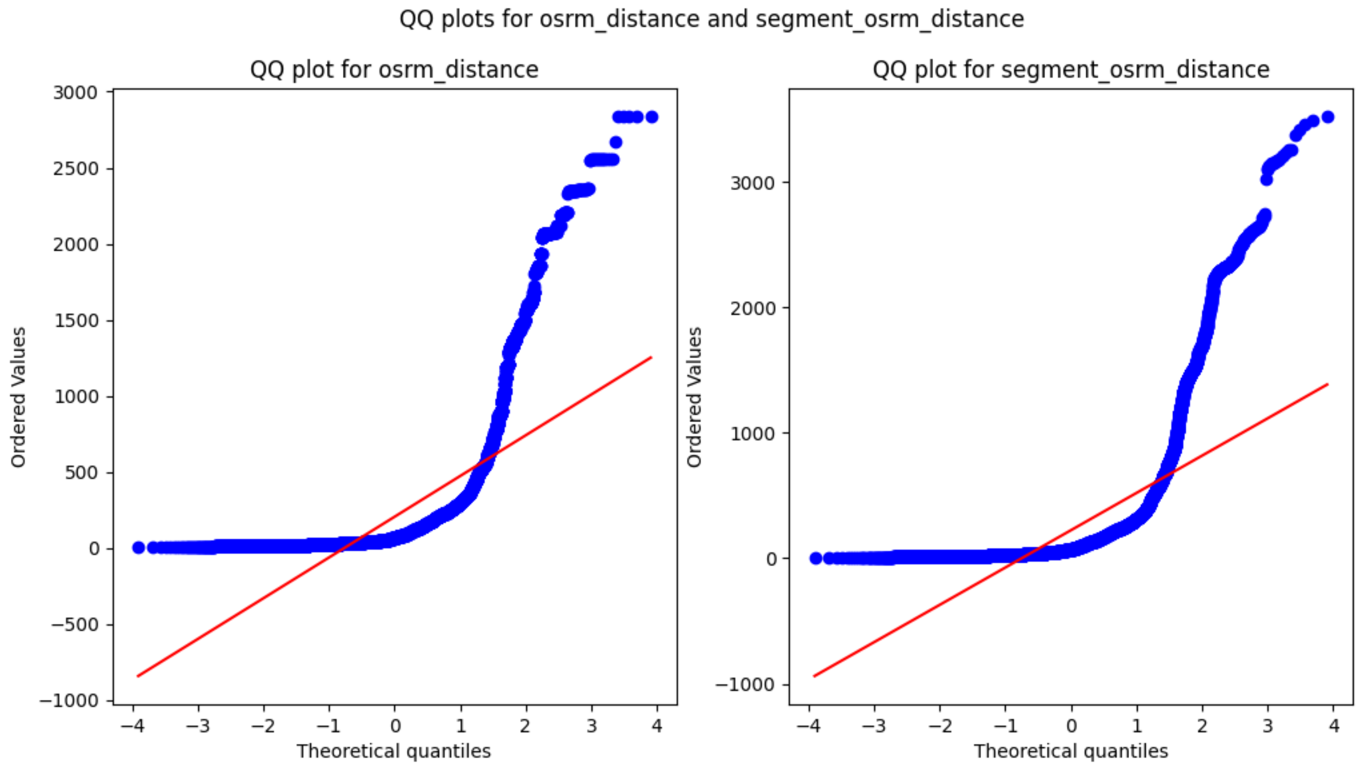
H0 : orsm_distance and segment_orsm_distance are same.

HA : orsm_distance and segment_orsm_distance are different

Visual Analysis of distribution using QQ Plot

```
plt.figure(figsize = (12, 6))
plt.subplot(1, 2, 1)
plt.suptitle('QQ plots for osrm_distance and segment_osrm_distance')
spy.probplot(df2['osrm_distance'], plot = plt, dist = 'norm')
plt.title('QQ plot for osrm_distance')
plt.subplot(1, 2, 2)
spy.probplot(df2['segment_osrm_distance'], plot = plt, dist = 'norm')
plt.title('QQ plot for segment_osrm_distance')
plt.plot()
```

```
[]
```



As we can infer distribution does not follow normal distribution

Shapiro-Wilk test for normality with alpha 0.05:

H0 : The sample follows normal distribution

H1 : The sample does not follow normal distribution

```
# Test for normality for osrm_distance column
test_stat, p_value = spy.shapiro(df2['osrm_distance'].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 for normality for segment_osrm_distance column
test_stat, p_value = spy.shapiro(df2['segment_osrm_distance'].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
```

Both the sample do not follow normal distribution therefore transforming the data using boxcox transformation to check if the transformed data follows normal distribution

```
# Box-cox  transormation for orsm_distance
transformed_osrm_distance = spy.boxcox(df2['osrm_distance'])[0]
test_stat, p_value = spy.shapiro(transformed_osrm_distance)
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 7.063104779582808e-41
The sample does not follow normal distribution
```

```
# Box-cox  transormation for segment_orsm_distance
transformed_segment_osrm_distance = spy.boxcox(df2['segment_osrm_distance'])[0]
test_stat, p_value = spy.shapiro(transformed_segment_osrm_distance)
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 3.049169406432229e-38
The sample does not follow normal distribution
```

