Business Case: Delhivery - Feature Engineering

About Delhivery

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

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

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

In [601…

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
```

```
warnings.filterwarnings('ignore')
from scipy import stats
from scipy.stats import ttest_ind,levene,shapiro,kruskal
```

In [602…

```
!wget "https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/551/original/delhivery_data.csv?1642751181" -O "delhivery.csv"
```

```
--2024-09-19 12:12:59--  https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/551/original/delhivery_data.csv?1642751181
Resolving d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)... 13.35.159.36, 13.35.159.92, 13.35.159.184, ...
Connecting to d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)|13.35.159.36|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 55617130 (53M) [text/plain]
Saving to: ‘delhivery.csv’

delhivery.csv       100%[===================>]  53.04M  26.0MB/s    in 2.0s

2024-09-19 12:13:01 (26.0 MB/s) - ‘delhivery.csv’ saved [55617130/55617130]
```

In [603…

```
data = pd.read_csv("delhivery.csv")     # Loading dataset
```

In [604…

```
data.head()
```

Out[604…

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_center	desti
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	Khambhat_
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	Khambhat_
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	Khambhat_
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	Khambhat_
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	Khambhat_

In [604…

In [605…

```
data.tail()
```

Out[605…

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_center	desti
144862	training	2018-09-20 16:24:28.436231	thanos::sroute:f0569d2f-4e20-4c31-8542-67b86d5...	Carting	trip-153746066843555182	IND131028AAB	Sonipat_Kundli_H (Haryana)	IND000000ACB	Gurgaoı
144863	training	2018-09-20 16:24:28.436231	thanos::sroute:f0569d2f-4e20-4c31-8542-67b86d5...	Carting	trip-153746066843555182	IND131028AAB	Sonipat_Kundli_H (Haryana)	IND000000ACB	Gurgaoı
144864	training	2018-09-20 16:24:28.436231	thanos::sroute:f0569d2f-4e20-4c31-8542-67b86d5...	Carting	trip-153746066843555182	IND131028AAB	Sonipat_Kundli_H (Haryana)	IND000000ACB	Gurgaoı
144865	training	2018-09-20 16:24:28.436231	thanos::sroute:f0569d2f-4e20-4c31-8542-67b86d5...	Carting	trip-153746066843555182	IND131028AAB	Sonipat_Kundli_H (Haryana)	IND000000ACB	Gurgaoı
144866	training	2018-09-20 16:24:28.436231	thanos::sroute:f0569d2f-4e20-4c31-8542-67b86d5...	Carting	trip-153746066843555182	IND131028AAB	Sonipat_Kundli_H (Haryana)	IND000000ACB	Gurgaoı

In [606…

```
data.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
```

In [607…

```
data.describe(include = ("all")).T
```

Out[607…

	count	unique	top	freq	mean	std	min	25%	50%	75%
data	144867	2	training	104858	NaN	NaN	NaN	NaN	NaN	NaN
trip_creation_time	144867	14817	2018-09-28 05:23:15.359220	101	NaN	NaN	NaN	NaN	NaN	NaN
route_schedule_uuid	144867	1504	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	1812	NaN	NaN	NaN	NaN	NaN	NaN
route_type	144867	2	FTL	99660	NaN	NaN	NaN	NaN	NaN	NaN
trip_uuid	144867	14817	trip-153811219535896559	101	NaN	NaN	NaN	NaN	NaN	NaN
source_center	144867	1508	IND000000ACB	23347	NaN	NaN	NaN	NaN	NaN	NaN
source_name	144574	1498	Gurgaon_Bilaspur_HB (Haryana)	23347	NaN	NaN	NaN	NaN	NaN	NaN
destination_center	144867	1481	IND000000ACB	15192	NaN	NaN	NaN	NaN	NaN	NaN
destination_name	144606	1468	Gurgaon_Bilaspur_HB (Haryana)	15192	NaN	NaN	NaN	NaN	NaN	NaN
od_start_time	144867	26369	2018-09-21 18:37:09.322207	81	NaN	NaN	NaN	NaN	NaN	NaN
od_end_time	144867	26369	2018-09-24 09:59:15.691618	81	NaN	NaN	NaN	NaN	NaN	NaN
start_scan_to_end_scan	144867.0	NaN	NaN	NaN	961.262986	1037.012769	20.0	161.0	449.0	1634.0
is_cutoff	144867	2	True	118749	NaN	NaN	NaN	NaN	NaN	NaN
cutoff_factor	144867.0	NaN	NaN	NaN	232.926567	344.755577	9.0	22.0	66.0	286.0
cutoff_timestamp	144867	93180	2018-09-24 05:19:20	40	NaN	NaN	NaN	NaN	NaN	NaN
actual_distance_to_destination	144867.0	NaN	NaN	NaN	234.073372	344.990009	9.000045	23.355874	66.126571	286.708875
actual_time	144867.0	NaN	NaN	NaN	416.927527	598.103621	9.0	51.0	132.0	513.0
osrm_time	144867.0	NaN	NaN	NaN	213.868272	308.011085	6.0	27.0	64.0	257.0
osrm_distance	144867.0	NaN	NaN	NaN	284.771297	421.119294	9.0082	29.9147	78.5258	343.19325
factor	144867.0	NaN	NaN	NaN	2.120107	1.715421	0.144	1.604264	1.857143	2.213483
segment_actual_time	144867.0	NaN	NaN	NaN	36.196111	53.571158	-244.0	20.0	29.0	40.0
segment_osrm_time	144867.0	NaN	NaN	NaN	18.507548	14.77596	0.0	11.0	17.0	22.0
segment_osrm_distance	144867.0	NaN	NaN	NaN	22.82902	17.86066	0.0	12.0701	23.513	27.81325
segment_factor	144867.0	NaN	NaN	NaN	2.218368	4.84753	-23.444444	1.347826	1.684211	2.25

🔍**Insights :**

- Trip Creation and UUID Analysis: The most frequent trip has a specific timestamp (2018-09-28 05:23:15.359220) and unique trip ID (trip-153811219535896559), appearing 101 times, indicating recurrent activities or routes.

- Route Type Dominance: The majority of trips (69%) are of type FTL, showing a preference for Full Truckload (FTL) over other types, which can influence fleet management strategies.
- Distance Comparison: 'actual_distance_to_destination' (mean 234 km) is higher than 'osrm_distance' (mean 284 km), indicating that trips often exceed planned distances, which may impact fuel and time efficiency.
- Time Delays: 'segment_actual_time' (mean of 36 mins) is consistently longer than 'segment_osrm_time' (mean of 18.5 mins), pointing to frequent delays in reaching intermediate destinations.
- Demand in Specific Source-Destination Routes: The top source and destination, "IND000000ACB" and "Gurgaon_Bilaspur_HB (Haryana)", appear frequently, suggesting heavy demand in this route, which could be critical for optimizing logistics.
- High Variability in Segment Distance: The 'segment_osrm_distance' shows a wide range (0 to 2191 km), with a mean of 22.8 km, indicating trips that can vary significantly in length, impacting planning and resource allocation.

In [608…

```
for i in data.columns:
  print(f"Unique Values of {i} : {data[i].nunique()}")
```

```
Unique Values of data : 2
Unique Values of trip_creation_time : 14817
Unique Values of route_schedule_uuid : 1504
Unique Values of route_type : 2
Unique Values of trip_uuid : 14817
Unique Values of source_center : 1508
Unique Values of source_name : 1498
Unique Values of destination_center : 1481
Unique Values of destination_name : 1468
Unique Values of od_start_time : 26369
Unique Values of od_end_time : 26369
Unique Values of start_scan_to_end_scan : 1915
Unique Values of is_cutoff : 2
Unique Values of cutoff_factor : 501
Unique Values of cutoff_timestamp : 93180
Unique Values of actual_distance_to_destination : 144515
Unique Values of actual_time : 3182
Unique Values of osrm_time : 1531
Unique Values of osrm_distance : 138046
Unique Values of factor : 45641
Unique Values of segment_actual_time : 747
Unique Values of segment_osrm_time : 214
Unique Values of segment_osrm_distance : 113799
Unique Values of segment_factor : 5675
```

Checking Null Values

In [609…

```
for i in data.columns:
  print(f"Percentage of Null Values in {i}  : {round((data[i].isnull().sum() / len(data))*100,2)}")
```

```
Percentage of Null Values in data  : 0.0
Percentage of Null Values in trip_creation_time  : 0.0
Percentage of Null Values in route_schedule_uuid  : 0.0
Percentage of Null Values in route_type  : 0.0
Percentage of Null Values in trip_uuid  : 0.0
Percentage of Null Values in source_center  : 0.0
Percentage of Null Values in source_name  : 0.2
Percentage of Null Values in destination_center  : 0.0
Percentage of Null Values in destination_name  : 0.18
Percentage of Null Values in od_start_time  : 0.0
Percentage of Null Values in od_end_time  : 0.0
Percentage of Null Values in start_scan_to_end_scan  : 0.0
Percentage of Null Values in is_cutoff  : 0.0
Percentage of Null Values in cutoff_factor  : 0.0
Percentage of Null Values in cutoff_timestamp  : 0.0
Percentage of Null Values in actual_distance_to_destination  : 0.0
Percentage of Null Values in actual_time  : 0.0
Percentage of Null Values in osrm_time  : 0.0
Percentage of Null Values in osrm_distance  : 0.0
Percentage of Null Values in factor  : 0.0
Percentage of Null Values in segment_actual_time  : 0.0
Percentage of Null Values in segment_osrm_time  : 0.0
Percentage of Null Values in segment_osrm_distance  : 0.0
Percentage of Null Values in segment_factor  : 0.0
```

🔍**Insights :**

Since less than 0.5% of the values are missing in the "destination_name" and "source_name" columns, it's more efficient to drop the rows with missing data.

In [610…

```
data.dropna(inplace = True)
```

In [611…

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 144316 entries, 0 to 144866
Data columns (total 24 columns):
 #   Column                          Non-Null Count   Dtype
---  ------                          --------------   -----
 0   data                            144316 non-null  object
 1   trip_creation_time              144316 non-null  object
 2   route_schedule_uuid             144316 non-null  object
 3   route_type                      144316 non-null  object
 4   trip_uuid                       144316 non-null  object
 5   source_center                   144316 non-null  object
 6   source_name                     144316 non-null  object
 7   destination_center              144316 non-null  object
 8   destination_name                144316 non-null  object
 9   od_start_time                   144316 non-null  object
 10  od_end_time                     144316 non-null  object
 11  start_scan_to_end_scan          144316 non-null  float64
 12  is_cutoff                       144316 non-null  bool
 13  cutoff_factor                   144316 non-null  int64
 14  cutoff_timestamp                144316 non-null  object
 15  actual_distance_to_destination  144316 non-null  float64
 16  actual_time                     144316 non-null  float64
 17  osrm_time                       144316 non-null  float64
 18  osrm_distance                   144316 non-null  float64
 19  factor                          144316 non-null  float64
 20  segment_actual_time             144316 non-null  float64
 21  segment_osrm_time               144316 non-null  float64
 22  segment_osrm_distance           144316 non-null  float64
 23  segment_factor                  144316 non-null  float64
dtypes: bool(1), float64(10), int64(1), object(12)
memory usage: 26.6+ MB
```

Checking Duplicates

In [612…
```
data.duplicated().sum()
```

Out[612…
```
0
```

🔍**Insights :**

No Duplicate values are present in the dataset.

