About Delhivery 🚚

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

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

Business Problem 💡

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

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

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Dataset 📊

Column Profiling | Field Name | Description | |----------|----------| | 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, 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_center | 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 |

Importing Required Libraries 🤝

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler, MinMaxScaler
import scipy.stats as stats
```

In [2]:
```
import warnings
warnings.filterwarnings("ignore")
```

In [3]:
```
# Set figure size
plt.rcParams['figure.figsize'] = [12, 6]

# set the seaborn style
```

```
palette = ['black', 'red']
sns.set(style='ticks', palette=palette)
```

In [4]:
```
# setting the option of displaying all the columns
pd.set_option('display.max_columns', 50)
```

Read Dataset 🔍

In [5]:
```
# Read the data
delhivery_data = pd.read_csv(r'../data/delhivery_data.csv')
dd = delhivery_data.copy()
dd.head()
```

Out[5]:

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_center
0	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB
1	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB
2	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB
3	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB
4	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB

In [6]:
```
print("Shape of the data: ", dd.shape)
print("The Given Dataset has {} rows and {} columns".format(dd.shape[0], dd.shape[1]))
print("Columns: ", dd.columns)
```

```
Shape of the data:  (144867, 24)
The Given Dataset has 144867 rows and 24 columns
Columns:  Index(['data', 'trip_creation_time', 'route_schedule_uuid', 'route_type',
       'trip_uuid', 'source_center', 'source_name', 'destination_center',
       'destination_name', 'od_start_time', 'od_end_time',
       'start_scan_to_end_scan', 'is_cutoff', 'cutoff_factor',
       'cutoff_timestamp', 'actual_distance_to_destination', 'actual_time',
       'osrm_time', 'osrm_distance', 'factor', 'segment_actual_time',
       'segment_osrm_time', 'segment_osrm_distance', 'segment_factor'],
      dtype='object')
```

Shape:

- The dataset comprises 144,867 rows and 24 columns, representing a substantial volume of data.
- Each row corresponds to transport between one source point to other point (delivery details of one package are divided into several rows)

Data Structure

In [7]:
```
# Drop the columns which are not required
unknown_fields = ['is_cutoff', 'cutoff_factor', 'cutoff_timestamp', 'factor', 'segment_factor']
dd = dd.drop(columns = unknown_fields)
```

In [8]:
```
dd.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144867 entries, 0 to 144866
Data columns (total 19 columns):
 #   Column                          Non-Null Count   Dtype  
---  ------                          --------------   -----  
 0   data                            144867 non-null  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  actual_distance_to_destination  144867 non-null  float64
 13  actual_time                     144867 non-null  float64
 14  osrm_time                       144867 non-null  float64
 15  osrm_distance                   144867 non-null  float64
 16  segment_actual_time             144867 non-null  float64
 17  segment_osrm_time               144867 non-null  float64
 18  segment_osrm_distance           144867 non-null  float64
dtypes: float64(8), object(11)
memory usage: 21.0+ MB
```

In [9]:

```python
# Datatype conversion for the columns
dd['trip_creation_time'] = pd.to_datetime(dd['trip_creation_time'])
dd['od_start_time'] = pd.to_datetime(dd['od_start_time'])
dd['od_end_time'] = pd.to_datetime(dd['od_end_time'])

cat_cols = dd.select_dtypes(include=['object', 'category']).columns
for col in cat_cols:
    dd[col] = dd[col].astype('category')

float_cols = dd.select_dtypes(include=['float64']).columns
for col in float_cols:
    dd[col] = dd[col].astype('float16')

dd.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144867 entries, 0 to 144866
Data columns (total 19 columns):
 #   Column                          Non-Null Count   Dtype
---  ------                          --------------   -----
 0   data                            144867 non-null  category
 1   trip_creation_time              144867 non-null  datetime64[ns]
 2   route_schedule_uuid             144867 non-null  category
 3   route_type                      144867 non-null  category
 4   trip_uuid                       144867 non-null  category
 5   source_center                   144867 non-null  category
 6   source_name                     144574 non-null  category
 7   destination_center              144867 non-null  category
 8   destination_name                144606 non-null  category
 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  float16
 12  actual_distance_to_destination  144867 non-null  float16
 13  actual_time                     144867 non-null  float16
 14  osrm_time                       144867 non-null  float16
 15  osrm_distance                   144867 non-null  float16
 16  segment_actual_time             144867 non-null  float16
 17  segment_osrm_time               144867 non-null  float16
 18  segment_osrm_distance           144867 non-null  float16
dtypes: category(8), datetime64[ns](3), float16(8)
memory usage: 8.3 MB
```

- Conversion of categorical attributes to 'category'
- Datetime fields to 'datetime'
- float64 to float16, to reduce the memory usage from ~21 MB to ~8 MB

In [10]:
```
# Missing values and their percentage
missing_values = dd.isnull().sum().reset_index(name='missing_values')
missing_values['percentage_%'] = (missing_values['missing_values']/dd.shape[0])*100
missing_values = missing_values.sort_values(by='missing_values', ascending=False)
missing_values = missing_values[missing_values['missing_values'] > 0]
missing_values
```

Out[10]:

	index	missing_values	percentage_%
6	source_name	293	0.202254
8	destination_name	261	0.180165

In [11]:
```
dd[dd['source_name'].isnull()].head()
```

Out[11]:

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_center	de
112	training	2018-09-25 08:53:04.377810	thanos::sroute:4460a38d-ab9b-484e-bd4e-f4201d0...	FTL	trip-153786558437756691	IND342902A1B	NaN	IND302014AAA	
113	training	2018-09-25 08:53:04.377810	thanos::sroute:4460a38d-ab9b-484e-bd4e-f4201d0...	FTL	trip-153786558437756691	IND342902A1B	NaN	IND302014AAA	
114	training	2018-09-25 08:53:04.377810	thanos::sroute:4460a38d-ab9b-484e-bd4e-f4201d0...	FTL	trip-153786558437756691	IND342902A1B	NaN	IND302014AAA	
115	training	2018-09-25 08:53:04.377810	thanos::sroute:4460a38d-ab9b-484e-bd4e-f4201d0...	FTL	trip-153786558437756691	IND342902A1B	NaN	IND302014AAA	
116	training	2018-09-25 08:53:04.377810	thanos::sroute:4460a38d-ab9b-484e-bd4e-f4201d0...	FTL	trip-153786558437756691	IND342902A1B	NaN	IND302014AAA	

In [12]:
```
# dd[(dd['source_name'].isnull()) & ~(dd['source_center'].isnull())]
missing_source_name = dd[dd['source_name'].isnull()]['source_center'].unique().tolist()
dd[(dd['source_center'].isin(missing_source_name)) & ~(dd['source_name'].isnull())]
```

Out[12]:

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_center	destination_name	od_s

In [13]:
```
missing_destination_name = dd[dd['destination_name'].isnull()]['destination_center'].unique().tolist()
dd[(dd['destination_center'].isin(missing_destination_name)) & ~(dd['destination_name'].isnull())]
```

Out[13]:

data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_center	destination_name	od_s

In [14]:
```
missing_trip_data = dd[(dd['source_name'].isnull()) | (dd['destination_name'].isnull())]['trip_uuid'].unique().tolist()
```

In [15]:
```
print(f"Number of Trips having missing data: {len(missing_trip_data)}")
print(f"Total number of Trips: {dd['trip_uuid'].nunique()}")
print(f"Missing Trip Percentage: {round(len(missing_trip_data)/dd['trip_uuid'].nunique()*100,2)}")
```

```
Number of Trips having missing data: 110
Total number of Trips: 14817
Missing Trip Percentage: 0.74
```

In [16]:
```
dd = dd[~dd['trip_uuid'].isin(missing_trip_data)]
```

- We have 0.7% of data missing, hence dropping those data

In [17]:
```
dd.duplicated().sum()
```

Out[17]:
```
0
```

In [18]:
```
dd.describe().T
```

Out[18]:

	count	mean	min	25%	50%	75%	
trip_creation_time	143713	2018-09-22 12:34:01.122491904	2018-09-12 00:00:16.535741	2018-09-17 02:33:32.314778112	2018-09-22 02:54:50.852296960	2018-09-27 17:28:45.461110016	2018 23:59:42.
od_start_time	143713	2018-09-22 17:01:31.270683136	2018-09-12 00:00:16.535741	2018-09-17 07:00:42.244400896	2018-09-22 06:36:29.552777984	2018-09-27 21:14:43.582704896	2018 04:27:23.
od_end_time	143713	2018-09-23 09:08:33.888178176	2018-09-12 00:50:10.814399	2018-09-18 01:02:03.127152896	2018-09-23 02:26:43.998577920	2018-09-28 12:11:21.606330880	2018 03:00:24.
start_scan_to_end_scan	143713.0	NaN	20.0	161.0	454.0	1660.0	
actual_distance_to_destination	143713.0	NaN	9.0	23.359375	66.1875	287.25	
actual_time	143713.0	NaN	9.0	52.0	132.0	519.0	
osrm_time	143713.0	NaN	6.0	27.0	65.0	262.0	
osrm_distance	143713.0	NaN	9.007812	29.921875	78.875	348.5	
segment_actual_time	143713.0	NaN	-244.0	20.0	28.0	40.0	
segment_osrm_time	143713.0	NaN	0.0	11.0	17.0	22.0	
segment_osrm_distance	143713.0	NaN	0.0	12.039062	23.5	27.8125	

In [19]:
```
dd.describe(include='category').T
```

Out[19]:

	count	unique	top	freq
data	143713	2	training	104358
route_schedule_uuid	143713	1485	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	1812
route_type	143713	2	FTL	98533
trip_uuid	143713	14707	trip-153846035308581166	101
source_center	143713	1494	IND000000ACB	23267
source_name	143713	1494	Gurgaon_Bilaspur_HB (Haryana)	23267
destination_center	143713	1465	IND000000ACB	15180
destination_name	143713	1465	Gurgaon_Bilaspur_HB (Haryana)	15180

Insights:

- Unknown columns are dropped
- ~0.7% of the record has missing source name and destination name, hence dropped
- There is no duplicate record found in the table
- The Given dataset has data from "2018-09-12" to "2018-10-03"

Data Aggregations

In [20]:
```
dd['unique_trip'] = dd['trip_uuid'].str.cat([dd['source_center'], dd['destination_center']], sep="_")
dd['unique_trip'].head()
```

Out[20]:
```
0    trip-153741093647649320_IND388121AAA_IND388620AAB
1    trip-153741093647649320_IND388121AAA_IND388620AAB
2    trip-153741093647649320_IND388121AAA_IND388620AAB
3    trip-153741093647649320_IND388121AAA_IND388620AAB
4    trip-153741093647649320_IND388121AAA_IND388620AAB
Name: unique_trip, dtype: object
```

In [21]:
```
agg_dict = {
    'trip_uuid': 'first',
    'data':'first',
    'trip_creation_time': 'first',
    'route_type': 'first',
    'source_name': 'first',
    'destination_name': 'first',
    'od_start_time': 'first',
    'od_end_time': 'first',
    'start_scan_to_end_scan': 'first',
    'actual_distance_to_destination': 'last',
    'actual_time': 'last',
    'osrm_time': 'last',
    'osrm_distance': 'last',
    'segment_actual_time': 'sum',
    'segment_osrm_time': 'sum',
    'segment_osrm_distance': 'sum',
}

dd_grouped = dd.groupby(by="unique_trip", as_index=False).agg(agg_dict)
```

In [22]:
```
dd_grouped.head()
```

Out[22]:

	unique_trip	trip_uuid	data	trip_creation_time	route_type	source_name	
0	trip-153671041653548748_IND209304AAA_IND000000ACB	trip-153671041653548748	training	2018-09-12 00:00:16.535741	FTL	Kanpur_Central_H_6 (Uttar Pradesh)	
1	trip-153671041653548748_IND462022AAA_IND209304AAA	trip-153671041653548748	training	2018-09-12 00:00:16.535741	FTL	Bhopal_Trnsport_H (Madhya Pradesh)	
2	trip-153671042288605164_IND561203AAB_IND562101AAA	trip-153671042288605164	training	2018-09-12 00:00:22.886430	Carting	Doddablpur_ChikaDPP_D (Karnataka)	
3	trip-153671042288605164_IND572101AAA_IND561203AAB	trip-153671042288605164	training	2018-09-12 00:00:22.886430	Carting	Tumkur_Veersagr_I (Karnataka)	Dc
4	trip-153671043369099517_IND000000ACB_IND160002AAC	trip-153671043369099517	training	2018-09-12 00:00:33.691250	FTL	Gurgaon_Bilaspur_HB (Haryana)	Cha

In [23]:
```
dd_grouped.shape
```

Out[23]:
```
(26037, 17)
```

In [24]:
```
dd_grouped['source_name']
```

Out[24]:
```
0        Kanpur_Central_H_6 (Uttar Pradesh)
1        Bhopal_Trnsport_H (Madhya Pradesh)
2         Doddablpur_ChikaDPP_D (Karnataka)
3             Tumkur_Veersagr_I (Karnataka)
4             Gurgaon_Bilaspur_HB (Haryana)
                      ...
26032    Tirchchndr_Shnmgprm_D (Tamil Nadu)
26033     Peikulam_SriVnktpm_D (Tamil Nadu)
26034          Eral_Busstand_D (Tamil Nadu)
26035         Sandur_WrdN1DPP_D (Karnataka)
26036                    Hospet (Karnataka)
Name: source_name, Length: 26037, dtype: category
Categories (1498, object): ['AMD_Memnagar (Gujarat)', 'AMD_Rakhial (Gujarat)', 'Abohar_DC (Punjab)', 'Achrol_BgwriDPP_D
(Rajasthan)', ..., 'YamunaNagar_DC (Haryana)', 'Yellandu_Sudimala_D (Telangana)', 'Yellareddy_JKRoad_D (Telangana)', 'Z
ahirabad_Mohim_D (Telangana)']
```

Feature Extraction ⚙

Extracting the city, state and code from source/destination name

In [25]:
```
dd_grouped['source_state'] = dd_grouped['source_name'].apply(lambda name: name[name.index('(')+1:name.index(')')])
dd_grouped['source_point'] = dd_grouped['source_name'].apply(lambda name: name[:name.index('(')-1])
dd_grouped['source_city'] = dd_grouped['source_point'].apply(lambda name: name.split('_')[0])
dd_grouped['source_code'] = dd_grouped['source_point'].apply(lambda name: "_".join(name.split('_')[1:]))
dd_grouped[['source_point','source_state','source_city','source_code']].head()
```

Out[25]:

	source_point	source_state	source_city	source_code
0	Kanpur_Central_H_6	Uttar Pradesh	Kanpur	Central_H_6
1	Bhopal_Trnsport_H	Madhya Pradesh	Bhopal	Trnsport_H
2	Doddablpur_ChikaDPP_D	Karnataka	Doddablpur	ChikaDPP_D
3	Tumkur_Veersagr_I	Karnataka	Tumkur	Veersagr_I
4	Gurgaon_Bilaspur_HB	Haryana	Gurgaon	Bilaspur_HB

In [26]:
```
dd_grouped['destination_state'] = dd_grouped['destination_name'].apply(lambda name: name[name.index('(')+1:name.index('
dd_grouped['destination_point'] = dd_grouped['destination_name'].apply(lambda name: name[:name.index('(')-1])
dd_grouped['destination_city'] = dd_grouped['destination_point'].apply(lambda name: name.split('_')[0])
dd_grouped['destination_code'] = dd_grouped['destination_point'].apply(lambda name: "_".join(name.split('_')[1:]))
dd_grouped[['destination_name','destination_state','destination_city','destination_code']].head()
```

Out[26]:

	destination_name	destination_state	destination_city	destination_code
0	Gurgaon_Bilaspur_HB (Haryana)	Haryana	Gurgaon	Bilaspur_HB
1	Kanpur_Central_H_6 (Uttar Pradesh)	Uttar Pradesh	Kanpur	Central_H_6
2	Chikblapur_ShntiSgr_D (Karnataka)	Karnataka	Chikblapur	ShntiSgr_D
3	Doddablpur_ChikaDPP_D (Karnataka)	Karnataka	Doddablpur	ChikaDPP_D
4	Chandigarh_Mehmdpur_H (Punjab)	Punjab	Chandigarh	Mehmdpur_H

Mapping the city short codes to city names

In [27]:
```
source_cities = dd_grouped[dd_grouped['source_city'].str.len() == 3]['source_city'].unique().tolist()
destination_cities = dd_grouped[dd_grouped['destination_city'].str.len() == 3]['destination_city'].unique().tolist()

source_cities.extend(destination_cities)
city_short_codes = list(set(source_cities))
city_short_codes

city_code_map = {
    'FBD': 'Faridabad',
    'GGN': 'Gurgaon',
    'DEL': 'Delhi',
    'BLR': 'Bangalore',
    'HYD': 'Hyderabad',
    'AMD': 'Ahmedabad',
    'MAA': 'Chennai',
    'BOM': 'Mumbai',
    'NOI': 'Noida',
    'GZB': 'Ghaziabad',
    'CJB': 'Coimbatore',
    'BENGALURU': 'Bangalore',
}

def map_city_code(city_code):
    return city_code_map.get(city_code.upper(), city_code)
```

