delhivery

November 16, 2023

0.0.1 PROBLEM STATEMENT

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

Before the data team can build any models, we need to clean and preprocess the data to get useful features out of raw fields. The data at the end of this case study should be able to make sense out of the raw data and help the data science team to build forecasting models on it.

So, the objective of this case study is to understand the raw fileds, analyze and visualize the fileds to get important insights from it. On the top of this EDA part, we aim to prepare the data for a machine learning model by doing feature engineering steps.

0.0.2 IMPORT LIBRARIES

[534]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from scipy.stats import ttest_ind,ttest_rel
from sklearn.preprocessing import OneHotEncoder, MinMaxScaler
```

0.0.3 IMPORTING DATASET

[535]:
```
orig_df = pd.read_csv('delhivery_data.csv')
df = orig_df.copy()
```

[536]:
```
pd.set_option('display.max_columns', None)
df.head()
```

[536]:
```
       data          trip_creation_time  \
0  training  2018-09-20 02:35:36.476840
1  training  2018-09-20 02:35:36.476840
2  training  2018-09-20 02:35:36.476840
3  training  2018-09-20 02:35:36.476840
4  training  2018-09-20 02:35:36.476840

                                 route_schedule_uuid route_type  \
```

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

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

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

                od_start_time                 od_end_time  \
0  2018-09-20 03:21:32.418600  2018-09-20 04:47:45.236797
1  2018-09-20 03:21:32.418600  2018-09-20 04:47:45.236797
2  2018-09-20 03:21:32.418600  2018-09-20 04:47:45.236797
3  2018-09-20 03:21:32.418600  2018-09-20 04:47:45.236797
4  2018-09-20 03:21:32.418600  2018-09-20 04:47:45.236797

   start_scan_to_end_scan  is_cutoff  cutoff_factor  \
0                    86.0       True              9
1                    86.0       True             18
2                    86.0       True             27
3                    86.0       True             36
4                    86.0      False             39

             cutoff_timestamp  actual_distance_to_destination  actual_time  \
0         2018-09-20 04:27:55                       10.435660         14.0
1         2018-09-20 04:17:55                       18.936842         24.0
2  2018-09-20 04:01:19.505586                       27.637279         40.0
3         2018-09-20 03:39:57                       36.118028         62.0
4         2018-09-20 03:33:55                       39.386040         68.0

   osrm_time  osrm_distance    factor  segment_actual_time  segment_osrm_time  \
0       11.0        11.9653  1.272727                 14.0               11.0
1       20.0        21.7243  1.200000                 10.0                9.0
2       28.0        32.5395  1.428571                 16.0                7.0
3       40.0        45.5620  1.550000                 21.0               12.0
4       44.0        54.2181  1.545455                  6.0                5.0
```

```
   segment_osrm_distance  segment_factor
0                11.9653        1.272727
1                 9.7590        1.111111
2                10.8152        2.285714
3                13.0224        1.750000
4                 3.9153        1.200000
```

0.0.4 STATISTICAL ANALYSIS

[537]:
```python
df.shape
```

[537]:
```
(144867, 24)
```

- The dataset has 144867 rows and 24 columns

[538]:
```python
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
```

[539]:
```
df.describe()
```

[539]:

	start_scan_to_end_scan	cutoff_factor	actual_distance_to_destination
count	144867.000000	144867.000000	144867.000000
mean	961.262986	232.926567	234.073372
std	1037.012769	344.755577	344.990009
min	20.000000	9.000000	9.000045
25%	161.000000	22.000000	23.355874
50%	449.000000	66.000000	66.126571
75%	1634.000000	286.000000	286.708875
max	7898.000000	1927.000000	1927.447705

	actual_time	osrm_time	osrm_distance	factor
count	144867.000000	144867.000000	144867.000000	144867.000000
mean	416.927527	213.868272	284.771297	2.120107
std	598.103621	308.011085	421.119294	1.715421
min	9.000000	6.000000	9.008200	0.144000
25%	51.000000	27.000000	29.914700	1.604264
50%	132.000000	64.000000	78.525800	1.857143
75%	513.000000	257.000000	343.193250	2.213483
max	4532.000000	1686.000000	2326.199100	77.387097

	segment_actual_time	segment_osrm_time	segment_osrm_distance
count	144867.000000	144867.000000	144867.00000
mean	36.196111	18.507548	22.82902
std	53.571158	14.775960	17.86066
min	-244.000000	0.000000	0.00000
25%	20.000000	11.000000	12.07010
50%	29.000000	17.000000	23.51300
75%	40.000000	22.000000	27.81325
max	3051.000000	1611.000000	2191.40370

	segment_factor
count	144867.000000
mean	2.218368
std	4.847530
min	-23.444444
25%	1.347826
50%	1.684211
75%	2.250000
max	574.250000

- we can see there are differences between mean and 50% values of few numerical columns, this means that outlier exists.

[540]:
```python
#finding the number of unique values in categorical columns
cat_cols = [col for col in df.columns if df[col].dtypes == 'object']
for col in cat_cols:
    print(f'unique values in {col} column = {df[col].nunique()}')
```

```
unique values in data column = 2
unique values in trip_creation_time column = 14817
unique values in route_schedule_uuid column = 1504
unique values in route_type column = 2
unique values in trip_uuid column = 14817
unique values in source_center column = 1508
unique values in source_name column = 1498
unique values in destination_center column = 1481
unique values in destination_name column = 1468
unique values in od_start_time column = 26369
unique values in od_end_time column = 26369
unique values in cutoff_timestamp column = 93180
```

[541]:
```python
# finding the null values
df.isnull().sum()*100/len(df)
```

[541]:
```
data                              0.000000
trip_creation_time                0.000000
route_schedule_uuid               0.000000
route_type                        0.000000
trip_uuid                         0.000000
source_center                     0.000000
source_name                       0.202254
destination_center                0.000000
destination_name                  0.180165
od_start_time                     0.000000
od_end_time                       0.000000
start_scan_to_end_scan            0.000000
is_cutoff                         0.000000
cutoff_factor                     0.000000
cutoff_timestamp                  0.000000
actual_distance_to_destination    0.000000
actual_time                       0.000000
osrm_time                         0.000000
osrm_distance                     0.000000
factor                            0.000000
segment_actual_time               0.000000
segment_osrm_time                 0.000000
segment_osrm_distance             0.000000
segment_factor                    0.000000
dtype: float64
```

- We can see that around 0.20 % of source_name and 0.18% of destination_name are having null values.

0.0.5 DATA STRUCTURING AND CLEANING

- few columns like 'od_start_time', 'od_end_time' and 'trip_creation_time' have values of data type 'datetime'. But they are of type 'object'. So changing the data type of those columns as 'datetime'

[542]:
```
df['trip_creation_time'] = pd.to_datetime(df['trip_creation_time'])
df['od_start_time'] = pd.to_datetime(df['od_start_time'])
df['od_end_time'] = pd.to_datetime(df['od_end_time'])
```

[543]:
```
#dropping unknown and unwanted columns
df = df.
 ↪drop(['is_cutoff','cutoff_factor','cutoff_timestamp','factor','segment_factor'],␣
 ↪axis=1)
```

0.0.6 MISSING VALUES TREATMENT

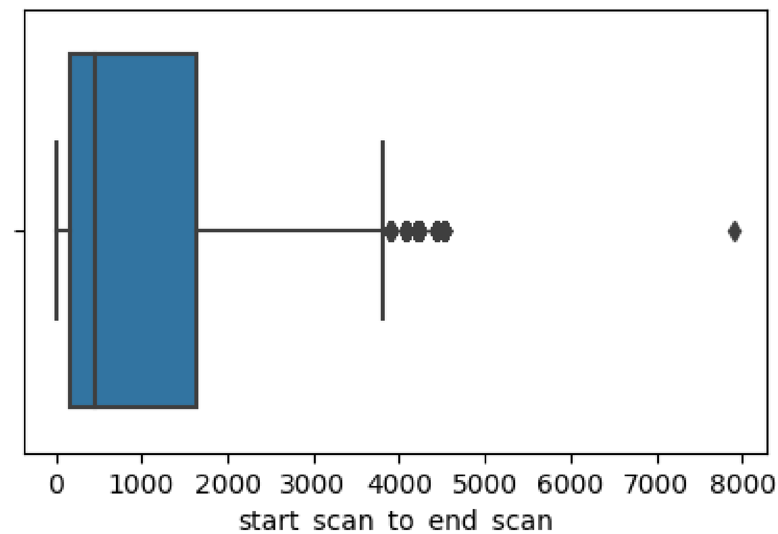
Since only 0.20 % of source_name and 0.18% of destination_name are having null values, we can drop these rows as it will not impact much on our dataset