Converting required columns to Datetime

In [613…
```
pd.set_option('display.max_columns',40)
data.head(3)
```

Out[613…

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_center	desti
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	Khambhat_
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	Khambhat_
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	Khambhat_

In [614…
```
data["od_start_time"] = pd.to_datetime(data["od_start_time"])
data["od_end_time"] = pd.to_datetime(data["od_end_time"])
data["trip_creation_time"] = pd.to_datetime(data["trip_creation_time"])
```

Droping Unknown Columns

In [615…
```
data = data.drop(columns = ["is_cutoff","cutoff_factor","cutoff_timestamp","factor","segment_factor"])
```

In [616…
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 144316 entries, 0 to 144866
Data columns (total 19 columns):
 #   Column                          Non-Null Count   Dtype
---  ------                          --------------   -----
 0   data                            144316 non-null  object
 1   trip_creation_time              144316 non-null  datetime64[ns]
 2   route_schedule_uuid             144316 non-null  object
 3   route_type                      144316 non-null  object
 4   trip_uuid                       144316 non-null  object
 5   source_center                   144316 non-null  object
 6   source_name                     144316 non-null  object
 7   destination_center              144316 non-null  object
 8   destination_name                144316 non-null  object
 9   od_start_time                   144316 non-null  datetime64[ns]
 10  od_end_time                     144316 non-null  datetime64[ns]
 11  start_scan_to_end_scan          144316 non-null  float64
 12  actual_distance_to_destination  144316 non-null  float64
 13  actual_time                     144316 non-null  float64
 14  osrm_time                       144316 non-null  float64
 15  osrm_distance                   144316 non-null  float64
 16  segment_actual_time             144316 non-null  float64
 17  segment_osrm_time               144316 non-null  float64
 18  segment_osrm_distance           144316 non-null  float64
dtypes: datetime64[ns](3), float64(8), object(8)
memory usage: 22.0+ MB
```

Since delivery details of one package are divided into several rows we can use inbuilt functions like groupby and aggregations like sum(), cumsum() to merge some rows based on their 1. Trip_uuid, Source ID and Destination ID.

Making Segment Key Based on Trip_uuid, Source ID and Destination ID

In [617…
```
data.head(5)
```

Out[617…

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_center	desti
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	Khambhat_
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	Khambhat_
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	Khambhat_
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	Khambhat_
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	Khambhat_

In [618…
```
data["segment_key"] = data["trip_uuid"] + "-" + data["source_center"] + "-" + data["destination_center"]

col = ["segment_actual_time", "segment_osrm_time", "segment_osrm_distance"]
```

In [619…
```
# Aggregating at segment level & Creating a dictionary for aggregation at segment level

segment_dict = {
  'trip_uuid' : 'first',
  'data': 'first',
  'route_type': 'first',
  'trip_creation_time': 'first',
  'source_name': 'first',
  'source_center' : 'first',
  'destination_name': 'last',
  'destination_center' : 'last',
  'od_start_time': 'first',
  'od_end_time': 'last',
  'start_scan_to_end_scan': 'first',
  'actual_distance_to_destination': 'last',
  'actual_time': 'last',
  'osrm_time': 'last',
  'osrm_distance': 'last',
  'segment_actual_time' : 'sum',
  'segment_osrm_time' : 'sum',
  'segment_osrm_distance' : 'sum'
}
```

In [620…
```
# Aggregating at segment level / every breakpoint level.

segment_data = data.groupby("segment_key").agg(segment_dict).reset_index()
segment_data = segment_data.sort_values(by=["segment_key","od_end_time"], ascending=True).reset_index(drop = True)
```

In [621…
```
segment_data.head(3)
```

Out[621…

	segment_key	trip_uuid	data	route_type	trip_creation_time	source_name	source_center	destination_name	desti
0	trip-153671041653548748-IND209304AAA-IND000000ACB	trip-153671041653548748	training	FTL	2018-09-12 00:00:16.535741	Kanpur_Central_H_6 (Uttar Pradesh)	IND209304AAA	Gurgaon_Bilaspur_HB (Haryana)	I
1	trip-153671041653548748-IND462022AAA-IND209304AAA	trip-153671041653548748	training	FTL	2018-09-12 00:00:16.535741	Bhopal_Trnsport_H (Madhya Pradesh)	IND462022AAA	Kanpur_Central_H_6 (Uttar Pradesh)	I
2	trip-153671042288605164-IND561203AAB-IND562101AAA	trip-153671042288605164	training	Carting	2018-09-12 00:00:22.886430	Doddablpur_ChikaDPP_D (Karnataka)	IND561203AAB	Chikblapur_ShntiSgr_D (Karnataka)	I

In [622…
```
segment_data = segment_data.rename(columns = {"segment_osrm_distance":"segment_osrm_distance_sum",
                                              "segment_osrm_time" : "segment_osrm_time_sum",
                                             "segment_actual_time" : "segment_actual_time_sum"}) # Renaming columns
```

In [623…
```
segment_data.head(3)
```

Out[623…

	segment_key	trip_uuid	data	route_type	trip_creation_time	source_name	source_center	destination_name	desti
0	trip-153671041653548748-IND209304AAA-IND000000ACB	trip-153671041653548748	training	FTL	2018-09-12 00:00:16.535741	Kanpur_Central_H_6 (Uttar Pradesh)	IND209304AAA	Gurgaon_Bilaspur_HB (Haryana)	I
1	trip-153671041653548748-IND462022AAA-IND209304AAA	trip-153671041653548748	training	FTL	2018-09-12 00:00:16.535741	Bhopal_Trnsport_H (Madhya Pradesh)	IND462022AAA	Kanpur_Central_H_6 (Uttar Pradesh)	I
2	trip-153671042288605164-IND561203AAB-IND562101AAA	trip-153671042288605164	training	Carting	2018-09-12 00:00:22.886430	Doddablpur_ChikaDPP_D (Karnataka)	IND561203AAB	Chikblapur_ShntiSgr_D (Karnataka)	I

🔍**Insights :**

Now data is at segment level.

In [624…
```
segment_data["trip_uuid"].value_counts()
```

Out[624…

trip_uuid	count
trip-153717306559016761	8
trip-153710494321650505	8
trip-153758895506669465	8
trip-153801215317324804	7
trip-153723403393244965	7
...	...
trip-153709428734920326	1
trip-153772871464594138	1
trip-153709414287625422	1
trip-153772883314236517	1
trip-153758755960894226	1

14787 rows × 1 columns

dtype: int64

Feature Engineering

Calculate the time taken between od_start_time and od_end_time

In [625…
```
segment_data["od_timetotal_hour"] = (segment_data["od_end_time"]-segment_data["od_start_time"]).dt.total_seconds()/3600
```

In [626…
```
segment_data["od_timetotal_hour"]
```

Out[626…

	od_timetotal_hour
0	21.010074
1	16.658423
2	0.980540
3	2.046325
4	13.910649
...	...
26217	1.035253
26218	1.518130
26219	0.736240
26220	4.791233
26221	1.115559

26222 rows × 1 columns

dtype: float64

Further aggregate on the basis of just Trip_uuid.

In [627…

```
# Making the data at trip level

trip_dict = {

    'data' : 'first',
    'trip_creation_time' : 'first',
    'route_type' : 'first',
    'trip_uuid' : 'first',
    'source_center' : 'first',
    'source_name' : 'first',
    'destination_center' : 'last',
    'destination_name' : 'last',
    'od_timetotal_hour':'sum',
    'start_scan_to_end_scan' : 'sum',
    'actual_distance_to_destination' : 'sum',
    'actual_time' : 'sum',
    'osrm_time' : 'sum',
    'osrm_distance' : 'sum',
    'segment_actual_time_sum' : 'sum',
    'segment_osrm_time_sum' : 'sum',
    'segment_osrm_distance_sum' : 'sum'

}
```

In [628…

```
trip_data = segment_data.groupby('trip_uuid').agg(trip_dict).reset_index(drop = True)
```

In [629…

```
trip_data["trip_uuid"].value_counts()
```

Out[629…

trip_uuid	count
trip-153671041653548748	1
trip-153791166614583191	1
trip-153791188846803726	1
trip-153791199511952768	1
trip-153791203866379915	1
...	...
trip-153730334220215546	1
trip-153730343361346090	1
trip-153730345417711989	1
trip-153730351817227074	1
trip-153861118270144424	1

14787 rows × 1 columns

dtype: int64

Trip level data

In [630…
```
trip_data.sample(3)
```

Out[630…

	data	trip_creation_time	route_type	trip_uuid	source_center	source_name	destination_center	destination_name	od
5630	training	2018-09-19 20:23:34.534054	Carting	trip-153738861453372983	IND411036AAA	Pune_Mundhawa_L (Maharashtra)	IND411033AAA	Pune_Tathawde_H (Maharashtra)	
9005	training	2018-09-24 18:27:59.801266	Carting	trip-153781367980088422	IND712311AAA	Kolkata_Dankuni_HB (West Bengal)	IND700028AAB	CCU_DumDum_DPC (West Bengal)	
6844	training	2018-09-21 14:18:26.057331	Carting	trip-153753950605706982	IND421302AAG	Bhiwandi_Mankoli_HB (Maharashtra)	IND400015AAA	Mumbai_CottonGreen_DPC (Maharashtra)	

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

In [631…
```
# Extracting city name


def city (val):
  i =  val.split("(")[0]
  if i.count(" ") >3:
    # print(i.split(" ")[0])
    return i.split(" ",maxsplit=1)[0]
  elif i.count(" ") >2:
    # print(i.split(" ")[0])
    return i.split(" ",maxsplit=1)[0]
  else:
    return i.split("_")[0]

# Extracting place name

def place (val):
  i =  val.split("(")[0]
  if i.count(" ") >3:
    # print(i.split(" ")[0])
    return i.split(" ",maxsplit=1)[1]
  elif i.count(" ") >2:
    # print(i.split(" ")[0])
    return i.split(" ",maxsplit=1)[1]
  elif i.count("_") >=1:
    return i.split("_")[1]
  else:
    return i.split(" ")[1]