```
dd_grouped['source_city'] = dd_grouped['source_city'].apply(map_city_code)
dd_grouped['destination_city'] = dd_grouped['destination_city'].apply(map_city_code)
```

Extracting the date, day and other features from xTrip creation timestamp

In [28]:
```
dd_grouped['trip_creation_date'] = dd_grouped['trip_creation_time'].dt.date
dd_grouped['trip_creation_day'] = dd_grouped['trip_creation_time'].dt.day
# dd_grouped['trip_creation_month'] = dd_grouped['trip_creation_time'].dt.month
# dd_grouped['trip_creation_year'] = dd_grouped['trip_creation_time'].dt.year
dd_grouped['trip_creation_hour'] = dd_grouped['trip_creation_time'].dt.hour
dd_grouped['trip_creation_weekday'] = dd_grouped['trip_creation_time'].dt.weekday
dd_grouped['trip_creation_week'] = dd_grouped['trip_creation_time'].dt.isocalendar().week
# dd_grouped['trip_creation_quarter'] = dd_grouped['trip_creation_time'].dt.quarter
dd_grouped.head()
```

Out[28]:

	unique_trip	trip_uuid	data	trip_creation_time	route_type	source_name	
0	trip-153671041653548748_IND209304AAA_IND000000ACB	trip-153671041653548748	training	2018-09-12 00:00:16.535741	FTL	Kanpur_Central_H_6 (Uttar Pradesh)	
1	trip-153671041653548748_IND462022AAA_IND209304AAA	trip-153671041653548748	training	2018-09-12 00:00:16.535741	FTL	Bhopal_Trnsport_H (Madhya Pradesh)	
2	trip-153671042288605164_IND561203AAB_IND562101AAA	trip-153671042288605164	training	2018-09-12 00:00:22.886430	Carting	Doddablpur_ChikaDPP_D (Karnataka)	
3	trip-153671042288605164_IND572101AAA_IND561203AAB	trip-153671042288605164	training	2018-09-12 00:00:22.886430	Carting	Tumkur_Veersagr_I (Karnataka)	Dc
4	trip-153671043369099517_IND000000ACB_IND160002AAC	trip-153671043369099517	training	2018-09-12 00:00:33.691250	FTL	Gurgaon_Bilaspur_HB (Haryana)	Cha

In [29]:
```
dd_grouped['trip_duration'] = dd_grouped['od_end_time'] - dd_grouped['od_start_time']
# dd_grouped['trip_speed'] = dd_grouped['actual_distance_to_destination'] / dd_grouped['actual_time']
dd_grouped.head()
```

Out[29]:

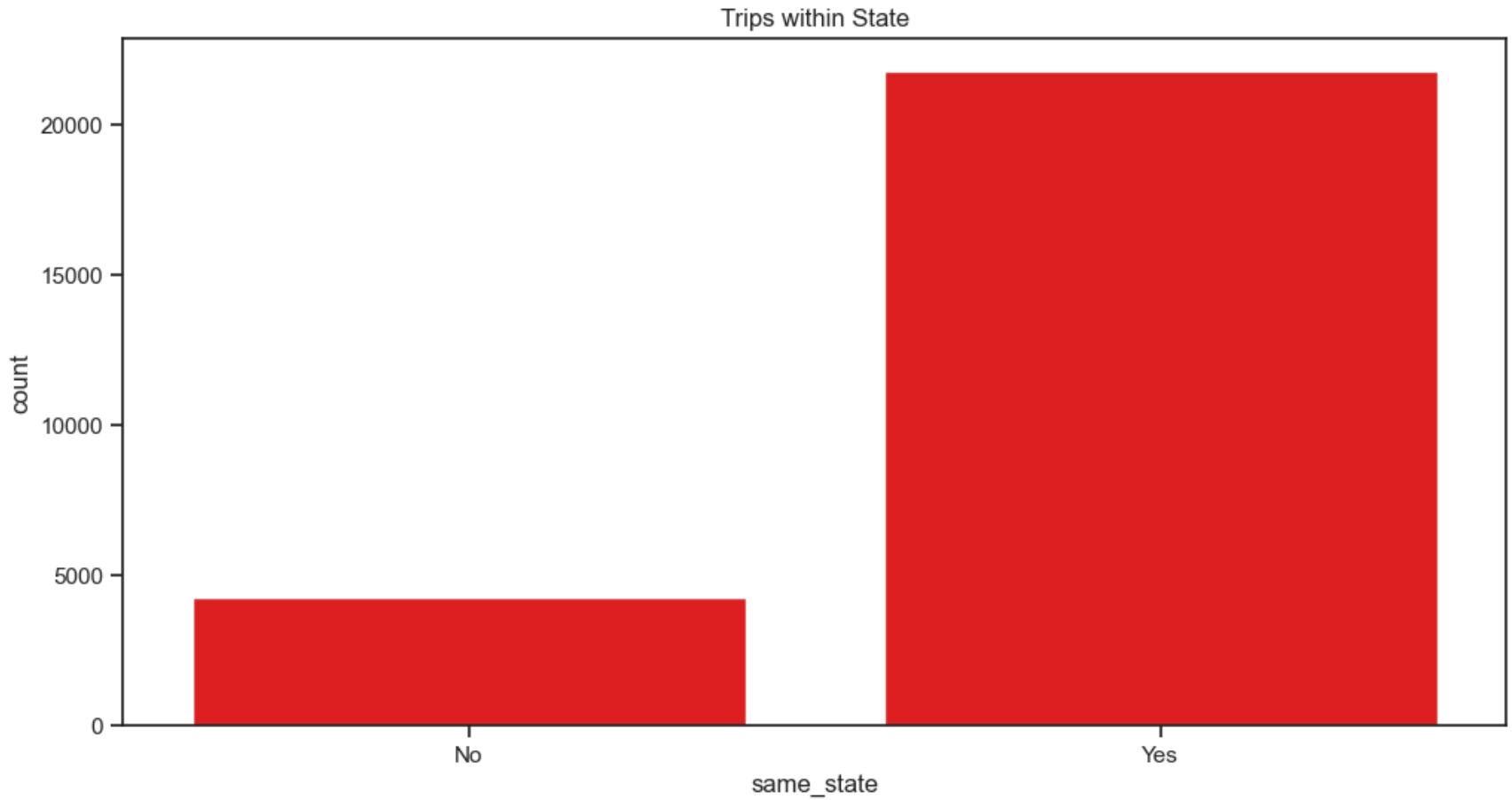
	unique_trip	trip_uuid	data	trip_creation_time	route_type	source_name	
0	trip-153671041653548748_IND209304AAA_IND000000ACB	trip-153671041653548748	training	2018-09-12 00:00:16.535741	FTL	Kanpur_Central_H_6 (Uttar Pradesh)	
1	trip-153671041653548748_IND462022AAA_IND209304AAA	trip-153671041653548748	training	2018-09-12 00:00:16.535741	FTL	Bhopal_Trnsport_H (Madhya Pradesh)	
2	trip-153671042288605164_IND561203AAB_IND562101AAA	trip-153671042288605164	training	2018-09-12 00:00:22.886430	Carting	Doddablpur_ChikaDPP_D (Karnataka)	
3	trip-153671042288605164_IND572101AAA_IND561203AAB	trip-153671042288605164	training	2018-09-12 00:00:22.886430	Carting	Tumkur_Veersagr_I (Karnataka)	Dc
4	trip-153671043369099517_IND000000ACB_IND160002AAC	trip-153671043369099517	training	2018-09-12 00:00:33.691250	FTL	Gurgaon_Bilaspur_HB (Haryana)	Cha

---

Analysis

In [30]:

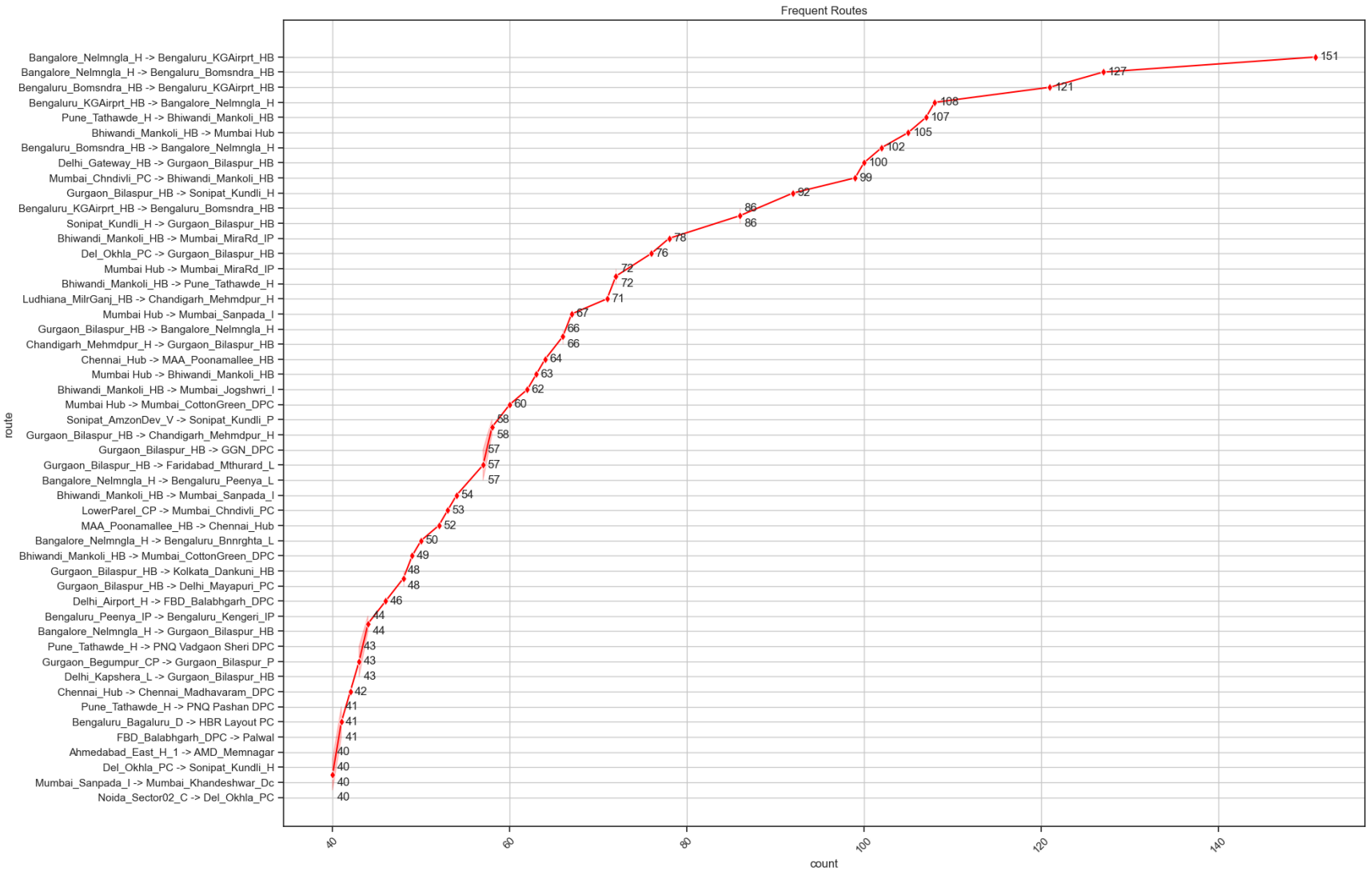
```
same_state_df = dd_grouped.apply(lambda row: "Yes" if row['source_state'] == row['destination_state'] else "No", axis=1

sns.countplot(x='same_state', data=same_state_df, color=palette[1])
plt.title("Trips within State")
plt.show()
```



- Most of the trip are intra-state deliveries

In [31]:
```
frequenct_routes = dd_grouped['source_point'].str.cat(dd_grouped['destination_point'], sep=" -> ").reset_index(name='ro
frequenct_routes = frequenct_routes['route'].value_counts().reset_index(name='count').head(50)
frequenct_routes