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

Homogeneity of Variances using Lavene's test

H0 - Same Variance

H1 - Non Homogenous Variance

```
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 0.00020976006524780905
The samples do not have Homogenous Variance
```

As 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

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

```
p-value 9.509410818847664e-07
The samples are not similar
```

Conclusion : As p_value < 0.05 we can conclude that 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 (aggregated values are the values you will get after merging the rows on the basis of trip_uuid))

Set up Null Hypothesis and Alternative hypothesis

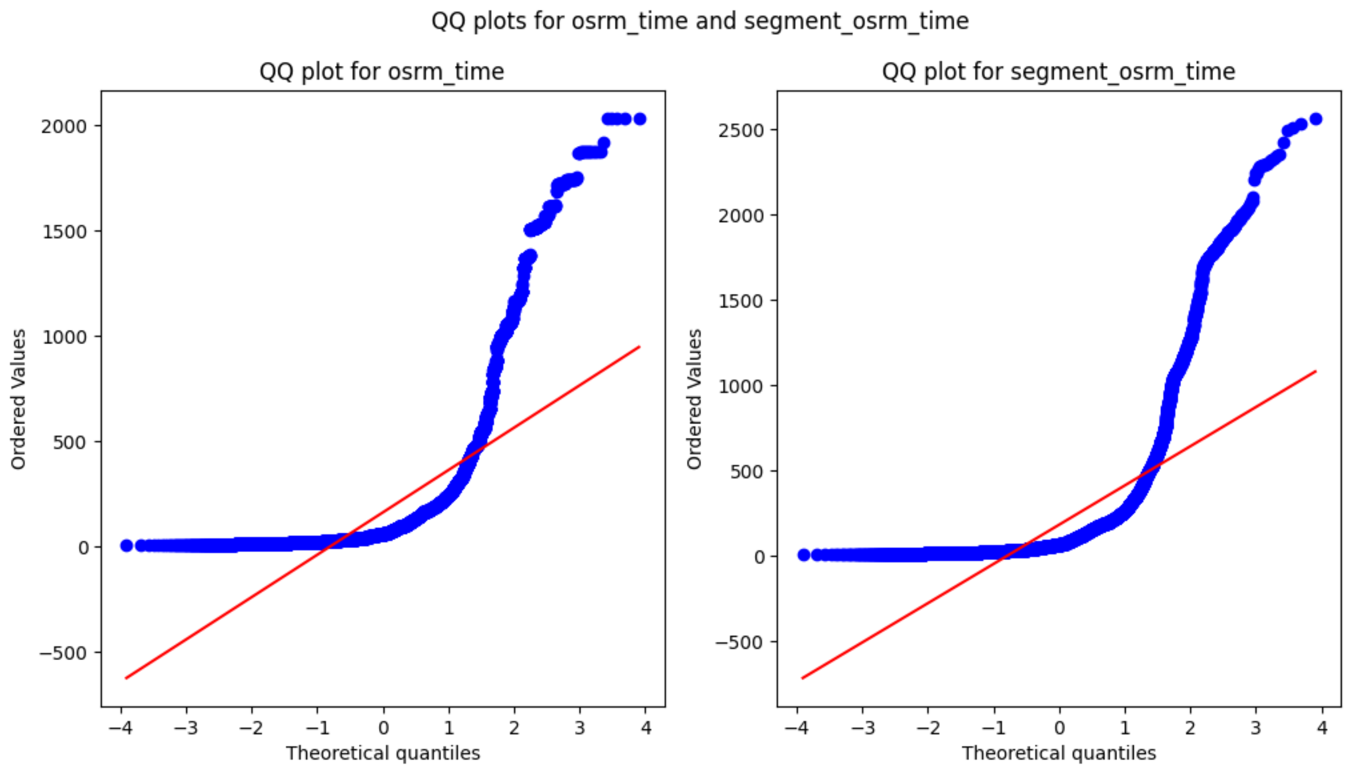
H0 : segment_orsm_time and orsm_time are same.

HA : segment_orsm_time and orsm_time are different

Visual Analysis of distribution using QQ Plot

```
plt.figure(figsize = (12, 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()
```

```
[]
```



As we can infer distribution does not follow normal distribution

Shapiro-Wilk test for normality with alpha 0.05:

H0 : The sample follows normal distribution

H1 : The sample does not follow normal distribution

```
# Test for normality for orsm_time column
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
```

```
# Test for normality for segment_osrm_time column
test_stat, p_value = spy.shapiro(df2['segment_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
```

Both the sample do not follow normal distribution therefore transforming the data using boxcox transformation to check if the transformed data follows normal distribution

```
# Box-cox transformation of orsm_time
transformed_osrm_time = spy.boxcox(df2['osrm_time'])[0]
test_stat, p_value = spy.shapiro(transformed_osrm_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 3.5882550510138333e-35
The sample does not follow normal distribution
```

```
# Box-cox transformation of segment_orsm_time
transformed_segment_osrm_time = spy.boxcox(df2['segment_osrm_time'])[0]
test_stat, p_value = spy.shapiro(transformed_segment_osrm_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 4.943039152219146e-34
The sample does not follow normal distribution
```

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

Homogeneity of Variances using Lavene's test

H0 - Same Variance

H1 - Non Homogenous Variance

```
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 8.349506135727595e-08
The samples do not 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.