# Extracting  code

def source_code(val):
  i =  val.split("(")[0]
  if i.count("_") >=2:
    return i.split("_")[-1]

  else:
    return "Unknown Code"
```

In [632…
```
trip_data["destination_state"] = trip_data["destination_name"].str.split("(").str[1].str[:-1] # Extracting State name
trip_data["destination_city"] = trip_data["destination_name"].apply(lambda x : city(x))
trip_data["destination_place"] = trip_data["destination_name"].apply(lambda x : place(x))
trip_data["destination_code"] = trip_data["destination_name"].apply(lambda x : source_code(x))
```

In [633…
```
trip_data[["destination_city","destination_state","destination_code","destination_place"]]
```

Out[633…

	destination_city	destination_state	destination_code	destination_place
0	Kanpur	Uttar Pradesh	6	Central
1	Doddablpur	Karnataka	D	ChikaDPP
2	Gurgaon	Haryana	HB	Bilaspur
3	Mumbai	Maharashtra	IP	MiraRd
4	Sandur	Karnataka	D	WrdN1DPP
...	...	...	...	...
14782	Chandigarh	Punjab	H	Mehmdpur
14783	Faridabad	Haryana	DC	Blbgarh
14784	Kanpur	Uttar Pradesh	DC	GovndNgr
14785	Tirchchndr	Tamil Nadu	D	Shnmgprm
14786	Sandur	Karnataka	D	WrdN1DPP

14787 rows × 4 columns

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

In [634…

```
trip_data["source_city"] = trip_data["source_name"].apply(lambda x : city(x))
trip_data["source_place"] = trip_data["source_name"].apply(lambda x : place(x))
trip_data["source_code"] = trip_data["source_name"].apply(lambda x : source_code(x))
trip_data["source_state"] = trip_data["source_name"].str.split("(").str[1].str[:-1] # Extracting State name
```

In [635…

```
trip_data[["source_city","source_state","source_code","source_place"]]
```

Out[635…

	source_city	source_state	source_code	source_place
0	Kanpur	Uttar Pradesh	6	Central
1	Doddablpur	Karnataka	D	ChikaDPP
2	Gurgaon	Haryana	HB	Bilaspur
3	Mumbai Hub	Maharashtra	Unknown Code	Hub
4	Bellary	Karnataka	Unknown Code	Dc
...	...	...	...	...
14782	Chandigarh	Punjab	H	Mehmdpur
14783	FBD	Haryana	DPC	Balabhgarh
14784	Kanpur	Uttar Pradesh	DC	GovndNgr
14785	Tirunelveli	Tamil Nadu	I	VdkkuSrt
14786	Sandur	Karnataka	D	WrdN1DPP

14787 rows × 4 columns

In [636…

```
trip_data.isnull().sum() # Null check
```

Out[636…

	0
data	0
trip_creation_time	0
route_type	0
trip_uuid	0
source_center	0
source_name	0
destination_center	0
destination_name	0
od_timetotal_hour	0
start_scan_to_end_scan	0
actual_distance_to_destination	0
actual_time	0
osrm_time	0
osrm_distance	0
segment_actual_time_sum	0
segment_osrm_time_sum	0
segment_osrm_distance_sum	0
destination_state	0
destination_city	0
destination_place	0
destination_code	0
source_city	0
source_place	0
source_code	0
source_state	0

dtype: int64

Trip_creation_time: Extract features like month, year and day,Week of year , week day , day name

In [637…
```
trip_data['trip_year'] = trip_data['trip_creation_time'].dt.year
trip_data['trip_month'] = trip_data['trip_creation_time'].dt.month
trip_data['trip_hour'] = trip_data['trip_creation_time'].dt.hour
trip_data['trip_day'] = trip_data['trip_creation_time'].dt.day
trip_data['trip_weekofyear'] = trip_data['trip_creation_time'].dt.isocalendar().week
trip_data['trip_weekday'] = trip_data['trip_creation_time'].dt.weekday
trip_data["trip_day_name"] = trip_data["trip_creation_time"].dt.day_name()
```

In [638…
```
trip_data[['trip_year','trip_month','trip_hour','trip_day','trip_weekofyear','trip_weekday','trip_day_name']].head(3)
```

Out[638…

	trip_year	trip_month	trip_hour	trip_day	trip_weekofyear	trip_weekday	trip_day_name
0	2018	9	0	12	37	2	Wednesday
1	2018	9	0	12	37	2	Wednesday
2	2018	9	0	12	37	2	Wednesday

In [639…
```
# Dropping Unwanted Columns

trip_data = trip_data.drop(columns = ["source_name","destination_name"])
```

In [640…
```
trip_data.shape
```

Out[640…
```
(14787, 30)
```

In [641…
```
trip_data.head(3)
```

Out[641…

	data	trip_creation_time	route_type	trip_uuid	source_center	destination_center	od_timetotal_hour	start_scan_to_end_scan	actual_dista
0	training	2018-09-12 00:00:16.535741	FTL	trip-153671041653548748	IND209304AAA	IND209304AAA	37.668497	2259.0	
1	training	2018-09-12 00:00:22.886430	Carting	trip-153671042288605164	IND561203AAB	IND561203AAB	3.026865	180.0	
2	training	2018-09-12 00:00:33.691250	FTL	trip-153671043369099517	IND000000ACB	IND000000ACB	65.572709	3933.0	

Analysis Of Trip Level Data

In [642…
```
trip_data.describe().T
```

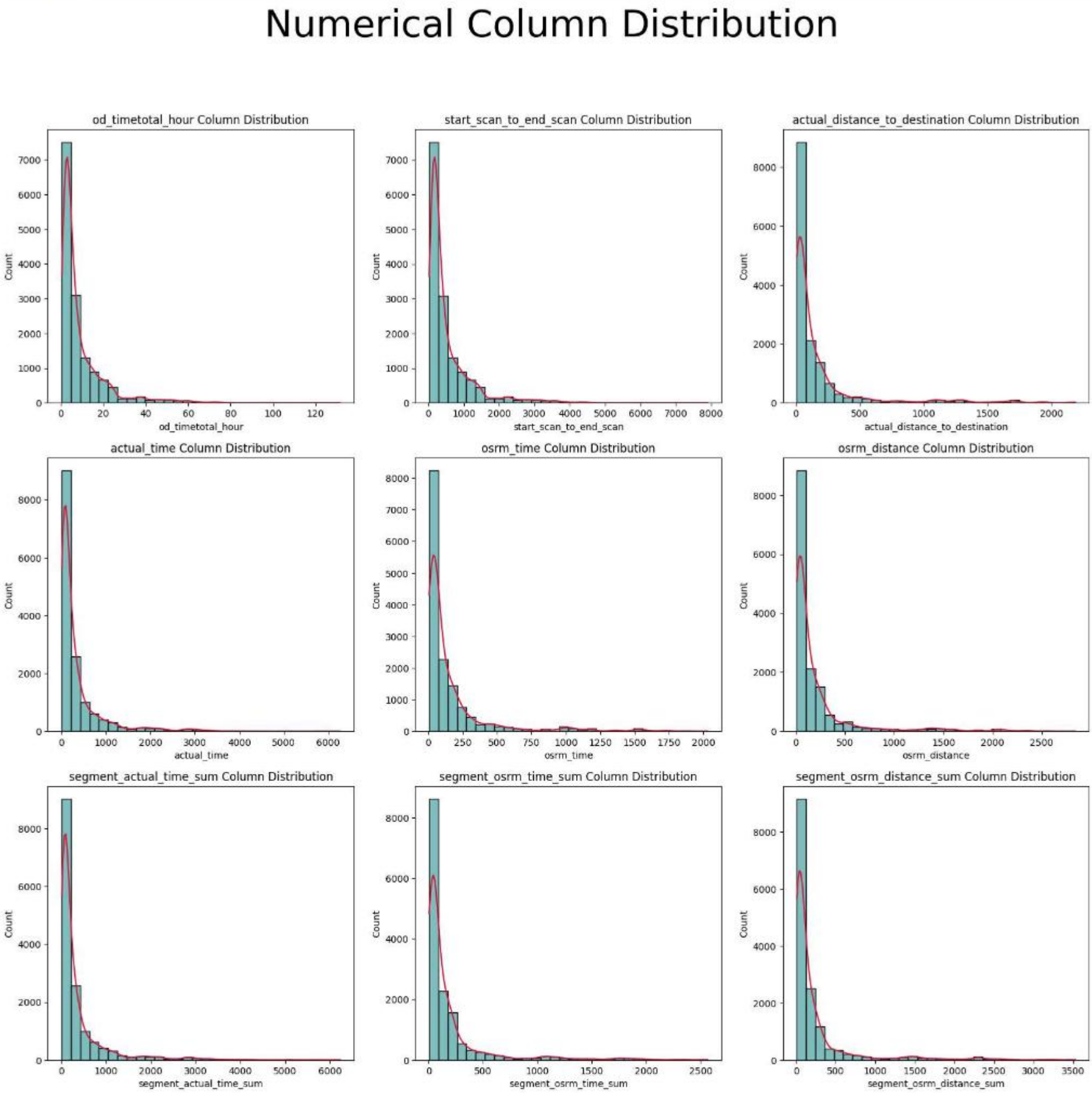
Out[642…

	count	mean	min	25%	50%	75%	max	
trip_creation_time	14787	2018-09-22 12:26:28.269885696	2018-09-12 00:00:16.535741	2018-09-17 02:38:18.128431872	2018-09-22 03:39:19.609193984	2018-09-27 19:23:14.074359552	2018-10-03 23:59:42.701692	
od_timetotal_hour	14787.0	8.840187	0.391024	2.494975	4.661846	10.558962	131.642533	1
start_scan_to_end_scan	14787.0	529.429025	23.0	149.0	279.0	632.0	7898.0	658
actual_distance_to_destination	14787.0	164.090196	9.002461	22.777099	48.287894	163.591258	2186.531787	305
actual_time	14787.0	356.306012	9.0	67.0	148.0	367.0	6265.0	561
osrm_time	14787.0	160.990938	6.0	29.0	60.0	168.0	2032.0	271
osrm_distance	14787.0	203.887411	9.0729	30.7569	65.3028	206.6442	2840.081	370
segment_actual_time_sum	14787.0	353.059174	9.0	66.0	147.0	364.0	6230.0	556
segment_osrm_time_sum	14787.0	180.511598	6.0	30.0	65.0	184.0	2564.0	314
segment_osrm_distance_sum	14787.0	222.705466	9.0729	32.57885	69.7842	216.5606	3523.6324	416
trip_year	14787.0	2018.0	2018.0	2018.0	2018.0	2018.0	2018.0	
trip_month	14787.0	9.120105	9.0	9.0	9.0	9.0	10.0	0
trip_hour	14787.0	12.456212	0.0	4.0	14.0	20.0	23.0	7
trip_day	14787.0	18.375127	1.0	14.0	19.0	25.0	30.0	7
trip_weekofyear	14787.0	38.293907	37.0	38.0	38.0	39.0	40.0	0
trip_weekday	14787.0	2.920944	0.0	1.0	3.0	5.0	6.0	

In [643…
```
num_col = ["od_timetotal_hour","start_scan_to_end_scan","actual_distance_to_destination","actual_time","osrm_time","osrm_distance",
           "segment_actual_time_sum","segment_osrm_time_sum","segment_osrm_distance_sum"]
```

In [644…
```
plt.figure(figsize=(20,18))
for i,j in enumerate(num_col):
```