# line plot
plt.figure(figsize=(20, 15))
sns.lineplot(y='route', x='count', data=frequenct_routes, marker='d', color='r')
plt.xticks(rotation=45)
plt.title("Frequent Routes")
plt.grid()

for i, count in frequenct_routes['count'].items():
```

```
    plt.text(count+0.5, i, str(count), ha='left', va='center')

plt.show()
```

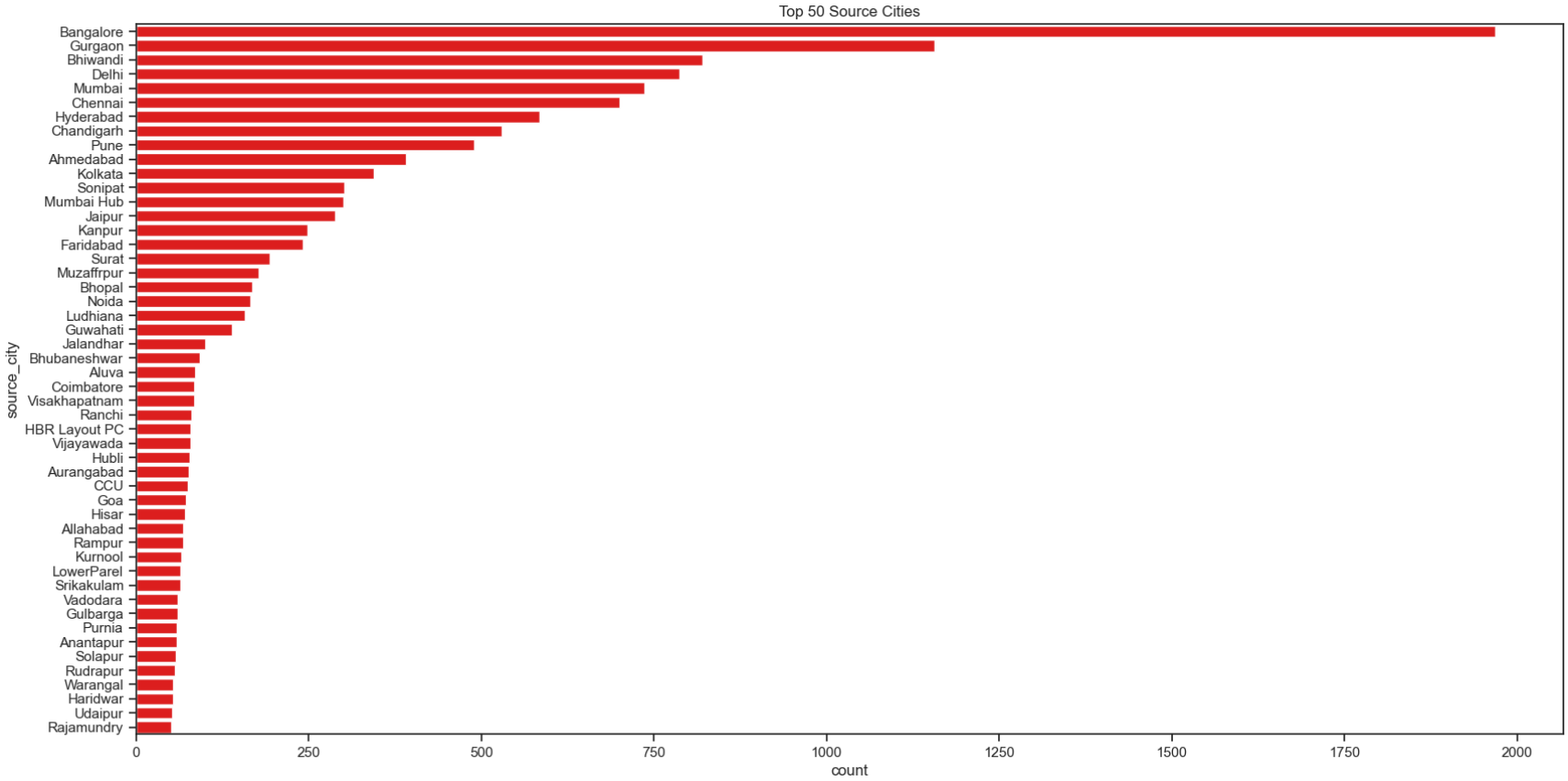


- Top 10 Busiest corridor
    - Bangalore_Nelmngla_H -> Bengaluru_KGAirprt_HB
    - Bangalore_Nelmngla_H -> Bengaluru_Bomsndra_HB
    - Bengaluru_Bomsndra_HB -> Bengaluru_KGAirprt_HB

- Bengaluru_KGAirprt_HB -> Bangalore_Nelmngla_H
- Pune_Tathawde_H -> Bhiwandi_Mankoli_HB
- Bhiwandi_Mankoli_HB -> Mumbai Hub
- Bengaluru_Bomsndra_HB -> Bangalore_Nelmngla_H
- Delhi_Gateway_HB -> Gurgaon_Bilaspur_HB
- Mumbai_Chndivli_PC -> Bhiwandi_Mankoli_HB
- Gurgaon_Bilaspur_HB -> Sonipat_Kundli_H
- Bengaluru_KGAirprt_HB -> Bengaluru_Bomsndra_HB

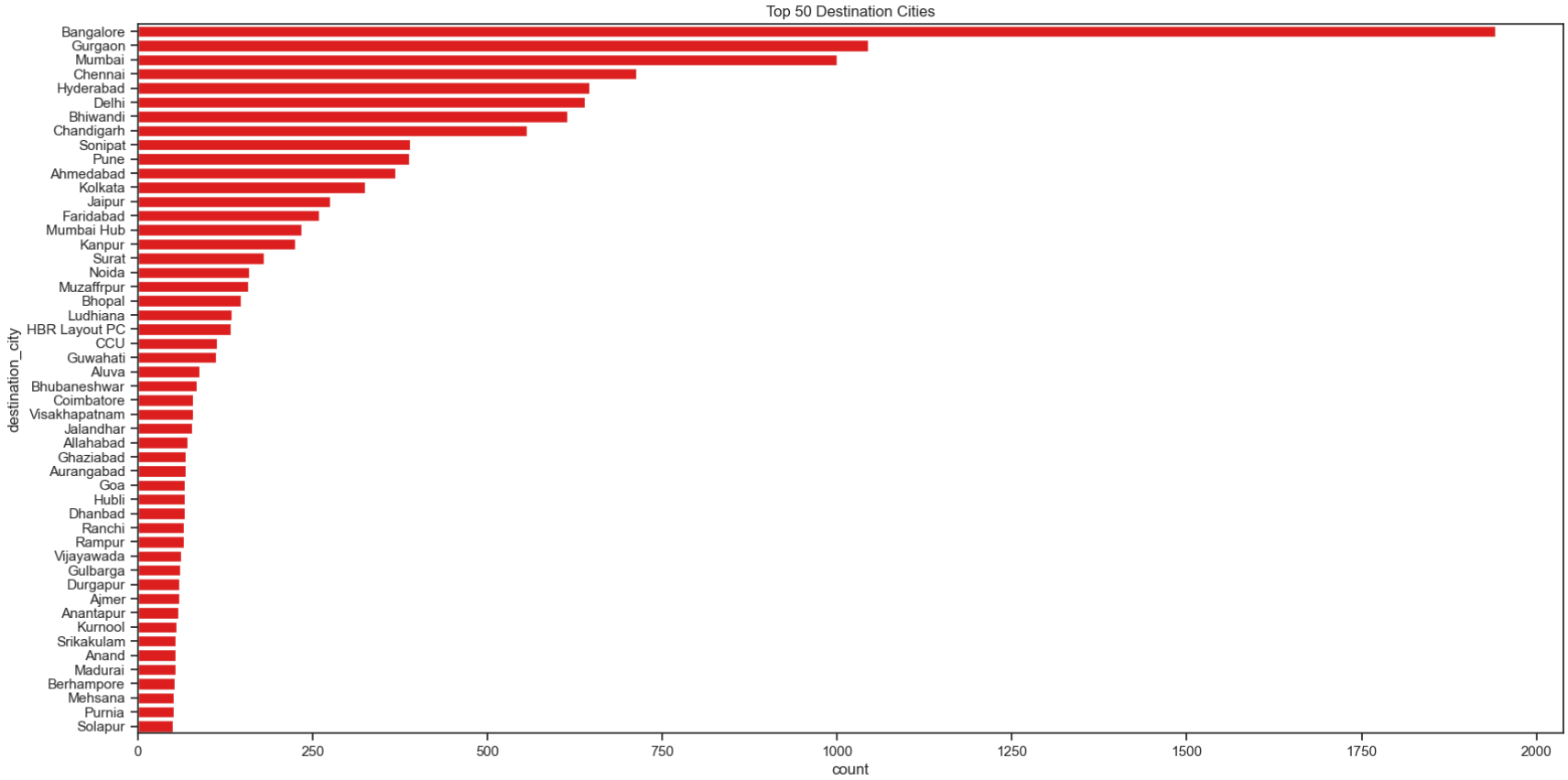
Most orders are coming from and delivery to?

In [32]:
```
# bar plot for the top 50 source city
frequenct_source_city = dd_grouped['source_city'].value_counts().reset_index(name='count').head(50)
plt.figure(figsize=(20, 10))
sns.barplot(y='source_city', x='count', data=frequenct_source_city, color='r')
plt.title("Top 50 Source Cities")
plt.show()
```



- Most of the orders are coming from:
  - Bangalore
  - Gurgaon
  - Bhiwandi
  - Delhi
  - Mumbai
  - Chennai

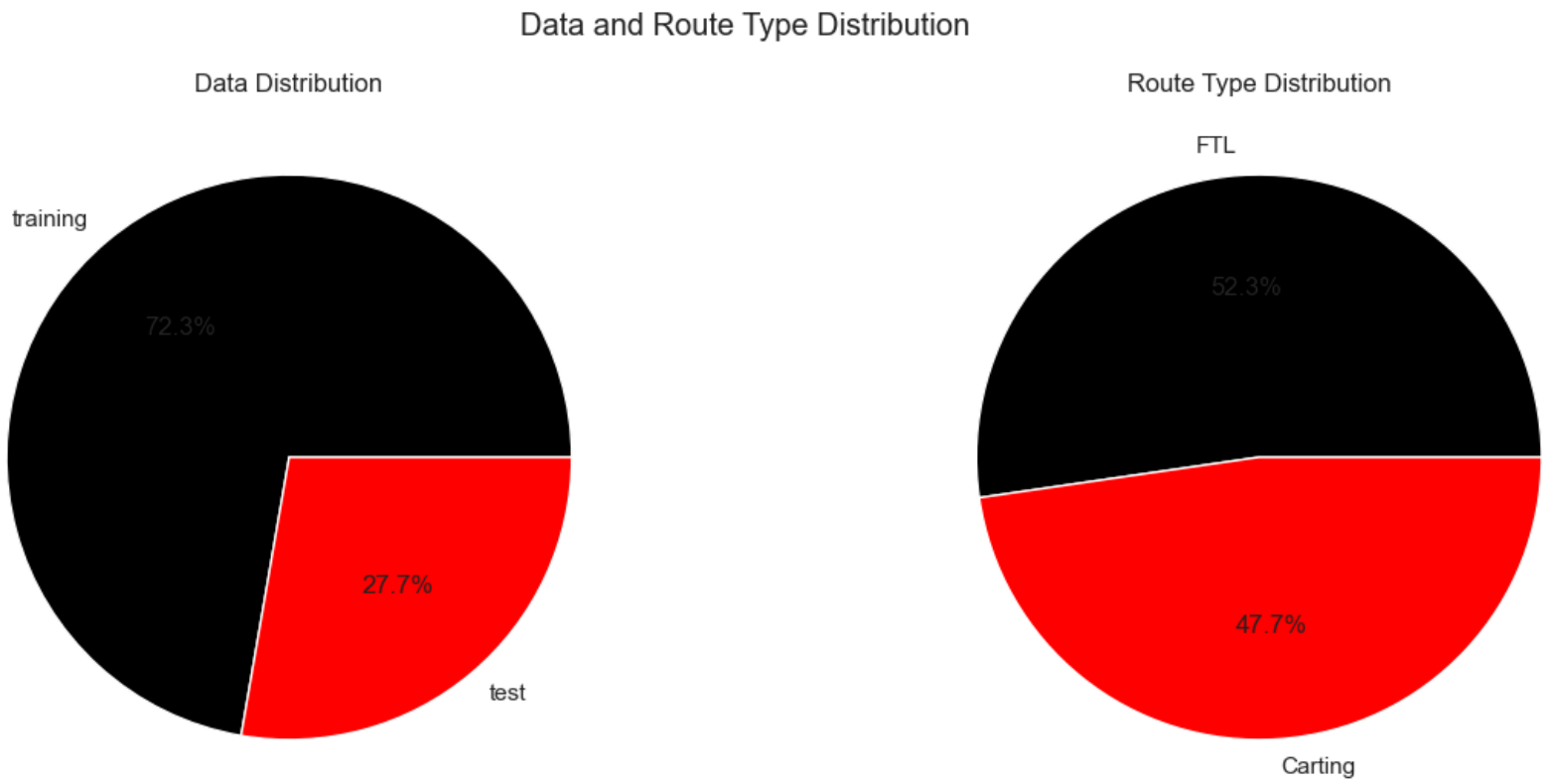
In [33]:
```
frequenct_destination_city = dd_grouped['destination_city'].value_counts().reset_index(name='count').head(50)
plt.figure(figsize=(20, 10))
sns.barplot(y='destination_city', x='count', data=frequenct_destination_city, color='r')
plt.title("Top 50 Destination Cities")
plt.show()
```



- Most of the Order are delivered to:
  - Bangalore
  - Gurgaon
  - Mumbai
  - Chennai
  - Hyderabad
  - Delhi

In [34]:
```
plt.figure(figsize=(15, 6))
plt.suptitle("Data and Route Type Distribution")