```
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
```

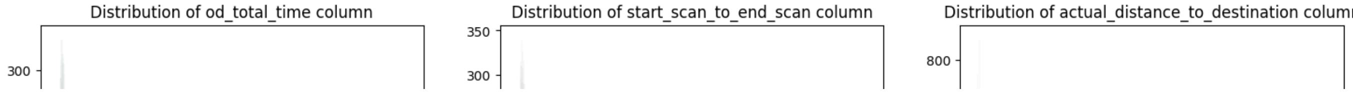
Conclusion : As p-value < 0.05 therfore it can be concluded that osrm_time and segment_osrm_time are not similar.

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

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

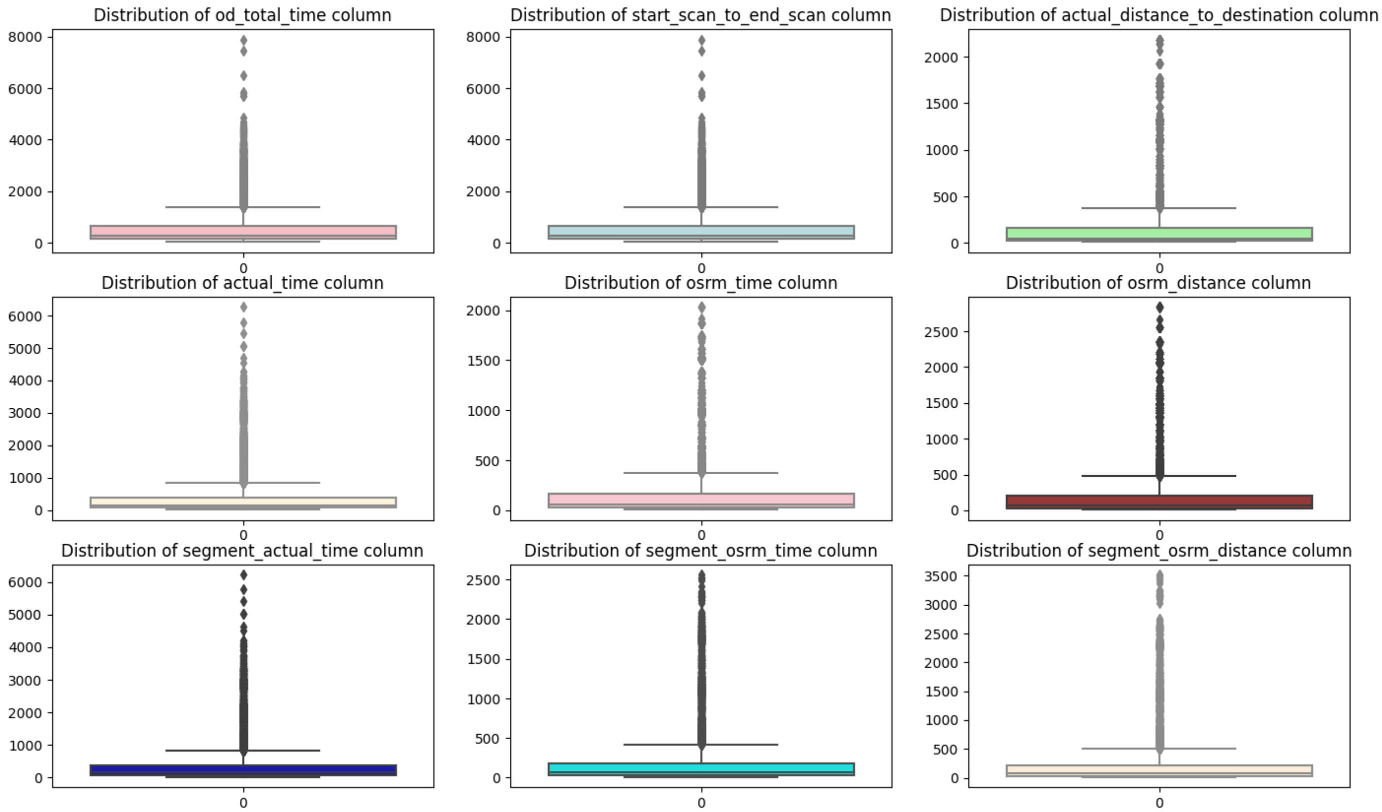
	count	mean	std	min	25%	50%	75%	max
od_total_time	14817.0	531.697630	658.868223	23.460000	149.930000	280.770000	638.200000	7898.550000
start_scan_to_end_scan	14817.0	530.810016	658.705957	23.000000	149.000000	280.000000	637.000000	7898.000000
actual_distance_to_destination	14817.0	164.477829	305.388153	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

```
#hist plot to understand the distribution of numerical columns
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()
```



We can infer from the above plots that data in all the numerical columns are rightly skewed.