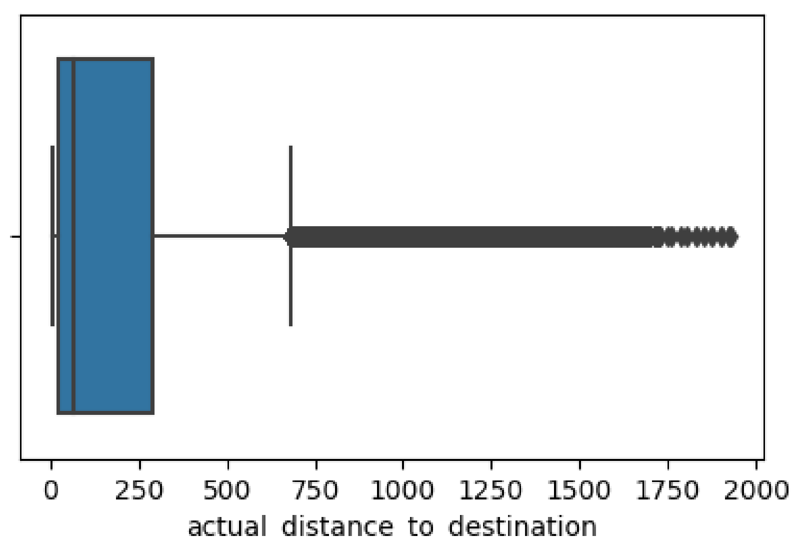
[544]:
```
df = df.dropna()
```

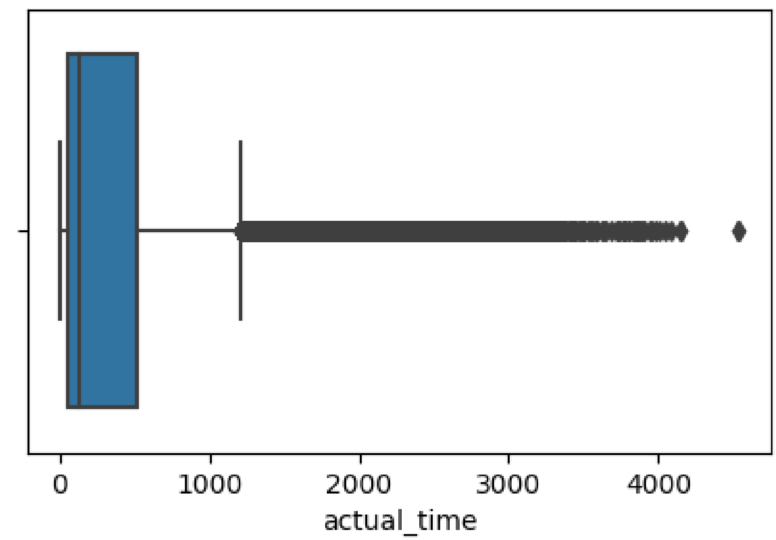
0.0.7 OUTLIER ANALYSIS

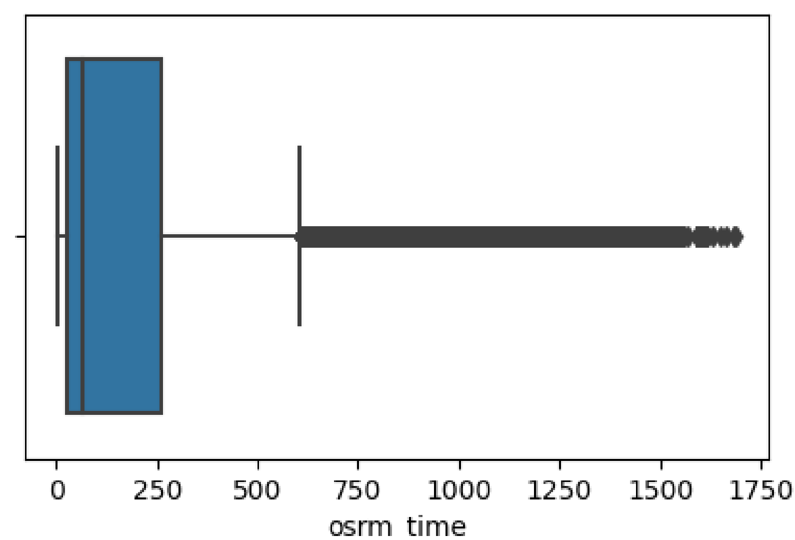
[545]:
```
numerical_cols = [col for col in df.columns if df[col].dtype in␣
 ↪['float64','int64']]
```

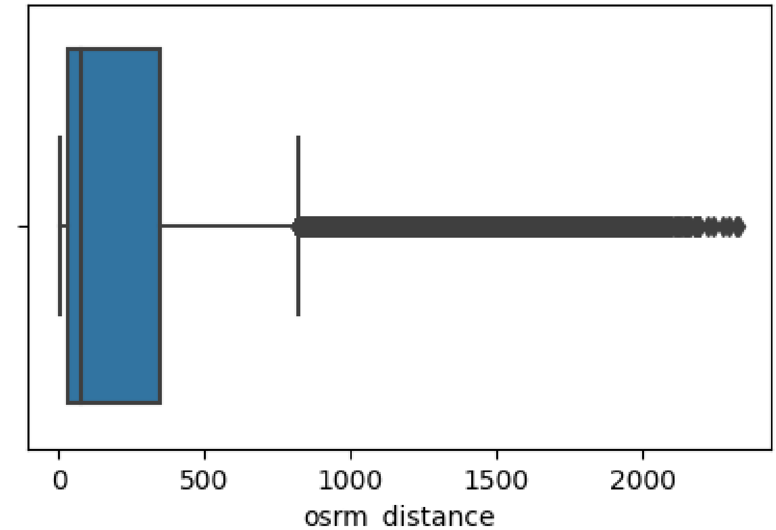
[546]:
```
#plotting boxplot for all the numerical columns to see if outliers exists
for col in numerical_cols:
    plt.figure(figsize=(5,3))
    sns.boxplot(data=df, x=col)
    plt.show()
```