plt.subplot(1, 2, 1)
plt.pie(dd_grouped['data'].value_counts(), labels = dd_grouped['data'].value_counts().index, autopct='%1.1f%%')
plt.title("Data Distribution")
```

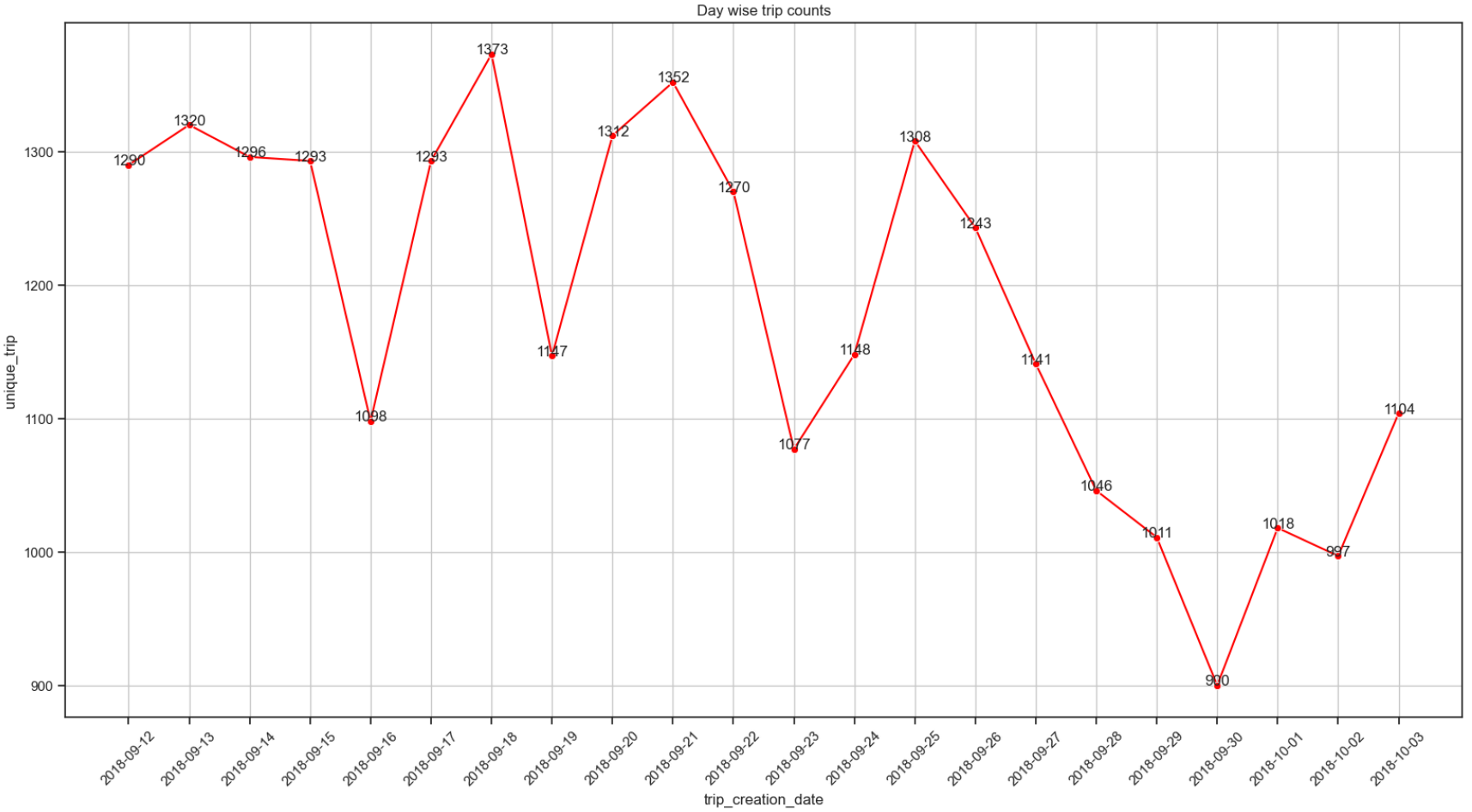
```
plt.subplot(1, 2, 2)
plt.pie(dd_grouped['route_type'].value_counts(), labels = dd_grouped['route_type'].value_counts().index, autopct='%1.1f
plt.title("Route Type Distribution")

plt.show()
```



- The Dataset has 72% data for Training and ~27% of data for Test
- Route Type distribution seems to have similar ratio of data's

In [35]:
```
plt_data = dd_grouped.groupby('trip_creation_date')['unique_trip'].count().reset_index()
plt_data['trip_creation_date'] = pd.to_datetime(plt_data['trip_creation_date'])

plt.figure(figsize=(20, 10))
sns.lineplot(x='trip_creation_date', y='unique_trip', data=plt_data, marker='o', color='r')
plt.title("Day wise trip counts")
```

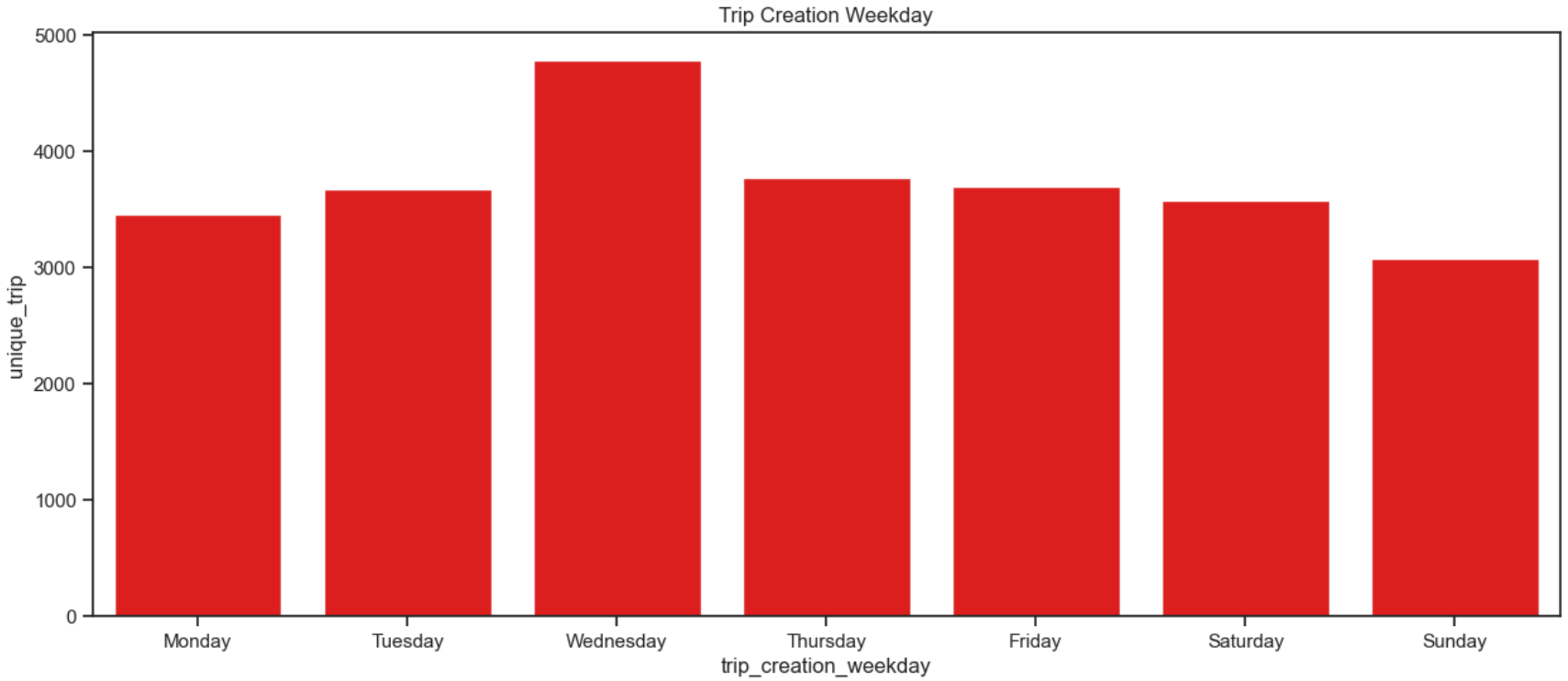
```
plt.xticks(plt_data['trip_creation_date'], rotation=45)
plt.grid()

for i, count in enumerate(plt_data['unique_trip']):
    plt.text(plt_data['trip_creation_date'][i], count, count, ha='center')

plt.show()
```



- Most of the trips are created in the mid of the month.

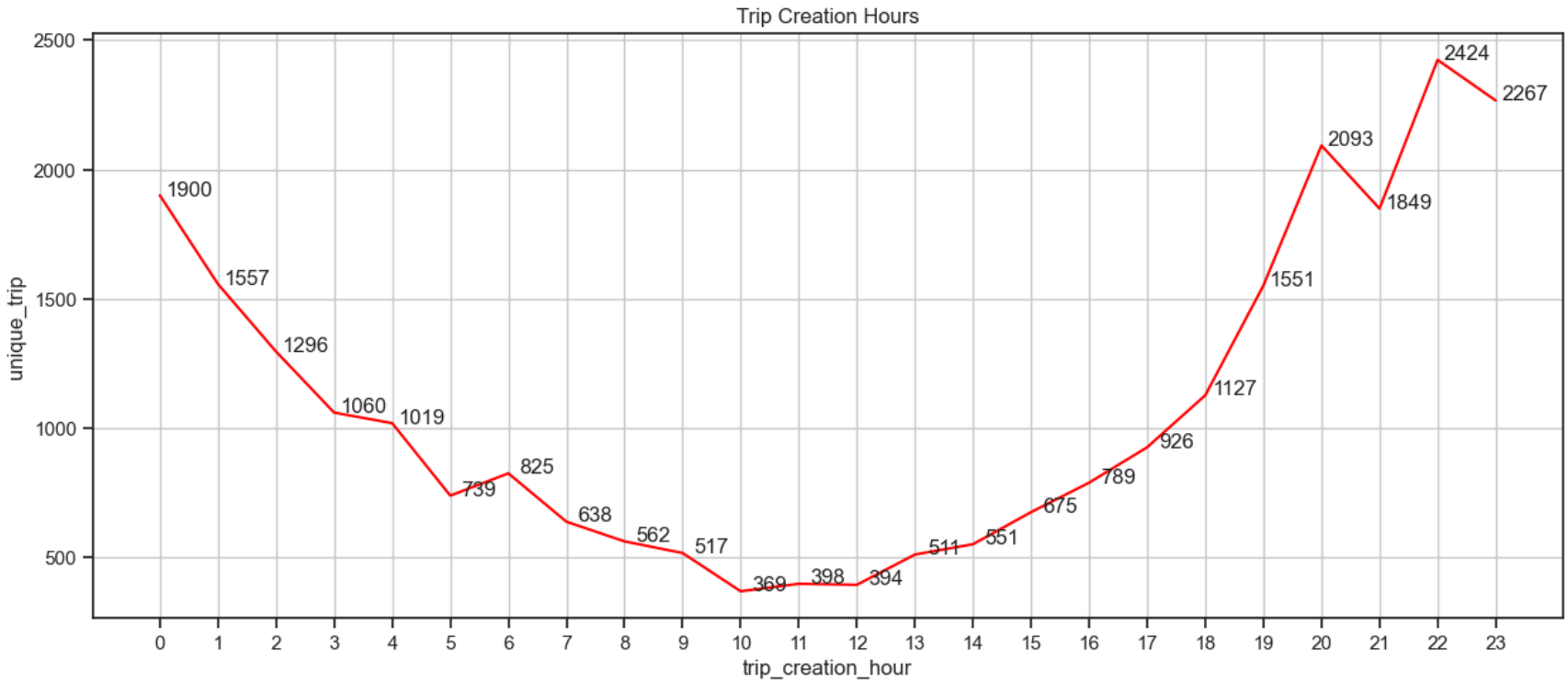
In [36]:
```
plt_data = dd_grouped.groupby('trip_creation_weekday')['unique_trip'].count().reset_index()
plt_data['trip_creation_weekday'] = plt_data['trip_creation_weekday'].map({0: 'Monday', 1: 'Tuesday', 2: 'Wednesday', 3

plt.figure(figsize=(15, 6))
```

```
sns.barplot(x='trip_creation_weekday', y='unique_trip', data=plt_data, color='r')
plt.title("Trip Creation Weekday")
plt.show()
```



- Wednesday has more one of trips compare to other days of the week

In [37]:
```
plt_data = dd_grouped.groupby('trip_creation_hour')['unique_trip'].count().reset_index()

plt.figure(figsize=(15, 6))
sns.lineplot(x='trip_creation_hour', y='unique_trip', data=plt_data, color='r', markers='o')
plt.title("Trip Creation Hours")

plt.xticks(plt_data['trip_creation_hour'])
plt.grid()

for i, count in enumerate(plt_data['unique_trip']):
    plt.text(plt_data['trip_creation_hour'][i]+0.5, count, count, ha='center')


plt.show()
```



- Number of trips start increasing after the noon, becomes maximum at 10 P.M and then start decreasing.

In-depth Analysis 🔬

In [38]:
```
dd_grouped.head()
```

Out[38]:

	unique_trip	trip_uuid	data	trip_creation_time	route_type	source_name	
0	trip-153671041653548748_IND209304AAA_IND000000ACB	trip-153671041653548748	training	2018-09-12 00:00:16.535741	FTL	Kanpur_Central_H_6 (Uttar Pradesh)	
1	trip-153671041653548748_IND462022AAA_IND209304AAA	trip-153671041653548748	training	2018-09-12 00:00:16.535741	FTL	Bhopal_Trnsport_H (Madhya Pradesh)	
2	trip-153671042288605164_IND561203AAB_IND562101AAA	trip-153671042288605164	training	2018-09-12 00:00:22.886430	Carting	Doddablpur_ChikaDPP_D (Karnataka)	
3	trip-153671042288605164_IND572101AAA_IND561203AAB	trip-153671042288605164	training	2018-09-12 00:00:22.886430	Carting	Tumkur_Veersagr_I (Karnataka)	Dc
4	trip-153671043369099517_IND000000ACB_IND160002AAC	trip-153671043369099517	training	2018-09-12 00:00:33.691250	FTL	Gurgaon_Bilaspur_HB (Haryana)	Cha

In [39]:

```
agg_dict = {
    'data':'first',
    'trip_creation_time': 'first',
    'route_type': 'first',
    'source_name': 'first',
    'destination_name': 'first',
    'od_start_time': 'first',
    'od_end_time': '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',
    'source_state': 'first',
    'source_city': 'first',
    'source_code': 'first',
    'destination_state': 'last',
    'destination_city': 'last',
    'destination_code': 'last',
    'trip_creation_date': 'first',
    'trip_creation_day': 'first',
    'trip_creation_hour': 'first',
    'trip_creation_weekday': 'first',
    'trip_creation_week': 'first',
```

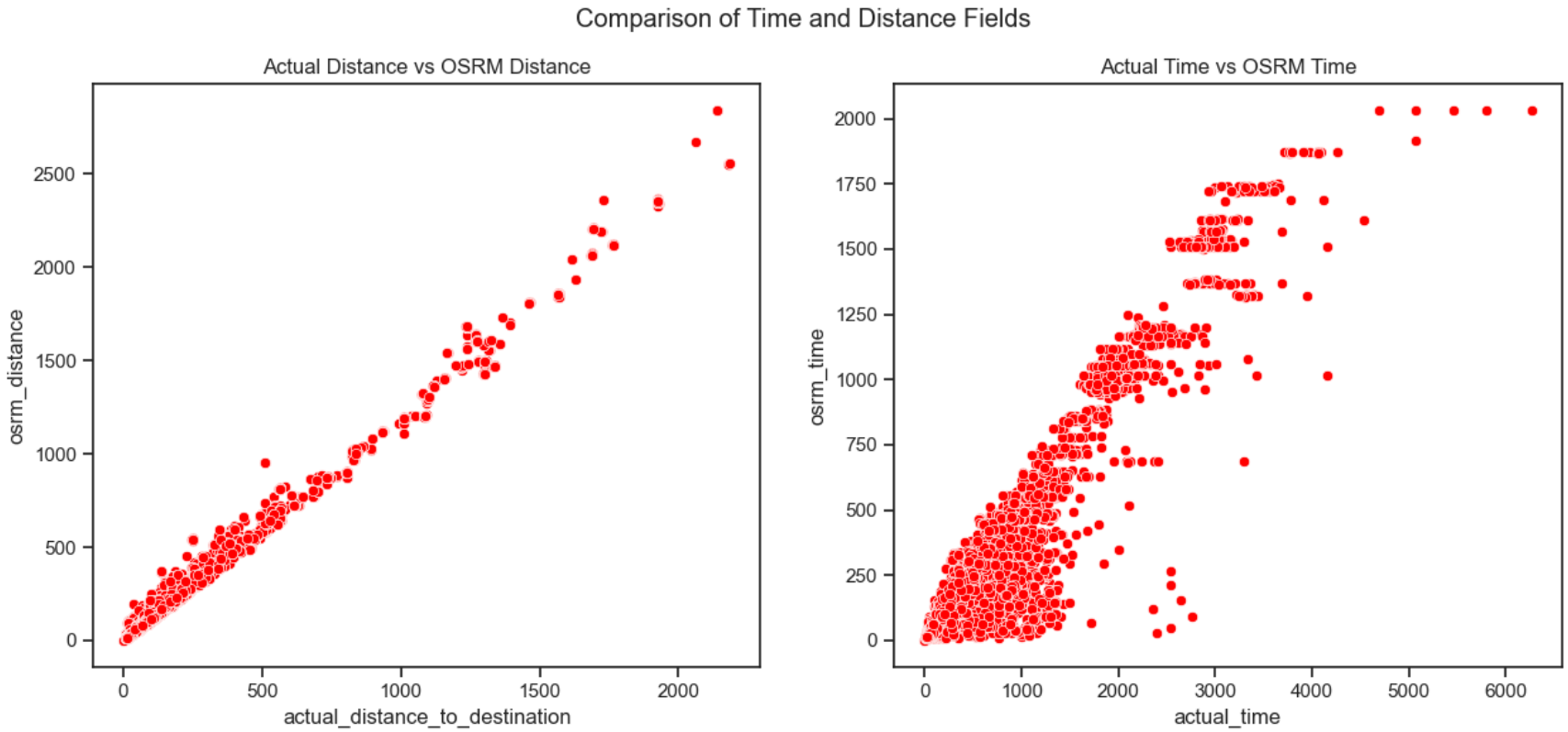
```
    'trip_duration': 'sum'
}

