Problem Statement

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

Objective of analysis is:

- Clean, sanitize and manipulate data to get useful features out of raw fields
- Make sense out of the raw data and help the data science team to build forecasting models on it

Column Profiling:

- data - tells whether the data is testing or training data
- trip_creation_time – Timestamp of trip creation
- route_schedule_uuid – Unique Id for a particular route schedule
- route_type – Transportation type
- FTL – Full Truck Load: FTL shipments get to the destination sooner, as the truck is making no other pickups or drop-offs along the way
- Carting: Handling system consisting of small vehicles (carts)
- trip_uuid - Unique ID given to a particular trip (A trip may include different source and destination centers)
- source_center - Source ID of trip origin
- source_name - Source Name of trip origin
- destination_cente – Destination ID
- destination_name – Destination Name
- od_start_time – Trip start time
- od_end_time – Trip end time
- start_scan_to_end_scan – Time taken to deliver from source to destination
- is_cutoff – Unknown field
- cutoff_factor – Unknown field
- cutoff_timestamp – Unknown field
- actual_distance_to_destination – Distance in Kms between source and destination warehouse
- actual_time – Actual time taken to complete the delivery (Cumulative)
- osrm_time – An open-source routing engine time calculator which computes the shortest path between points in a given map (Includes usual traffic, distance through major and minor roads) and gives the time (Cumulative)
- osrm_distance – An open-source routing engine which computes the shortest path between points in a given map (Includes usual traffic, distance through major and minor roads) (Cumulative)
- factor – Unknown field
- segment_actual_time – This is a segment time. Time taken by the subset of the package delivery
- segment_osrm_time – This is the OSRM segment time. Time taken by the subset of the package delivery
- segment_osrm_distance – This is the OSRM distance. Distance covered by subset of the package delivery
- segment_factor – Unknown field

Loading dependencies and dataset

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import levene
from scipy.stats import ttest_ind, ttest_rel
from scipy.stats import f_oneway, kruskal
from scipy.stats import chi2_contingency
from statsmodels.graphics.gofplots import qqplot
```

In [2]:
```
df = pd.read_csv('./data/delhivery_data.txt')
df.head(5)
```

Out[2]:

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_na
0	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_ (Guja
1	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_ (Guja
2	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_ (Guja
3	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_ (Guja
4	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_ (Guja

5 rows × 24 columns

Initial Observations

Shape

In [3]:
```
df.shape
```

Out[3]:
```
(144867, 24)
```

Datatypes of the columns

In [4]:
```
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
```

Changing the data-type of the date columns from object to datetime:

In [5]:
```
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'])
```

In [6]:
```
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  datetime64[ns]
 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  datetime64[ns]
 10  od_end_time                     144867 non-null  datetime64[ns]
 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), datetime64[ns](3), float64(10), int64(1), object(9)
memory usage: 25.6+ MB
```

Missing values

- We see that we have some missing values in 2 columnns --> source_name & destination_name
- However we will handle them once we condense the data at the required granular level

In [7]:
```
df.isna().sum()
```

Out[7]:
```
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
is_cutoff                           0
cutoff_factor                       0
cutoff_timestamp                    0
actual_distance_to_destination      0
actual_time                         0
osrm_time                           0
osrm_distance                       0
factor                              0
segment_actual_time                 0
segment_osrm_time                   0
segment_osrm_distance               0
segment_factor                      0
dtype: int64
```

Condensing the data

Groupby the data at the trip_id, source_center & destination_center level

- source name, destiination name, route_type, trip_creation_time, od_start_time, od_end_time, start_scan_to_end_scan:
  - All these column values repeat for the entire group of rows and hence we choose the FIRST value
- actual_time, osrm_time, actual_distance_to_destination, osrm_distance:
  - The values in these columns are running/cumulative values and hence only the LAST value per group is of our interest
- segment_actual_time, segment_osrm_time, segment_osrm_distance:
  - The values in these columns need aggregation --> hence we use a sum aggregation for the rows in each group

In [8]:
```
df_trip_src_des = df.groupby(['trip_uuid',
                              'source_center',
                              'destination_center'])[['source_name', 'destination_name',
                                                      'route_type', 'trip_creation_time',
                                                      'od_start_time', 'od_end_time', 'start_scan_
                                                      'actual_time', 'osrm_time',
                                                      'segment_actual_time', 'segment_osrm_time',
                                                      'actual_distance_to_destination', 'osrm_dista
                                                      'segment_osrm_distance']].agg({'source_name':
                                                                                     'route_type':
                                                                                     'od_start_time
                                                                                     'actual_time':
                                                                                     'segment_actua
                                                                                     'actual_distan
                                                                                     'segment_osrm_
df_trip_src_des.sort_values(by=['trip_uuid', 'od_start_time'], ascending=[True, True], inplace=True
df_trip_src_des.head()
```

Out[8]:

	trip_uuid	source_center	destination_center	source_name	destination_name	route_type
1	trip-153671041653548748	IND462022AAA	IND209304AAA	Bhopal_Trnsport_H (Madhya Pradesh)	Kanpur_Central_H_6 (Uttar Pradesh)	FTL
0	trip-153671041653548748	IND209304AAA	IND000000ACB	Kanpur_Central_H_6 (Uttar Pradesh)	Gurgaon_Bilaspur_HB (Haryana)	FTL
3	trip-153671042288605164	IND572101AAA	IND561203AAB	Tumkur_Veersagr_I (Karnataka)	Doddablpur_ChikaDPP_D (Karnataka)	Carting
2	trip-153671042288605164	IND561203AAB	IND562101AAA	Doddablpur_ChikaDPP_D (Karnataka)	Chikblapur_ShntiSgr_D (Karnataka)	Carting
5	trip-153671043369099517	IND562132AAA	IND000000ACB	Bangalore_Nelmngla_H (Karnataka)	Gurgaon_Bilaspur_HB (Haryana)	FTL

We have condensed the data from ~145k rows to ~26.5k rows

In [9]:
```
df_trip_src_des.shape
```

Out[9]:
```
(26368, 17)
```

In [10]:
```
# df_trip_src_des.loc[df_trip_src_des['trip_uuid'] == 'trip-153671041653548748']
```

In [11]:
```
# df_trip_src_des.loc[df_trip_src_des['trip_uuid'] == 'trip-153741093647649320']
```

In [12]:
```
# df_trip_src_des.loc[(df_trip_src_des['destination_name'] == 'Gurgaon_Bilaspur_HB (Haryana)') & ((
```

Groupby the data at the trip_id level

- source_center, destination_center, source name, destiination name, od_start_time, od_end_time:
  - For source center, source name & od_start_time, we want the FIRST value (source name and start time @ origin of the package)
  - For destination center, destination name & od_end_time, we want the LAST value (destination name and end time @ last stop of the package)

- route_type, trip_creation_time:
  - All these column values repeat for the entire group of rows and hence we choose the FIRST value
- start_scan_to_end_scan, actual_time, osrm_time, actual_distance_to_destination, osrm_distance, segment_actual_time, segment_osrm_time, segment_osrm_distance:
  - The values in these columns need aggregation --> hence we use a sum aggregation for the rows in each group

In [13]:
```
df_trip = df_trip_src_des.groupby(['trip_uuid'])[['source_center', 'destination_center',
                                                  'source_name','destination_name',
                                                  'route_type', 'trip_creation_time',
                                                  'od_start_time', 'od_end_time', 'start_scan_to_er
                                                  'actual_time', 'osrm_time',
                                                  'segment_actual_time', 'segment_osrm_time',
                                                  'actual_distance_to_destination', 'osrm_distance
                                                  'segment_osrm_distance']].agg({'source_center':'
                                                                                 'source_name':'fi
                                                                                 'route_type': 'fi
                                                                                 'od_start_time':'
                                                                                 'actual_time':'su
                                                                                 'segment_actual_t
                                                                                 'actual_distance_
                                                                                 'segment_osrm_dis


df_trip.columns = [col[0] if col[1]!='count' else 'stops' for col in df_trip.columns]
df_trip.head()
```

Out[13]:

	trip_uuid	source_center	destination_center	source_name	destination_name	stops	route
0	trip-153671041653548748	IND462022AAA	IND000000ACB	Bhopal_Trnsport_H (Madhya Pradesh)	Gurgaon_Bilaspur_HB (Haryana)	2	
1	trip-153671042288605164	IND572101AAA	IND562101AAA	Tumkur_Veersagr_I (Karnataka)	Chikblapur_ShntiSgr_D (Karnataka)	2	C
2	trip-153671043369099517	IND562132AAA	IND160002AAC	Bangalore_Nelmngla_H (Karnataka)	Chandigarh_Mehmdpur_H (Punjab)	2	
3	trip-153671046011330457	IND400072AAB	IND401104AAA	Mumbai Hub (Maharashtra)	Mumbai_MiraRd_IP (Maharashtra)	1	C
4	trip-153671052974046625	IND583101AAA	IND583101AAA	Bellary_Dc (Karnataka)	Bellary_Dc (Karnataka)	3	

We have condensed the data from ~26.5k rows to ~15k rows

In [14]:
```
df_trip.shape
```

Out[14]:
```
(14817, 18)
```

Dealing with missing values

In [15]:
```
df_trip.isna().sum()
```

Out[15]:
```
trip_uuid                          0
source_center                      0
destination_center                 0
source_name                       10
destination_name                   8
stops                              0
route_type                         0
trip_creation_time                 0
od_start_time                      0
od_end_time                        0
start_scan_to_end_scan             0
actual_time                        0
osrm_time                          0
segment_actual_time                0
segment_osrm_time                  0
actual_distance_to_destination     0
osrm_distance                      0
segment_osrm_distance              0
dtype: int64
```

Identifying faulty data

- Each source center should point to a unique source name
- Each destination center should point to a unique destination name
- We try to identify any such source/destination centers which points to more than 1 source/destination names respectively

In [16]:
```
x = df_trip.groupby('source_center')['source_name'].agg(['count', 'nunique'])
faulty_centers1 = x.loc[x['nunique']>1]
faulty_centers1
```

Out[16]:

source_center	count	nunique
IND282002AAD	8	2

In [17]:
```
y = df_trip.groupby('destination_center')['destination_name'].agg(['count', 'nunique'])
faulty_centers2 = y.loc[y['nunique']>1]
faulty_centers2
```

Out[17]:

destination_center	count	nunique
IND282002AAD	18	3

- Clearly there is something wrong with the source/destination center: 'IND282002AAD'
- We plan to drop all such rows where the above center is a source or destination

In [18]:
```
rows_to_drop = df_trip.loc[df_trip['source_center'].isin(faulty_centers1.index) | df_trip['destina
df_trip.drop(rows_to_drop, axis=0, inplace=True)
df_trip.shape
```

Out[18]:
```
(14785, 18)
```

In [19]:
```
df_trip.isna().sum()
```

Out[19]:
```
trip_uuid                         0
source_center                     0
destination_center                0
source_name                       2
destination_name                  7
stops                             0
route_type                        0
trip_creation_time                0
od_start_time                     0
od_end_time                       0
start_scan_to_end_scan            0
actual_time                       0
osrm_time                         0
segment_actual_time               0
segment_osrm_time                 0
actual_distance_to_destination    0
osrm_distance                     0
segment_osrm_distance             0
dtype: int64
```

Locating all the source/destination centers with unknown names:

In [20]:
```
unknown_source_centers = set(df_trip.loc[(df_trip['source_name'].isna()), 'source_center'].unique(
print('Unknown source centers:', unknown_source_centers)
print('-'*100)
unknown_dest_centers = set(df_trip.loc[(df_trip['destination_name'].isna()), 'destination_center']
print('Unknown destination centers:', unknown_dest_centers)
```