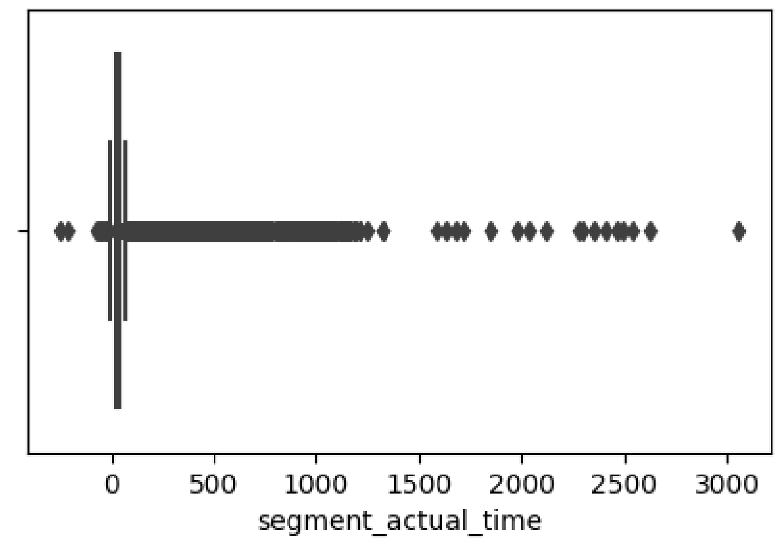

0 1000 2000 3000 4000 5000 6000 7000 8000
start_scan_to_end_scan

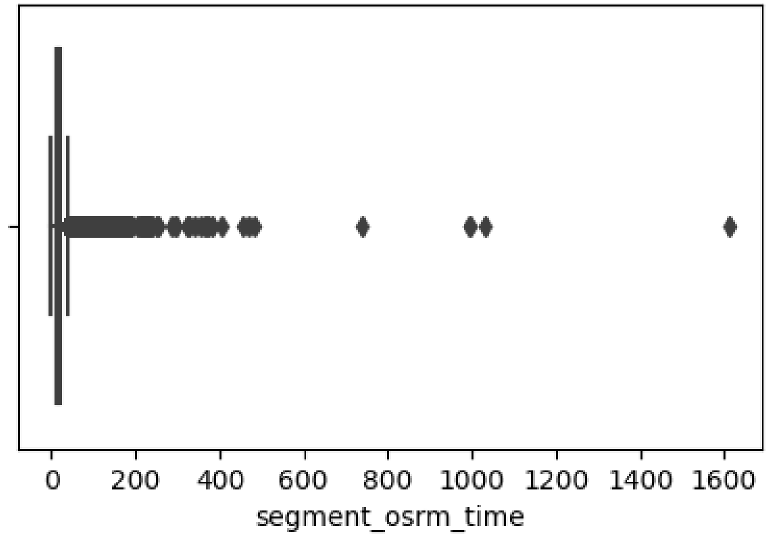

0 250 500 750 1000 1250 1500 1750 2000
actual_distance_to_destination

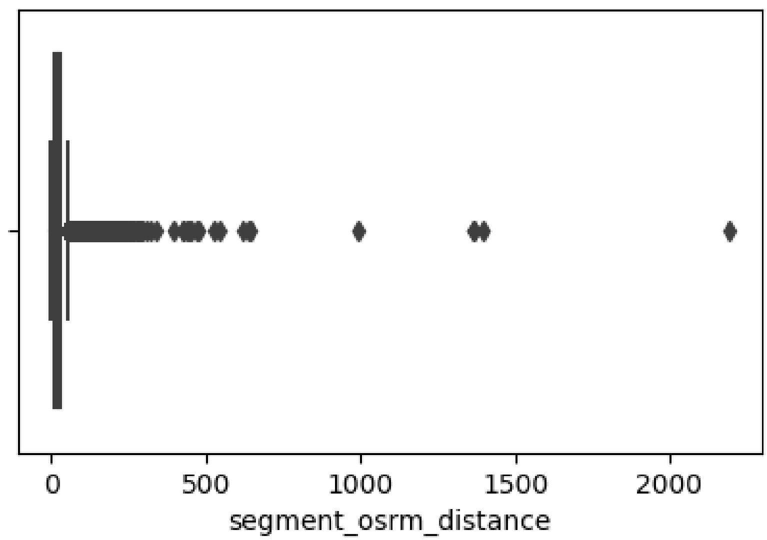

0
1000
2000
3000
4000
actual_time


0
250
500
750
1000
1250
1500
1750
osrm_time


0
500
1000
1500
2000
osrm_distance


0
500
1000
1500
2000
2500
3000
segment_actual_time



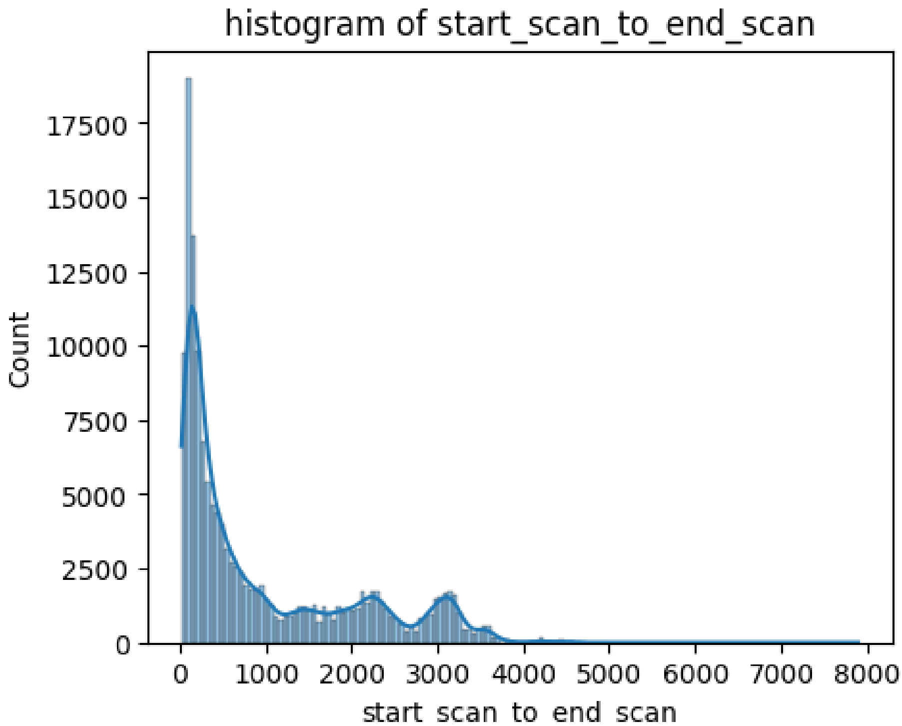


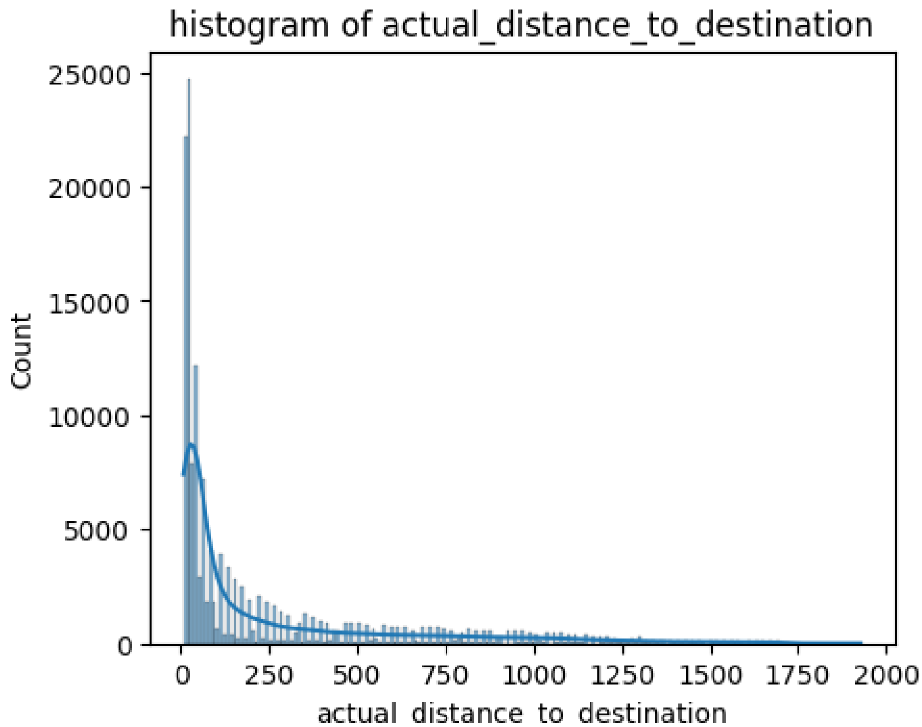
- we can see that there are a lot of outliers present in the dataset. We will handle the outliers later.

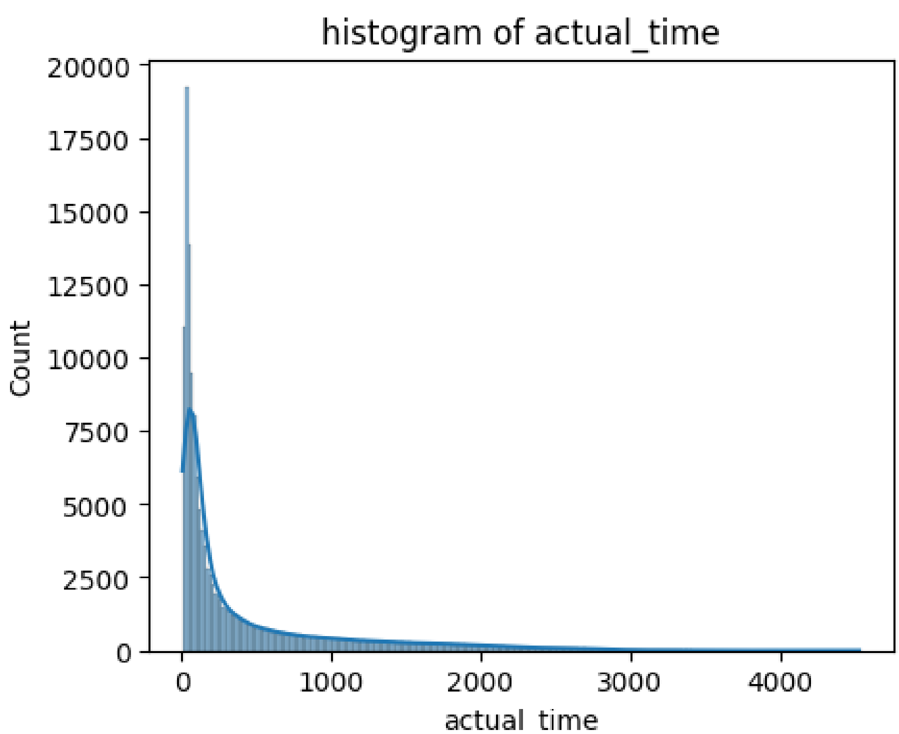
0.0.8 UNIVARIATE AND BIVARIATE ANALYSIS

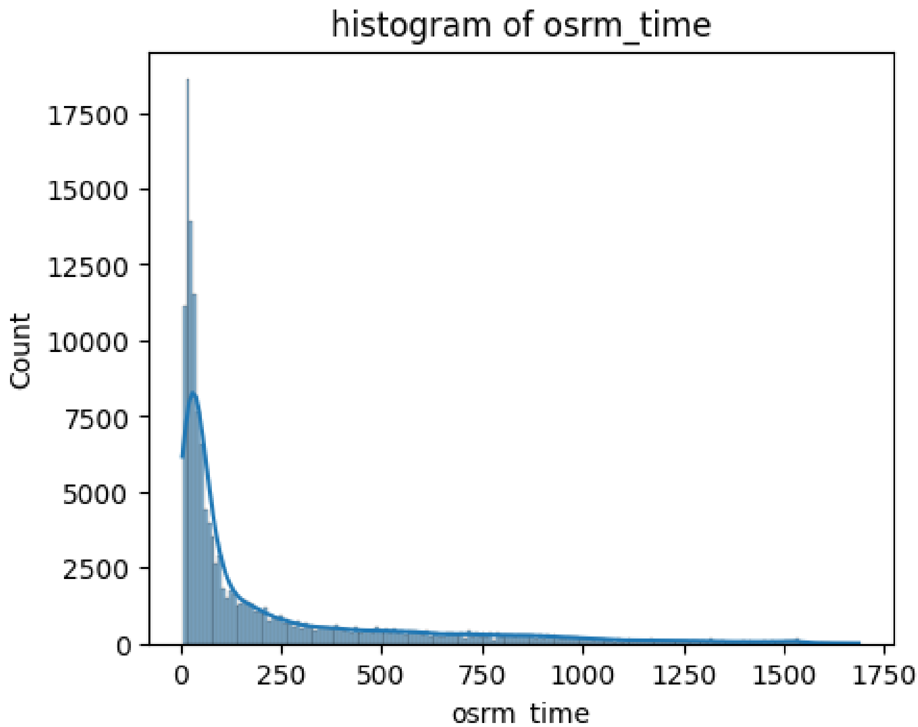
[549]:
```
def dist_plot(col):
    plt.figure(figsize=(5,4))
    sns.histplot(x=df[col], kde=True)
    plt.title(f'histogram of {col}')
    plt.show()
```

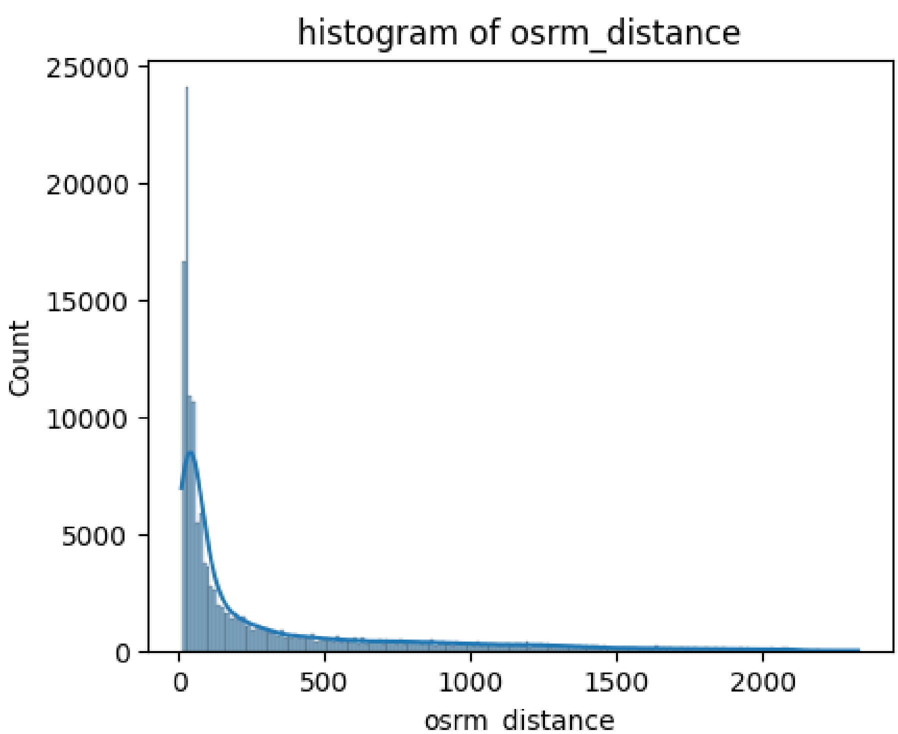
```python
for col in numerical_cols:
    dist_plot(col)
```