dd_trips = dd_grouped.groupby(by="trip_uuid", as_index=False).agg(agg_dict)
```

In [40]:
```
dd_trips.head()
```

Out[40]:

	trip_uuid	data	trip_creation_time	route_type	source_name	destination_name	od_start_time	od_end_tim
0	trip-153671041653548748	training	2018-09-12 00:00:16.535741	FTL	Kanpur_Central_H_6 (Uttar Pradesh)	Gurgaon_Bilaspur_HB (Haryana)	2018-09-12 16:39:46.858469	2018-09-16:39:46.8584
1	trip-153671042288605164	training	2018-09-12 00:00:22.886430	Carting	Doddablpur_ChikaDPP_D (Karnataka)	Chikblapur_ShntiSgr_D (Karnataka)	2018-09-12 02:03:09.655591	2018-09-02:03:09.6555
2	trip-153671043369099517	training	2018-09-12 00:00:33.691250	FTL	Gurgaon_Bilaspur_HB (Haryana)	Chandigarh_Mehmdpur_H (Punjab)	2018-09-14 03:40:17.106733	2018-09-03:40:17.1067
3	trip-153671046011330457	training	2018-09-12 00:01:00.113710	Carting	Mumbai Hub (Maharashtra)	Mumbai_MiraRd_IP (Maharashtra)	2018-09-12 00:01:00.113710	2018-09-01:41:29.8098
4	trip-153671052974046625	training	2018-09-12 00:02:09.740725	FTL	Bellary_Dc (Karnataka)	Hospet (Karnataka)	2018-09-12 00:02:09.740725	2018-09-03:54:43.1144

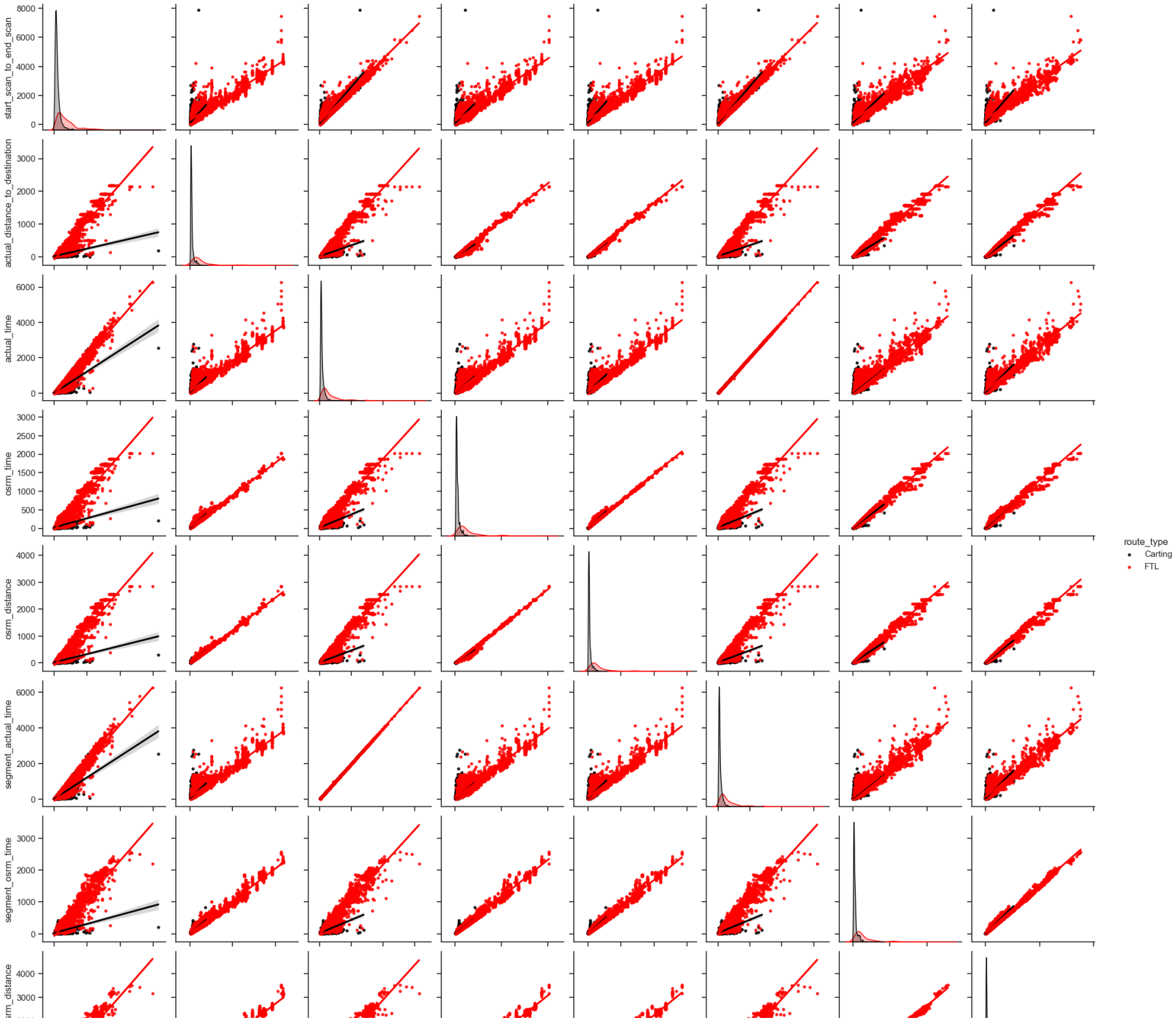
In [41]:
```
# Comparison & Visualization of time and distance fields
plt.figure(figsize=(15, 6))
plt.suptitle("Comparison of Time and Distance Fields")

plt.subplot(1, 2, 1)
sns.scatterplot(x='actual_distance_to_destination', y='osrm_distance', data=dd_trips, color='r')
plt.title("Actual Distance vs OSRM Distance")

plt.subplot(1, 2, 2)
sns.scatterplot(x='actual_time', y='osrm_time', data=dd_trips, color='r')
plt.title("Actual Time vs OSRM Time")

plt.show()
```

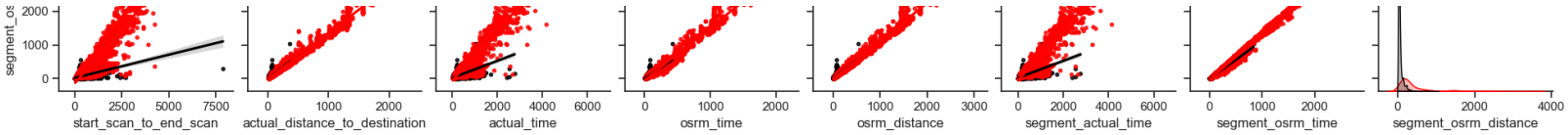


- Actual Time taken is higher than the OSRM time, An open-source routing engine time calculator need to be improved

In [42]:
```
numeric_cols = dd_trips.select_dtypes(include=['float16', 'float32']).columns
```

In [43]:
```
sns.pairplot(data = dd_trips,
 vars = numeric_cols,
 kind = 'reg',
 hue = 'route_type',
 markers = '.')
plt.plot()
plt.show()
```


start_scan_to_end_scan
actual_distance_to_destination
actual_time
osrm_time
osrm_distance
segment_actual_time
segment_osrm_time
osrm_distance
route_type
Carting
FTL

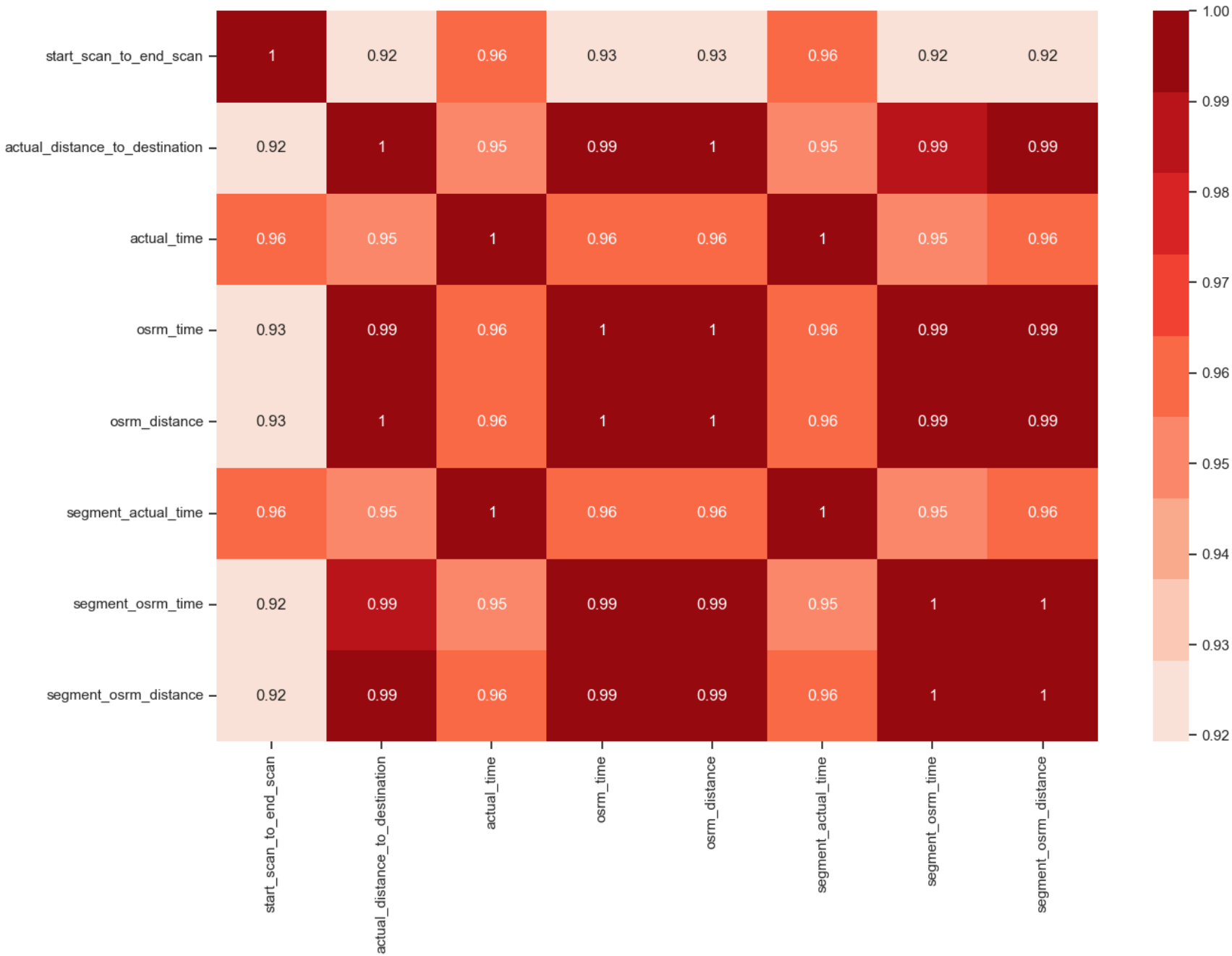


In [44]:
```
df_corr = dd_trips[numeric_cols].corr()
df_corr
```

Out[44]:

	start_scan_to_end_scan	actual_distance_to_destination	actual_time	osrm_time	osrm_distance	segment_actual_tim
start_scan_to_end_scan	1.000000	0.919262	0.961725	0.927717	0.925342	0.9617
actual_distance_to_destination	0.919262	1.000000	0.954023	0.993579	0.997276	0.9530
actual_time	0.961725	0.954023	1.000000	0.958931	0.959503	0.9999
osrm_time	0.927717	0.993579	0.958931	1.000000	0.997591	0.9581
osrm_distance	0.925342	0.997276	0.959503	0.997591	1.000000	0.9586
segment_actual_time	0.961748	0.953092	0.999989	0.958108	0.958648	1.0000
segment_osrm_time	0.919690	0.987587	0.954207	0.993287	0.991830	0.9533
segment_osrm_distance	0.920326	0.993094	0.957256	0.991639	0.994726	0.9564

In [45]:
```
plt.figure(figsize=(15, 10))
sns.heatmap(df_corr, annot=True, cmap=sns.color_palette("Reds", n_colors=9))
plt.show()
```



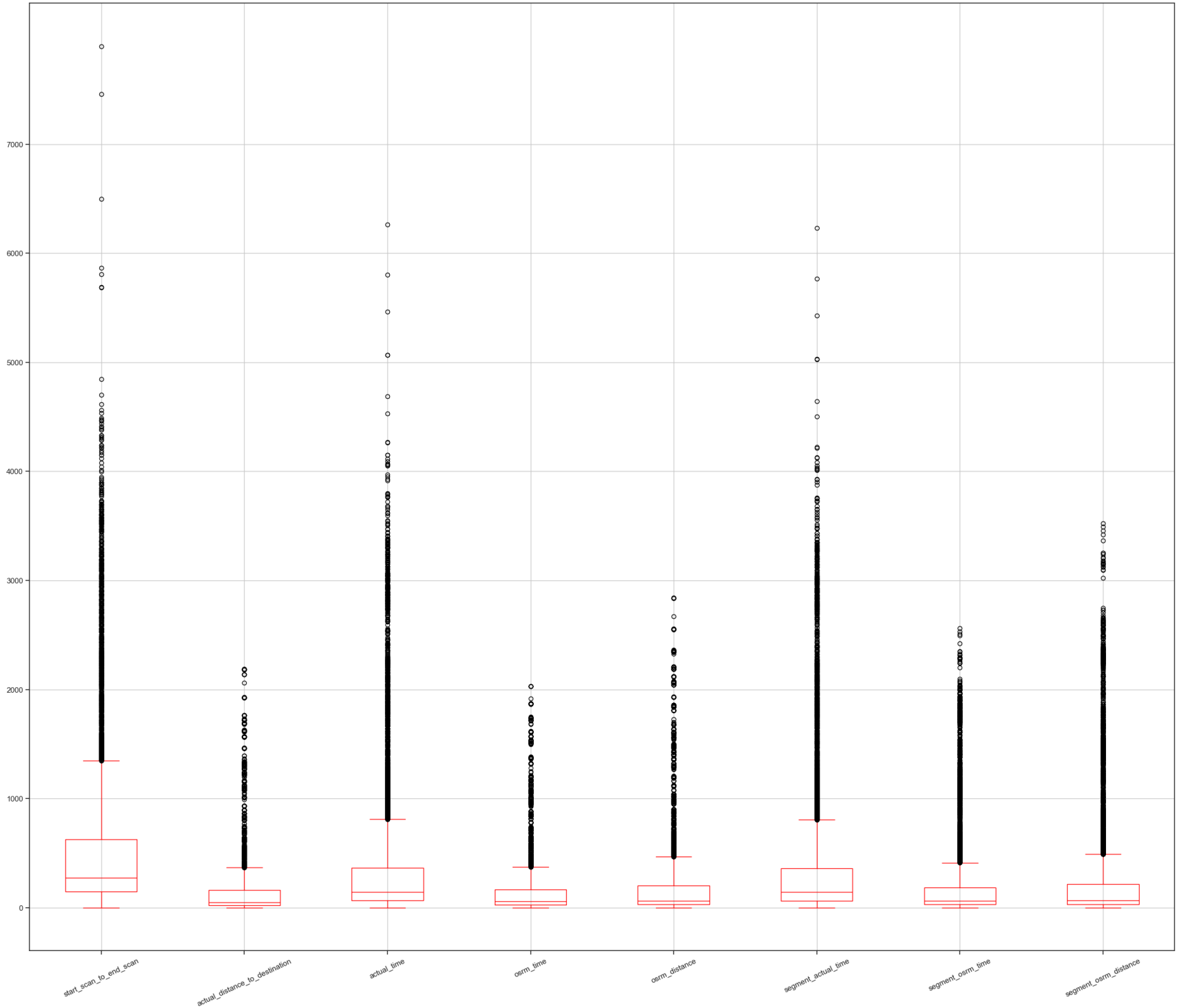
- Seems all the numerical data are highly correlated

In [46]:
```
dd_trips.skew(numeric_only = True)
```

Out[46]:
```
start_scan_to_end_scan            2.895575
actual_distance_to_destination    3.567667
actual_time                       3.377693
osrm_time                             <NA>
osrm_distance                     3.557269
segment_actual_time               3.374549
segment_osrm_time                 3.605595
segment_osrm_distance             3.717643
trip_creation_day                -0.693341
trip_creation_hour                -0.20518
trip_creation_weekday             0.065151
trip_creation_week                0.187824
dtype: Float64
```

- Most of the data are Right-Skewed.

In [47]:
```
plt.figure(figsize=(30, 25))
dd_trips[numeric_cols].boxplot(rot=25, figsize=(35,20), color = 'r')