```
Unknown source centers: {'IND577116AAA', 'IND331022A1B'}
--------------------------------------------------------------------------------------------------
--
Unknown destination centers: {'IND505326AAB', 'IND122015AAC', 'IND250002AAC', 'IND331001A1C'}
```

Trying to locate if:

- The unknown destination centers show up as source centers and whether the source name is present or not
- The unknown source centers show up as destination centers and whether the destination name is present or not

In [21]:
```
df_trip.loc[df_trip['source_center'].isin(unknown_dest_centers)]
```

Out[21]:

trip_uuid	source_center	destination_center	source_name	destination_name	stops	route_type	trip_creation_time	c

In [22]:
```
df_trip.loc[df_trip['destination_center'].isin(unknown_source_centers)]
```

Out[22]:

	trip_uuid	source_center	destination_center	source_name	destination_name	stops	route_
7844	trip-153764981783105349	IND573201AAB	IND577116AAA	Hassan_Pandrnga_I (Karnataka)	Sakleshpur_RgvdrDPP_D (Karnataka)	1	

In [23]:
```
df_trip.loc[df_trip['source_center'] == 'IND577116AAA', 'source_name'] = 'Sakleshpur_RgvdrDPP_D (Ka
```

In [24]:
```
df_trip.isna().sum()
```

Out[24]:
```
trip_uuid                         0
source_center                     0
destination_center                0
source_name                       1
destination_name                  7
stops                             0
route_type                        0
trip_creation_time                0
od_start_time                     0
od_end_time                       0
start_scan_to_end_scan            0
actual_time                       0
osrm_time                         0
segment_actual_time               0
segment_osrm_time                 0
actual_distance_to_destination    0
osrm_distance                     0
segment_osrm_distance             0
dtype: int64
```

Dropping the trips where we could not find source name or destination name or both

- We have data for arounf ~15k trips and
- There are only 7 trips for which we have missing data as shown below
- Thus we go ahead and drop them

In [25]:
```
df_trip.loc[(df_trip['source_name'].isna()) | (df_trip['destination_name'].isna())]
```

Out[25]:

	trip_uuid	source_center	destination_center	source_name	destination_name	stops	route_
5289	trip-153733592611290696	IND000000ACB	IND122015AAC	Gurgaon_Bilaspur_HB (Haryana)	None	0	C
5778	trip-153739792417979729	IND504215AAA	IND505326AAB	Luxettipet_ShivaDPP_D (Telangana)	None	0	
5961	trip-153741501937042684	IND000000ACB	IND122015AAC	Gurgaon_Bilaspur_HB (Haryana)	None	0	C
10562	trip-153800051661903546	IND331022A1B	IND331001A1C	None	None	0	
13313	trip-153839879406683648	IND131028AAB	IND250002AAC	Sonipat_Kundli_H (Haryana)	None	0	
13408	trip-153841850974526339	IND110037AAM	IND250002AAC	Delhi_Airport_H (Delhi)	None	0	
14453	trip-153857174991144707	IND110037AAM	IND250002AAC	Delhi_Airport_H (Delhi)	None	0	

In [26]:

```
rows_to_drop = df_trip.loc[(df_trip['source_name'].isna()) | (df_trip['destination_name'].isna())]
df_trip.drop(rows_to_drop, axis=0, inplace=True)
df_trip.shape
```

Out[26]:

```
(14778, 18)
```

In [27]:

```
df_trip.isna().sum()
```

Out[27]:

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

Feature Creation

- We have already created the number of stops for each trip earlier --> column name: 'stops'
  - For example: If a package travels directly from origin to final destination; then stops = 1
  - If a package has 1 intermediate stop b/w origin & final destination; then stops = 2 and so on
- source name --> State, City, Place
- destination name --> State, City, Place
- trip_creation_time --> Year, Month, Day

In [28]:

```
df_trip.head(10)
```

Out[28]:

	trip_uuid	source_center	destination_center	source_name	destination_name	stops	ro
0	trip-153671041653548748	IND462022AAA	IND000000ACB	Bhopal_Trnsport_H (Madhya Pradesh)	Gurgaon_Bilaspur_HB (Haryana)	2	
1	trip-153671042288605164	IND572101AAA	IND562101AAA	Tumkur_Veersagr_I (Karnataka)	Chikblapur_ShntiSgr_D (Karnataka)	2	
2	trip-153671043369099517	IND562132AAA	IND160002AAC	Bangalore_Nelmngla_H (Karnataka)	Chandigarh_Mehmdpur_H (Punjab)	2	
3	trip-153671046011330457	IND400072AAB	IND401104AAA	Mumbai Hub (Maharashtra)	Mumbai_MiraRd_IP (Maharashtra)	1	
4	trip-153671052974046625	IND583101AAA	IND583101AAA	Bellary_Dc (Karnataka)	Bellary_Dc (Karnataka)	3	
5	trip-153671055416136166	IND600116AAB	IND602105AAB	Chennai_Porur_DPC (Tamil Nadu)	Chennai_Sriperumbudur_Dc (Tamil Nadu)	2	
6	trip-153671066201138152	IND600044AAD	IND600048AAA	Chennai_Chrompet_DPC (Tamil Nadu)	Chennai_Vandalur_Dc (Tamil Nadu)	1	
7	trip-153671066826362165	IND560043AAC	IND560043AAC	HBR Layout PC (Karnataka)	HBR Layout PC (Karnataka)	2	
8	trip-153671074033284934	IND395023AAD	IND395023AAD	Surat_Central_I_4 (Gujarat)	Surat_Central_I_4 (Gujarat)	2	
9	trip-153671079956500691	IND110024AAA	IND110014AAA	Delhi_Lajpat_IP (Delhi)	Delhi_Bhogal (Delhi)	1	

In [29]:

```
df_trip['s_state'] = df_trip['source_name'].apply(lambda x: x.split('(')[-1][:-1].strip())
df_trip['s_city'] = df_trip['source_name'].apply(lambda x: x.split('(')[0].split('_')[0].strip())
```

In [30]:

```
df_trip['d_state'] = df_trip['destination_name'].apply(lambda x: x.split('(')[-1][:-1].strip())
df_trip['d_city'] = df_trip['destination_name'].apply(lambda x: x.split('(')[0].split('_')[0].stri
```

In [31]:

```
def place_extract(s):
    s_lst = s.split('(')[0].split('_')
    if len(s_lst) == 1:
        return 'NA'
    elif len(s_lst) == 2:
        if len(s_lst[1].strip()) <= 3:
            return s_lst[1].upper().strip()
        else:
            return ('-').join(s_lst[1].split())
    elif len(s_lst) == 3:
        if len(s_lst[1].strip()) <= 4:
            place_1 = s_lst[1].upper().strip()
        else:
            place_1 = s_lst[1].strip()
        return place_1 + '-' + s_lst[2].upper().strip()

    place_1 = s_lst[1].strip()
    place_2 =  s_lst[2].strip()
    place_3 =  s_lst[3].strip()
    return place_1+'-'+place_2+place_3


df_trip['s_place'] = df_trip['source_name'].apply(place_extract)
df_trip['d_place'] = df_trip['destination_name'].apply(place_extract)
```

In [32]:

```
df_trip['trip_creation_year'] = df_trip['trip_creation_time'].dt.year
df_trip['trip_creation_month'] = df_trip['trip_creation_time'].dt.month
df_trip['trip_creation_day'] = df_trip['trip_creation_time'].dt.day
```

Final Touches

In [33]:

```
df_trip.loc[df_trip['s_city']=='Bengaluru', 's_city'] = 'Bangalore'
df_trip.loc[df_trip['d_city']=='Bengaluru', 'd_city'] = 'Bangalore'
```

Final dataset

In [34]:

```
# df_trip.columns
```

In [35]:
```
df_final = df_trip[['trip_uuid', 'trip_creation_year', 'trip_creation_month', 'trip_creation_day',
                    's_state', 's_city', 'd_state', 'd_city', 's_place', 'd_place', 'stops',
                    'route_type', 'od_start_time', 'od_end_time', 'start_scan_to_end_scan',
                    'actual_time', 'osrm_time', 'segment_actual_time', 'segment_osrm_time',
                    'actual_distance_to_destination', 'osrm_distance', 'segment_osrm_distance']].co
df_final.reset_index(inplace=True, drop=True)
```

In [36]:
```
df_final
```

Out[36]:

	trip_uuid	trip_creation_year	trip_creation_month	trip_creation_day	s_state	s_city	d_
0	trip-153671041653548748	2018	9	12	Madhya Pradesh	Bhopal	Ha
1	trip-153671042288605164	2018	9	12	Karnataka	Tumkur	Karn
2	trip-153671043369099517	2018	9	12	Karnataka	Bangalore	P
3	trip-153671046011330457	2018	9	12	Maharashtra	Mumbai Hub	Mahara
4	trip-153671052974046625	2018	9	12	Karnataka	Bellary	Karn
...	...	...	...	...	...	...	...
14773	trip-153861095625827784	2018	10	3	Punjab	Chandigarh	P
14774	trip-153861104386292051	2018	10	3	Haryana	FBD	Ha
14775	trip-153861106442901555	2018	10	3	Uttar Pradesh	Kanpur	Pra
14776	trip-153861115439069069	2018	10	3	Tamil Nadu	Tirunelveli	Tamil
14777	trip-153861118270144424	2018	10	3	Karnataka	Hospet	Karn

14778 rows × 22 columns

Hypothesis Tests

Difference b/w od_end_time & od_start_time

In [37]:
```
df_final['trip_total_time'] = (df_final['od_end_time'] - df_final['od_start_time'])/pd.Timedelta(m
df_final['trip_total_time']
```

Out[37]:
```
0        2260.109800
1         181.611874
2        3934.362520
3         100.494935
4         718.349042
            ...
14773     405.485842
14774      60.590521
14775     422.119867
14776     348.512862
14777     354.407571
Name: trip_total_time, Length: 14778, dtype: float64
```

Compare the difference between trip_total_time and start_scan_to_end_scan.

In [38]:
```
df_final[['trip_total_time', 'start_scan_to_end_scan']]
```

Out[38]:

	trip_total_time	start_scan_to_end_scan
0	2260.109800	2259.0
1	181.611874	180.0
2	3934.362520	3933.0
3	100.494935	100.0
4	718.349042	717.0
...	...	...
14773	405.485842	257.0
14774	60.590521	60.0
14775	422.119867	421.0
14776	348.512862	347.0
14777	354.407571	353.0

14778 rows × 2 columns

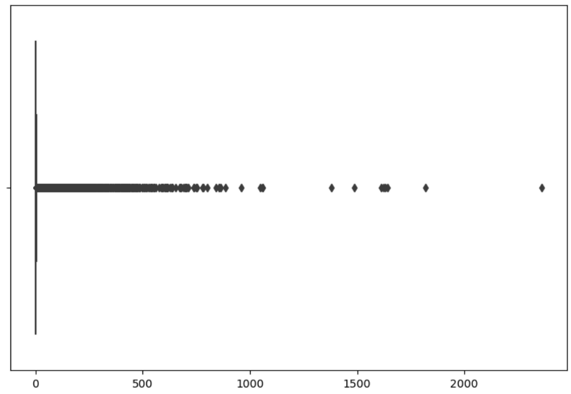
In [39]:
```
df_final[['trip_total_time', 'start_scan_to_end_scan']].describe()
```

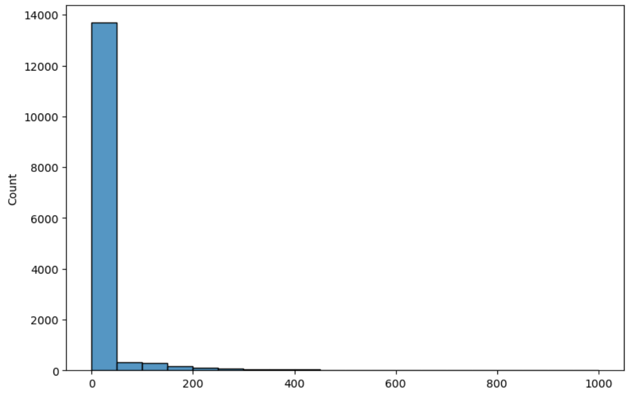
Out[39]:

	trip_total_time	start_scan_to_end_scan
count	14778.000000	14778.000000
mean	547.580485	530.903776
std	669.158573	659.193963
min	23.461468	23.000000
25%	150.964456	149.000000
50%	288.241140	279.000000
75%	673.867606	638.000000
max	7898.551955	7898.000000

In [40]:
```
diff_1 = (df_final['trip_total_time']-df_final['start_scan_to_end_scan'])
diff_1_filtered = diff_1.loc[diff_1<1000]
```

In [41]:
```
plt.figure(figsize=(20, 6))
plt.subplot(1, 2, 1)
sns.boxplot(x=diff_1.values)
plt.subplot(1, 2, 2)
sns.histplot(x=diff_1_filtered.values, binwidth=50)
plt.show()
```





Null and Alternate hypothesis:

- H0: u_total_trip_time = u_start_scan_to_end_scan
- Ha: u_total_trip_time > u_start_scan_to_end_scan

In [42]:
```
t_stat, p_value=ttest_rel(df_final['trip_total_time'], df_final['start_scan_to_end_scan'], alterna
print('p_value:', p_value, 't_stat:', t_stat)
if p_value<0.05:
    print('Reject H0')
```

```
else:
    print('Fail to Reject H0')
```

```
p_value: 1.6104839185585e-154 t_stat: 26.771511487181606
Reject H0
```

Actual Time (Aggregated) vs OSRM Time (Aggregated)

In [43]:
```
df_final[['actual_time', 'osrm_time']]
```

Out[43]:

	actual_time	osrm_time
0	1562.0	717.0
1	143.0	68.0
2	3347.0	1740.0
3	59.0	15.0
4	341.0	117.0
...	...	...
14773	83.0	62.0
14774	21.0	12.0
14775	282.0	48.0
14776	264.0	179.0
14777	275.0	68.0

14778 rows × 2 columns

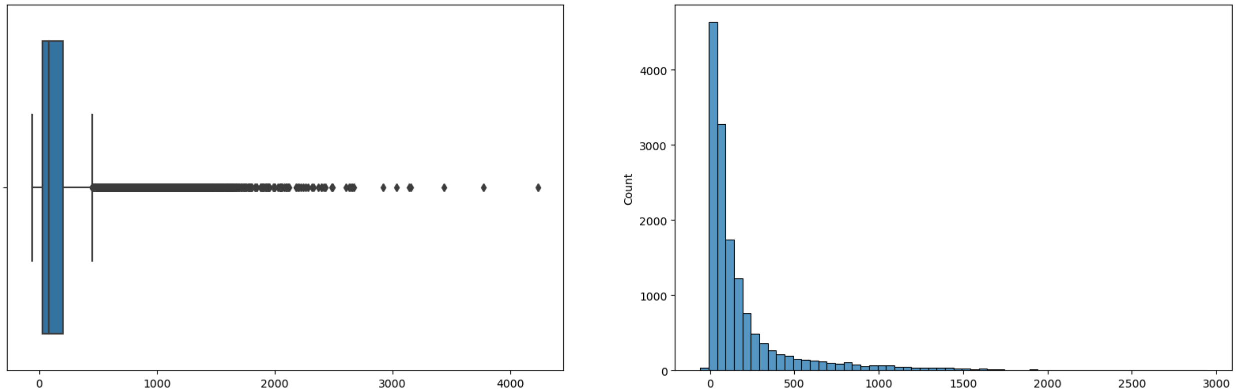
In [44]:
```
df_final[['actual_time', 'osrm_time']].describe()
```

Out[44]:

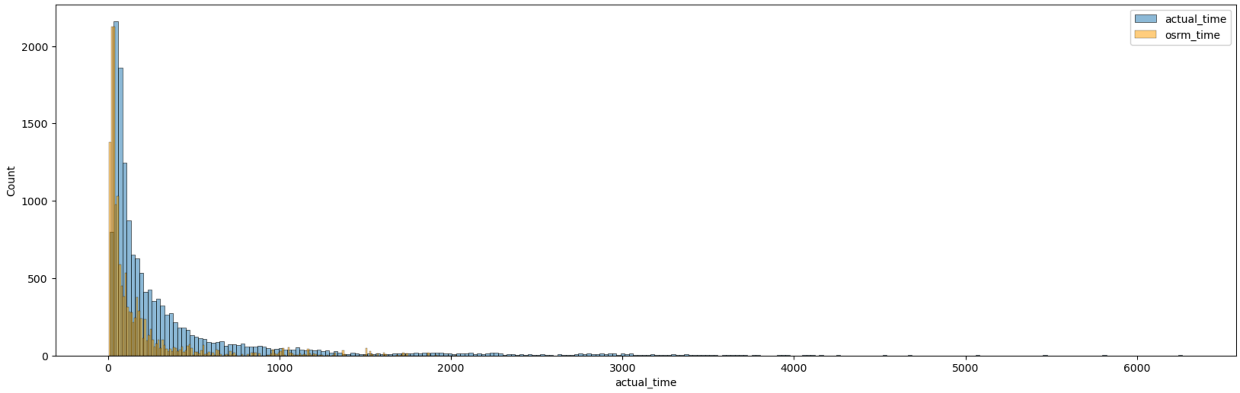
	actual_time	osrm_time
count	14778.000000	14778.000000
mean	357.255312	161.461700
std	562.004628	271.698104
min	9.000000	6.000000
25%	67.000000	29.000000
50%	148.500000	60.000000
75%	369.750000	168.000000
max	6265.000000	2032.000000

In [45]:
```
diff_2 = (df_final['actual_time']-df_final['osrm_time'])
diff_2_filtered = diff_2.loc[diff_2<3000]
```

In [46]:
```
plt.figure(figsize=(20, 6))
plt.subplot(1, 2, 1)
sns.boxplot(x=diff_2.values)
plt.subplot(1, 2, 2)
sns.histplot(x=diff_2_filtered.values, binwidth=50)
plt.show()
```



In [47]:
```
plt.figure(figsize=(20, 6))
sns.histplot(x=df_final['actual_time'], alpha=0.5, label='actual_time')
sns.histplot(x=df_final['osrm_time'], color='orange', alpha=0.5, label='osrm_time')
plt.legend()
plt.show()
```



Null and Alternate hypothesis:

- H0: u_actual_time = u_osrm_time
- Ha: u_actual_time > u_osrm_time

In [48]:
```
t_stat, p_value=ttest_rel(df_final['actual_time'], df_final['osrm_time'], alternative='greater')
print('p_value:', p_value, 't_stat:', t_stat)
if p_value<0.05:
    print('Reject H0')
else:
    print('Fail to Reject H0')
```

```
p_value: 0.0 t_stat: 76.47825181448023
Reject H0
```

Actual Time (Aggregated) vs Segment Actual Time (Aggregated)

In [49]:
```
df_final[['actual_time', 'segment_actual_time']]
```

Out[49]:

	actual_time	segment_actual_time
0	1562.0	1548.0
1	143.0	141.0
2	3347.0	3308.0
3	59.0	59.0
4	341.0	340.0
...	...	...
14773	83.0	82.0
14774	21.0	21.0
14775	282.0	281.0
14776	264.0	258.0
14777	275.0	274.0

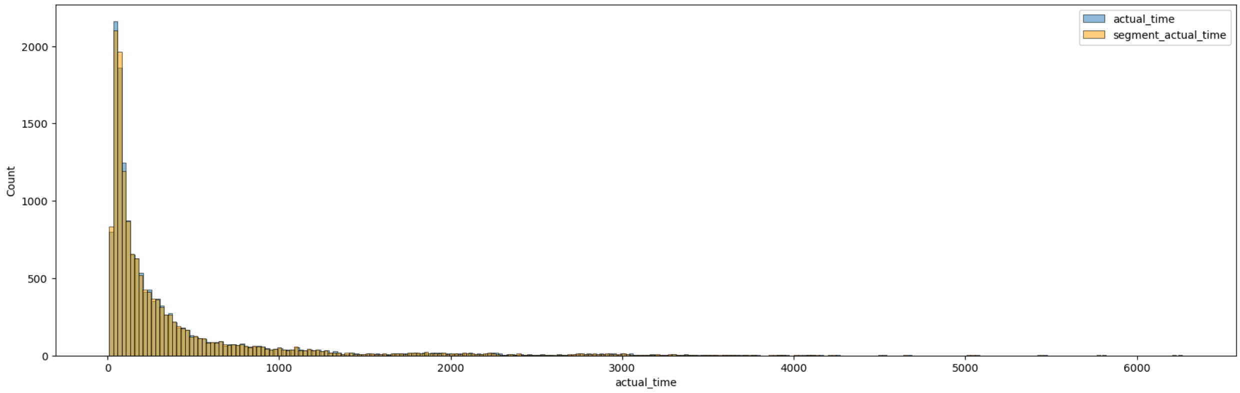
14778 rows × 2 columns

In [50]:
```
df_final[['actual_time', 'segment_actual_time']].describe()
```

Out[50]:

	actual_time	segment_actual_time
count	14778.000000	14778.000000
mean	357.255312	354.000068
std	562.004628	556.848773
min	9.000000	9.000000
25%	67.000000	66.000000
50%	148.500000	147.000000
75%	369.750000	367.000000
max	6265.000000	6230.000000

In [51]:
```
plt.figure(figsize=(20, 6))
sns.histplot(x=df_final['actual_time'], alpha=0.5, label='actual_time')
sns.histplot(x=df_final['segment_actual_time'], color='orange', alpha=0.5, label='segment_actual_ti
plt.legend()
plt.show()
```



Null and Alternate hypothesis:

- H0: u_actual_time = u_segment_actual_time
- Ha: u_actual_time > u_segment_actual_time

In [52]:
```
t_stat, p_value=ttest_ind(df_final['actual_time'], df_final['segment_actual_time'], equal_var=Fals
print('p_value:', p_value, 't_stat:', t_stat)
if p_value<0.05:
    print('Reject H0')
else:
    print('Fail to Reject H0')
```