```
  i = i+1
  plt.subplot(3,3,i)
  sns.histplot(trip_data[j],bins = 30 ,kde = True,color = "teal" ).lines[0].set_color("crimson")
  plt.title(f"{j} Column Distribution")
plt.suptitle("Numerical Column Distribution" , fontsize = 40)
plt.show()
```



Insights 🧐

- od_timetotal_hour: The average total trip time is around 8.84 hours, but with high variability, as some trips can last over 131 hours.
- start_scan_to_end_scan: The median scan time is 279 minutes, but the data shows significant variability, with some trips taking up to 7898 minutes from start to end scan.
- actual_distance_to_destination: The average trip covers 164 km, with a maximum distance of over 2186 km, indicating trips of varying lengths.
- actual_time: The median trip time is 148 minutes, while the longest trips take over 6265 minutes (over 4 days).
- osrm_time: Planned trip times ('osrm_time') are generally lower than actual times, with a median planned time of 60 minutes.
- osrm_distance: The median planned distance is 65 km, but some planned routes span up to 2840 km.
- segment_actual_time_sum: Total segment time closely mirrors actual trip times, suggesting most delays occur over the entire route.
- segment_osrm_time_sum: Planned segment times are generally shorter, with a median of 65 minutes, reflecting underestimation of actual trip duration.
- segment_osrm_distance_sum: The planned segment distance has a median of 69.8 km, with a maximum of over 3523 km, showing variability in trip segments.

In [645…

```
trip_data.describe(include="object").T
```

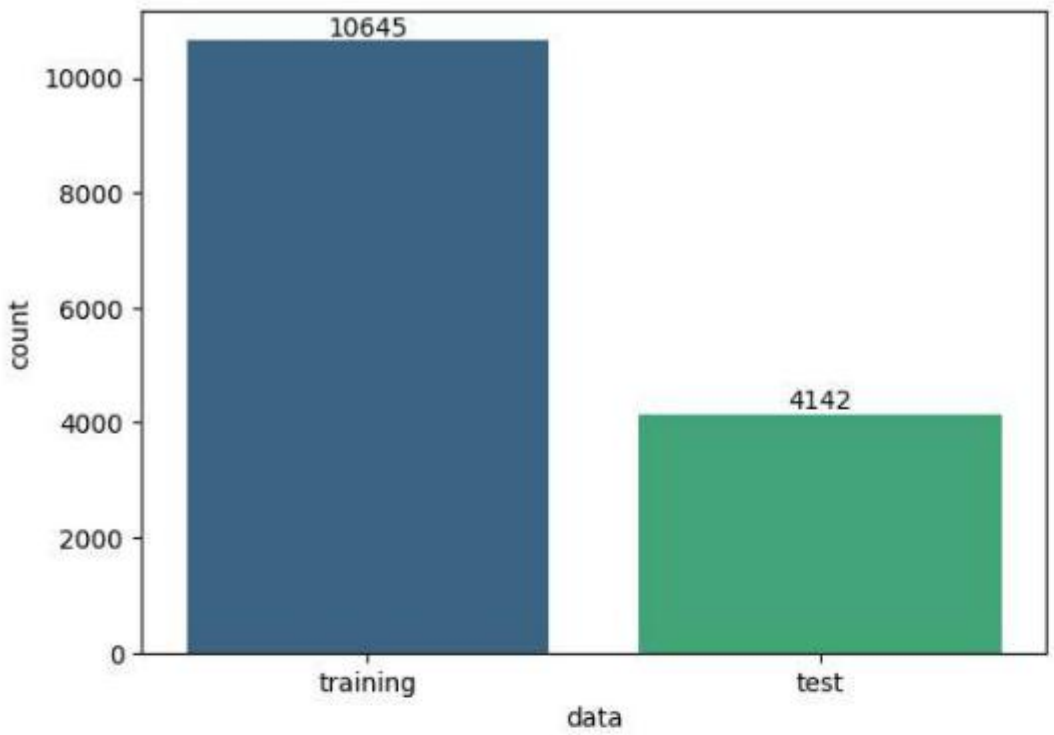
Out[645…

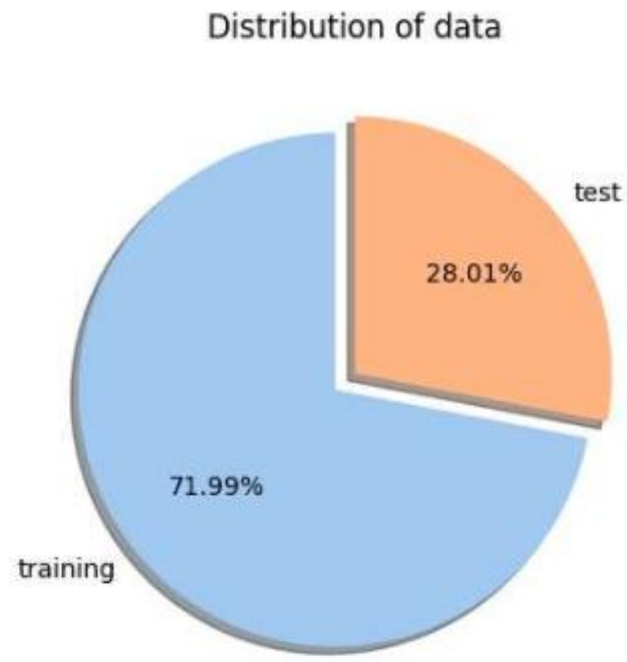
	count	unique	top	freq
data	14787	2	training	10645
route_type	14787	2	Carting	8906
trip_uuid	14787	14787	trip-153671041653548748	1
source_center	14787	930	IND000000ACB	1052
destination_center	14787	1035	IND000000ACB	821
destination_state	14787	31	Maharashtra	2561
destination_city	14787	853	Bengaluru	1088
destination_place	14787	808	Bilaspur	864
destination_code	14787	34	D	2883
source_city	14787	728	Gurgaon	1128
source_place	14787	716	Bilaspur	1074
source_code	14787	33	HB	3211
source_state	14787	29	Maharashtra	2714
trip_day_name	14787	7	Wednesday	2731

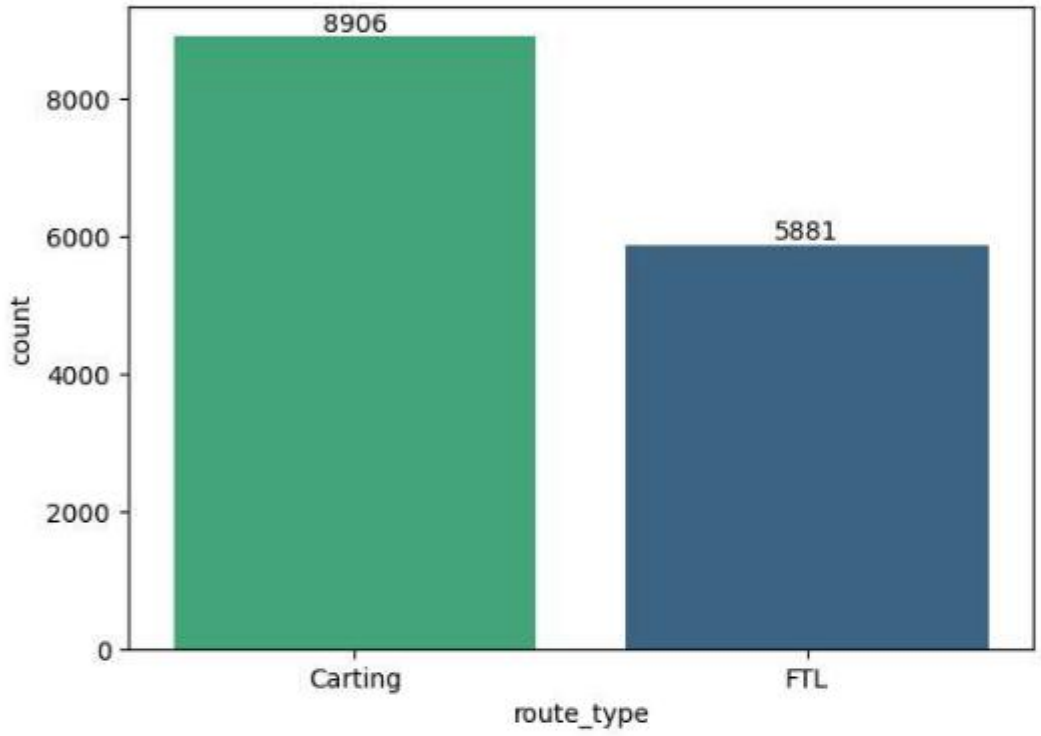
In [646…

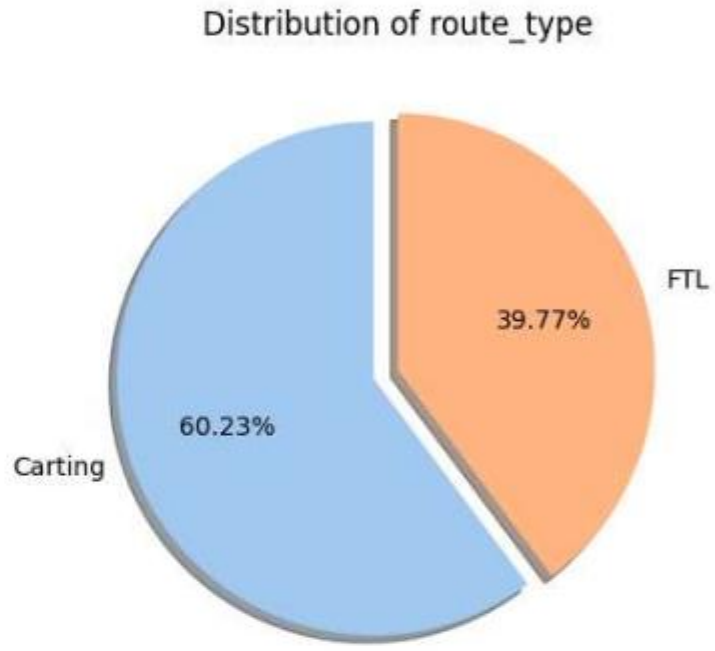
```
col = ["data","route_type"]
counter = 1
plt.figure(figsize = (14,10))
for i , j in enumerate(col):
  i = i+counter
  plt.subplot(2,2,i)
  bar = sns.countplot(x = j,data = trip_data,hue = j,legend = False,order = trip_data[j].value_counts().index,
                      palette = "viridis")
  for k in bar.containers:
    bar.bar_label(k)
  plt.subplot(2,2,i+1)
  plt.pie(trip_data[j].value_counts(),labels =trip_data[j].value_counts().index, autopct = "%.2f%%",explode = [0.1,0],
          shadow = True,startangle = 90,colors = sns.color_palette("pastel") )
  plt.title(f"Distribution of {j}")
  counter = counter + 1
plt.suptitle("Distribution Of 'data' & 'route_type' Column" , fontsize = 25)
plt.show()
```

Distribution Of 'data' & 'route_type' Column







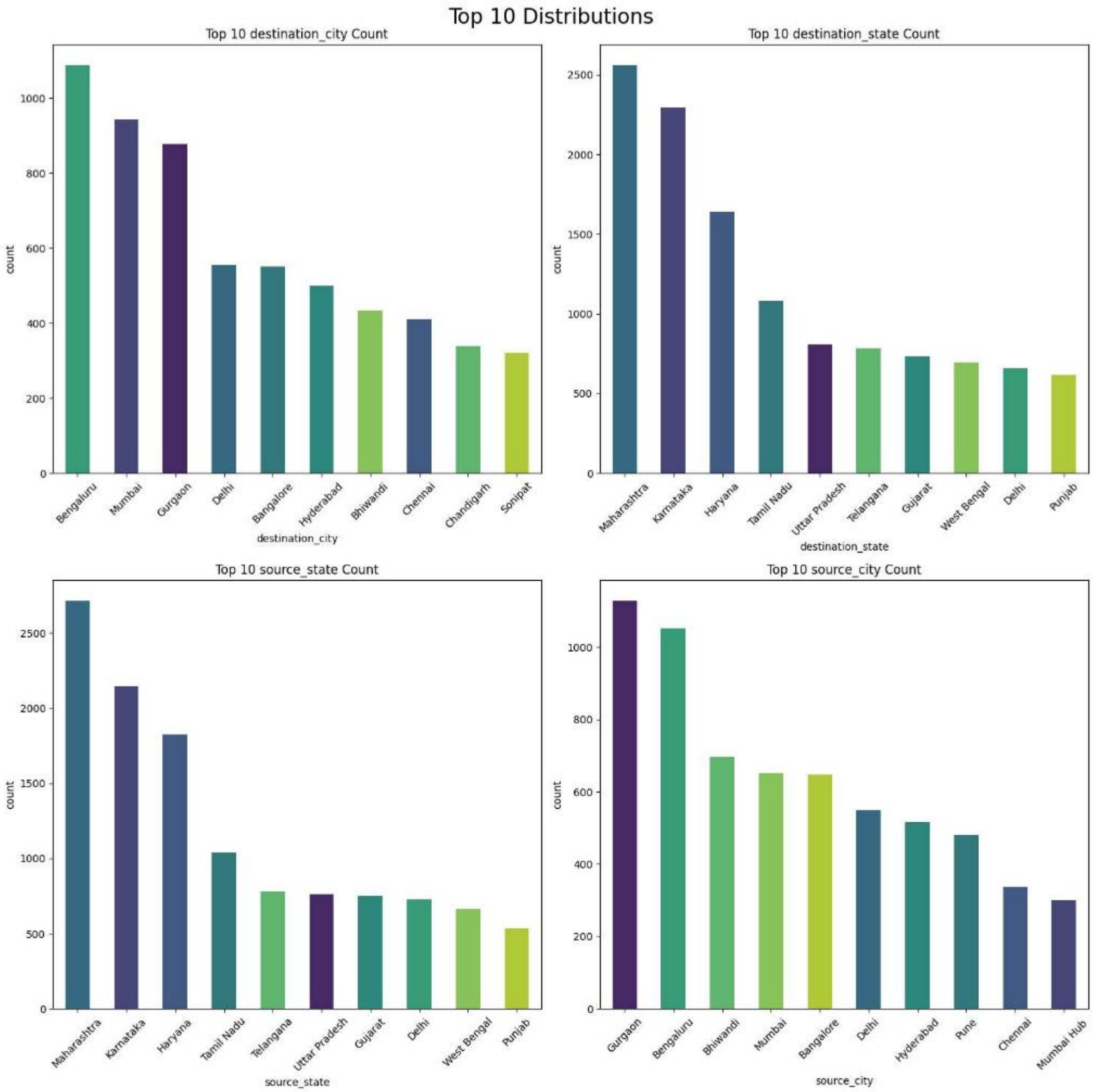


🔍 Insights

- The dataset contains 10,645 entries for training and 4,142 entries for testing.
- Carting is the most common route type, appearing 8,906 times, suggesting it is a popular choice among users.

In [647…