```
# Using box plot to check the outliers
plt.figure(figsize = (17, 10))
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()
```



We can clearly see that there are outliers in all the numerical columns

3.8 Handle the outliers using the IQR method

```
for i in numerical_columns:
  Q1 =np.quantile(df2[i],.25)
  Q3 =np.quantile(df2[i],.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,end = "\n")
  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('----------------------------------')
```

```
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
Q3 : 185.0
IQR : 154.0
LB : -200.0
UB : 416.0
Number of outliers : 1492
----------------------------------
Column : segment_osrm_distance
Q1 : 32.65449905395508
Q3 : 218.80239868164062
IQR : 186.14789962768555
LB : -246.56735038757324
UB : 498.02424812316895
Number of outliers : 1548
----------------------------------
```

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

3.9) Do one-hot encoding of categorical variables (route_type)

```
# Get value counts before one-hot encoding
df2['route_type'].value_counts()
```

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

```
# Perform one-hot encoding on categorical column route type
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
```

-- One-hot encoding for data column --

```
# Get value counts before one-hot encoding
df2['data'].value_counts()
```

```
training    10654
test         4163
Name: data, dtype: int64
```

```
# Perform one-hot encoding on categorical column data
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()
df2['data'] = label_encoder.fit_transform(df2['data'])

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

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

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

```
from sklearn.preprocessing import MinMaxScaler
```

```
#Normalizing od_total_time
plt.figure(figsize = (5, 5))
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.legend('od_total_time')
plt.plot()
```

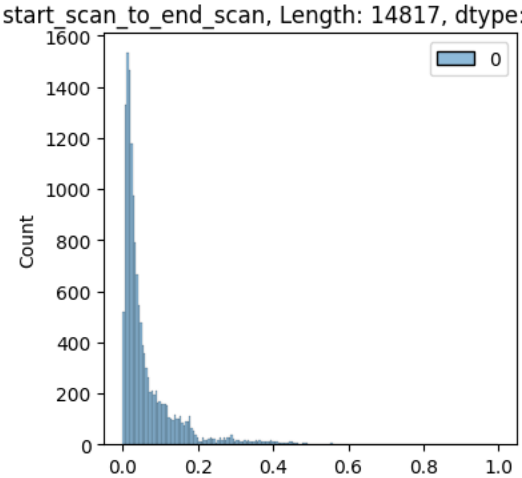
[]

Normalized 0 2260.11
1 181.61
2 3934.36
3 100.49
4 718.34
...
14812 258.03

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

[]

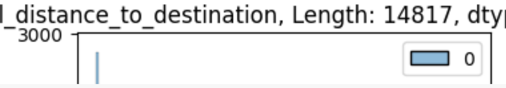
Normalized 0 2259.0
1 180.0
2 3933.0
3 100.0
4 717.0
...
14812 257.0
14813 60.0
14814 421.0
14815 347.0
14816 353.0
Name: start_scan_to_end_scan, Length: 14817, dtype: float64 column




```
#Normalize the actual_distance_to_destination column
plt.figure(figsize = (4, 4))
scaler = MinMaxScaler()
scaled = scaler.fit_transform(df2['actual_distance_to_destination'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Normalized {df2['actual_distance_to_destination']} column")
plt.plot()
```

[]

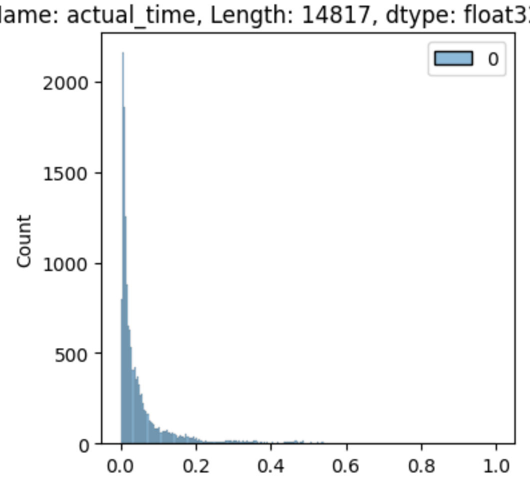
Normalized 0   824.732849
1   73.186905
2   1927.404297
3   17.175274
4   127.448502
...
14812   57.762333
14813   15.513784
14814   38.684837
14815   134.723831
14816   66.081528
Name: actual_distance_to_destination, Length: 14817, dtype: float32 column




```
#Normalize the actual_time column
plt.figure(figsize = (4, 4))
scaler = MinMaxScaler()
scaled = scaler.fit_transform(df2['actual_time'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Normalized {df2['actual_time']} column")
plt.plot()
```