max_y = dd_trips[numeric_cols].max().max()
yticks = np.arange(0, max_y, 1000)

plt.yticks(yticks)
plt.show()
```


7000
6000
5000
4000
3000
2000
1000
0
start_scan_to_end_scan
actual_distance_to_destination
actual_time
osrm_time
osrm_distance
segment_actual_time
segment_osrm_time
segment_osrm_distance

- The outliers present in our sample data.

In [48]:
```
for col in numeric_cols:
    Q1 = np.quantile(dd_trips[col], 0.25)
    Q3 = np.quantile(dd_trips[col], 0.75)
    IQR = Q3 - Q1
    LB = Q1 - 1.5 * IQR
    UB = Q3 + 1.5 * IQR
    outliers = dd_trips.loc[(dd_trips[col] < LB) | (dd_trips[col] > UB)]
    print('Column :', col)
    print(f'\t Q1 : {round(Q1,3)}\n\t Q3 : {round(Q3,3)}\n\t IQR : {round(IQR,3)}\n\t LB : {round(LB,3)}\n\t UB : {roun
    print("- -"*20)
```

```
Column : start_scan_to_end_scan
         Q1 : 147.0
         Q3 : 628.0
         IQR : 481.0
         LB : -574.5
         UB : 1349.5
         Number of outliers : 1301
- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -
Column : actual_distance_to_destination
         Q1 : 22.328
         Q3 : 161.562
         IQR : 139.234
         LB : -186.523
         UB : 370.414
         Number of outliers : 1477
- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -
Column : actual_time
         Q1 : 66.0
         Q3 : 364.0
         IQR : 298.0
         LB : -381.0
         UB : 811.0
         Number of outliers : 1660
- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -
Column : osrm_time
         Q1 : 29.0
         Q3 : 167.0
         IQR : 138.0
         LB : -178.0
         UB : 374.0
         Number of outliers : 1510
- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -
Column : osrm_distance
         Q1 : 30.203
         Q3 : 204.969
         IQR : 174.766
         LB : -231.945
         UB : 467.117
         Number of outliers : 1531
- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -
Column : segment_actual_time
         Q1 : 65.0
         Q3 : 362.0
         IQR : 297.0
         LB : -380.5
```

```
        UB : 807.5
        Number of outliers : 1655
- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -
Column : segment_osrm_time
        Q1 : 30.0
        Q3 : 183.0
        IQR : 153.0
        LB : -199.5
        UB : 412.5
        Number of outliers : 1501
- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -
Column : segment_osrm_distance
        Q1 : 31.828
        Q3 : 215.195
        IQR : 183.367
        LB : -243.223
        UB : 490.246
        Number of outliers : 1558
- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -
```

Outlier Treatment

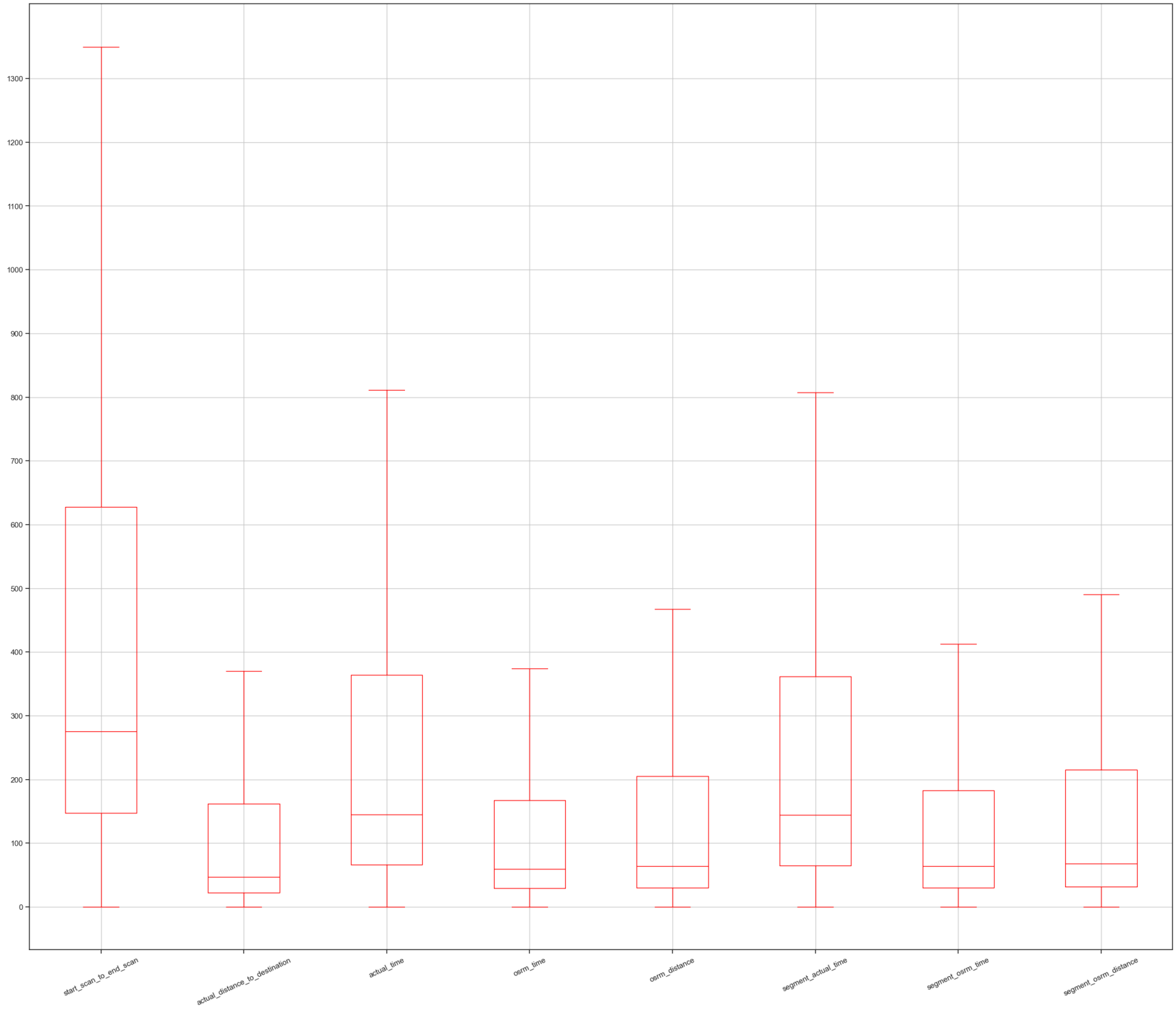
- Removing the outliers, but some outliers represent natural variations in the population

In [49]:
```python
# Reduce the outliers

for col in numeric_cols:
    Q1 = np.quantile(dd_trips[col], 0.25)
    Q3 = np.quantile(dd_trips[col], 0.75)
    IQR = Q3 - Q1
    LB = Q1 - 1.5 * IQR
    UB = Q3 + 1.5 * IQR
    dd_trips[col] = np.where(dd_trips[col] < LB, LB, dd_trips[col])
    dd_trips[col] = np.where(dd_trips[col] > UB, UB, dd_trips[col])
```

In [50]:
```python
dd_trips.skew(numeric_only = True)
```

Out[50]:
```
start_scan_to_end_scan            1.161804
actual_distance_to_destination    1.276377
actual_time                       1.167957
osrm_time                             <NA>
osrm_distance                     1.273736
segment_actual_time               1.172869
segment_osrm_time                 1.242727
segment_osrm_distance             1.260448
trip_creation_day                -0.693341
trip_creation_hour                -0.20518
trip_creation_weekday             0.065151
trip_creation_week                0.187824
dtype: Float64
```

In [51]:
```
plt.figure(figsize=(30, 25))
dd_trips[numeric_cols].boxplot(rot=25, figsize=(35,20), color = 'r')

max_y = dd_trips[numeric_cols].max().max()
yticks = np.arange(0, max_y,100)

plt.yticks(yticks)
plt.show()
```


1300
1200
1100
1000
900
800
700
600
500
400
300
200
100
0
start_scan_to_end_scan
actual_distance_to_destination
actual_time
osrm_time
osrm_distance
segment_actual_time
segment_osrm_time
segment_osrm_distance

Column Encoding *

- Using one-hot encoding

In [52]:
```
one_hot_cols = ['data', 'route_type']
dd_trips = pd.get_dummies(dd_trips, columns=one_hot_cols, drop_first=True)
dd_trips.head()
```

Out[52]:

	trip_uuid	trip_creation_time	source_name	destination_name	od_start_time	od_end_time	start_scan_to_end_
0	trip-153671041653548748	2018-09-12 00:00:16.535741	Kanpur_Central_H_6 (Uttar Pradesh)	Gurgaon_Bilaspur_HB (Haryana)	2018-09-12 16:39:46.858469	2018-09-12 16:39:46.858469	1
1	trip-153671042288605164	2018-09-12 00:00:22.886430	Doddablpur_ChikaDPP_D (Karnataka)	Chikblapur_ShntiSgr_D (Karnataka)	2018-09-12 02:03:09.655591	2018-09-12 02:03:09.655591	
2	trip-153671043369099517	2018-09-12 00:00:33.691250	Gurgaon_Bilaspur_HB (Haryana)	Chandigarh_Mehmdpur_H (Punjab)	2018-09-14 03:40:17.106733	2018-09-14 03:40:17.106733	1
3	trip-153671046011330457	2018-09-12 00:01:00.113710	Mumbai Hub (Maharashtra)	Mumbai_MiraRd_IP (Maharashtra)	2018-09-12 00:01:00.113710	2018-09-12 01:41:29.809822	
4	trip-153671052974046625	2018-09-12 00:02:09.740725	Bellary_Dc (Karnataka)	Hospet (Karnataka)	2018-09-12 00:02:09.740725	2018-09-12 03:54:43.114421	

In-depth analysis 🔎

Hypothesis testing between actual_time aggregated value and OSRM time aggregated value

- STEP-1 : Set up Null Hypothesis
  - Null Hypothesis (H0) - actual_time (Actual time taken to complete the delivery) and OSRM time (An open-source routing engine time calculator time) are same.
  - Alternate Hypothesis (HA) - actual_time and OSRM time are different.
- STEP-2 : Checking for basic assumptions for the hypothesis

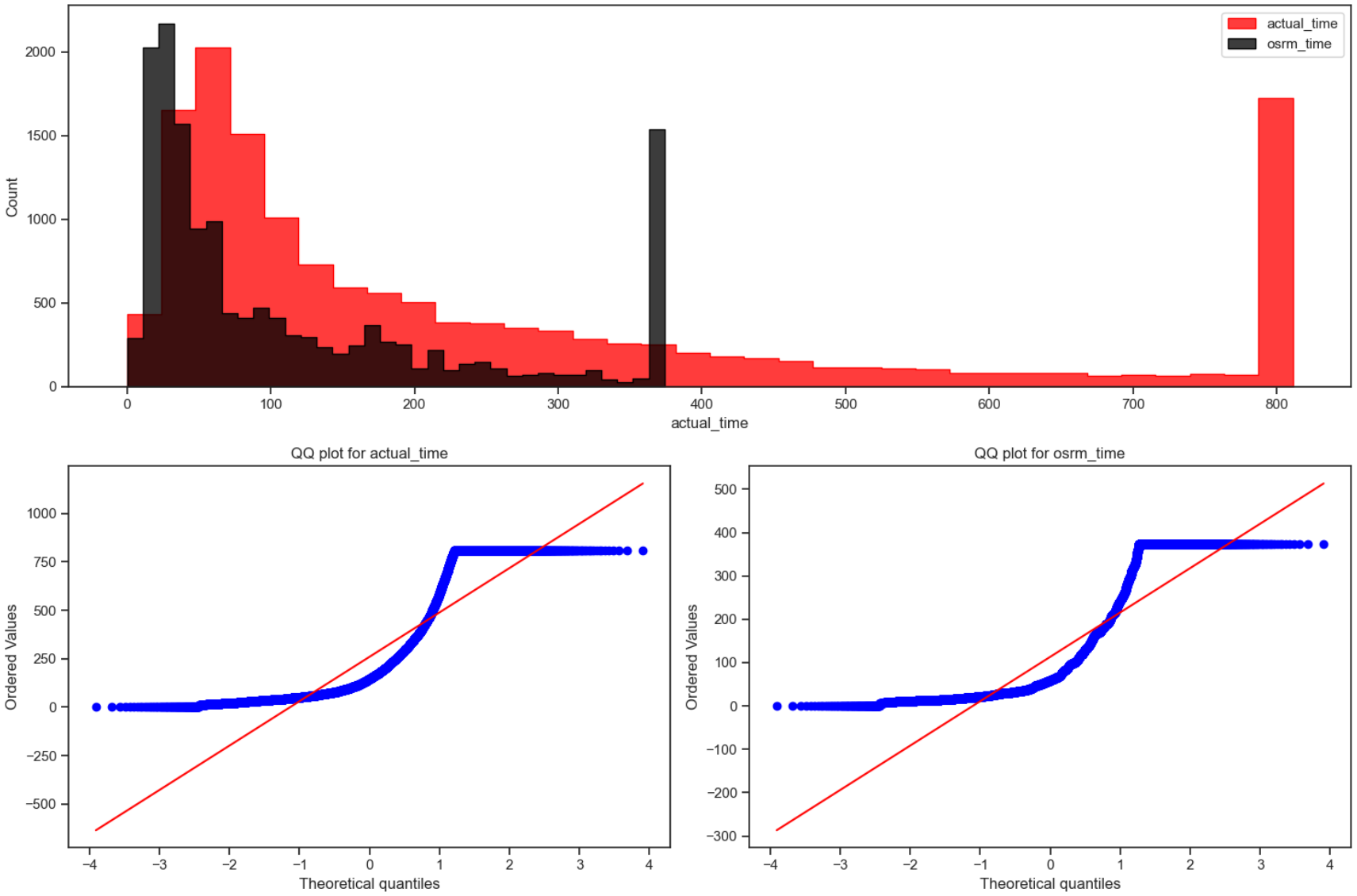
- STEP-3: Define Test statistics; Distribution of T under H0.
- STEP-4: Compute the p-value and fix value of alpha. We set our alpha to be 0.05
- STEP-5: Compare p-value and alpha. Based on p-value, we will accept or reject H0.
    1. p-val > alpha : Accept H0
    2. p-val < alpha : Reject H0

In [53]:
```
dd_trips[['actual_time', 'osrm_time']].describe()
```

Out[53]:

	actual_time	osrm_time
count	14817.000000	14817.0
mean	259.478088	inf
std	257.924866	inf
min	0.000000	0.0
25%	66.000000	29.0
50%	145.000000	59.0
75%	364.000000	167.0
max	811.000000	374.0

In [54]:
```
plt.figure(figsize=(15, 10))