```
col2 = ["destination_city","destination_state","source_state","source_city"]

plt.figure(figsize=(15,15))
for i,j in enumerate(col2):
  i = i+1
  plt.subplot(2,2,i)
  data = trip_data[trip_data[j].isin(trip_data[j].value_counts().head(10).index)]
  sns.countplot(x = j,data = data,hue = j,legend = False,order = data[j].value_counts().index,
                palette = "viridis",width = 0.5)
  plt.title(f"Top 10 {j} Count")
  plt.xticks(rotation = 45)
plt.suptitle("Top 10 Distributions" , fontsize = 20)
plt.tight_layout()
plt.show()
```



Insights 🔍

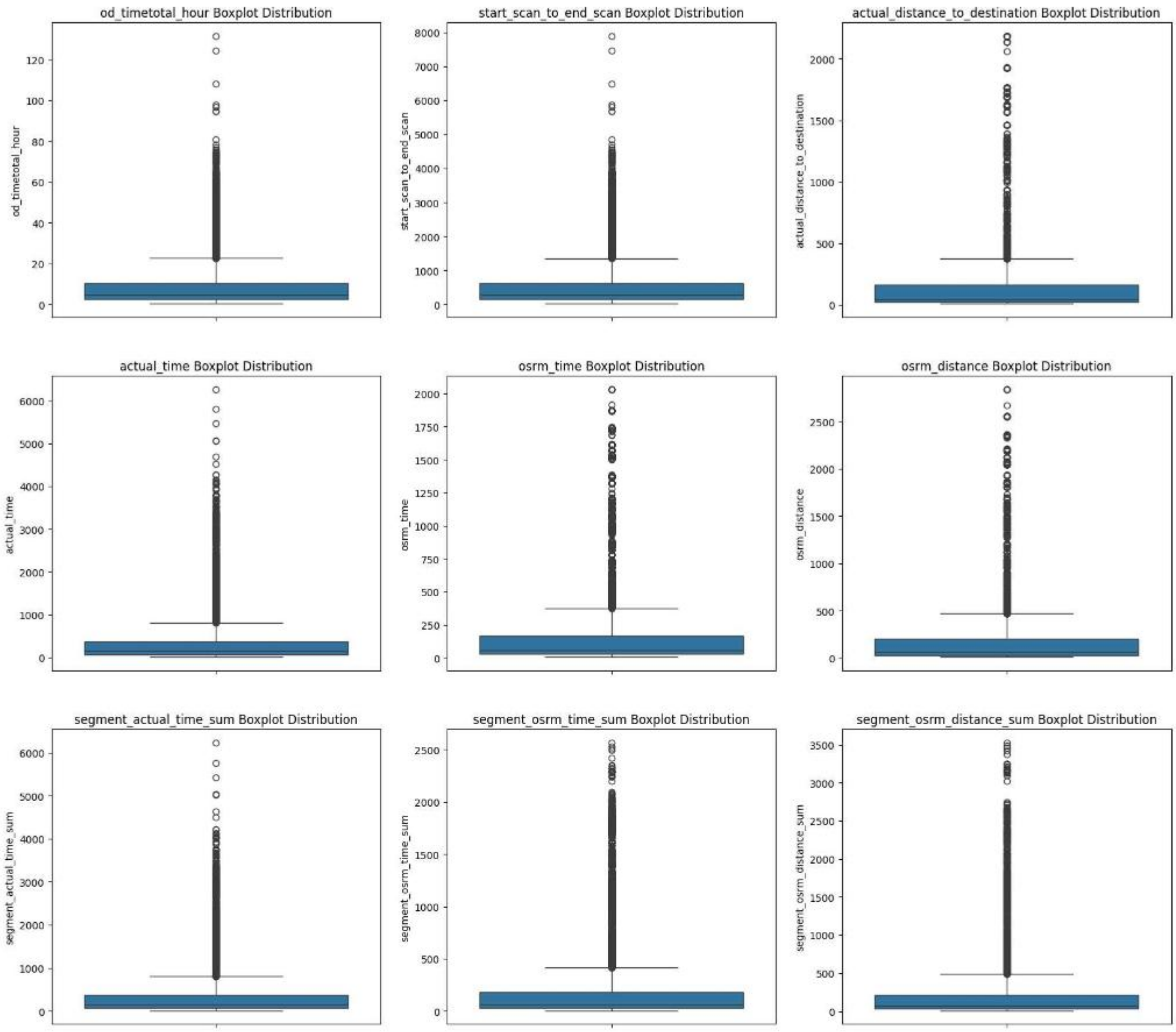
- Bengaluru is the top destination city, followed closely by Mumbai and Gurgaon.
- Maharashtra and Karnataka dominate both the source and destination states, with Maharashtra leading.
- Gurgaon is the most frequent source city, surpassing Bengaluru and Bhubaneswar.
- Haryana is a major contributor to destination states, while Tamil Nadu shows strong activity on both the source and destination sides.

Outlier Detection And Handling

In [648…

```
plt.figure(figsize=(20,18))
for i,j in enumerate(num_col):
  i = i+1
  plt.subplot(3,3,i)
  sns.boxplot(y =  trip_data[j])
  plt.title(f"{j} Boxplot Distribution")
plt.suptitle("Boxplot Distribution" , fontsize = 40)
plt.show()
```

Boxplot Distribution



In [649…