[]

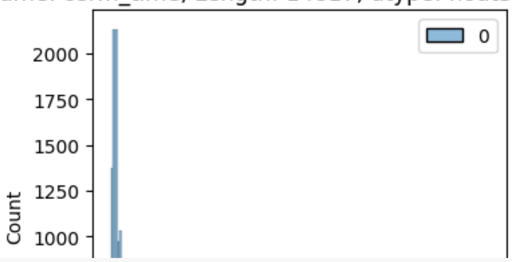
Normalized 0   1562.0
1   143.0
2   3347.0
3   59.0
4   341.0
...
14812   83.0
14813   21.0
14814   282.0
14815   264.0
14816   275.0
Name: actual_time, Length: 14817, dtype: float32 column




```
#Normalize the orsm_time column
plt.figure(figsize = (4, 4))
scaler = MinMaxScaler()
scaled = scaler.fit_transform(df2['osrm_time'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Normalized {df2['osrm_time']} column")
plt.plot()
```

[]

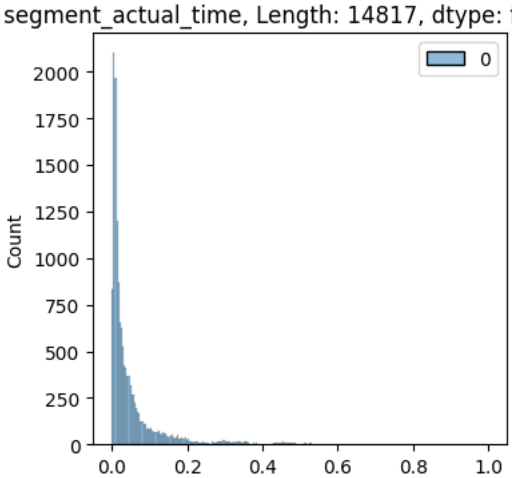
Normalized 0 717.0
1 68.0
2 1740.0
3 15.0
4 117.0
...
14812 62.0
14813 12.0
14814 48.0
14815 179.0
14816 68.0
Name: osrm_time, Length: 14817, dtype: float32 column




```
#Normalize the segment_actual_time column
plt.figure(figsize = (4, 4))
scaler = MinMaxScaler()
scaled = scaler.fit_transform(df2['segment_actual_time'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Normalized {df2['segment_actual_time']} column")
plt.plot()
```

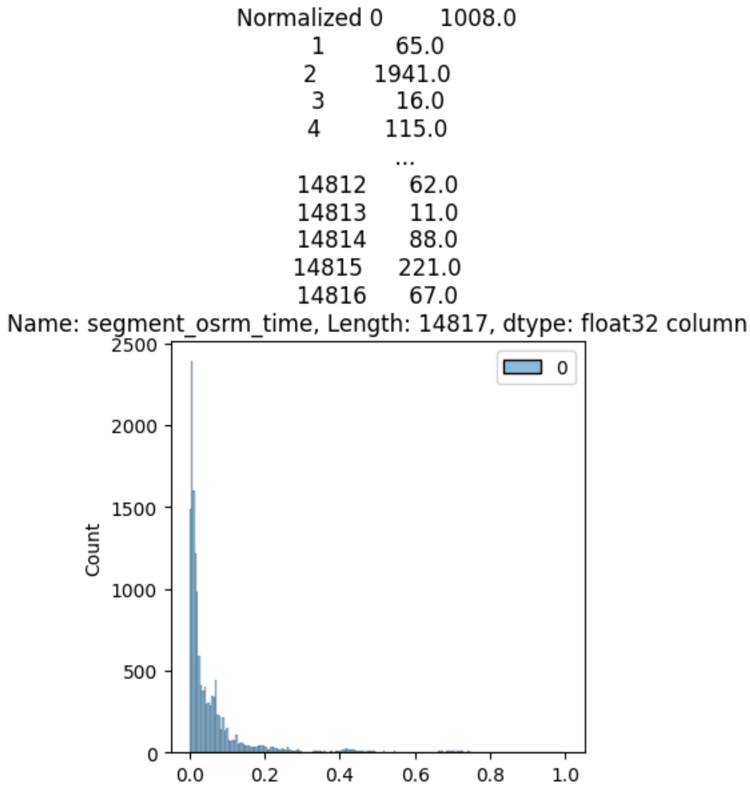
[]

Normalized 0 1548.0
1 141.0
2 3308.0
3 59.0
4 340.0
...
14812 82.0
14813 21.0
14814 281.0
14815 258.0
14816 274.0
Name: segment_actual_time, Length: 14817, dtype: float32 column




```
#Normalize the segment_actual_time column
plt.figure(figsize = (4, 4))
scaler = MinMaxScaler()
scaled = scaler.fit_transform(df2['segment_osrm_time'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Normalized {df2['segment_osrm_time']} column")
plt.plot()
```

```
[]
```