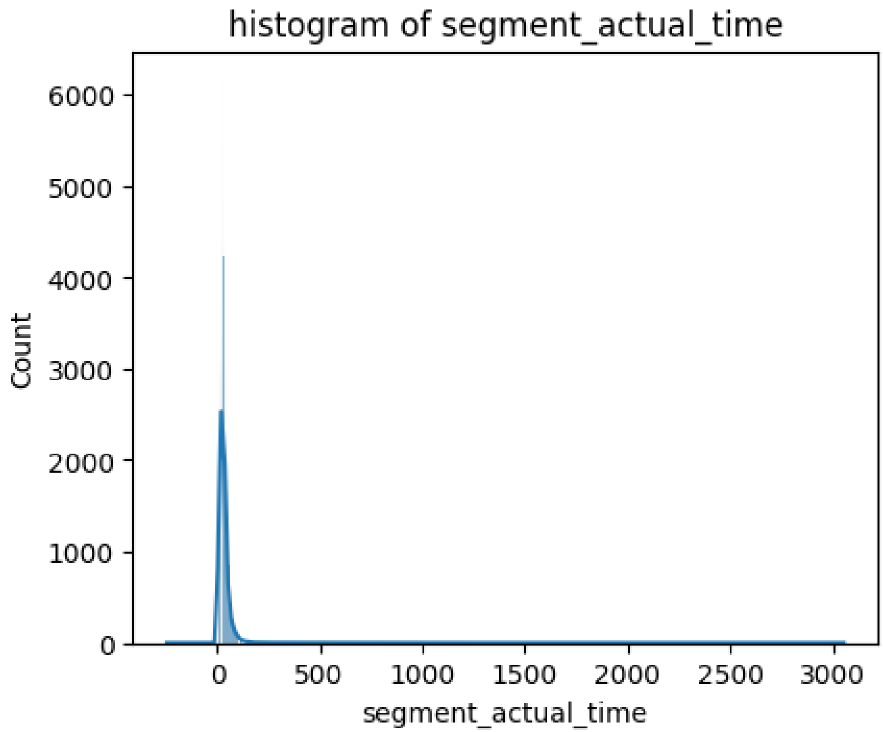


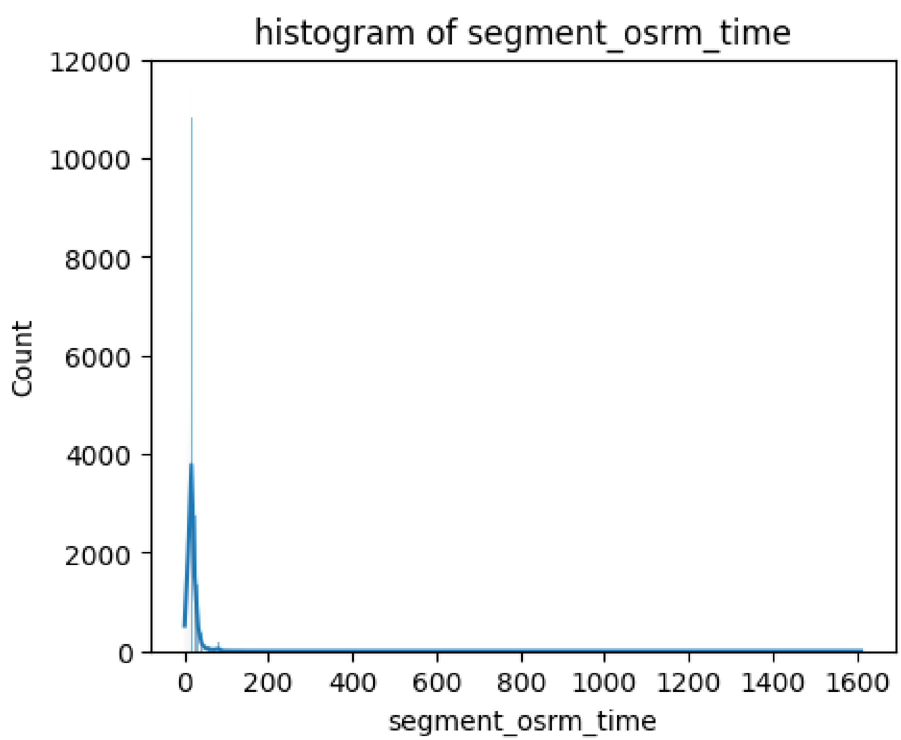

histogram of actual_distance_to_destination
Count
25000
20000
15000
10000
5000
0
0
250
500
750
1000
1250
1500
1750
2000
actual_distance_to_destination

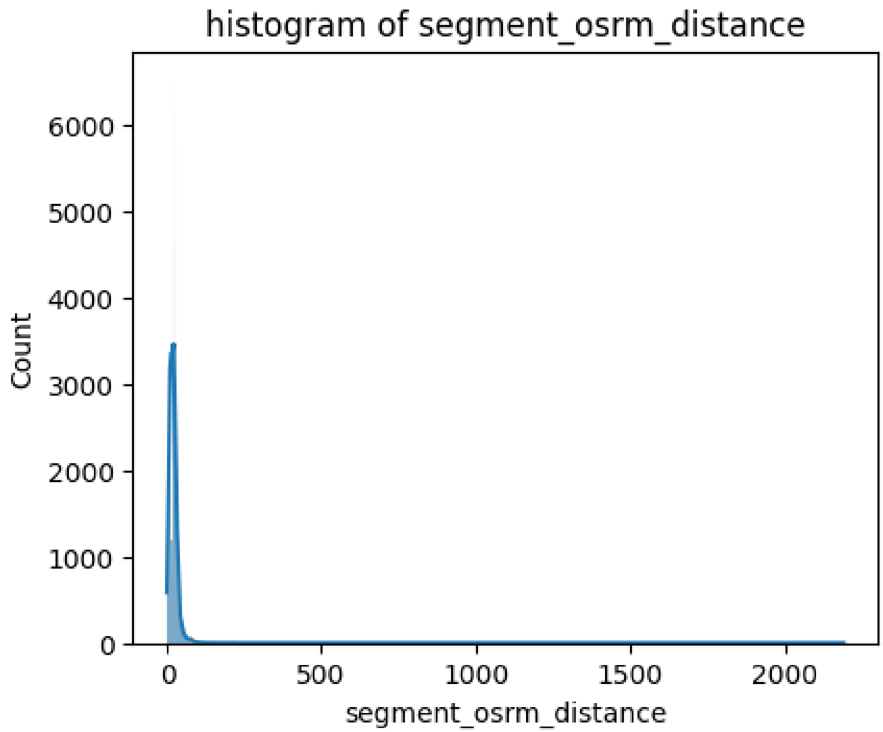

histogram of actual_time
Count
20000
17500
15000
12500
10000
7500
5000
2500
0
0
1000
2000
3000
4000
actual_time


histogram of osrm_time
17500
15000
12500
10000
7500
5000
2500
0
Count
0
250
500
750
1000
1250
1500
1750
osrm_time


histogram of osrm_distance
25000
20000
15000
10000
5000
0
Count
0
500
1000
1500
2000
osrm_distance


histogram of segment_actual_time
Count
6000
5000
4000
3000
2000
1000
0
0
500
1000
1500
2000
2500
3000
segment_actual_time


histogram of segment_osrm_time
Count
12000
10000
8000
6000
4000
2000
0
0
200
400
600
800
1000
1200
1400
1600
segment_osrm_time



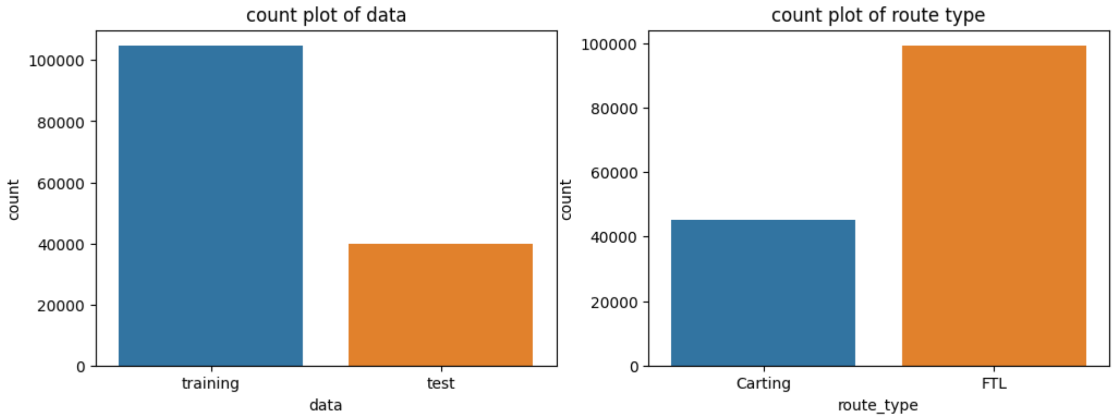
- From the above plots, we can see that our data is highly **right skewed**.

UNIVARIATE ANALYISIS BETWEEN CATEGORICAL VARIABLES

[550]:
```
plt.figure(figsize=(12,4))

plt.subplot(1,2,1)
sns.countplot(data=df, x='data')
plt.title('count plot of data')

plt.subplot(1,2,2)
sns.countplot(data=df, x='route_type')
plt.title('count plot of route type')
plt.show()
```



1. **Data:** We have more training data than test data. Which is a standard practice to follow when working on Machine Learning model to train the model on huge data.
2. **Route Type:** We have more shipments going through FTL(Full Truck Load) than carting. This ensures faster delivery, as the truck is making no other pickups or drop-offs along the way.

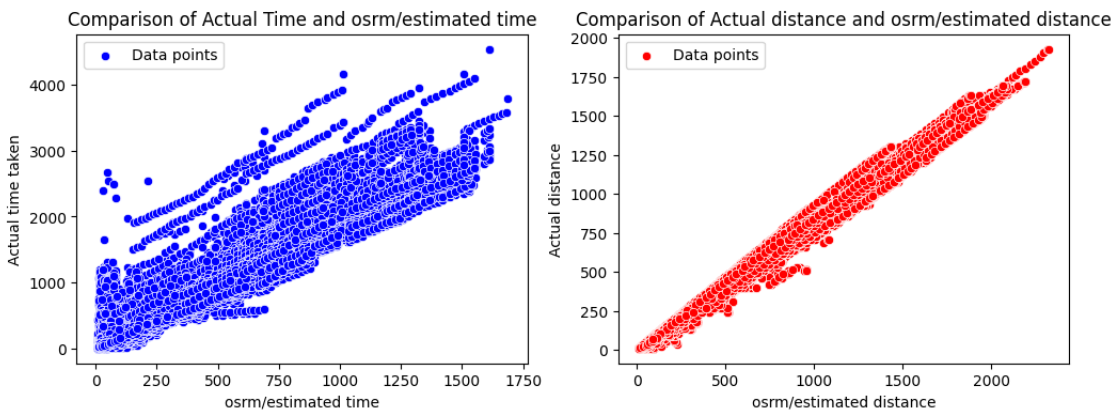
0.0.9 COMPARISON & VISUALIZATION OF TIME AND DISTANCE FIELDS

[551]:
```
plt.figure(figsize=(12, 4))

plt.subplot(1,2,1)
sns.scatterplot(y='actual_time', x='osrm_time', data=df, color='blue',␣
↪label='Data points')
plt.ylabel('Actual time taken')
plt.xlabel('osrm/estimated time')
plt.title('Comparison of Actual Time and osrm/estimated time')

plt.subplot(1,2,2)
sns.scatterplot(y='actual_distance_to_destination', x='osrm_distance', data=df,␣
↪color='red', label='Data points')
plt.ylabel('Actual distance')
plt.xlabel('osrm/estimated distance')
plt.title('Comparison of Actual distance and osrm/estimated distance')

plt.show()
```



- We can see a linear relationship between estimated time and actual time. Although for most of the estimated time points, the corresponding actual time is higher than estimated time.
- We can see a linear relationship between estimated distance and actual distance. Although for most of the estimated distance points, the corresponding actual distance is lower than estimated distance.