```
trip_data[num_col].describe().T
```

Out[649…

	count	mean	std	min	25%	50%	75%	max
od_timetotal_hour	14787.0	8.840187	10.978880	0.391024	2.494975	4.661846	10.558962	131.642533
start_scan_to_end_scan	14787.0	529.429025	658.254936	23.000000	149.000000	279.000000	632.000000	7898.000000
actual_distance_to_destination	14787.0	164.090196	305.502982	9.002461	22.777099	48.287894	163.591258	2186.531787
actual_time	14787.0	356.306012	561.517936	9.000000	67.000000	148.000000	367.000000	6265.000000
osrm_time	14787.0	160.990938	271.459495	6.000000	29.000000	60.000000	168.000000	2032.000000
osrm_distance	14787.0	203.887411	370.565564	9.072900	30.756900	65.302800	206.644200	2840.081000
segment_actual_time_sum	14787.0	353.059174	556.365911	9.000000	66.000000	147.000000	364.000000	6230.000000
segment_osrm_time_sum	14787.0	180.511598	314.679279	6.000000	30.000000	65.000000	184.000000	2564.000000
segment_osrm_distance_sum	14787.0	222.705466	416.846279	9.072900	32.578850	69.784200	216.560600	3523.632400

In [650…

```
for i in num_col:
  Q1 = np.quantile(trip_data[i],0.25)
  Q3 = np.quantile(trip_data[i],0.75)
  IQR = Q3 - Q1
  upper_bound = Q3 + (1.5*IQR)
  lower_bound = Q1 - (1.5*IQR)
  outliers = trip_data[(trip_data[i]< lower_bound)| (trip_data[i]>upper_bound)]
  print('Column Name :', i)
  print(f'25th Percentile Value : {Q1} , 75th Percentile Value : {Q3} ')
  print(f'IQR Value : {IQR}')
  print(f'Lower Bound : {lower_bound} , Upper Bound : {upper_bound}')
```

```
    print(f"Number of Outliers : {len(outliers)}")
    print(f"Percentage Of Outliers : {(len(outliers)/len(trip_data[i]))*100} \n")
```

```
Column Name : od_timetotal_hour
25th Percentile Value : 2.494974930972222 , 75th Percentile Value : 10.558961618055555
IQR Value : 8.063986687083332
Lower Bound : -9.601005099652777 , Upper Bound : 22.654941648680555
Number of Outliers : 1275
Percentage Of Outliers : 8.622438628525057

Column Name : start_scan_to_end_scan
25th Percentile Value : 149.0 , 75th Percentile Value : 632.0
IQR Value : 483.0
Lower Bound : -575.5 , Upper Bound : 1356.5
Number of Outliers : 1282
Percentage Of Outliers : 8.669777507269899

Column Name : actual_distance_to_destination
25th Percentile Value : 22.777098943155323 , 75th Percentile Value : 163.5912581579725
IQR Value : 140.81415921481718
Lower Bound : -188.44413987907043 , Upper Bound : 374.81249698019826
Number of Outliers : 1452
Percentage Of Outliers : 9.81943599107324

Column Name : actual_time
25th Percentile Value : 67.0 , 75th Percentile Value : 367.0
IQR Value : 300.0
Lower Bound : -383.0 , Upper Bound : 817.0
Number of Outliers : 1646
Percentage Of Outliers : 11.13139920200176

Column Name : osrm_time
25th Percentile Value : 29.0 , 75th Percentile Value : 168.0
IQR Value : 139.0
Lower Bound : -179.5 , Upper Bound : 376.5
Number of Outliers : 1506
Percentage Of Outliers : 10.184621627104889

Column Name : osrm_distance
25th Percentile Value : 30.7569 , 75th Percentile Value : 206.6442
IQR Value : 175.8873
Lower Bound : -233.07405000000003 , Upper Bound : 470.47515000000004
Number of Outliers : 1522
Percentage Of Outliers : 10.292824778521673

Column Name : segment_actual_time_sum
25th Percentile Value : 66.0 , 75th Percentile Value : 364.0
IQR Value : 298.0
Lower Bound : -381.0 , Upper Bound : 811.0
Number of Outliers : 1644
Percentage Of Outliers : 11.11787380807466

Column Name : segment_osrm_time_sum
25th Percentile Value : 30.0 , 75th Percentile Value : 184.0
IQR Value : 154.0
Lower Bound : -201.0 , Upper Bound : 415.0
Number of Outliers : 1485
Percentage Of Outliers : 10.042604990870359

Column Name : segment_osrm_distance_sum
25th Percentile Value : 32.57885 , 75th Percentile Value : 216.5606
IQR Value : 183.98174999999998
Lower Bound : -243.393775 , Upper Bound : 492.533225
Number of Outliers : 1550
Percentage Of Outliers : 10.482180293501047
```

Insights 🔍

- On average, about 10% of the data consists of outliers across various columns. Given this percentage and the nature of the data, these outliers likely represent important variations rather than anomalies.
- Instead of removing these outliers, we will retain them for further analysis, as they could provide valuable insights, especially in understanding extremes or unique cases in the dataset.

Hypothesis Testing & Visual Analysis

1. Time Comparision Between "od_timetotal_hour" & "start_scan_to_end_scan"

In [651…

```
# start_scan_to_end_scan column is currently in minutes , need to convert that into hours.

trip_data["start_scan_to_end_scan_hours"] = trip_data["start_scan_to_end_scan"]/60

trip_data["start_scan_to_end_scan_hours"].head()
```

Out[651…

	start_scan_to_end_scan_hours
0	37.650000
1	3.000000
2	65.550000
3	1.666667
4	11.950000

dtype: float64

In [652…

```
trip_data[["od_timetotal_hour","start_scan_to_end_scan_hours"]].describe()
```

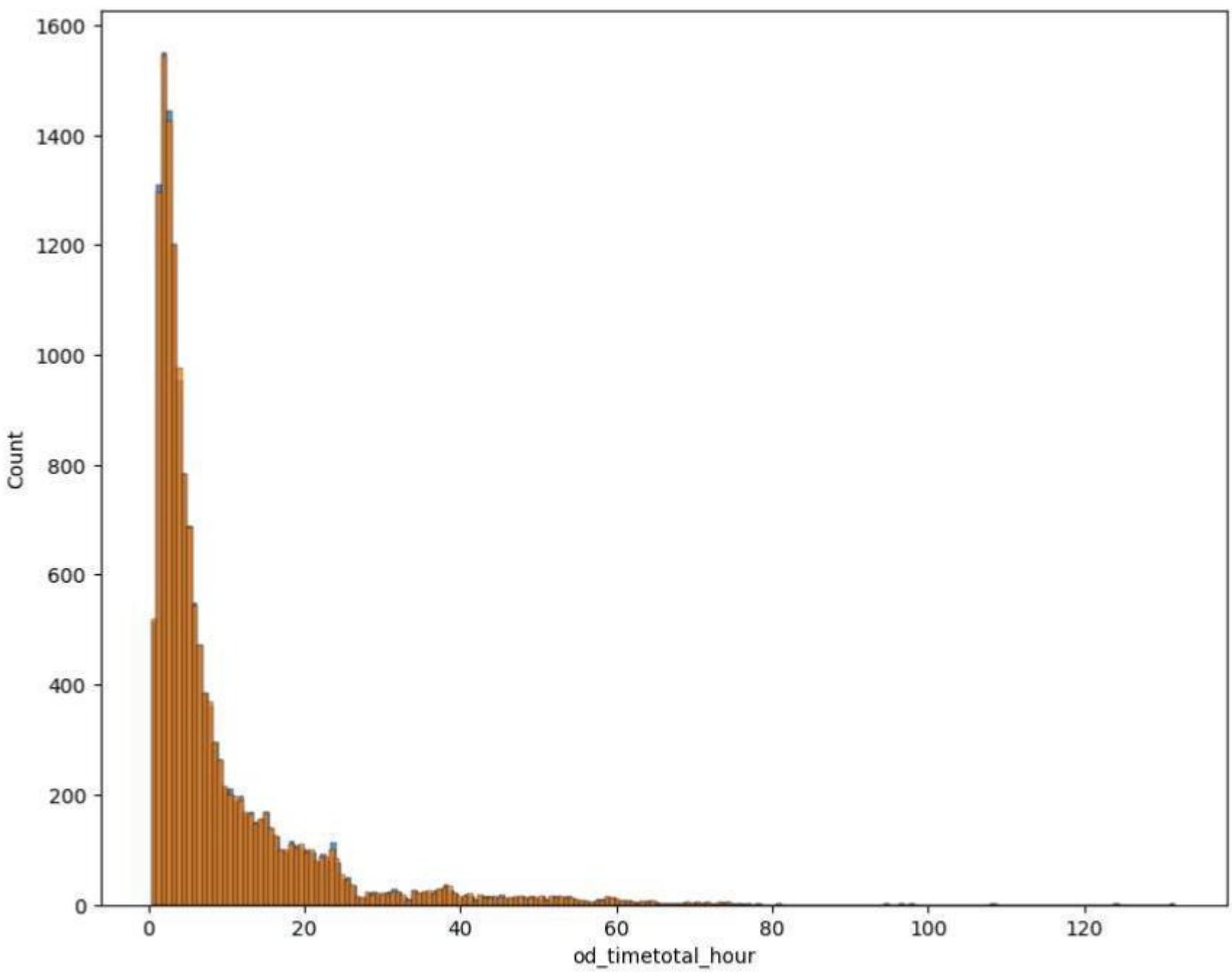
Out[652…

	od_timetotal_hour	start_scan_to_end_scan_hours
count	14787.000000	14787.000000
mean	8.840187	8.823817
std	10.978880	10.970916
min	0.391024	0.383333
25%	2.494975	2.483333
50%	4.661846	4.650000
75%	10.558962	10.533333
max	131.642533	131.633333

Visual Analysis

In [653…