Column Standardization

```
from sklearn.preprocessing import StandardScaler
```

```
# Standardizing the od_total_time column
plt.figure(figsize = (5, 5))
scaler = StandardScaler() # define standard scaler
scaled = scaler.fit_transform(df2['od_total_time'].to_numpy().reshape(-1, 1)) # transform data
sns.histplot(scaled)
plt.title(f"Standardized {df2['od_total_time']} column")
plt.legend('')
plt.plot()
```

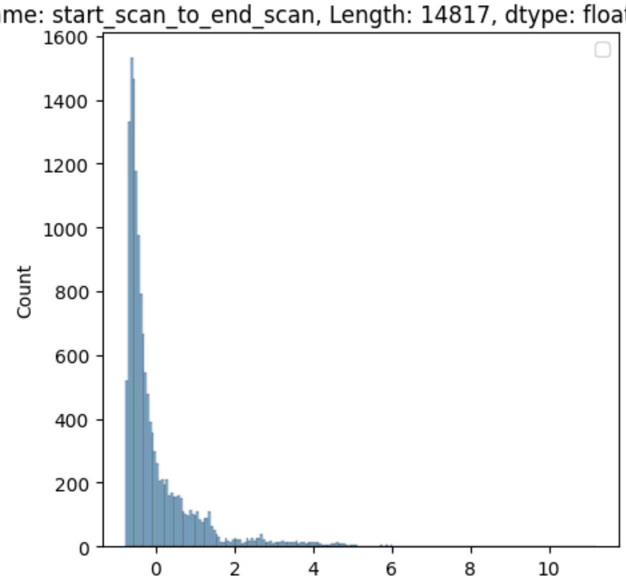
[]

Standardized 0 2260.11
1 181.61
2 3934.36
3 100.49
4 718.34
...

```
# Standardizing the start_scan_to_end_scan column
plt.figure(figsize = (5, 5))
scaler = StandardScaler() # define standard scaler
scaled = scaler.fit_transform(df2['start_scan_to_end_scan'].to_numpy().reshape(-1, 1)) # transform data
sns.histplot(scaled)
plt.title(f"Standardized {df2['start_scan_to_end_scan']} column")
plt.legend('')
plt.plot()
```

[]

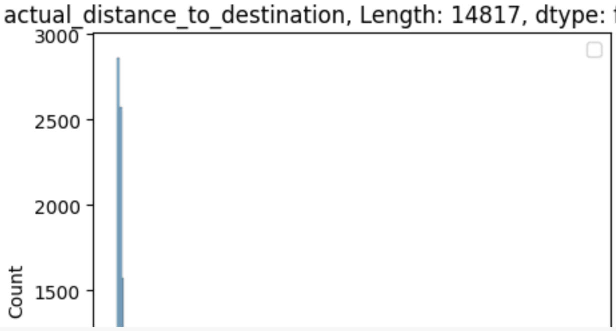
Standardized 0 2259.0
1 180.0
2 3933.0
3 100.0
4 717.0
...
14812 257.0
14813 60.0
14814 421.0
14815 347.0
14816 353.0
Name: start_scan_to_end_scan, Length: 14817, dtype: float64 column




```
# Standardizing the actual_distance_to_destination column
plt.figure(figsize = (5, 5))
scaler = StandardScaler() # define standard scaler
scaled = scaler.fit_transform(df2['actual_distance_to_destination'].to_numpy().reshape(-1, 1)) # transform data
sns.histplot(scaled)
plt.title(f"Standardized {df2['actual_distance_to_destination']} column")
plt.legend('')
plt.plot()
```

[]

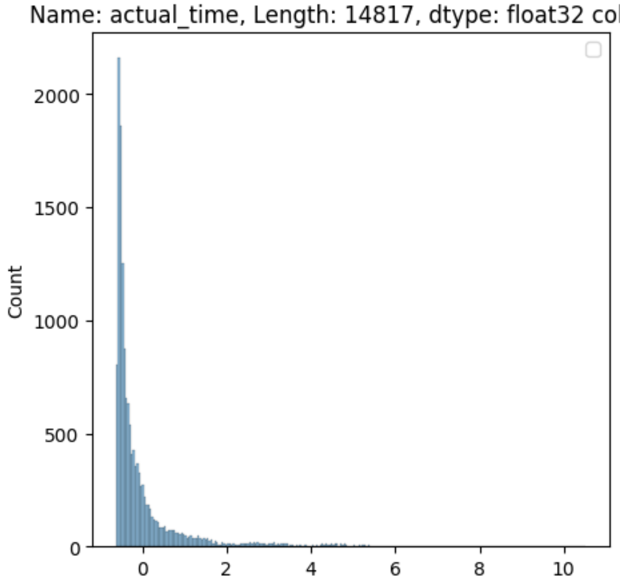
Standardized 0 824.732849
1 73.186905
2 1927.404297
3 17.175274
4 127.448502
...
14812 57.762333
14813 15.513784
14814 38.684837
14815 134.723831
14816 66.081528
Name: actual_distance_to_destination, Length: 14817, dtype: float32 column




```
# Standardizing the actual_time column
plt.figure(figsize = (5, 5))
scaler = StandardScaler() # define standard scaler
scaled = scaler.fit_transform(df2['actual_time'].to_numpy().reshape(-1, 1)) # transform data
sns.histplot(scaled)
plt.title(f"Standardized {df2['actual_time']} column")
plt.legend('')
plt.plot()
```