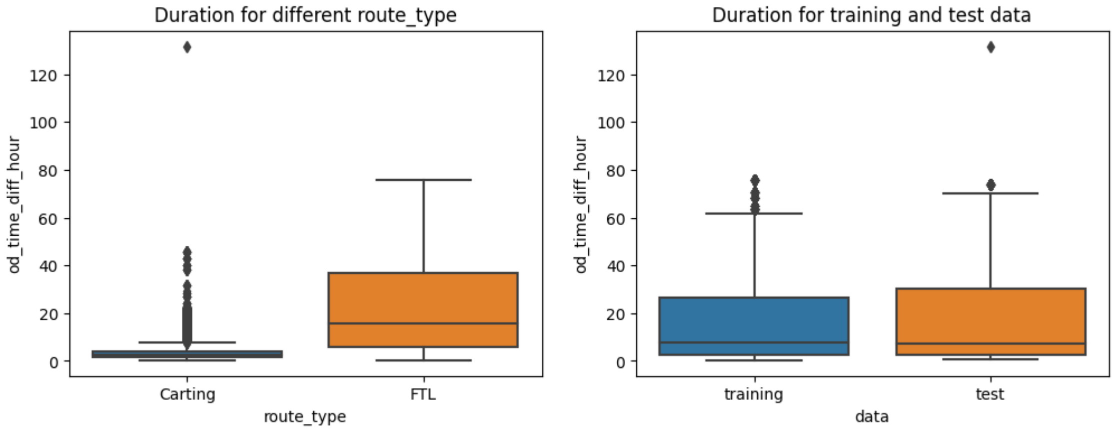
0.0.10 FEATURE CREATION

1. duration: time between 'od_end_time' and od_start_time' to get the duration of trip start and end time.
2. Source Name: Split and extract features out of destination. City-place-code (State)
3. Destination Name: Split and extract features out of destination. City-place-code (State)
4. Trip_creation_time: Extract features like month, year and day etc

[552]:
```
plt.figure(figsize=(12,4))
df['od_time_diff_hour'] = (df['od_end_time'] - df['od_start_time']).dt.
 ↪total_seconds() / 3600 #Total duration in hours
df = df.drop(['od_end_time','od_start_time'], axis=1)    #dropping original␣
 ↪columns

plt.subplot(1,2,1)
sns.boxplot(data=df,y= 'od_time_diff_hour', x='route_type')
plt.title('Duration for different route_type')

plt.subplot(1,2,2)
sns.boxplot(data=df,y= 'od_time_diff_hour', x='data')
plt.title('Duration for training and test data')
plt.show()
```



[553]:
```
# extracting source city, place, code and state
pattern = r'(?P<s_city>[\w]+)_(?P<s_place>[\w]+)_(?P<s_code>[\w]+)\s\((?
 ↪P<s_state>[\w]+)\)'

df_extracted = df['source_name'].str.extract(pattern)
df = pd.concat([df, df_extracted], axis=1)

# extracting destination city, place, code and state
pattern = r'(?P<d_city>[\w]+)_(?P<d_place>[\w]+)_(?P<d_code>[\w]+)\s\((?
 ↪P<d_state>[\w]+)\)'

df_extracted = df['destination_name'].str.extract(pattern)
df = pd.concat([df, df_extracted], axis=1)
```

[554]:
```
df['day_trip_created'] = df['trip_creation_time'].dt.day
df['month_trip_created'] = df['trip_creation_time'].dt.month
df['year_trip_created'] = df['trip_creation_time'].dt.year
```

[555]:
```
df['s_state'].nunique(),df['d_state'].nunique(),
```

[555]: (22, 22)

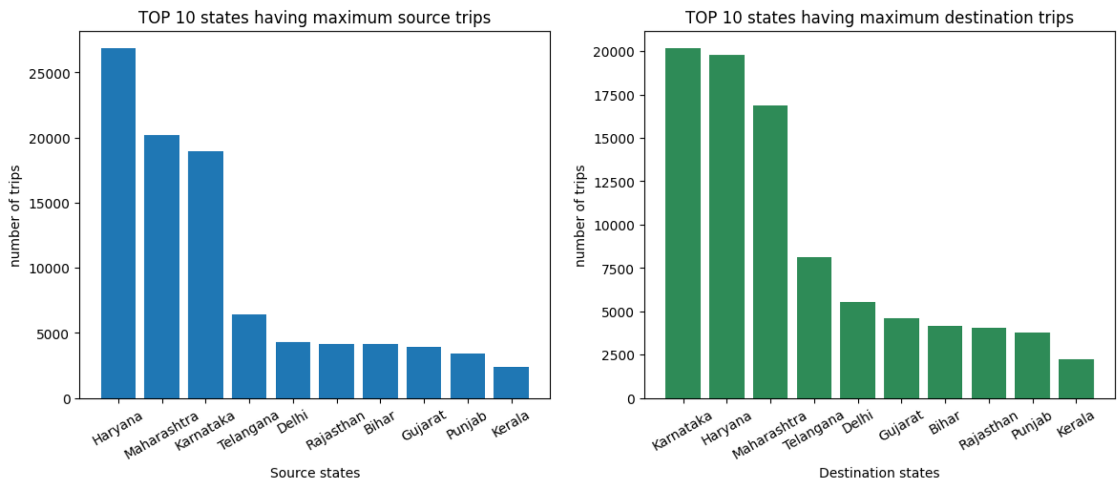
[556]:
```
top_source_states = df['s_state'].value_counts()[0:10]
top_destination_states = df['d_state'].value_counts()[0:10]

fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(14, 5)) #createing sub plot

x = top_source_states.index
y = top_source_states
ax[0].bar(x,y) #bar plot
ax[0].set_title("TOP 10 states having maximum source trips")
ax[0].set_xlabel("Source states")
```

```
ax[0].set_ylabel("number of trips")
ax[0].tick_params(axis='x', rotation=30)

x = top_destination_states.index
y = top_destination_states
ax[1].bar(x,y,color='seagreen')
ax[1].set_title("TOP 10 states having maximum destination trips")
ax[1].set_xlabel("Destination states")
ax[1].set_ylabel("number of trips")
ax[1].tick_params(axis='x', rotation=30)
plt.show()
```



- From the above plots, we can see that:
  - Busiest Source states: Haryana, Maharashtra, Karnataka
  - Busiest Destination states: Karnataka, Haryana, Maharashtra

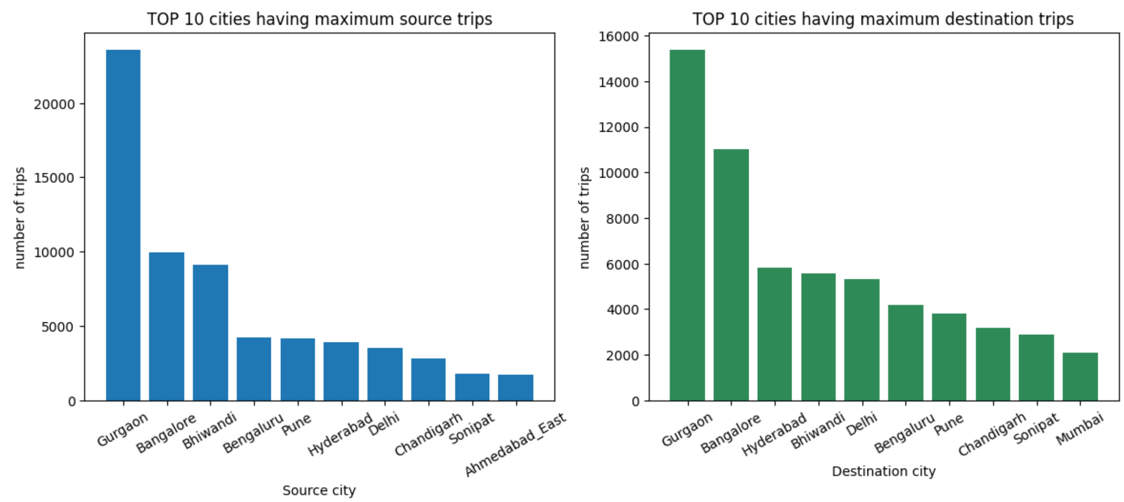
[557]:
```
top_source_city = df['s_city'].value_counts()[0:10]
top_destination_city = df['d_city'].value_counts()[0:10]

fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(14, 5)) #createing sub plot

x = top_source_city.index
y = top_source_city
ax[0].bar(x,y) #bar plot
ax[0].set_title("TOP 10 cities having maximum source trips")
ax[0].set_xlabel("Source city")
ax[0].set_ylabel("number of trips")
ax[0].tick_params(axis='x', rotation=30)

x = top_destination_city.index
y = top_destination_city
```

```
ax[1].bar(x,y,color='seagreen')
ax[1].set_title("TOP 10 cities having maximum destination trips")
ax[1].set_xlabel("Destination city")
ax[1].set_ylabel("number of trips")
ax[1].tick_params(axis='x', rotation=30)
plt.show()
```



- From the above plots, we can see that:
  - Busiest Source cities: Gurgaon, Bangalore, Bhiwandi
  - Busiest Destination cities: Gurgaon, Bangalore, Hyderabad

BUSIEST STATES ROUTE

[558]:
```
busiest_state_route = df.groupby(['s_state','d_state'])['trip_uuid'].size().reset_index(name='count')
busiest_route = busiest_state_route.loc[busiest_state_route['count'].idxmax()]
print(f'The busiest route between state is between {busiest_route[0]} and {busiest_route[1]} with total {busiest_route[2]} trips.')
```

```
The busiest route between state is between Karnataka and Karnataka with total
9724 trips.
```

BUSIEST CITIES ROUTE

[559]:
```
busiest_city_route = df.groupby(['s_city','d_city'])['trip_uuid'].size().reset_index(name='count')
busiest_route = busiest_city_route.loc[busiest_city_route['count'].idxmax()]
print(f'The busiest route between cities is between {busiest_route[0]} and {busiest_route[1]} with total {busiest_route[2]} trips.')
```

```
The busiest route between cities is between Gurgaon and Bangalore with total
4976 trips.
```

BUSIEST CORRIDOR ROUTE

[560]:
```
busiest_corridor_route = df.
 ↪groupby(['s_city','s_place','s_code','s_state','d_city','d_place','d_code','d_state'])['tri
 ↪size().reset_index(name='count')
busiest_route = busiest_corridor_route.loc[busiest_corridor_route['count'].
 ↪idxmax()]
print(f'The busiest corridor is between␣
 ↪{busiest_route[0]}_{busiest_route[1]}_{busiest_route[2]}_{busiest_route[3]}␣
 ↪and␣
 ↪{busiest_route[4]}_{busiest_route[5]}_{busiest_route[6]}_{busiest_route[7]}␣
 ↪with total {busiest_route[8]} trips.')
```

```
The busiest corridor is between Gurgaon_Bilaspur_HB_Haryana and
Bangalore_Nelmngla_H_Karnataka with total 4976 trips.
```