```
plt.figure(figsize=(10,8))
sns.histplot(x = "od_timetotal_hour", data = trip_data)
sns.histplot(x ="start_scan_to_end_scan_hours", data = trip_data)
plt.show()
```

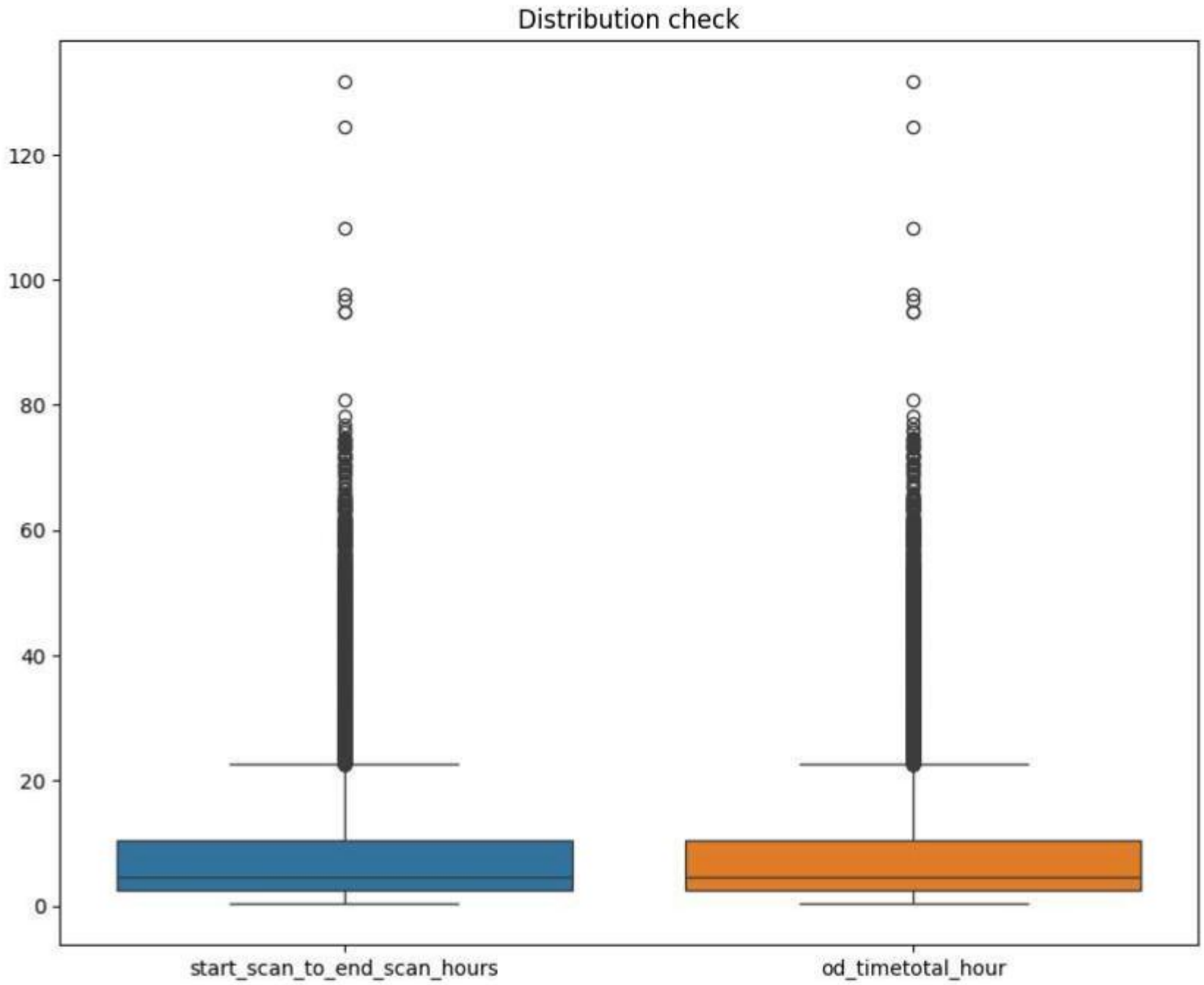


In [654…

```
plt.figure(figsize=(10,8))
sns.boxplot( trip_data[["start_scan_to_end_scan_hours","od_timetotal_hour"]])
plt.title("Distribution check")
```

Out[654…

```
Text(0.5, 1.0, 'Distribution check')
```



Testing Difference Between Variances with the help of Lavene's Test

Significance Level - 0.5

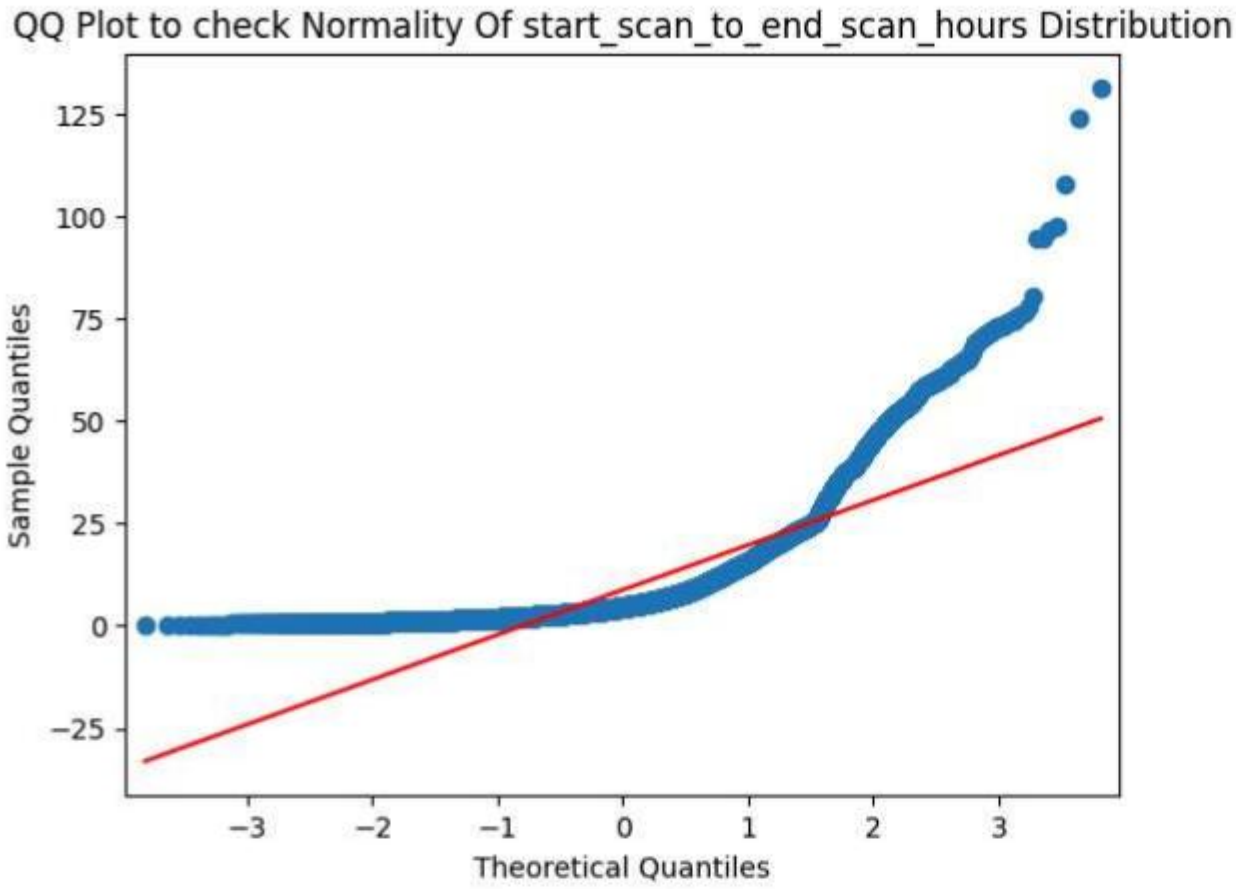
In [655…
```
start_scant_to_end_scan_hours = trip_data["start_scan_to_end_scan_hours"]
od_timetotal_hour = trip_data["od_timetotal_hour"]
```

In [656…
```
stats , pval = levene(start_scant_to_end_scan_hours,od_timetotal_hour)

if pval < 0.05:
  print(" Both od_timetotal_hour & start_scan_to_end_scan DON'T have  equal variance")
else:
  print("Both od_timetotal_hour & start_scan_to_end_scan  HAVE  equal variance")
print(f"Test Statistics = {stats} , pvalue = {pval}")
```

```
Both od_timetotal_hour & start_scan_to_end_scan  HAVE  equal variance
Test Statistics = 0.0030519030240502014 , pvalue = 0.9559444235657867
```

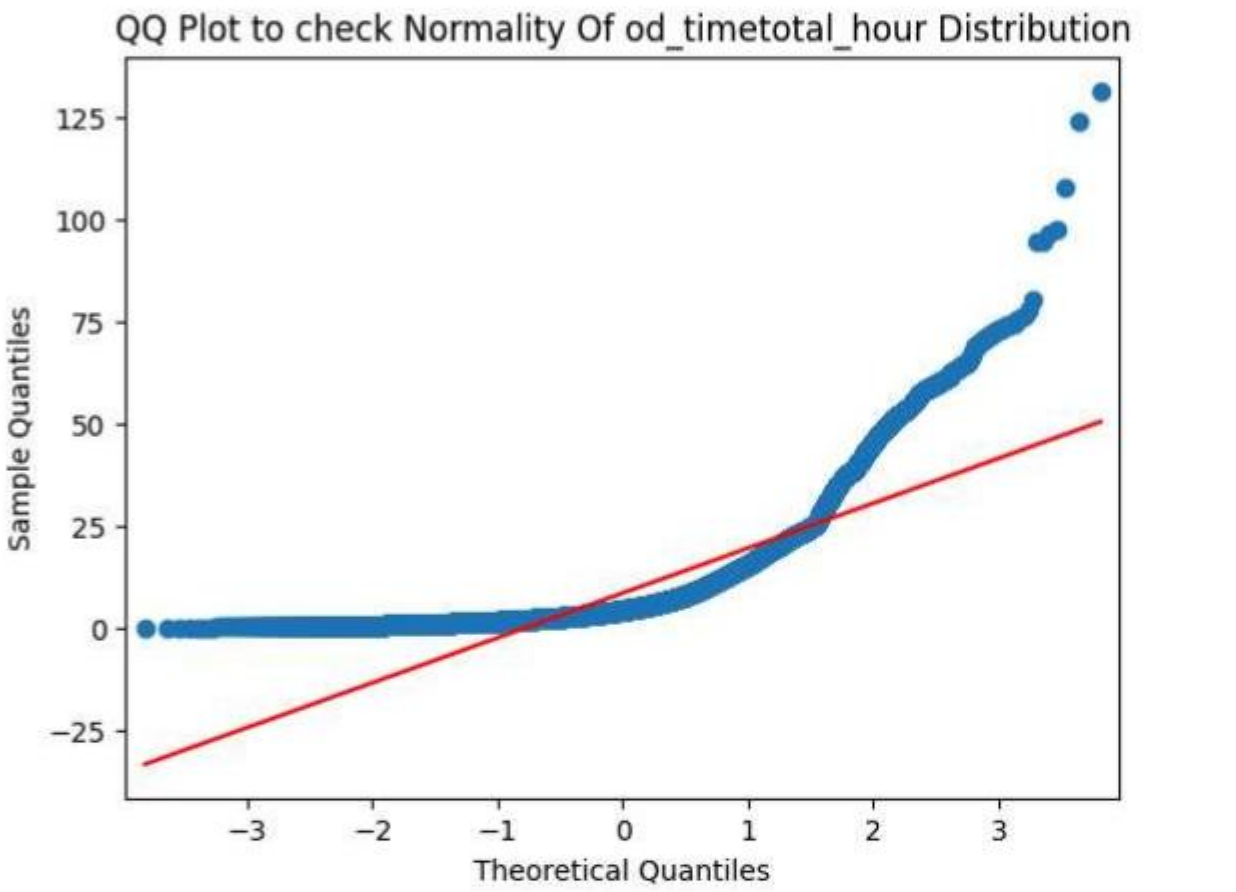
Distribution Check With QQ Plot

In [657…
```
from statsmodels.graphics.gofplots import qqplot

qqplot(start_scant_to_end_scan_hours , line = 's')
plt.title("QQ Plot to check Normality Of start_scan_to_end_scan_hours Distribution")
plt.show()
```



In [658…