```
p_value: 0.30847510201695505 t_stat: 0.5001826420167255
Fail to Reject H0
```

OSRM Time (Aggregated) vs Segment OSRM Time (Aggregated)

In [53]:
```
df_final[['osrm_time', 'segment_osrm_time']]
```

Out[53]:

	osrm_time	segment_osrm_time
0	717.0	1008.0
1	68.0	65.0
2	1740.0	1941.0
3	15.0	16.0
4	117.0	115.0
...	...	...
14773	62.0	62.0
14774	12.0	11.0
14775	48.0	88.0
14776	179.0	221.0
14777	68.0	67.0

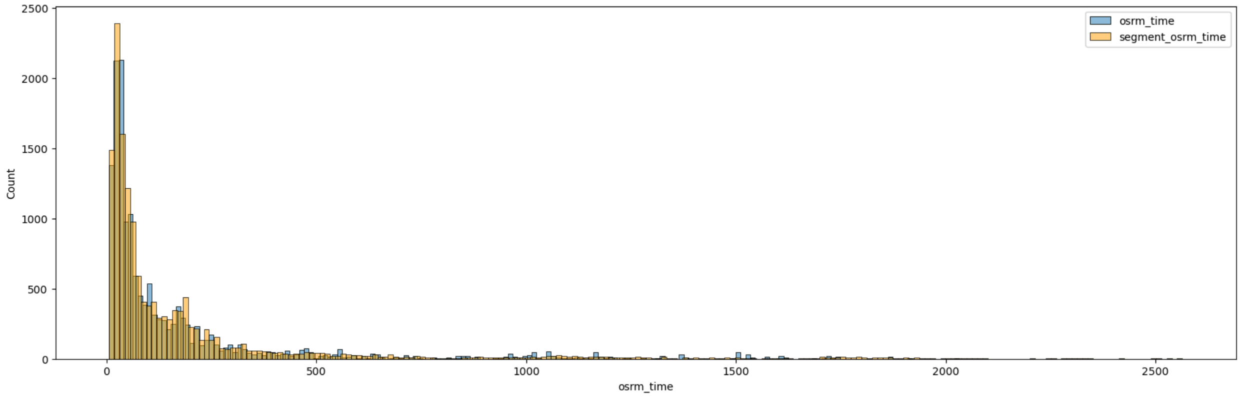
14778 rows × 2 columns

In [54]:
```
df_final[['osrm_time', 'segment_osrm_time']].describe()
```

Out[54]:

	osrm_time	segment_osrm_time
count	14778.000000	14778.000000
mean	161.461700	181.048518
std	271.698104	314.935879
min	6.000000	6.000000
25%	29.000000	30.000000
50%	60.000000	65.000000
75%	168.000000	184.000000
max	2032.000000	2564.000000

In [55]:
```
plt.figure(figsize=(20, 6))
sns.histplot(x=df_final['osrm_time'], alpha=0.5, label='osrm_time')
sns.histplot(x=df_final['segment_osrm_time'], color='orange', alpha=0.5, label='segment_osrm_time'
plt.legend()
plt.show()
```



Null and Alternate hypothesis:

- H0: u_osrm_time = u_segment_osrm_time
- Ha: u_osrm_time < u_segment_osrm_time

In [56]:
```
t_stat, p_value=ttest_ind(df_final['osrm_time'], df_final['segment_osrm_time'], equal_var=False, a
print('p_value:', p_value, 't_stat:', t_stat)
if p_value<0.05:
    print('Reject H0')
else:
    print('Fail to Reject H0')
```

```
p_value: 5.23595006768526e-09 t_stat: -5.724572572707915
Reject H0
```

OSRM Distance (Aggregated) vs Segment OSRM Distance (Aggregated)

In [57]:
```
df_final[['osrm_distance', 'segment_osrm_distance']]
```

Out[57]:

	osrm_distance	segment_osrm_distance
0	991.3523	1320.4733
1	85.1110	84.1894
2	2354.0665	2545.2678
3	19.6800	19.8766
4	146.7918	146.7919
...	...	...
14773	73.4630	64.8551
14774	16.0882	16.0883
14775	58.9037	104.8866
14776	171.1103	223.5324
14777	80.5787	80.5787

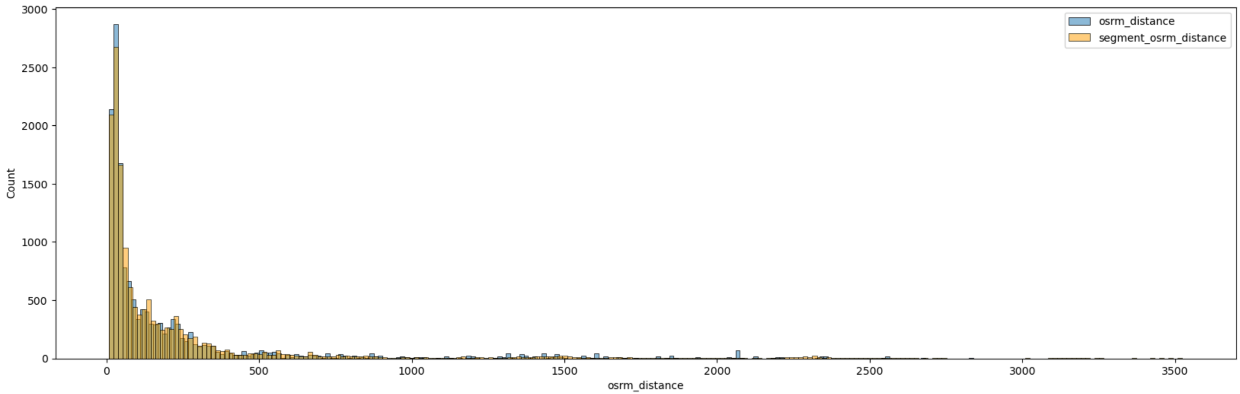
14778 rows × 2 columns

In [58]:
```
df_final[['osrm_distance', 'segment_osrm_distance']].describe()
```

Out[58]:

	osrm_distance	segment_osrm_distance
count	14778.000000	14778.000000
mean	204.468060	223.356999
std	370.856986	417.149848
min	9.072900	9.072900
25%	30.752100	32.541325
50%	65.365100	69.862800
75%	208.199975	218.636000
max	2840.081000	3523.632400

In [59]:
```
plt.figure(figsize=(20, 6))
sns.histplot(x=df_final['osrm_distance'], alpha=0.5, label='osrm_distance')
sns.histplot(x=df_final['segment_osrm_distance'], color='orange', alpha=0.5, label='segment_osrm_di
plt.legend()
plt.show()
```



Null and Alternate hypothesis:

- H0: u_osrm_distance = u_segment_osrm_distance
- Ha: u_osrm_distance < u_segment_osrm_distance

In [60]:
```
t_stat, p_value=ttest_ind(df_final['osrm_distance'], df_final['segment_osrm_distance'], equal_var=
print('p_value:', p_value, 't_stat:', t_stat)
```

```
if p_value<0.05:
    print('Reject H0')
else:
    print('Fail to Reject H0')
```

```
p_value: 1.950602542129753e-05 t_stat: -4.11388624271749
Reject H0
```

Outliers

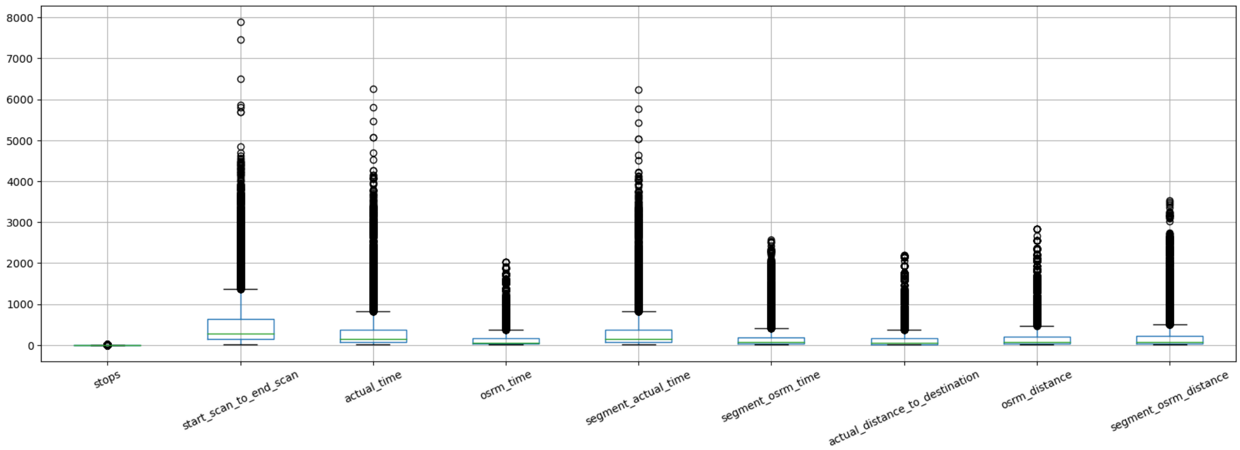
Boxplot

- We just identifying outliers using the boxplot

In [61]:
```
# df_final.columns
```

In [62]:
```
cont_columns = ['stops', 'start_scan_to_end_scan', 'actual_time', 'osrm_time', 'segment_actual_time
                'actual_distance_to_destination', 'osrm_distance','segment_osrm_distance']
```

In [63]:
```
df_final[cont_columns].boxplot(rot=25, figsize=(20,6))
plt.show()
```



Handling outliers

- We identify the iqr and the upper and lower whiskers using the 1.5*IQR method
- We choose NOT to handle the outliers since we may disturb the true characteristics of the data

In [64]:
```
for col in cont_columns:
    print(f'Feature: {col}')
    print('-'*50)
    p_25 = np.percentile(df_final[col], 25)
    p_75 = np.percentile(df_final[col], 75)
    iqr = p_75 - p_25
    print('1st_quantile:', p_25)
    print('3rd_quantile:', p_75)
    print('IQR:', iqr)
    print('Lower Whisker:', max(p_25-(1.5*iqr), df_final[col].min()))
    print('Upper Whisker:', min(p_75+(1.5*iqr), df_final[col].max()))
    print('*'*100)
```