DISTANCE BETWEEN BUSIEST ROUTE

[561]:
```
x = df.
 ↪groupby(['s_city','s_place','s_code','s_state','d_city','d_place','d_code','d_state'])['act
 ↪last().reset_index(name='distance')

busiest_corridor_distance = x[(x['s_city']==busiest_route[0]) &␣
 ↪(x['s_place']==busiest_route[1]) & (x['s_code']==busiest_route[2]) &␣
 ↪(x['s_state']==busiest_route[3]) & (x['d_city']==busiest_route[4]) &␣
 ↪(x['d_place']==busiest_route[5]) & (x['d_code']==busiest_route[6]) &␣
 ↪(x['d_state']==busiest_route[7])]
print(f'The distance between busiest corridor(Gurgaon_Bilaspur_HB_Haryana and␣
 ↪Bangalore_Nelmngla_H_Karnataka) is {round(busiest_corridor_distance.distance.
 ↪values[0], 2)}kms')
```

```
The distance between busiest corridor(Gurgaon_Bilaspur_HB_Haryana and
Bangalore_Nelmngla_H_Karnataka) is 1689.64kms
```

0.0.11 MERGING OF ROWS AND AGGREGATION OF FIELDS

Dataset contains cumulative values few numerical columns. Let's group by columns 'trip_uuid','source_center','destination_center' and find the last value(cumulative sum value)

- First, let's group the data by 'trip_uuid','source_center' and 'destination_center',
- Aggregation details:
  - source_name: taking the first value
  - destination_name: taking the last value
  - start_scan_to_end_scan: taking the first value
  - 'actual_distance_to_destination':taking the last value ,
  - 'actual_time':taking the last value
  - 'osrm_time':'taking the last value
  - 'osrm_distance':taking the last value
  - 'segment_actual_time':taking the sum value
  - 'segment_osrm_time':taking the sum value

– 'segment_osrm_distance': taking the sum value

[562]:
```
df1 = df.groupby(['trip_uuid','source_center','destination_center']).agg({
    'data':'first',
    'trip_creation_time':'first',
    'route_schedule_uuid':'first', 'route_type':'first',
    'source_name': 'first',
    'destination_name':'last',
    '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',
    'od_time_diff_hour':'last',
    's_city': 'first', 's_place': 'first', 's_code': 'first','s_state': 'first',
    'd_city': 'last', 'd_place': 'last', 'd_code': 'last', 'd_state': 'last',
    'day_trip_created': 'first', 'month_trip_created':␣
 ↪'first','year_trip_created': 'first'
}).reset_index()
```

[563]:
```
df1.shape
```

[563]:
```
(26222, 29)
```

After merging the data we have reduced the size of dataset to 26,222 rows

[564]:
```
df1.head()
```

[564]:
```
                  trip_uuid source_center destination_center      data  \
0  trip-153671041653548748  IND209304AAA       IND000000ACB  training
1  trip-153671041653548748  IND462022AAA       IND209304AAA  training
2  trip-153671042288605164  IND561203AAB       IND562101AAA  training
3  trip-153671042288605164  IND572101AAA       IND561203AAB  training
4  trip-153671043369099517  IND000000ACB       IND160002AAC  training

          trip_creation_time  \
0 2018-09-12 00:00:16.535741
1 2018-09-12 00:00:16.535741
2 2018-09-12 00:00:22.886430
3 2018-09-12 00:00:22.886430
4 2018-09-12 00:00:33.691250

                                 route_schedule_uuid route_type  \
0  thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6…        FTL
1  thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6…        FTL
```

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

                           source_name                    destination_name  \
0  Kanpur_Central_H_6 (Uttar Pradesh)       Gurgaon_Bilaspur_HB (Haryana)
1  Bhopal_Trnsport_H (Madhya Pradesh)  Kanpur_Central_H_6 (Uttar Pradesh)
2   Doddablpur_ChikaDPP_D (Karnataka)   Chikblapur_ShntiSgr_D (Karnataka)
3       Tumkur_Veersagr_I (Karnataka)   Doddablpur_ChikaDPP_D (Karnataka)
4       Gurgaon_Bilaspur_HB (Haryana)      Chandigarh_Mehmdpur_H (Punjab)

   start_scan_to_end_scan  actual_distance_to_destination  actual_time  \
0                  1260.0                      383.759164        732.0
1                   999.0                      440.973689        830.0
2                    58.0                       24.644021         47.0
3                   122.0                       48.542890         96.0
4                   834.0                      237.439610        611.0

   osrm_time  osrm_distance  segment_actual_time  segment_osrm_time  \
0      329.0       446.5496                728.0              534.0
1      388.0       544.8027                820.0              474.0
2       26.0        28.1994                 46.0               26.0
3       42.0        56.9116                 95.0               39.0
4      212.0       281.2109                608.0              231.0

   segment_osrm_distance  od_time_diff_hour      s_city   s_place s_code  \
0               670.6205          21.010074        None      None   None
1               649.8528          16.658423        None      None   None
2                28.1995           0.980540  Doddablpur  ChikaDPP      D
3                55.9899           2.046325      Tumkur  Veersagr      I
4               317.7408          13.910649     Gurgaon  Bilaspur     HB

     s_state      d_city   d_place d_code    d_state  day_trip_created  \
0       None     Gurgaon  Bilaspur     HB    Haryana                12
1       None        None      None   None       None                12
2  Karnataka  Chikblapur  ShntiSgr      D  Karnataka                12
3  Karnataka  Doddablpur  ChikaDPP      D  Karnataka                12
4    Haryana  Chandigarh  Mehmdpur      H     Punjab                12

   month_trip_created  year_trip_created
0                   9               2018
1                   9               2018
2                   9               2018
3                   9               2018
4                   9               2018
```

- Now we have eliminated all the duplicate rows for trip_uuid, and have got the aggregated

values for each group of 'trip_uuid','source_center','destination_center'.
- Now since we want to understand the overall picture of how is the platform performing in delivering the package from a source to destination, we need to group the rows by 'trip_uuid' and get the aggregated values for each trip_uuid

- For this, we will group by 'trip_uuid' and get the aggregated values like: - 'first' value for 'source_center' and 'last' value for 'destination_center' - 'sum' of the values for features like 'actual_time', 'actual_distance', 'osrm_time' etc

[565]:
```
df2 = df1.groupby('trip_uuid').agg({
    'data':'first',
    'trip_creation_time':'first',
    'route_schedule_uuid':'first', 'route_type':'first',
    'source_center':'first',
    'destination_center':'last',
    'source_name': 'first',
    'destination_name':'last',
    'start_scan_to_end_scan': 'sum',
    'actual_distance_to_destination':'sum',
    'actual_time':'sum',
    'osrm_time':'sum',
    'osrm_distance':'sum',
    'segment_actual_time':'sum',
    'segment_osrm_time':'sum',
    'segment_osrm_distance':'sum',
    'od_time_diff_hour':'sum',
    's_city': 'first', 's_place': 'first', 's_code': 'first','s_state': 'first',
    'd_city': 'last', 'd_place': 'last', 'd_code': 'last', 'd_state': 'last',
    'day_trip_created': 'first', 'month_trip_created':␣
↪'first','year_trip_created': 'first'
}).reset_index()
```

[566]:
```
df2.shape
```

[566]:
```
(14787, 29)
```

After merging the data just by 'trip_uuid', we have reduced the size of dataset to 14,787 rows

[567]:
```
df2.head()
```

[567]:
```
                 trip_uuid      data          trip_creation_time  \
0  trip-153671041653548748  training 2018-09-12 00:00:16.535741
1  trip-153671042288605164  training 2018-09-12 00:00:22.886430
2  trip-153671043369099517  training 2018-09-12 00:00:33.691250
3  trip-153671046011330457  training 2018-09-12 00:01:00.113710
4  trip-153671052974046625  training 2018-09-12 00:02:09.740725
```

```
                            route_schedule_uuid route_type source_center  \
0  thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6…        FTL  IND209304AAA
1  thanos::sroute:3a1b0ab2-bb0b-4c53-8c59-eb2a2c0…    Carting  IND561203AAB
2  thanos::sroute:de5e208e-7641-45e6-8100-4d9fb1e…        FTL  IND000000ACB
3  thanos::sroute:f0176492-a679-4597-8332-bbd1c7f…    Carting  IND400072AAB
4  thanos::sroute:d9f07b12-65e0-4f3b-bec8-df06134…        FTL  IND583101AAA

  destination_center                          source_name  \
0       IND209304AAA  Kanpur_Central_H_6 (Uttar Pradesh)
1       IND561203AAB   Doddablpur_ChikaDPP_D (Karnataka)
2       IND000000ACB       Gurgaon_Bilaspur_HB (Haryana)
3       IND401104AAA            Mumbai Hub (Maharashtra)
4       IND583119AAA              Bellary_Dc (Karnataka)

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

   actual_distance_to_destination  actual_time  osrm_time  osrm_distance  \
0                      824.732854       1562.0      717.0       991.3523
1                       73.186911        143.0       68.0        85.1110
2                     1927.404273       3347.0     1740.0      2354.0665
3                       17.175274         59.0       15.0        19.6800
4                      127.448500        341.0      117.0       146.7918

   segment_actual_time  segment_osrm_time  segment_osrm_distance  \
0               1548.0             1008.0              1320.4733
1                141.0               65.0                84.1894
2               3308.0             1941.0              2545.2678
3                 59.0               16.0                19.8766
4                340.0              115.0               146.7919

   od_time_diff_hour      s_city   s_place s_code    s_state      d_city  \
0          37.668497        None      None   None       None     Gurgaon
1           3.026865  Doddablpur  ChikaDPP      D  Karnataka  Doddablpur
2          65.572709     Gurgaon  Bilaspur     HB    Haryana     Gurgaon
3           1.674916        None      None   None       None      Mumbai
4          11.972484      Sandur  WrdN1DPP      D  Karnataka      Sandur

    d_place d_code       d_state  day_trip_created  month_trip_created  \
0  Bilaspur     HB       Haryana                12                   9
1  ChikaDPP      D     Karnataka                12                   9
2  Bilaspur     HB       Haryana                12                   9
3    MiraRd     IP   Maharashtra                12                   9
```