[]

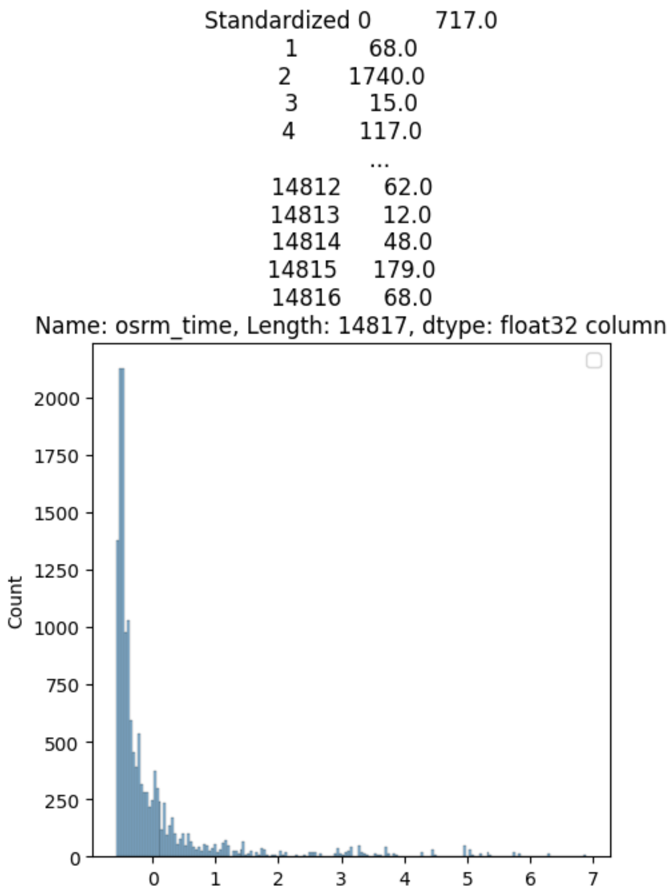
Standardized 0 1562.0
1 143.0
2 3347.0
3 59.0
4 341.0
...
14812 83.0
14813 21.0
14814 282.0
14815 264.0
14816 275.0
Name: actual_time, Length: 14817, dtype: float32 column




```
# Standardizing the osrm_time column
plt.figure(figsize = (5, 5))
```

```
scaler = StandardScaler() # define standard scaler
scaled = scaler.fit_transform(df2['osrm_time'].to_numpy().reshape(-1, 1)) # transform data
sns.histplot(scaled)
plt.title(f"Standardized {df2['osrm_time']} column")
plt.legend('')
plt.plot()
```

```
[]
```




```
# Standardizing the segment_actual_time column
plt.figure(figsize = (5, 5))
scaler = StandardScaler() # define standard scaler
scaled = scaler.fit_transform(df2['segment_actual_time'].to_numpy().reshape(-1, 1)) # transform data
sns.histplot(scaled)
plt.title(f"Standardized {df2['segment_actual_time']} column")
plt.legend('')
plt.plot()
```

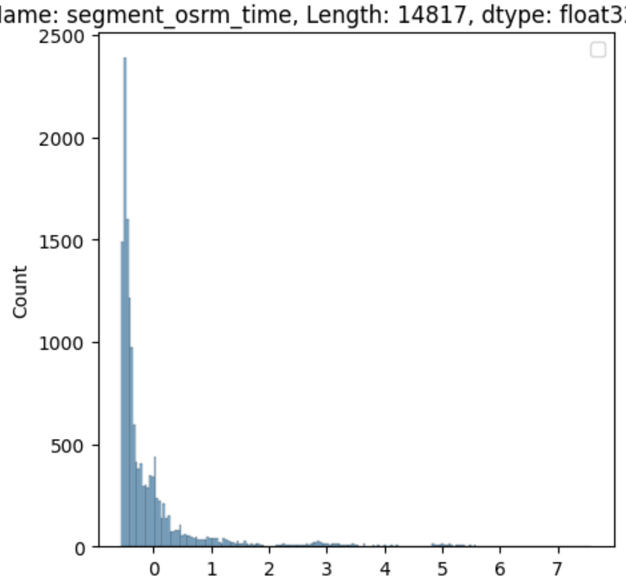
[]