```
Feature: stops
--------------------------------------------------
1st_quantile: 1.0
3rd_quantile: 2.0
IQR: 1.0
Lower Whisker: 1
Upper Whisker: 3.5
****************************************************************************************************
**
Feature: start_scan_to_end_scan
--------------------------------------------------
1st_quantile: 149.0
3rd_quantile: 638.0
IQR: 489.0
Lower Whisker: 23.0
Upper Whisker: 1371.5
****************************************************************************************************
**
Feature: actual_time
--------------------------------------------------
1st_quantile: 67.0
3rd_quantile: 369.75
IQR: 302.75
Lower Whisker: 9.0
Upper Whisker: 823.875
****************************************************************************************************
**
Feature: osrm_time
--------------------------------------------------
1st_quantile: 29.0
3rd_quantile: 168.0
IQR: 139.0
Lower Whisker: 6.0
Upper Whisker: 376.5
****************************************************************************************************
**
Feature: segment_actual_time
--------------------------------------------------
1st_quantile: 66.0
3rd_quantile: 367.0
IQR: 301.0
Lower Whisker: 9.0
Upper Whisker: 818.5
****************************************************************************************************
**
Feature: segment_osrm_time
--------------------------------------------------
1st_quantile: 30.0
3rd_quantile: 184.0
IQR: 154.0
Lower Whisker: 6.0
Upper Whisker: 415.0
****************************************************************************************************
**
Feature: actual_distance_to_destination
--------------------------------------------------
1st_quantile: 22.767056485699186
3rd_quantile: 164.22630775203464
IQR: 141.45925126633546
Lower Whisker: 9.00246144174878
Upper Whisker: 376.41518465153786
****************************************************************************************************
**
Feature: osrm_distance
--------------------------------------------------
1st_quantile: 30.752100000000002
3rd_quantile: 208.199975
IQR: 177.44787499999998
Lower Whisker: 9.0729
Upper Whisker: 474.3717875
****************************************************************************************************
**
Feature: segment_osrm_distance
--------------------------------------------------
1st_quantile: 32.541325
3rd_quantile: 218.636
IQR: 186.094675
Lower Whisker: 9.0729
Upper Whisker: 497.77801249999993
```

****

Encoding for categorical variables

In [65]:
```
# df_final.columns
```

In [66]:
```
# df_final.info()
```

In [67]:
```
cat_cols = ['trip_uuid', 's_state', 's_city', 'd_state', 'd_city', 's_place', 'd_place', 'route_typ
```

In [68]:
```
for col in cat_cols:
    print(f'Feature: {col}')
    print('Number of unique values:', df_final[col].nunique())
    print('-'*50)
```

```
Feature: trip_uuid
Number of unique values: 14778
--------------------------------------------------
Feature: s_state
Number of unique values: 29
--------------------------------------------------
Feature: s_city
Number of unique values: 670
--------------------------------------------------
Feature: d_state
Number of unique values: 32
--------------------------------------------------
Feature: d_city
Number of unique values: 764
--------------------------------------------------
Feature: s_place
Number of unique values: 687
--------------------------------------------------
Feature: d_place
Number of unique values: 768
--------------------------------------------------
Feature: route_type
Number of unique values: 2
--------------------------------------------------
```

One Hot Encoding

- Since route_type is only of 2 types, we can perform one hot encoding for this column

In [69]:
```
from sklearn.preprocessing import OneHotEncoder
enc = OneHotEncoder()
```

In [70]:
```
one_hot_enc_transform = enc.fit_transform(df_final[['route_type']]).toarray()
route_type_one_hot_enc = pd.DataFrame(one_hot_enc_transform)
route_type_one_hot_enc
```

Out[70]:

	0	1
0	0.0	1.0
1	1.0	0.0
2	0.0	1.0
3	1.0	0.0
4	0.0	1.0
...	...	...
14773	1.0	0.0
14774	1.0	0.0
14775	1.0	0.0
14776	1.0	0.0
14777	0.0	1.0

14778 rows × 2 columns

In [71]:
```
df_temp = pd.concat([df_final, route_type_one_hot_enc], axis=1)
# df_temp[cat_cols]
df_temp.drop(cat_cols, axis=1, inplace=True)
df_temp.drop(['trip_creation_year', 'trip_creation_month', 'trip_creation_day', 'od_start_time', '(
df_temp.rename(columns={0: 'Carting', 1:'FTL'}, inplace=True)
df_temp
```

Out[71]:

	stops	start_scan_to_end_scan	actual_time	osrm_time	segment_actual_time	segment_osrm_time	actual_dista
0	2	2259.0	1562.0	717.0	1548.0	1008.0	
1	2	180.0	143.0	68.0	141.0	65.0	
2	2	3933.0	3347.0	1740.0	3308.0	1941.0	
3	1	100.0	59.0	15.0	59.0	16.0	
4	3	717.0	341.0	117.0	340.0	115.0	
...	...	...	...	...	...	...	
14773	2	257.0	83.0	62.0	82.0	62.0	
14774	1	60.0	21.0	12.0	21.0	11.0	
14775	2	421.0	282.0	48.0	281.0	88.0	
14776	5	347.0	264.0	179.0	258.0	221.0	
14777	2	353.0	275.0	68.0	274.0	67.0	

14778 rows × 12 columns

Column Normalization /Column Standardization

In [72]:
```
from sklearn.preprocessing import StandardScaler, MinMaxScaler
```

In [73]:
```
scaler = StandardScaler()
std_data = scaler.fit_transform(df_temp)
std_data = pd.DataFrame(std_data, columns=df_temp.columns)
std_data.head()
```

Out[73]:

	stops	start_scan_to_end_scan	actual_time	osrm_time	segment_actual_time	segment_osrm_time	actual_distai
0	0.187032	2.621618	2.143729	2.044759	2.144281	2.625866	
1	0.187032	-0.532341	-0.381247	-0.344003	-0.382523	-0.368495	
2	0.187032	5.161169	5.319967	5.810095	5.305031	5.588474	
3	-0.647244	-0.653705	-0.530717	-0.539079	-0.529785	-0.524088	
4	1.021307	0.282318	-0.028925	-0.163649	-0.025142	-0.209728	

EDA

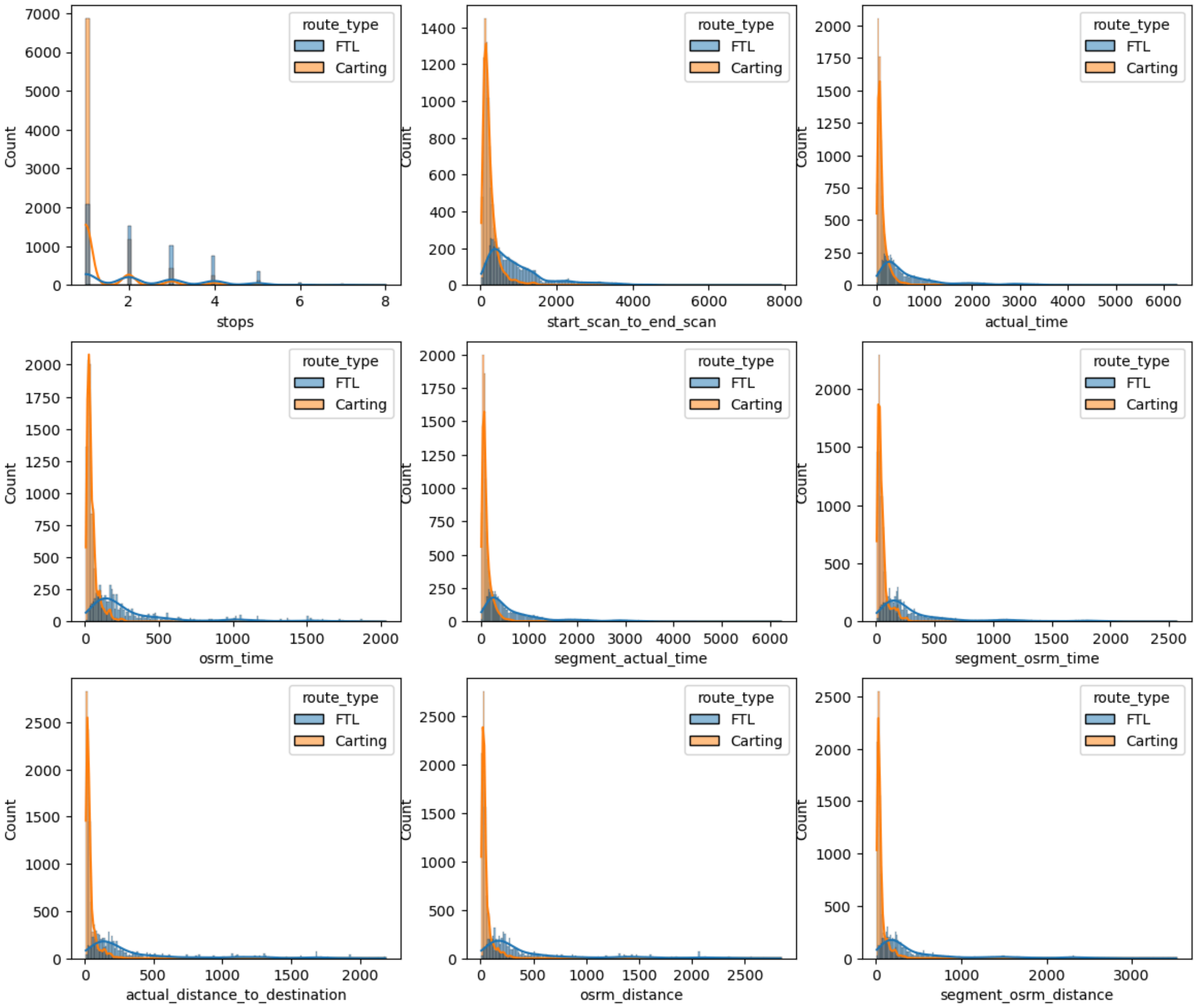
Histogram of continuous variables

In [74]:
```
cont_columns
```

Out[74]:
```
['stops',
 'start_scan_to_end_scan',
 'actual_time',
 'osrm_time',
 'segment_actual_time',
 'segment_osrm_time',
 'actual_distance_to_destination',
 'osrm_distance',
 'segment_osrm_distance']
```

In [75]:
```
f,ax=plt.subplots(nrows=3,ncols=3, figsize=(14,12))
index=0
for row in range(3):
    for col in range(3):
```