```
4  WrdN1DPP      D    Karnataka                 12                    9

   year_trip_created
0               2018
1               2018
2               2018
3               2018
4               2018
```

- Now, we have a unique row for each trip_uuid, with the first source point, final destination point, total time taken, total distance travelled and other aggregated values corresponding to it.
- We have also reduced the data size having clean and sensible data obtained from raw data

0.0.12 IN-DEPTH ANALYSIS AND HYPOTHESIS TESTING OF AGGREGATED FIELDS

- Let's compare the columns like 'actual_time', 'osrm_time' and 'actual_distance_to_destination','osrm_distance' to analyze how delhivery platform is performing
- For In-depth analysis, we will do:
  1. Statistical analysis
  2. Visual analysis
  3. Hypothesis testing

[568]:
```
df2.columns
```

[568]:
```
Index(['trip_uuid', 'data', 'trip_creation_time', 'route_schedule_uuid',
       'route_type', 'source_center', 'destination_center', 'source_name',
       'destination_name', 'start_scan_to_end_scan',
       'actual_distance_to_destination', 'actual_time', 'osrm_time',
       'osrm_distance', 'segment_actual_time', 'segment_osrm_time',
       'segment_osrm_distance', 'od_time_diff_hour', 's_city', 's_place',
       's_code', 's_state', 'd_city', 'd_place', 'd_code', 'd_state',
       'day_trip_created', 'month_trip_created', 'year_trip_created'],
      dtype='object')
```

[569]:
```
# taking only the columns required for analysis
data = df2[['trip_uuid','source_center', 'source_name',␣
 ↪'destination_center','destination_name',
            'start_scan_to_end_scan','actual_distance_to_destination',␣
 ↪'actual_time','osrm_time',
             'osrm_distance', 'segment_actual_time','segment_osrm_time',␣
 ↪'segment_osrm_distance']]
```

1. STATISTICAL SUMMARY

[570]:
```
data.describe()
```

[570]:

```
       start_scan_to_end_scan  actual_distance_to_destination   actual_time  \
count            14787.000000                    14787.000000  14787.000000
mean               529.429025                      164.090196    356.306012
std                658.254936                      305.502982    561.517936
min                 23.000000                        9.002461      9.000000
25%                149.000000                       22.777099     67.000000
50%                279.000000                       48.287894    148.000000
75%                632.000000                      163.591258    367.000000
max               7898.000000                     2186.531787   6265.000000

          osrm_time  osrm_distance  segment_actual_time  segment_osrm_time  \
count  14787.000000   14787.000000         14787.000000       14787.000000
mean     160.990938     203.887411           353.059174         180.511598
std      271.459495     370.565564           556.365911         314.679279
min        6.000000       9.072900             9.000000           6.000000
25%       29.000000      30.756900            66.000000          30.000000
50%       60.000000      65.302800           147.000000          65.000000
75%      168.000000     206.644200           364.000000         184.000000
max     2032.000000    2840.081000          6230.000000        2564.000000

       segment_osrm_distance
count           14787.000000
mean              222.705466
std               416.846279
min                 9.072900
25%                32.578850
50%                69.784200
75%               216.560600
max              3523.632400
```

- **comparison between osrm_time (estimated delivery time) and actual_time (actual delivery time):**
  - mean of osrm_time: 160.99 mins
  - mean of actual_time: 356.30 mins

(mean values for both the columns are far apart. We can see that, on an average, actual_time is higher than the osrm/estimated delivery time.)

- **comparison between osrm_distance (estimated delivery distance) and actual_distance_to_destination (actual delivery distance) :**
  - mean of osrm_distance: 203.88 km
  - mean of actual_distance_to_destination: 164.09 km

(mean values for both the columns are far apart. We can see that, on an average, actual_distance_to_destination is less than the osmr/estimated delivery distance.)

- **comparison between actual_time (actual delivery time) and segment_actual_time (sum of in-between delivery time):**
  - mean of actual_time: 356.30 mins
  - mean of segment_actual_time: 353.06 mins

(mean values for both the columns are close to each other)

- **comparison between osrm_distance (estimated delivery distance) and segment_osrm_distance (sum of in-between delivery distance) :**
  - mean of osrm_distance: 203.88 km
  - mean of segment_osrm_distance: 222.70 km

(mean values for both the columns do not have large difference)

- **comparison between start_scan_to_end_scan and actual_time:**
  - mean of start_scan_to_end_scan: 529.42 mins
  - mean of actual_time: 356.30 mins

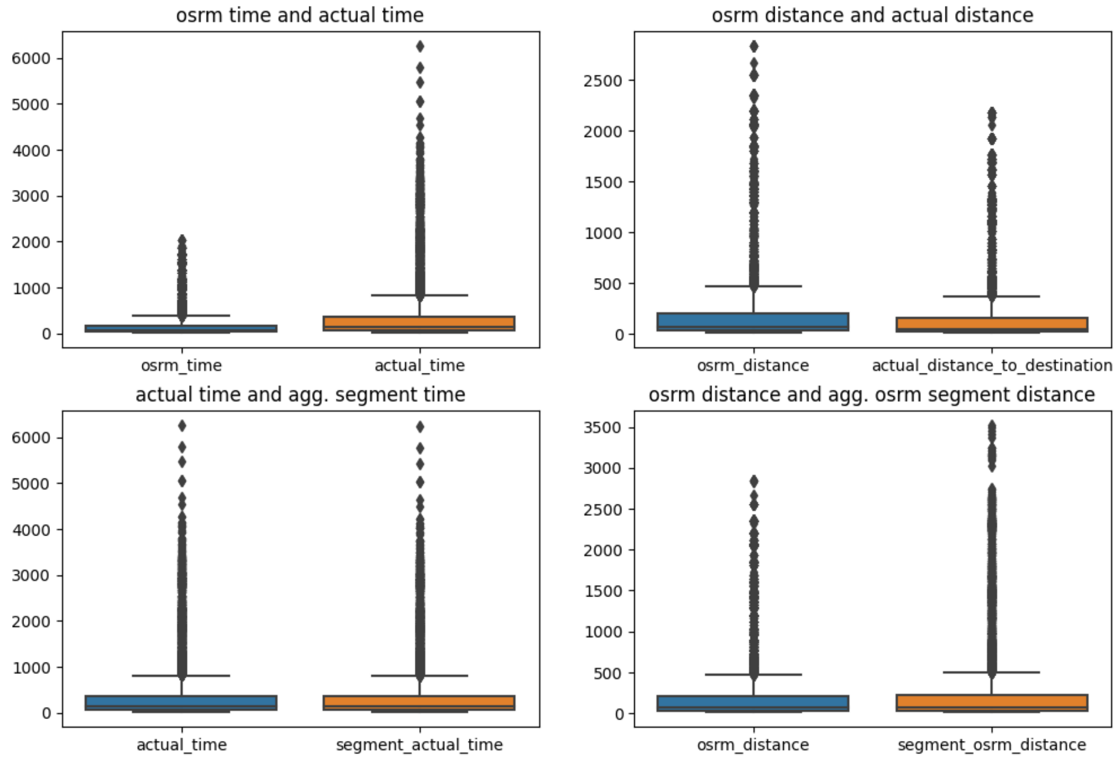
2. VISUAL ANALYSIS

[571]:
```
plt.figure(figsize=(12, 8))
plt.subplot(2,2,1)
sns.boxplot(data=data[['osrm_time', 'actual_time']])
plt.title('osrm time and actual time')

plt.subplot(2,2,2)
sns.boxplot(data=data[['osrm_distance', 'actual_distance_to_destination']])
plt.title('osrm distance and actual distance')

plt.subplot(2,2,3)
sns.boxplot(data=data[['actual_time', 'segment_actual_time']])
plt.title('actual time and agg. segment time')

plt.subplot(2,2,4)
sns.boxplot(data=data[['osrm_distance', 'segment_osrm_distance']])
plt.title('osrm distance and agg. osrm segment distance')
plt.show()
```



- From the boxplots, we can see that:
  - mean value of actual time is greater than mean value of osrm time.
  - mean value of actual distance is less than osrm distance.
  - mean values of actual and segment time are very close.
  - mean values of osrm and segment distance are close.

3. HYPOTHESIS TESTING

- Hypothesis testing parameters:
  - determine whether there is a significant difference between the means of the two groups.
  - null hypothesis: H0: means are equal
  - alternate hypothesis: Ha: means are unequal
  - alpha: 0.05

[572]:
```
alpha = 0.05 #taking 95% confidence interval
```

1. Taking the **'osrm_time'** and **'actual_time'** of a package from a source to destination

[573]:
```
stat, p = ttest_ind(data['osrm_time'],data['actual_time'])
print(f'p value: {p}')
if(p<alpha):
    print('reject null hypothesis: mean values of estimated delivery time and actual delivery time are not equal.')
else:
```

```
    print('fail to reject null hypothesis: means values of estimated delivery␣
↪time and actual delivery time are equal.')
```

```
p value: 8.2146191343466e-310
reject null hypothesis: mean values of estimated delivery time and actual
delivery time are not equal.
```

- From statistical analysis, we saw that mean of osrm_time < mean of actual_time, so, we can also have another null and alternative hypothesis as:
  - H0: means are equal
  - Ha: mean of osrm_time < mean of actual_time

Let's see if this hypothesis holds true:

[574]:
```
stat, p = ttest_ind(data['osrm_time'],data['actual_time'], alternative='less')
print(f'p value: {p}')
if(p<alpha):
    print('reject null hypothesis: mean of osrm_time < mean of actual_time')
else:
    print('fail to reject null hypothesis: means values of estimated delivery␣
↪time and actual delivery time are equal.')
```

```
p value: 4.1073095671733e-310
reject null hypothesis: mean of osrm_time < mean of actual_time
```

2. Taking **osrm_distance** and **actual_distance_to_destination** values to compare

[575]:
```
stat, p =␣
↪ttest_ind(data['osrm_distance'],data['actual_distance_to_destination'])
print(f'p value: {p}')
if(p<alpha):
    print('reject null hypothesis: mean values of estimated delivery distance␣
↪and actual delivery distance are not equal.')
else:
    print('fail to reject null hypothesis:mean values of estimated delivery␣
↪distance and actual delivery distance are equal.')
```

```
p value: 7.659056588899532e-24
reject null hypothesis: mean values of estimated delivery distance and actual
delivery distance are not equal.
```

[576]:
```
stat, p =␣
↪ttest_ind(data['osrm_distance'],data['actual_distance_to_destination'],␣
↪alternative='greater')
print(f'p value: {p}')
if(p<alpha):
    print('reject null hypothesis: mean of osrm_distance > mean of␣
↪actual_distance_to_destination')
else:
```

```
    print('fail to reject null hypothesis:mean values of estimated delivery␣
↪distance and actual delivery distance are equal.')
```

```
p value: 3.82952829449766e-24
reject null hypothesis: mean of osrm_distance > mean of
actual_distance_to_destination
```

3. Taking **actual_time** and **segment_actual_time** values to compare

[577]:
```
stat, p = ttest_ind(data['segment_actual_time'],data['actual_time'])
print(f'p value: {p}')
if(p<alpha):
    print('reject null hypothesis: mean values of actual_time and␣
↪segment_actual_time are not equal.')
else:
    print('fail to reject null hypothesis: mean values of actual_time and␣
↪segment_actual_time are equal.')
```