# Histogram for actual_time and osrm_time
plt.subplot(2, 1, 1)
sns.histplot(dd_trips['actual_time'], element = 'step', color = 'red')
sns.histplot(dd_trips['osrm_time'], element = 'step', color = 'black')
plt.legend(['actual_time', 'osrm_time'])

plt.subplot(2, 2, 3)
stats.probplot(dd_trips['actual_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for actual_time')

plt.subplot(2, 2, 4)
stats.probplot(dd_trips['osrm_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for osrm_time')

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



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

In [55]:
```
test_stat, p_value = stats.mannwhitneyu(dd_trips['actual_time'], dd_trips['osrm_time'])
print('p-value', p_value)
if p_value < 0.05:
 print('actual_time and OSRM time are different.')
```

```
else:
 print('actual_time (Actual time taken to complete the delivery) and OSRM time (An open-source routing engine time calcu
```

```
p-value 0.0
actual_time and OSRM time are different.
```

👁 Since P Value is less that the significance threshold, therfore it can be concluded that actual_time (Actual time taken to complete the delivery) and OSRM time (An open-source routing engine time calculator time) are different

---

Hypothesis testing between actual_time aggregated value and segment actual time aggregated value

- STEP-1 : Set up Null Hypothesis
  - Null Hypothesis (H0) - actual_time (Actual time taken to complete the delivery) and segment actual time (Time taken by the subset of the package delivery) are same.
  - Alternate Hypothesis (HA) - actual_time and segment actual time are different.
- STEP-2 : Checking for basic assumptions for the hypothesis
- STEP-3: Define Test statistics; Distribution of T under H0.
- STEP-4: Compute the p-value and fix value of alpha. We set our alpha to be 0.05
- STEP-5: Compare p-value and alpha. Based on p-value, we will accept or reject H0.
  1. p-val > alpha : Accept H0
  2. p-val < alpha : Reject H0

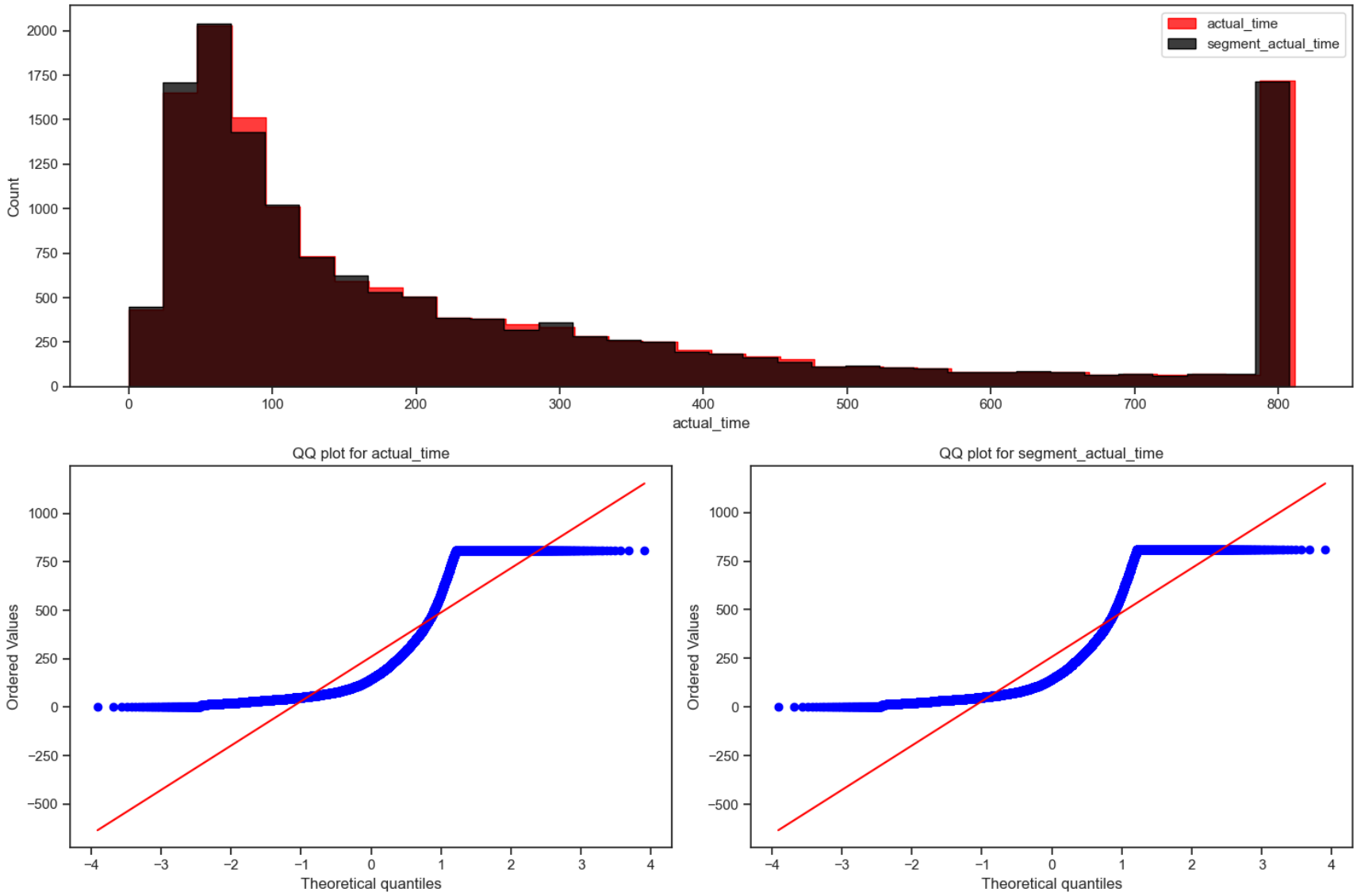
In [56]:
```
dd_trips[['actual_time', 'segment_actual_time']].describe()
```

Out[56]:

	actual_time	segment_actual_time
count	14817.000000	14817.000000
mean	259.478088	257.503387
std	257.924866	256.707428
min	0.000000	0.000000
25%	66.000000	65.000000
50%	145.000000	144.000000
75%	364.000000	362.000000
max	811.000000	807.500000

In [57]:

```
plt.figure(figsize=(15, 10))

# Histogram for actual_time and segment_actual_time
plt.subplot(2, 1, 1)
sns.histplot(dd_trips['actual_time'], element = 'step', color = 'red')
sns.histplot(dd_trips['segment_actual_time'], element = 'step', color = 'black')
plt.legend(['actual_time', 'segment_actual_time'])

plt.subplot(2, 2, 3)
stats.probplot(dd_trips['actual_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for actual_time')

plt.subplot(2, 2, 4)
stats.probplot(dd_trips['segment_actual_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for segment_actual_time')

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



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

In [58]:
```
test_stat, p_value = stats.mannwhitneyu(dd_trips['actual_time'], dd_trips['segment_actual_time'])
print('p-value', p_value)
if p_value < 0.05:
 print('actual_time and segment actual time are different.')
else:
 print('actual_time (Actual time taken to complete the delivery) and segment actual time (Time taken by the subset of th
```

```
p-value 0.007404217536110528
actual_time and segment actual time are different.
```

👁 Since P Value is less that the significance threshold, therfore it can be concluded that actual_time (Actual time taken to complete the delivery) and segment actual time (Time taken by the subset of the package delivery) are different

---

Hypothesis testing between osrm distance aggregated value and segment osrm distance aggregated value

- STEP-1 : Set up Null Hypothesis
  - Null Hypothesis (H0) - osrm distance (An open-source routing engine which computes the shortest path between points) and segment osrm distance (OSRM Distance covered by subset of the package delivery) are same.
  - Alternate Hypothesis (HA) - osrm distance and segment osrm distance are different.
- STEP-2 : Checking for basic assumptions for the hypothesis
- STEP-3: Define Test statistics; Distribution of T under H0.
- STEP-4: Compute the p-value and fix value of alpha. We set our alpha to be 0.05
- STEP-5: Compare p-value and alpha. Based on p-value, we will accept or reject H0.
  1. p-val > alpha : Accept H0
  2. p-val < alpha : Reject H0

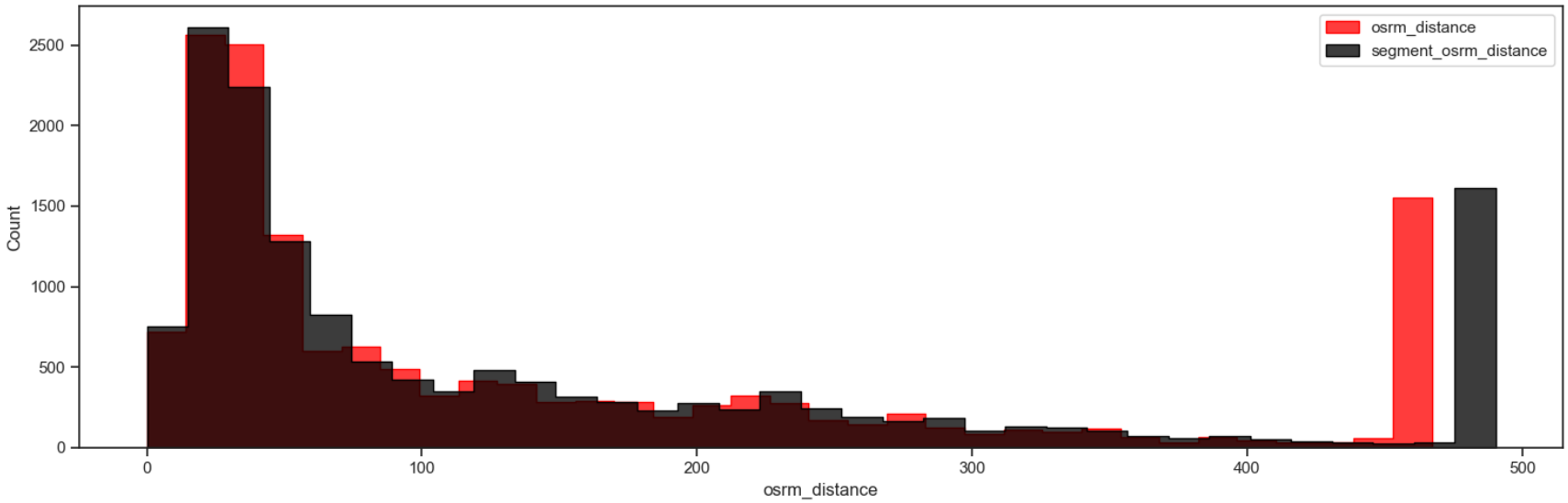
In [59]:
```
dd_trips[['osrm_distance', 'segment_actual_time']].describe()
```

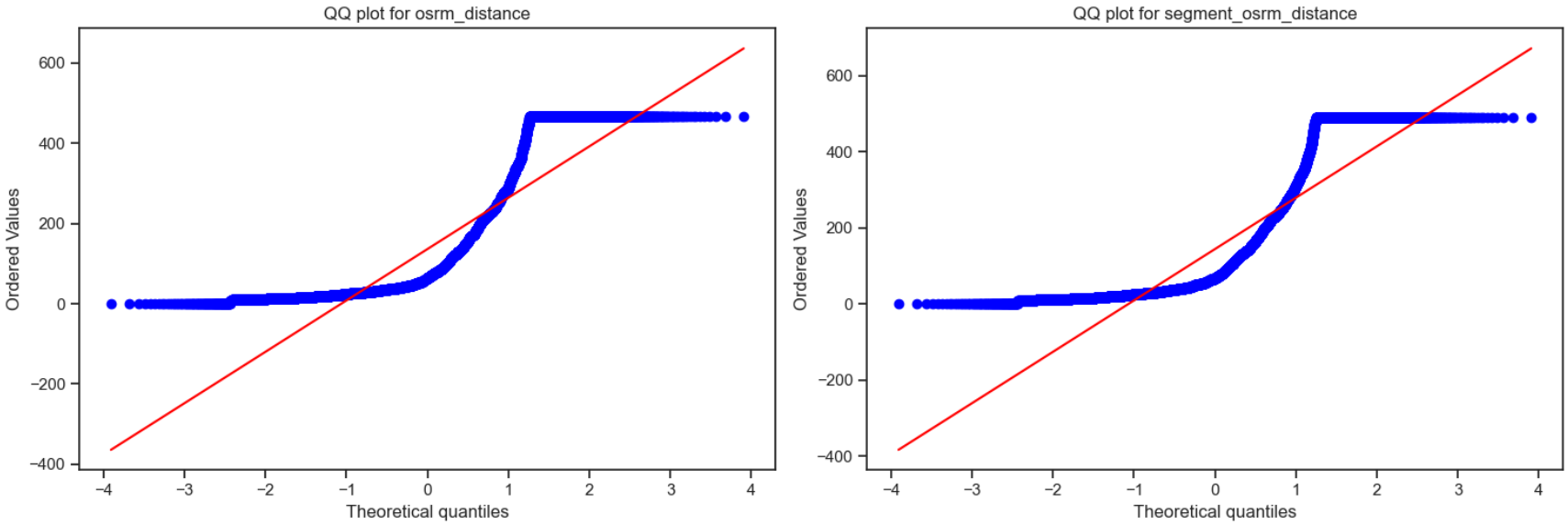
Out[59]:

	osrm_distance	segment_actual_time
count	14817.000000	14817.000000
mean	136.059814	257.503387
std	145.850739	256.707428
min	0.000000	0.000000
25%	30.203125	65.000000
50%	64.078125	144.000000
75%	204.968750	362.000000
max	467.117188	807.500000

In [60]:

```
plt.figure(figsize=(15, 10))

# Histogram for osrm_distance and segment_osrm_distance
plt.subplot(2, 1, 1)
sns.histplot(dd_trips['osrm_distance'], element = 'step', color = 'red')
sns.histplot(dd_trips['segment_osrm_distance'], element = 'step', color = 'black')
plt.legend(['osrm_distance', 'segment_osrm_distance'])

plt.subplot(2, 2, 3)
stats.probplot(dd_trips['osrm_distance'], plot = plt, dist = 'norm')
plt.title('QQ plot for osrm_distance')

plt.subplot(2, 2, 4)
stats.probplot(dd_trips['segment_osrm_distance'], plot = plt, dist = 'norm')
plt.title('QQ plot for segment_osrm_distance')

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





In [61]:
```
test_stat, p_value = stats.mannwhitneyu(dd_trips['osrm_distance'], dd_trips['segment_osrm_distance'])
print('p-value', p_value)
if p_value < 0.05:
 print('osrm distance and segment osrm distance are different.')
else:
 print('osrm distance (An open-source routing engine which computes the shortest path between points) and segment osrm (
```

```
p-value 1.156125417216877e-10
osrm distance and segment osrm distance are different.
```

👁 Since P Value is less that the significance threshold, therfore it can be concluded that osrm distance (An open-source routing engine which computes the shortest path between points) and segment osrm distance (OSRM Distance covered by subset of the package delivery) are different

---

Hypothesis testing between osrm time aggregated value and segment osrm time aggregated value

- STEP-1 : Set up Null Hypothesis
  - Null Hypothesis (H0) - osrm time (An open-source routing engine time) and segment osrm time (OSRM segment time taken by the subset of the package delivery) are same.
  - Alternate Hypothesis (HA) - osrm time and segment osrm time are different.
- STEP-2 : Checking for basic assumptions for the hypothesis
- STEP-3: Define Test statistics; Distribution of T under H0.
- STEP-4: Compute the p-value and fix value of alpha. We set our alpha to be 0.05
- STEP-5: Compare p-value and alpha. Based on p-value, we will accept or reject H0.
  1. p-val > alpha : Accept H0
  2. p-val < alpha : Reject H0

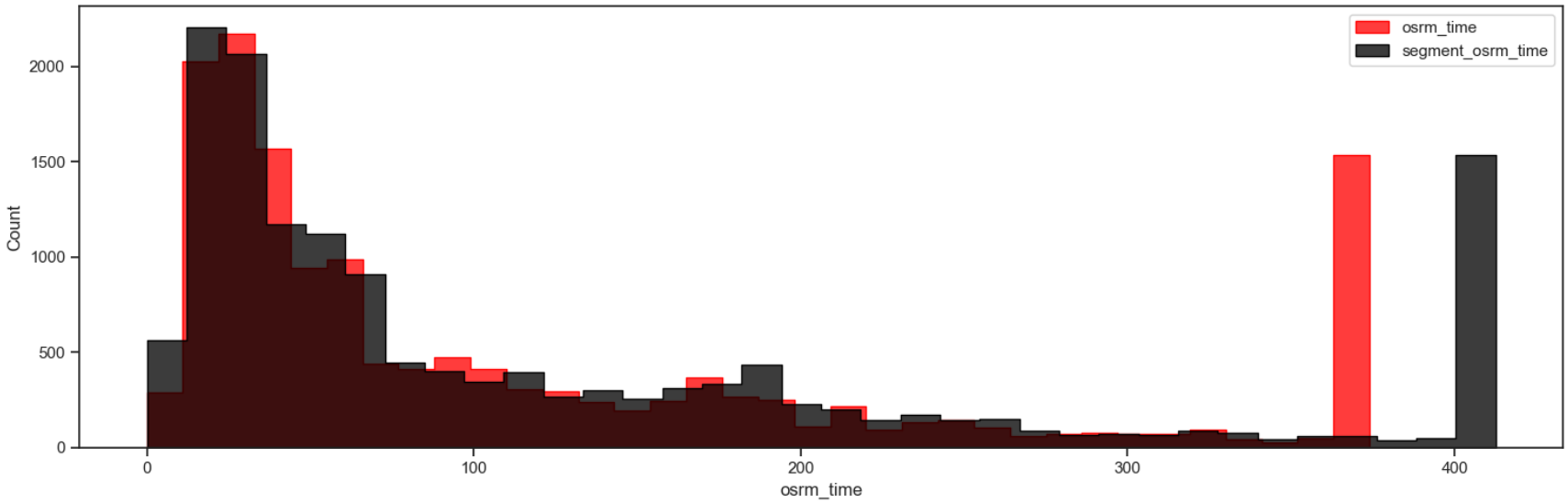
In [62]:
```
dd_trips[['osrm_time', 'segment_osrm_time']].describe()
```

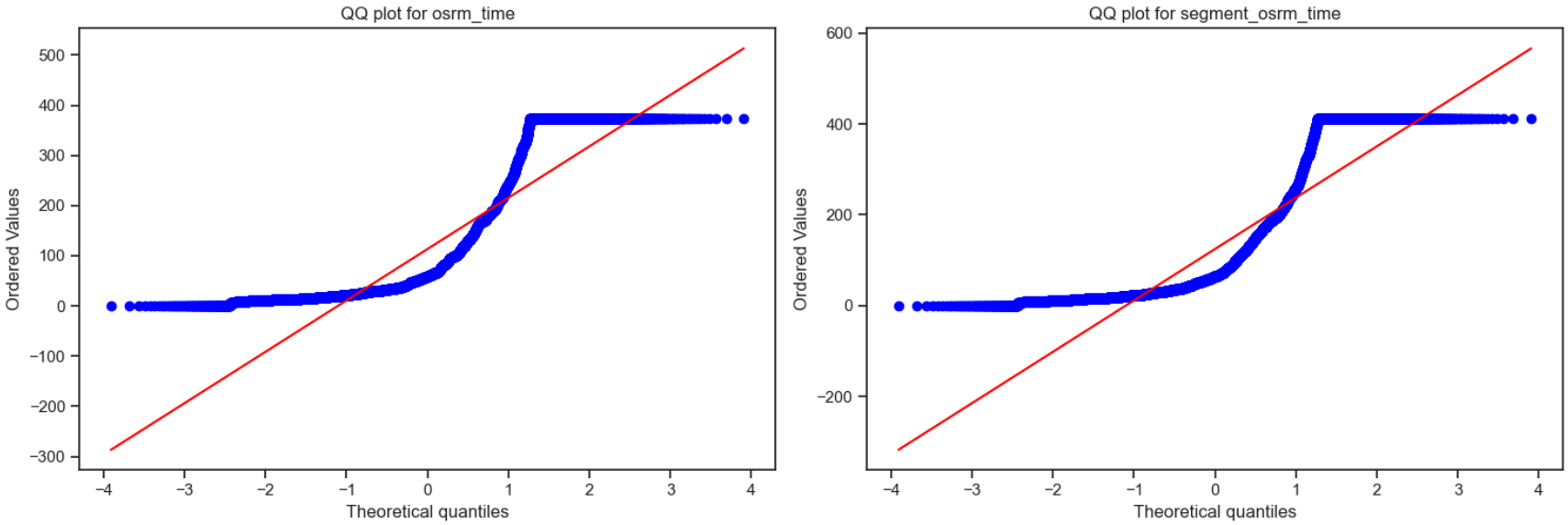
Out[62]:

	osrm_time	segment_osrm_time
count	14817.0	14817.000000
mean	inf	124.304619
std	inf	127.660896
min	0.0	0.000000
25%	29.0	30.000000
50%	59.0	64.000000
75%	167.0	183.000000
max	374.0	412.500000

In [63]:

```
plt.figure(figsize=(15, 10))

# Histogram for osrm_time and segment_osrm_time
plt.subplot(2, 1, 1)
sns.histplot(dd_trips['osrm_time'], element = 'step', color = 'red')
sns.histplot(dd_trips['segment_osrm_time'], element = 'step', color = 'black')
plt.legend(['osrm_time', 'segment_osrm_time'])

plt.subplot(2, 2, 3)
stats.probplot(dd_trips['osrm_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for osrm_time')

plt.subplot(2, 2, 4)
stats.probplot(dd_trips['segment_osrm_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for segment_osrm_time')

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





In [64]:
```
test_stat, p_value = stats.mannwhitneyu(dd_trips['osrm_time'], dd_trips['segment_osrm_time'])
print('p-value', p_value)
if p_value < 0.05:
 print('osrm time and segment osrm time are different.')
else:
 print('osrm time (An open-source routing engine time) and segment osrm time (OSRM segment time taken by the subset of t
```

```
p-value 1.7858750648454436e-12
osrm time and segment osrm time are different.
```

👁 Since P Value is less that the significance threshold, therfore it can be concluded that osrm time (An open-source routing engine time) and segment osrm time (OSRM segment time taken by the subset of the package delivery) are different

---

Data Normalization

- Preforming Min-Max Scaling since the data is not gaussian

In [65]:
```
min_max_scaler = MinMaxScaler()
dd_trips[numeric_cols] = min_max_scaler.fit_transform(dd_trips[numeric_cols])
dd_trips.head()
```

Out[65]:

	trip_uuid	trip_creation_time	source_name	destination_name	od_start_time	od_end_time	start_scan_to_end_
0	trip-153671041653548748	2018-09-12 00:00:16.535741	Kanpur_Central_H_6 (Uttar Pradesh)	Gurgaon_Bilaspur_HB (Haryana)	2018-09-12 16:39:46.858469	2018-09-12 16:39:46.858469	1.00
1	trip-153671042288605164	2018-09-12 00:00:22.886430	DoddaBlpur_ChikaDPP_D (Karnataka)	Chikblapur_ShntiSgr_D (Karnataka)	2018-09-12 02:03:09.655591	2018-09-12 02:03:09.655591	0.13
2	trip-153671043369099517	2018-09-12 00:00:33.691250	Gurgaon_Bilaspur_HB (Haryana)	Chandigarh_Mehmdpur_H (Punjab)	2018-09-14 03:40:17.106733	2018-09-14 03:40:17.106733	1.00
3	trip-153671046011330457	2018-09-12 00:01:00.113710	Mumbai Hub (Maharashtra)	Mumbai_MiraRd_IP (Maharashtra)	2018-09-12 00:01:00.113710	2018-09-12 01:41:29.809822	0.07
4	trip-153671052974046625	2018-09-12 00:02:09.740725	Bellary_Dc (Karnataka)	Hospet (Karnataka)	2018-09-12 00:02:09.740725	2018-09-12 03:54:43.114421	0.53

In [66]:
```
dd_trips[numeric_cols].describe().T
```

Out[66]:

	count	mean	std	min	25%	50%	75%	max
start_scan_to_end_scan	14817.0	0.331236	0.301328	0.0	0.108929	0.203779	0.465358	1.0
actual_distance_to_destination	14817.0	0.288992	0.312620	0.0	0.060279	0.127729	0.436167	1.0
actual_time	14817.0	0.319948	0.318033	0.0	0.081381	0.178792	0.448829	1.0
osrm_time	14817.0	0.302846	0.309433	0.0	0.077540	0.157754	0.446524	1.0
osrm_distance	14817.0	0.291276	0.312236	0.0	0.064659	0.137178	0.438795	1.0
segment_actual_time	14817.0	0.318890	0.317904	0.0	0.080495	0.178328	0.448297	1.0
segment_osrm_time	14817.0	0.301345	0.309481	0.0	0.072727	0.155152	0.443636	1.0
segment_osrm_distance	14817.0	0.294505	0.312726	0.0	0.064923	0.138963	0.438954	1.0

Business Insights 🔎

1. Data Overview:
    - The data spans from '2018-09-12' to '2018-10-03'.
    - There are 14,707 unique trip IDs.
    - The dataset includes 1,494 unique source centers and 1,465 unique destination centers.
    - There are 704 unique source cities and 828 unique destination cities.
2. Data Distribution:
    - A larger portion of the data is for testing rather than training.
    - The most common route type is Carting.
3. Data Gaps:
    - The names of 14 unique location IDs are missing from the data.
4. Trip Timing and Frequency:
    - The number of trips starts to increase after noon, peaks at 10 P.M., and then begins to decrease.
    - Most orders are placed mid-month, indicating a higher customer activity during this period.
5. Geographical Insights:

- Orders are primarily sourced from Maharashtra, Karnataka, Haryana, Tamil Nadu, and Telangana.
- Most of the Order are delivered to Bangalore followed by Gurgaon, Mumbai, Chennai, Hyderabad, Delhi.
- Most of the orders are coming from Bangalore followed by Gurgaon, Bhiwandi, Delhi, Mumbai, Chennai.

6. Feature Analysis:

- The features actual_time and osrm_time are statistically different.
- The features actual_time and segment_actual_time are statistically different.
- The features osrm_distance and segment_osrm_distance are statistically different.
- The features osrm_time and segment_osrm_time are not statistically the same.

Recommendations 💡

1. Enhance the OSRM Trip Planning System:

- The OSRM trip planning system requires improvement to better cater to transporters and ensure optimal routing results.

2. Address Discrepancies in Time Predictions:

- The significant difference between osrm_time and actual_time needs to be minimized. The team should work on reducing this discrepancy to provide more accurate delivery time predictions, improving customer satisfaction with precise delivery expectations.

3. Improve Distance Accuracy:
    - The observed difference between osrm_distance and the actual distance covered suggests that delivery personnel may not be following the predefined route, or the OSRM system is not accurately predicting routes based on factors such as distance, traffic, and other conditions. This could lead to late deliveries. The team should investigate and resolve these issues to enhance delivery efficiency and reliability.