```
        sns.histplot(x=df_final[cont_columns[index]],ax=ax[row,col],data=df_final, kde=True, hue='
        index+=1
plt.show()
```

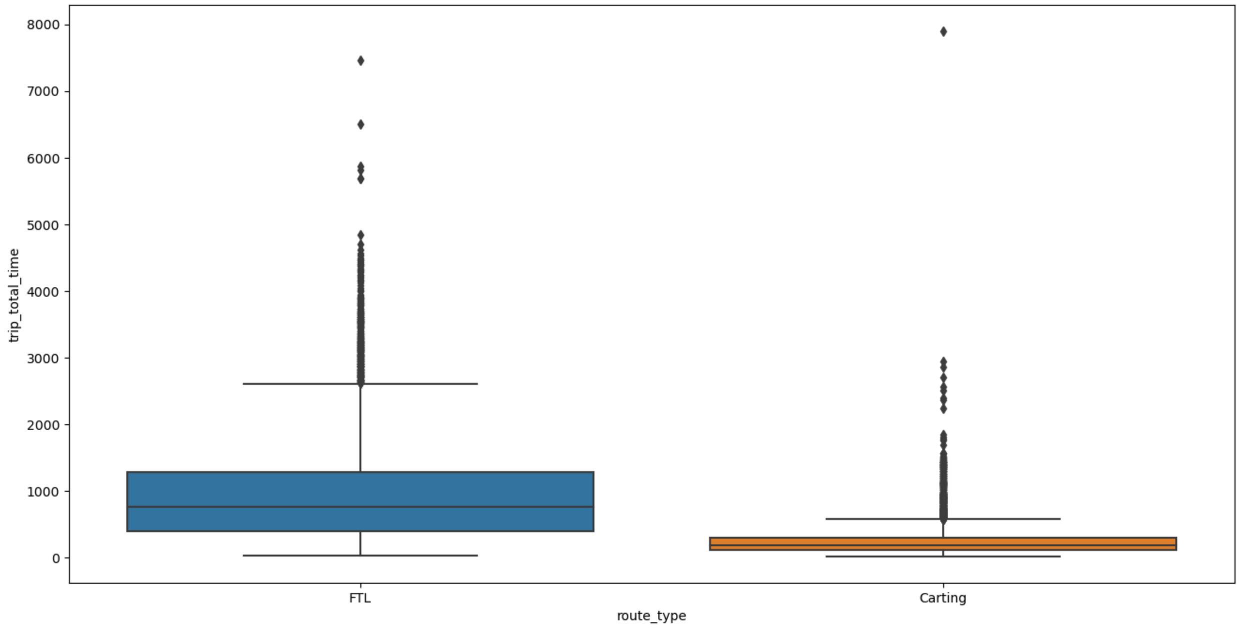


Observation:

- As per the plot above all numerical variables seem to follow log-normal distribution

Trip total time vs Route Type

In [76]:
```
plt.figure(figsize=(16, 8))
sns.boxplot(x='route_type',y='trip_total_time', data=df_final)
plt.show()
```

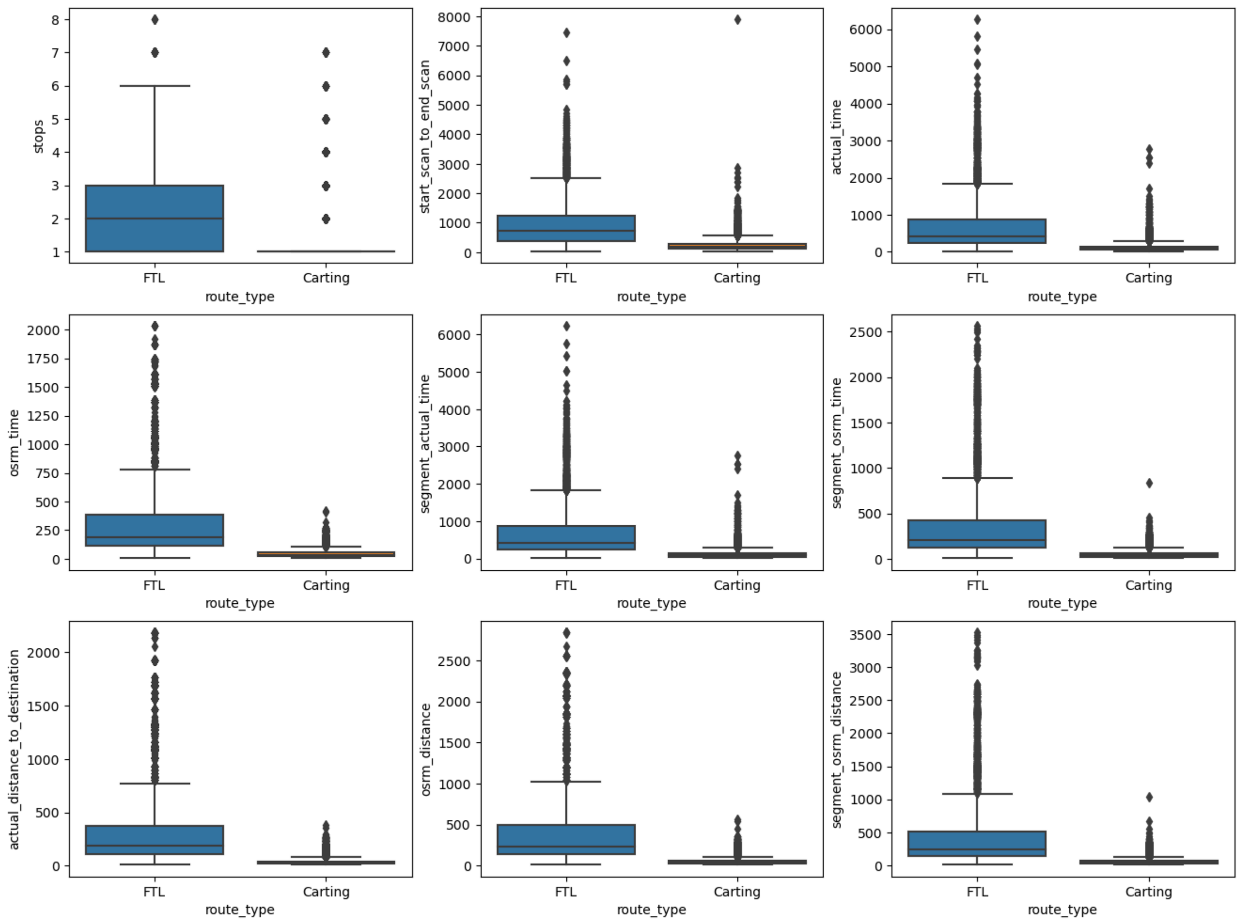


Observation:

- As per the figure carting takes less time than Full Truck Load

Box plot of continuous columns across Route Type

In [77]:
```
f,axes=plt.subplots(nrows=3,ncols=3, figsize=(16,12))
index=0
for row in range(3):
    for col in range(3):
        sns.boxplot(data=df_final,x='route_type',y=df_final[cont_columns[index]],ax=axes[row,col])
        index+=1
plt.show()
```



Observations:

- As evident from the above plots Carting is used for small distances and Full Truck Load is long distances

Actual Tine vs OSRM Distance across Route Type

In [78]:
```
g=sns.FacetGrid(data=df_final, col='s_state',col_wrap=5,hue="route_type")
g.map(sns.scatterplot, "actual_time", "osrm_distance" )
g.add_legend()
plt.show()
```

Observations:

- The actual_time and osrm_distance have linear relationship as expected

Temporal aspects

Count of Trips per month

In [79]:
```
df_final.groupby(['trip_creation_year', 'trip_creation_month'])['trip_uuid'].agg('count')
```

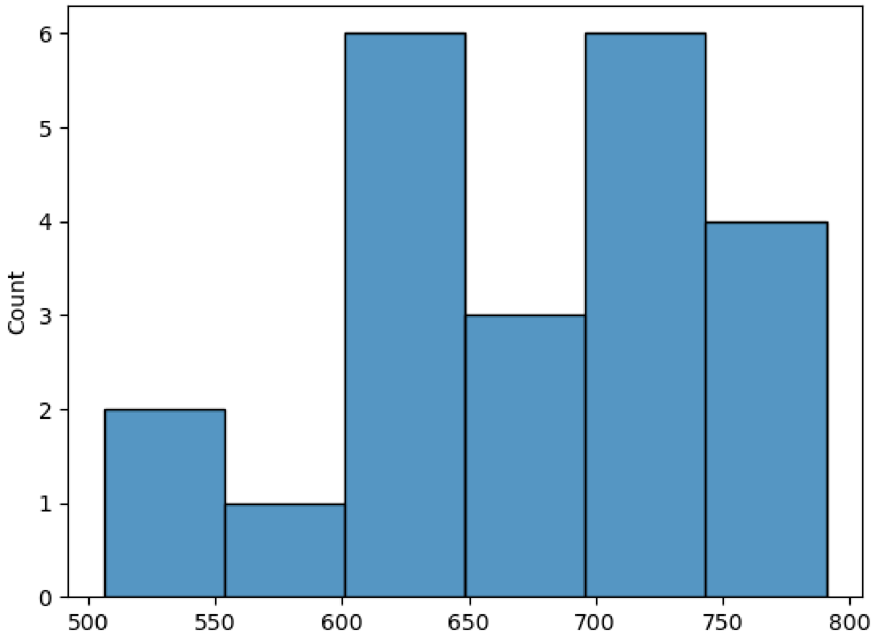
Out[79]:
```
trip_creation_year  trip_creation_month
2018                9                      13003
                    10                      1775
Name: trip_uuid, dtype: int64
```

Count of Trips per day

In [80]:
```
df_final.groupby(['trip_creation_year', 'trip_creation_month', 'trip_creation_day'])['trip_uuid'].a
```

Out[80]:
```
trip_creation_year  trip_creation_month  trip_creation_day
2018                9                    12                   747
                                         13                   750
                                         14                   712
                                         15                   783
                                         16                   616
                                         17                   722