Standardized 0 1548.0
1 141.0
2 3308.0
3 59.0
4 340.0
...
14812 82.0
14813 21.0
14814 281.0
14815 258.0
14816 274.0
Name: segment_actual_time, Length: 14817, dtype: float32 column

```
# Standardizing the segment_osrm_time column
plt.figure(figsize = (5, 5))
scaler = StandardScaler() # define standard scaler
scaled = scaler.fit_transform(df2['segment_osrm_time'].to_numpy().reshape(-1, 1)) # transform data
sns.histplot(scaled)
plt.title(f"Standardized {df2['segment_osrm_time']} column")
plt.legend('')
plt.plot()
```

[]

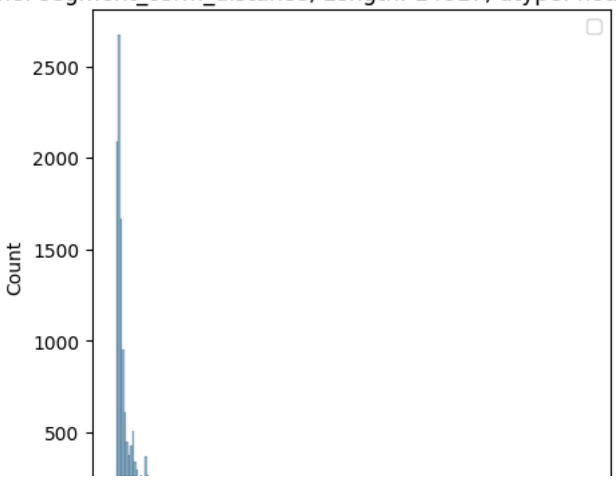
Standardized 0 1008.0
1 65.0
2 1941.0
3 16.0
4 115.0
...
14812 62.0
14813 11.0
14814 88.0
14815 221.0
14816 67.0
Name: segment_osrm_time, Length: 14817, dtype: float32 column




```
# Standardizing the segment_osrm_distance column
plt.figure(figsize = (5, 5))
scaler = StandardScaler() # define standard scaler
scaled = scaler.fit_transform(df2['segment_osrm_distance'].to_numpy().reshape(-1, 1)) # transform data
sns.histplot(scaled)
plt.title(f"Standardized {df2['segment_osrm_distance']} column")
plt.legend('')
plt.plot()
```

[]

```
Standardized 0        1320.473267
            1          84.189400
            2        2545.267822
            3          19.876600
            4         146.791901
                         ...
            14812      64.855103
            14813      16.088299
            14814     104.886597
            14815     223.532394
            14816      80.578705
Name: segment_osrm_distance, Length: 14817, dtype: float32 column
```



9. 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 common route type is Carting.
4. The names of 14 unique location ids are missing in the data.
5. Most of the data is for testing than for training.
6. Maximum trips are created in the 38th week.
7. The number of trips start increasing after the noon, becomes maximum at 10 P.M and then start decreasing.
8. Most orders come mid-month. That means customers usually make more orders in the mid of the month.
9. Most orders are sourced from the states like Maharashtra, Karnataka, Haryana, Tamil Nadu, Telangana.
10. Maximum number of trips originated from Mumbai city followed by Gurgaon Delhi, Bengaluru and Bhiwandi. That means that the seller base is strong in these cities.
11. Maximum number of trips ended in Mumbai city followed by Bengaluru, Gurgaon, Delhi and Chennai. That means that the number of orders placed in these cities is significantly high.
12. Maximum number of 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.
13. Most orders in terms of destination are coming from cities like bengaluru, mumbai, gurgaon, bangalore, Delhi.
14. Features start_scan_to_end_scan and od_total_time(created feature) are statistically similar.
15. Features actual_time & osrm_time are statitically different.
16. Features osrm_distance and segment_osrm_distance are statistically different from each other.
17. Features start_scan_to_end_scan and segment_actual_time are statistically similar.
18. Both the osrm_time & segment_osrm_time are not statistically same

10. Recommendations

1. Customer profiling of the customers belonging to the states Maharashtra, Karnataka, Haryana, Tamil Nadu and Uttar Pradesh has to be done to get to know why major orders are coming from these atates and to improve customers' buying and delivery experience
2. Most of the orders are coming from/reaching to states like Maharashtra, Karnataka, Haryana and Tamil Nadu. The existing corridors can be further enhanced to improve the penetration in these areas.
3. From state point of view, we might have very heavy traffic in certain states and bad terrain conditions in certain states. This will be a good indicator to plan and cater to demand during peak festival seasons.

4. osrm_time and actual_time are different. Team needs to make sure this difference is reduced, so that better delivery time prediction can be made and it becomes convenient for the customer to expect an accurate delivery time.
5. North, South and West Zones comidors have significant traffic of orders. But, we have a smaller presence in Central, Eastern and North-Eastern zone. However it would be difficult to conclude this, by looking at just 2 months data. It is worth investigating and increasing our presence in these regions.
6. Revisit information fed to routing engine for trip planning. Check for discrepancies with transporters, if the routing engine is configured for optimum result
7. The OSRM trip planning system needs to be improved
8. osrm_time and actual_time are different. Team needs to make sure this difference is reduced, so that better delivery time prediction can be made and it becomes convenient for the customer to expect an accurate delivery time