```
p value: 0.6174479719707524
fail to reject null hypothesis: mean values of actual_time and
segment_actual_time are equal.
```

4. Taking **osrm_distance** and **segment_osrm_distance** values to compare

[578]:
```
stat, p = ttest_ind(data['segment_osrm_distance'],data['osrm_distance'])
print(f'p value: {p}')
if(p<alpha):
    print('reject null hypothesis: means of segment_osrm_distance and␣
↪osrm_distance are not equal.')
else:
    print('fail to reject null hypothesis: means of segment_osrm_distance and␣
↪osrm_distance are equal.')
```

```
p value: 4.092957819120332e-05
reject null hypothesis: means of segment_osrm_distance and osrm_distance are not
equal.
```

[579]:
```
stat, p = ttest_ind(data['segment_osrm_distance'],data['osrm_distance'],␣
↪alternative='greater')
print(f'p value: {p}')
if(p<alpha):
    print('reject null hypothesis: mean of segment_osrm_distance > mean of␣
↪osrm_distance')
else:
    print('fail to reject null hypothesis: means of segment_osrm_distance and␣
↪osrm_distance are equal.')
```

```
p value: 2.046478909560166e-05
reject null hypothesis: mean of segment_osrm_distance > mean of osrm_distance
```

5. Hypothesis testing between **start__scan__to__end__scan** and **actual__time** values

[580]:
```
stat, p = ttest_ind(data['start_scan_to_end_scan'],data['actual_time'],␣
 ↪alternative='greater')
print(f'p value: {p}')
if(p<alpha):
    print('reject null hypothesis: mean value of start_scan_to_end_scan > mean␣
 ↪of actual_delivery_time.')
else:
    print('fail to reject null hypothesis: mean values of␣
 ↪start_scan_to_end_scan and actual_delivery_time  are equal.')
```

```
p value: 8.550982839644418e-130
reject null hypothesis: mean value of start_scan_to_end_scan > mean of
actual_delivery_time.
```

From the plots that we saw above, we can say that outliers exists in dataset. Let's remove outliers using IQR method ### OUTLIER TREATMENT - IQR METHOD

[581]:
```
numerical_cols = [col for col in df2.columns if df2[col].dtype in ['int64',␣
 ↪'float64']]
print(numerical_cols)
```

```
['start_scan_to_end_scan', 'actual_distance_to_destination', 'actual_time',
'osrm_time', 'osrm_distance', 'segment_actual_time', 'segment_osrm_time',
'segment_osrm_distance', 'od_time_diff_hour']
```

[582]:
```
#defining a method to remove outliers from numerical columns
def iqr_method(col,df_out, multiplier):
    q1 = df_out[col].quantile(0.25)
    q3 = df_out[col].quantile(0.75)
    iqr = q3-q1

    lb = q1 - (iqr*multiplier)
    ub = q3 + (iqr*multiplier)

    outlier = df_out[(df_out[col]>=lb) & (df_out[col]<=ub)]
    return outlier

df_out = df2.copy()
for col in numerical_cols:
    df_out = iqr_method(col, df_out, 2)
```

[583]:
```
df_out.shape
```

[583]: (11496, 29)

[584]:
```
len(df_out)/len(df2)
```

[584]: 0.7774396429296003

- 77% of data is left with us after outlier removal

0.0.13 HANDLING CATEGORICAL VARIABLES: ONE HOT ENCODING

[585]:
```
cat_cols = [col for col in df_out.columns if df_out[col].dtype in ['object']]
print(cat_cols)
```

```
['trip_uuid', 'data', 'route_schedule_uuid', 'route_type', 'source_center',
'destination_center', 'source_name', 'destination_name', 's_city', 's_place',
's_code', 's_state', 'd_city', 'd_place', 'd_code', 'd_state']
```

[586]:
```
# initializing one hot encoder
ohe = OneHotEncoder(sparse_output=False,drop='first')
# creating one hot encoded array from category columns
enc_array = ohe.fit_transform(df_out[cat_cols])
# getting feature names
enc_feat_names = ohe.get_feature_names_out(cat_cols)
#creating dataframe with encoded values
enc_df = pd.DataFrame(enc_array, columns = enc_feat_names)
#concatenating encoded and original dataframes
df_new = pd.concat([df_out.reset_index(drop=True),enc_df.
↪reset_index(drop=True)], axis=1)
#dropping the category columns
df_new.drop(cat_cols, inplace=True, axis=1)
```

[587]:
```
df_new.shape
```

[587]: (11496, 18219)

0.0.14 HANDLING NUMERICAL COLUMNS: NORMALIZATION

- Since our features have skewed distributions(as seen in boxplot and histogram), we will use normalization to bring out data between [0,1].

[589]:
```
scaler = MinMaxScaler()
```

[590]:
```
numerical_cols.extend(['day_trip_created', 'month_trip_created',␣
↪'year_trip_created'])
print(numerical_cols)
```

```
['start_scan_to_end_scan', 'actual_distance_to_destination', 'actual_time',
'osrm_time', 'osrm_distance', 'segment_actual_time', 'segment_osrm_time',
'segment_osrm_distance', 'od_time_diff_hour', 'day_trip_created',
'month_trip_created', 'year_trip_created']
```

[591]:
```
df_new[numerical_cols] = scaler.fit_transform(df_new[numerical_cols])
```

[592]:
```
df_new.shape
```

[592]:
```
(11496, 18219)
```

Now, our dataset is clean and pre-processed. This dataset can be used by data scientists at delhivery for their forecasting model.

0.0.15 BUSINESS INSIGHTS

1. Route type: - The analysis reveals that a higher proportion of shipments are routed through Full Truck Load (FTL) as opposed to carting. This has important implications for the efficiency and speed of the delivery process.

2. Geographical Focus: Finding Busiest routes

Understanding the busiest routes and distances can help in optimizing logistics operations, improving transportation efficiency, and potentially reducing costs.

a. State: The states of Haryana, Maharashtra, and Karnataka are not only busy source states but also emerge as the busiest source states, indicating a high demand or significant business activities originating from these regions.

b. source city: Gurgaon, Bangalore, and Bhiwandi are identified as the busiest source cities, suggesting that these cities play a crucial role in contributing to the overall business operations or transportation activities.

c. destination city: Gurgaon, Bangalore, and Hyderabad are identified as the busiest destination cities, underscoring their significance in terms of business activities or population movement.

d. Busiest corridor: Overall, the busiest corridor is Gurgaon_Bilaspur_HB_Haryana and Bangalore_Nelmngla_H_Karnataka which has the maximum trips.

Distance Analysis: The distance between the busiest corridor (Gurgaon_Bilaspur_HB_Haryana and Bangalore_Nelmngla_H_Karnataka) is approximately 1689.64 kilometers. This information can be used for fuel efficiency planning, cost estimation, and route optimization.

3. Delivery Time & Distance Accuracy:

a. OSRM Time vs. Actual Time: - The difference between the mean values of estimated delivery time and actual delivery time suggests that there may be variations or delays in the actual delivery process compared to the initial estimates. - The fact that the mean of OSRM time is less than the mean of actual delivery time indicates that the estimated times provided by the OSRM (Open Source Routing Machine) service tend to be optimistic.

b. OSRM Distance vs. Actual Distance: - The mean of OSRM distance being greater than the mean of actual distance to the destination suggests that the OSRM might overestimate the distances. This could impact route planning and fuel efficiency calculations.

c. Segment-wise time Analysis: - The equality in the mean values of actual time and segment actual time suggests that the time measurements are consistent across different segments of the delivery process

d. Segment-wise distance Analysis: - The mean of segment OSRM distance being greater than the mean of OSRM distance implies that the OSRM might provide more conservative estimates for distance within individual segments.

e. Start-to-End Scan Time: - The mean value of start_scan_to_end_scan being greater than the mean of actual delivery time suggests that there are additional processes or delays between the start and end scan points. Identifying and addressing the factors contributing to this time difference could lead to more efficient operations and potentially faster deliveries.

0.0.16 RECOMMENDATION:

1. Route Optimization: - Given that the busiest state route is within Karnataka, it might be beneficial to optimize the transportation network within Karnataka to improve efficiency and reduce congestion. Consider implementing route optimization algorithms and real-time traffic monitoring to enhance the transportation system. - Since Gurgaon and Bangalore are identified as the busiest source and destination cities, respectively, focus on city-specific strategies to manage the high traffic volume.

2. Operational Efficiency: - Since mean of OSRM time is less than the mean of actual delivery time, Businesses could use this insight to set more realistic delivery time expectations for customers. - Since the mean of OSRM distance greater than the mean of actual distance, Businesses should consider adjusting their distance estimations for more accurate logistics planning. - Since the mean of segment OSRM distance greater than the mean of OSRM distance, along with this, we have the actual distance travelled, Businesses can use this information to fine-tune their route planning and optimize segment-specific logistics. - Implement advanced demand forecasting techniques to anticipate peak travel times and adjust transportation services accordingly. This proactive approach can help in better resource allocation and minimize the impact of congestion during peak hours. - Overall, the analysis hints at potential areas for operational improvement. Businesses could focus on refining their route planning algorithms, addressing discrepancies in estimated times and distances, and streamlining processes between different stages of delivery to enhance overall operational efficiency.

3. Customer Satisfaction: - Improving accuracy in estimated delivery times and distances can contribute to increased customer satisfaction. - FTL shipments: Faster delivery times, facilitated by a higher proportion of FTL shipments, can directly impact customer satisfaction. Customers typically value timely deliveries, and this strategic choice aligns with meeting or exceeding customer expectations in terms of shipment speed.

4. Cost Optimization: - Understanding the differences in estimated and actual times and distances can aid in cost optimization efforts. - Fine-tuning logistics planning based on more accurate measurements can lead to better resource allocation and potentially reduce operational costs.

5. Strategic Decision-making: - The preference for FTL over carting reflects a strategic decision by the logistics management. - Understanding the reasons behind this choice and continuously evaluating its impact can guide future decision-making processes and help adapt to evolving business needs.

6. Collaboration with Stakeholders: - Collaborate with relevant stakeholders, including government authorities, transportation companies, and local communities, to develop and implement comprehensive strategies for managing and optimizing transportation in the identified busy corridors and cities.

7. Training and Skill Development: - Invest in training programs for drivers and logistics personnel to enhance their skills in navigating busy routes and handling transportation challenges. Skilled and well-trained staff can contribute to the overall efficiency of the transportation system.

8. Continuous Monitoring and Analysis: - Establish a system for continuous monitoring and analysis of transportation data. Regularly assess the effectiveness of implemented strategies and be agile in adapting to changing traffic patterns and demands.