                                         18                   791
                                         19                   674
                                         20                   703
                                         21                   740
                                         22                   740
                                         23                   631
                                         24                   658
                                         25                   696
                                         26                   681
                                         27                   648
                                         28                   603
                                         29                   602
                                         30                   506
                    10                   1                    599
                                         2                    548
                                         3                    628
Name: trip_uuid, dtype: int64
```

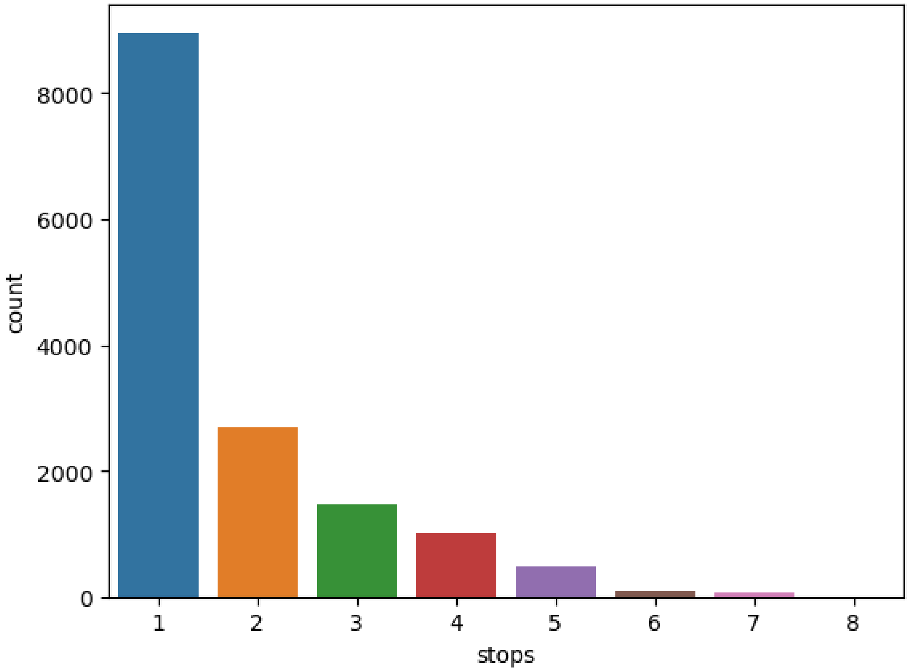
In [81]:
```
sns.histplot(x=df_final.groupby(['trip_creation_year', 'trip_creation_month', 'trip_creation_day']]
plt.show()
```



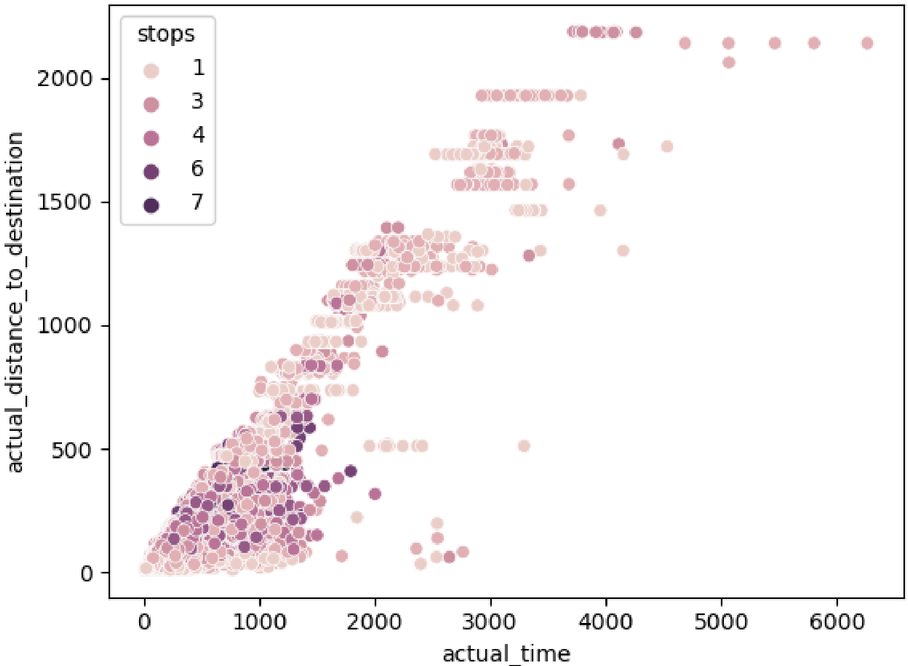
Effect of stops on the actual time taken and actual distance covered per trip

Number of stops per trip

In [82]:
```
sns.countplot(x=df_final['stops'])
plt.show()
```



In [83]:
```
sns.scatterplot(x=df_final['actual_time'], y=df_final['actual_distance_to_destination'], hue=df_fi
plt.show()
```



Interstate trips

In [84]:
```
df_interstate = df_final.loc[df_final['s_state'] != df_final['d_state']].copy()
df_interstate.head()
```

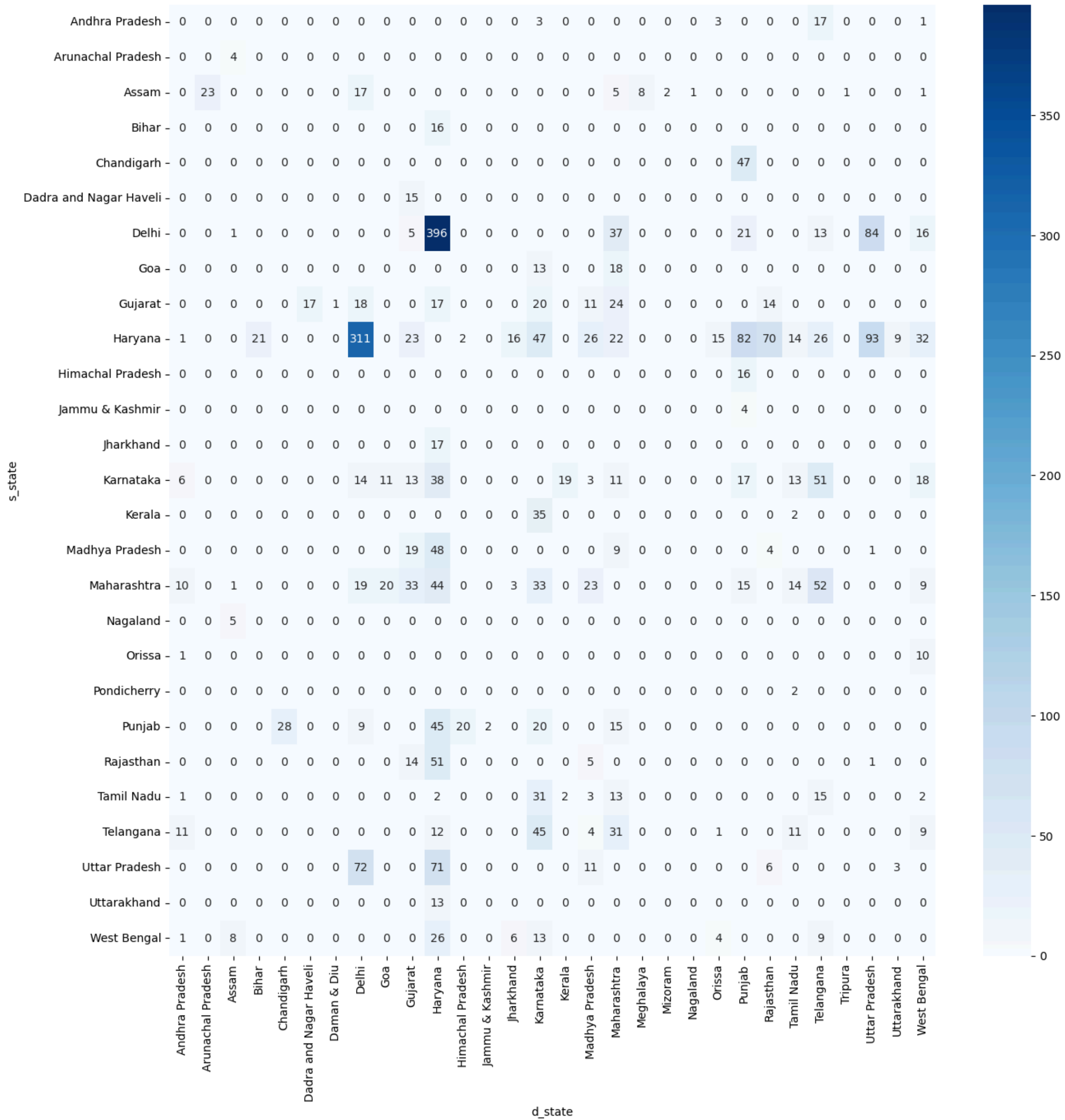
Out[84]:

	trip_uuid	trip_creation_year	trip_creation_month	trip_creation_day	s_state	s_city	d_state
0	trip-153671041653548748	2018	9	12	Madhya Pradesh	Bhopal	Haryana
2	trip-153671043369099517	2018	9	12	Karnataka	Bangalore	Punjab
13	trip-153671121411074590	2018	9	12	Telangana	Hyderabad	Karnataka
17	trip-153671143043841452	2018	9	12	Uttar Pradesh	Allahabad	Madhya Pradesh
39	trip-153671320412492075	2018	9	12	Karnataka	Bangalore	Telangana

5 rows × 23 columns

In [85]:

```
plt.figure(figsize=(15, 15))
sns.heatmap(pd.crosstab(index=df_interstate['s_state'], columns=df_interstate['d_state']), cmap='B
plt.show()
```



Defining delivery speed of trip

- trip_delivery_speed = actual_distance/actual_time

In [86]:
```
df_interstate.head()
```

Out[86]:

	trip_uuid	trip_creation_year	trip_creation_month	trip_creation_day	s_state	s_city	d_state	
0	trip-153671041653548748	2018	9	12	Madhya Pradesh	Bhopal	Haryana	
2	trip-153671043369099517	2018	9	12	Karnataka	Bangalore	Punjab	Cl
13	trip-153671121411074590	2018	9	12	Telangana	Hyderabad	Karnataka	I
17	trip-153671143043841452	2018	9	12	Uttar Pradesh	Allahabad	Madhya Pradesh	
39	trip-153671320412492075	2018	9	12	Karnataka	Bangalore	Telangana	H

5 rows × 23 columns

In [87]:
```
df_interstate['trip_speed_kmph'] = (df_interstate['actual_distance_to_destination']/df_interstate[
```

In [88]:
```
df_interstate_speed = df_interstate.groupby(['s_state', 'd_state'])['trip_speed_kmph'].agg(['mean',
df_interstate_speed.sort_values(by='mean', ascending=False, inplace=True)
df_interstate_speed
```

Out[88]:

	s_state	d_state	mean	count
3	Andhra Pradesh	West Bengal	40.550575	1
39	Haryana	Jharkhand	33.255447	16
40	Haryana	Karnataka	32.693659	47
37	Haryana	Gujarat	32.542952	23
50	Haryana	West Bengal	32.468825	32
...	...	...	...	...
51	Himachal Pradesh	Punjab	9.322701	16
90	Punjab	Chandigarh	8.946907	28
10	Assam	Nagaland	8.197893	1
86	Nagaland	Assam	5.390627	5
87	Orissa	Andhra Pradesh	1.492312	1

130 rows × 4 columns

Top-10 Source-Destination States pairs with Fastest Delivery Speed:

In [89]:
```
df_interstate_speed.iloc[:10, :-1]
```

Out[89]:

	s_state	d_state	mean
3	Andhra Pradesh	West Bengal	40.550575
39	Haryana	Jharkhand	33.255447
40	Haryana	Karnataka	32.693659
37	Haryana	Gujarat	32.542952
50	Haryana	West Bengal	32.468825
13	Bihar	Haryana	31.972790
125	West Bengal	Haryana	31.944301
78	Maharashtra	Haryana	31.638510
108	Tamil Nadu	West Bengal	31.586047
58	Karnataka	Haryana	31.577576

Bottom-10 Source-Destination States pairs with Slowest Delivery Speed:

In [90]:
```
df_interstate_speed.sort_values(by='mean', ascending=True).iloc[:10, :-1]
```

Out[90]:

	s_state	d_state	mean
87	Orissa	Andhra Pradesh	1.492312
86	Nagaland	Assam	5.390627
10	Assam	Nagaland	8.197893
90	Punjab	Chandigarh	8.946907
51	Himachal Pradesh	Punjab	9.322701
117	Uttar Pradesh	Delhi	9.803156
27	Gujarat	Daman & Diu	9.892707
122	Uttarakhand	Haryana	10.470766
12	Assam	West Bengal	10.540807
124	West Bengal	Assam	11.139528

Intrastate trips

In [91]:
```
df_intrastate = df_final.loc[df_final['s_state'] == df_final['d_state']].copy()
df_intrastate.head()
```

Out[91]:

	trip_uuid	trip_creation_year	trip_creation_month	trip_creation_day	s_state	s_city	d_state	
1	trip-153671042288605164	2018	9	12	Karnataka	Tumkur	Karnataka	C
3	trip-153671046011330457	2018	9	12	Maharashtra	Mumbai Hub	Maharashtra	
4	trip-153671052974046625	2018	9	12	Karnataka	Bellary	Karnataka	
5	trip-153671055416136166	2018	9	12	Tamil Nadu	Chennai	Tamil Nadu	
6	trip-153671066201138152	2018	9	12	Tamil Nadu	Chennai	Tamil Nadu	

5 rows × 23 columns

Top-10 States with highest intrastate trips

In [92]:
```
df_intrastate['s_state'].value_counts()[:10]
```

Out[92]:
```
Maharashtra       2406
Karnataka         2016
Tamil Nadu        1016
Haryana            871
Telangana          655
Gujarat            624
West Bengal        610
Uttar Pradesh      542
Punjab             491
Rajasthan          422
Name: s_state, dtype: int64
```

Top-10 Source-Destination City Pairs with highest count of trips

In [93]:
```
df_intrastate[['s_city', 'd_city']].value_counts()[:20]
```

Out[93]:
```
s_city      d_city
Bangalore   Bangalore          1376
Hyderabad   Hyderabad           398
Bhiwandi    Mumbai              332
Mumbai      Mumbai              264
Mumbai Hub  Mumbai              227
Mumbai      Bhiwandi            207
Chennai     Chennai             201
MAA         Chennai             178
Chandigarh  Chandigarh          176
Jaipur      Jaipur              155
Sonipat     Sonipat             150
Delhi       Delhi               149
Kolkata     Kolkata             145
Muzaffrpur  Muzaffrpur          130
Pune        Pune                130
Ahmedabad   Ahmedabad           125
Chennai     MAA                 115
Bhiwandi    Bhiwandi            113
            Mumbai Hub          105
Bangalore   HBR Layout PC        96
dtype: int64
```

Defining delivery speed of trip

- trip_delivery_speed = actual_distance/actual_time

In [94]:
```
df_intrastate.head()
```

Out[94]:

	trip_uuid	trip_creation_year	trip_creation_month	trip_creation_day	s_state	s_city	d_state	C
1	trip-153671042288605164	2018	9	12	Karnataka	Tumkur	Karnataka	
3	trip-153671046011330457	2018	9	12	Maharashtra	Mumbai Hub	Maharashtra	
4	trip-153671052974046625	2018	9	12	Karnataka	Bellary	Karnataka	
5	trip-153671055416136166	2018	9	12	Tamil Nadu	Chennai	Tamil Nadu	
6	trip-153671066201138152	2018	9	12	Tamil Nadu	Chennai	Tamil Nadu	

5 rows × 23 columns

In [95]:
```
df_intrastate['trip_speed_kmph'] = (df_intrastate['actual_distance_to_destination']/df_intrastate[
```

In [96]:
```
df_intrastate_speed = df_interstate.groupby('s_state')['trip_speed_kmph'].agg(['mean', 'count']).re
df_intrastate_speed.sort_values(by='mean', ascending=False, inplace=True)
df_intrastate_speed
```

Out[96]:

	s_state	mean	count
3	Bihar	31.972790	16
12	Jharkhand	29.625398	17
16	Maharashtra	27.553644	276
26	West Bengal	27.216028	67
11	Jammu & Kashmir	27.005957	4
15	Madhya Pradesh	26.345403	81
23	Telangana	25.950325	124
13	Karnataka	25.883637	214
22	Tamil Nadu	25.322107	69
0	Andhra Pradesh	24.162380	24
8	Gujarat	22.233304	122
7	Goa	21.638024	31
21	Rajasthan	21.293057	71
20	Punjab	20.453266	139
19	Pondicherry	20.134275	2
9	Haryana	19.681613	810
14	Kerala	19.413454	37
2	Assam	16.720027	58
6	Delhi	15.723216	573
24	Uttar Pradesh	14.129549	163
18	Orissa	12.756500	11
1	Arunachal Pradesh	12.476545	4
5	Dadra and Nagar Haveli	12.398680	15
4	Chandigarh	11.949038	47
25	Uttarakhand	10.470766	13
10	Himachal Pradesh	9.322701	16
17	Nagaland	5.390627	5

Top-5 states where the intrastate delivery speed is highest

In [97]:
```
df_intrastate_speed.iloc[:5, :-1]
```

Out[97]:

	s_state	mean
3	Bihar	31.972790
12	Jharkhand	29.625398
16	Maharashtra	27.553644
26	West Bengal	27.216028
11	Jammu & Kashmir	27.005957

Bottom-5 states where the intrastate delivery speed is lowest

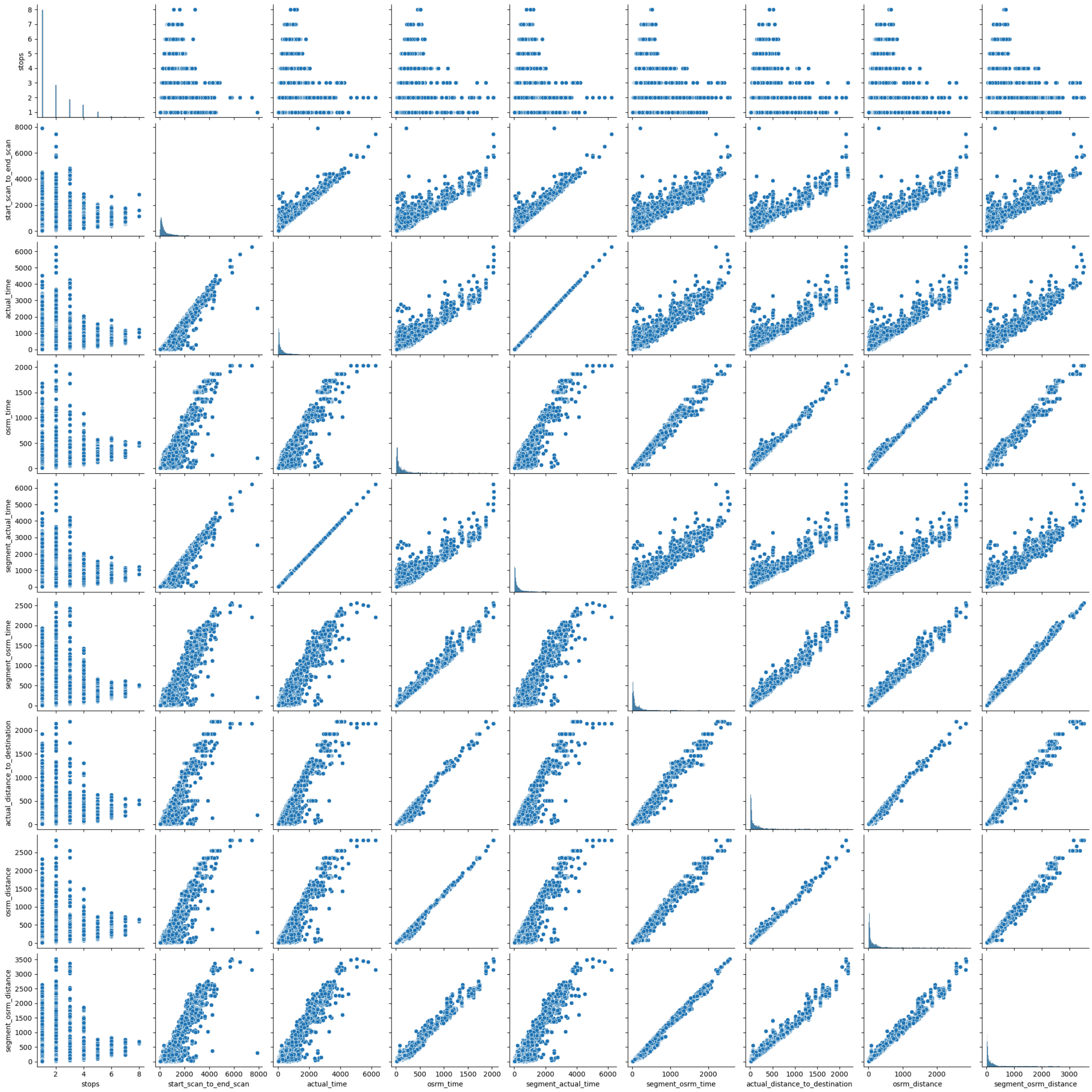
In [98]:
```
df_intrastate_speed.iloc[-5:, :-1]
```

Out[98]:

	s_state	mean
5	Dadra and Nagar Haveli	12.398680
4	Chandigarh	11.949038
25	Uttarakhand	10.470766
10	Himachal Pradesh	9.322701
17	Nagaland	5.390627

Pairplot

In [99]:
```
sns.pairplot(data=df_final[cont_columns])
plt.show()
```



Heatmap

In [100…
```
df_temp.drop(['stops', 'Carting', 'FTL'], axis=1).corr()
```

Out[100]:

	start_scan_to_end_scan	actual_time	osrm_time	segment_actual_time	segment_osrm_
start_scan_to_end_scan	1.000000	0.961229	0.927085	0.961251	0.91
actual_time	0.961229	1.000000	0.958806	0.999989	0.95
osrm_time	0.927085	0.958806	1.000000	0.957982	0.99
segment_actual_time	0.961251	0.999989	0.957982	1.000000	0.95
segment_osrm_time	0.919047	0.954062	0.993263	0.953232	1.00
actual_distance_to_destination	0.918833	0.953972	0.993564	0.953040	0.98
osrm_distance	0.924825	0.959431	0.997582	0.958574	0.99
segment_osrm_distance	0.919801	0.957168	0.991615	0.956311	0.99
trip_total_time	0.993612	0.952647	0.916555	0.952721	0.90

In [101…

```
plt.figure(figsize=(10, 6))
sns.heatmap(df_temp.drop(['stops', 'Carting', 'FTL'], axis=1).corr(), cmap='Blues', annot=True)
plt.show()
```