```
qqplot(od_timetotal_hour , line = 's')
plt.title("QQ Plot to check Normality Of od_timetotal_hour Distribution")
plt.show()
```



Insights 🔍

Both of the distribution doesn't follow Normal Distribution

Hypothesis Testing

Performing Kruskal-Wallis Test to check the difference between Medians

Significance level - 0.5

In [659…

```
stats,pvalue = kruskal(od_timetotal_hour,start_scant_to_end_scan_hours)
if pvalue < 0.05:
  print("Reject Null Hypothesis : Median of od_timetotal_hour is significantly different from median of start_scant_to_end_scan_hours")
else :
  print("Fail to reject Null Hypothesis :  Median of od_timetotal_hour is similar with median of start_scant_to_end_scan_hours ")

print(f"Test Statistics = {stats} , pvalue = {pvalue}")
```

```
Fail to reject Null Hypothesis :  Median of od_timetotal_hour is similar with median of start_scant_to_end_scan_hours
Test Statistics = 0.07772644614037329 , pvalue = 0.7804024351892083
```

Note : Though od_timetotal_hour & start_scan_to_end_scan Not normally Distributed , Still we are going to perform Ttest.

Performing Ttest independent

Significance level - 0.5

In [660…

```
stats,pvalue = ttest_ind(od_timetotal_hour,start_scant_to_end_scan_hours)
if pvalue < 0.05:
  print("Reject Null Hypothesis : Mean of od_timetotal_hour is significantly different from mean of start_scant_to_end_scan_hours")
else :
  print("Fail to reject Null Hypothesis :  Mean of od_timetotal_hour is similar with mean of start_scant_to_end_scan_hours ")

print(f"Test Statistics = {stats} , pvalue = {pvalue}")
```

```
Fail to reject Null Hypothesis :  Mean of od_timetotal_hour is similar with mean of start_scant_to_end_scan_hours
Test Statistics = 0.1282568191862211 , pvalue = 0.8979466082545831
```

2. Analysis between actual_time aggregated value and OSRM time aggregated value

In [661…

```
trip_data[["actual_time","segment_osrm_time_sum"]].describe()
```

Out[661…

	actual_time	segment_osrm_time_sum
count	14787.000000	14787.000000
mean	356.306012	180.511598
std	561.517936	314.679279
min	9.000000	6.000000
25%	67.000000	30.000000
50%	148.000000	65.000000
75%	367.000000	184.000000
max	6265.000000	2564.000000

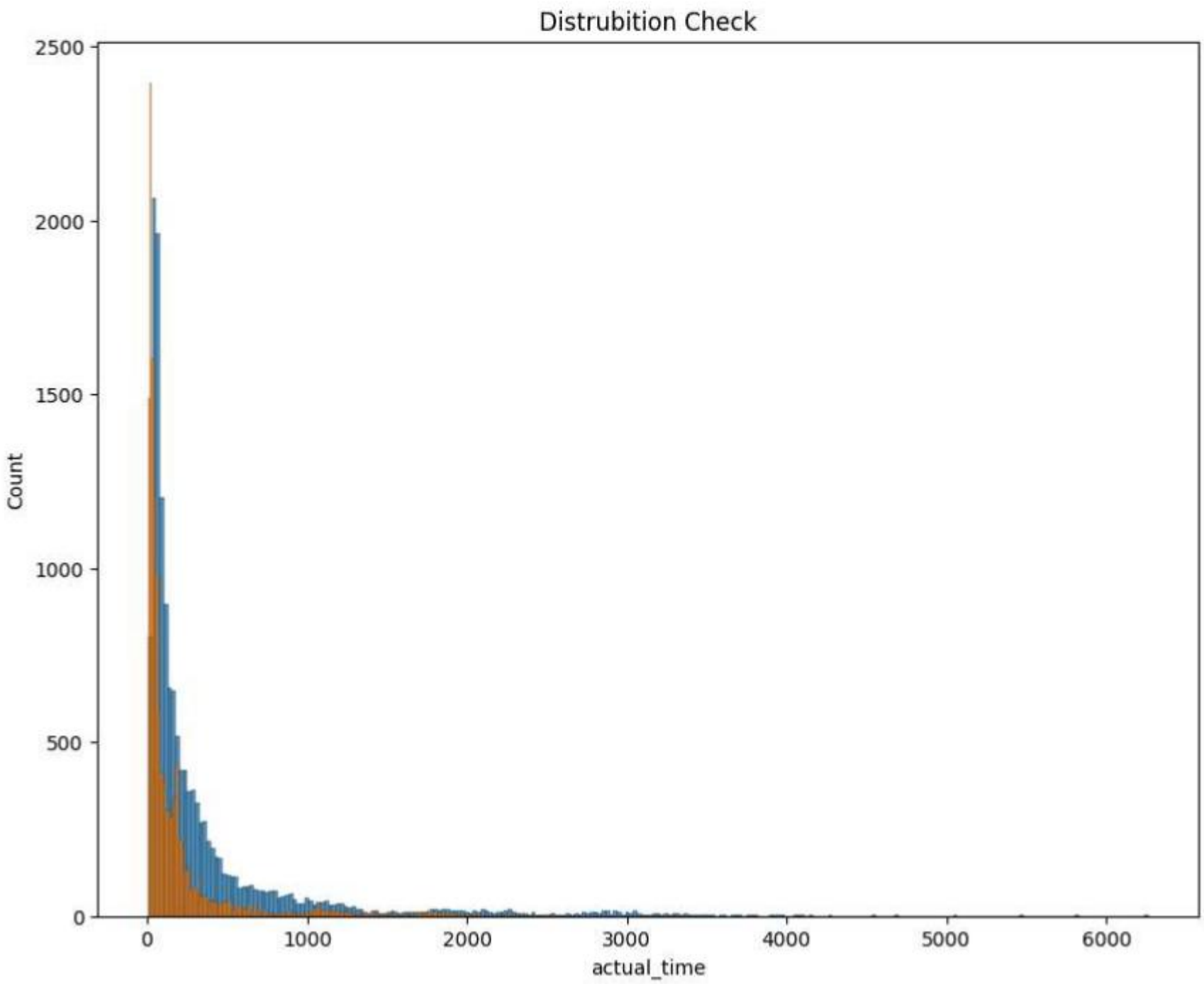
In [662…

```
actual_time = trip_data["actual_time"]
osrm_time_sum = trip_data["segment_osrm_time_sum"]
```

Visual Analysis

In [663…

```
plt.figure(figsize=(10,8))
sns.histplot(actual_time)
sns.histplot(osrm_time_sum)
plt.title("Distrubition Check")
plt.show()
```

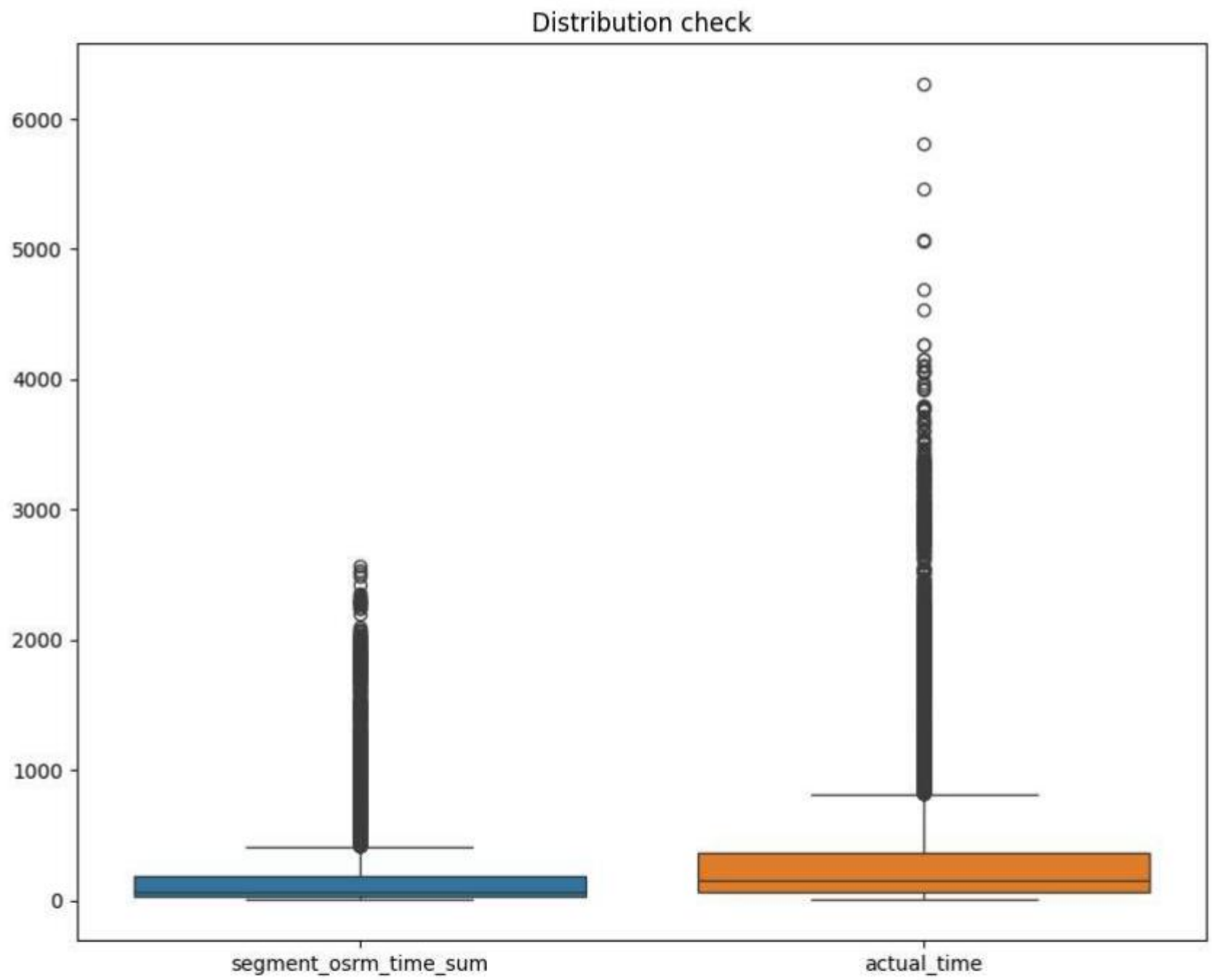


In [664…

```
plt.figure(figsize=(10,8))
sns.boxplot(trip_data[["segment_osrm_time_sum","actual_time"]])
plt.title("Distribution check")
```

Out[664…

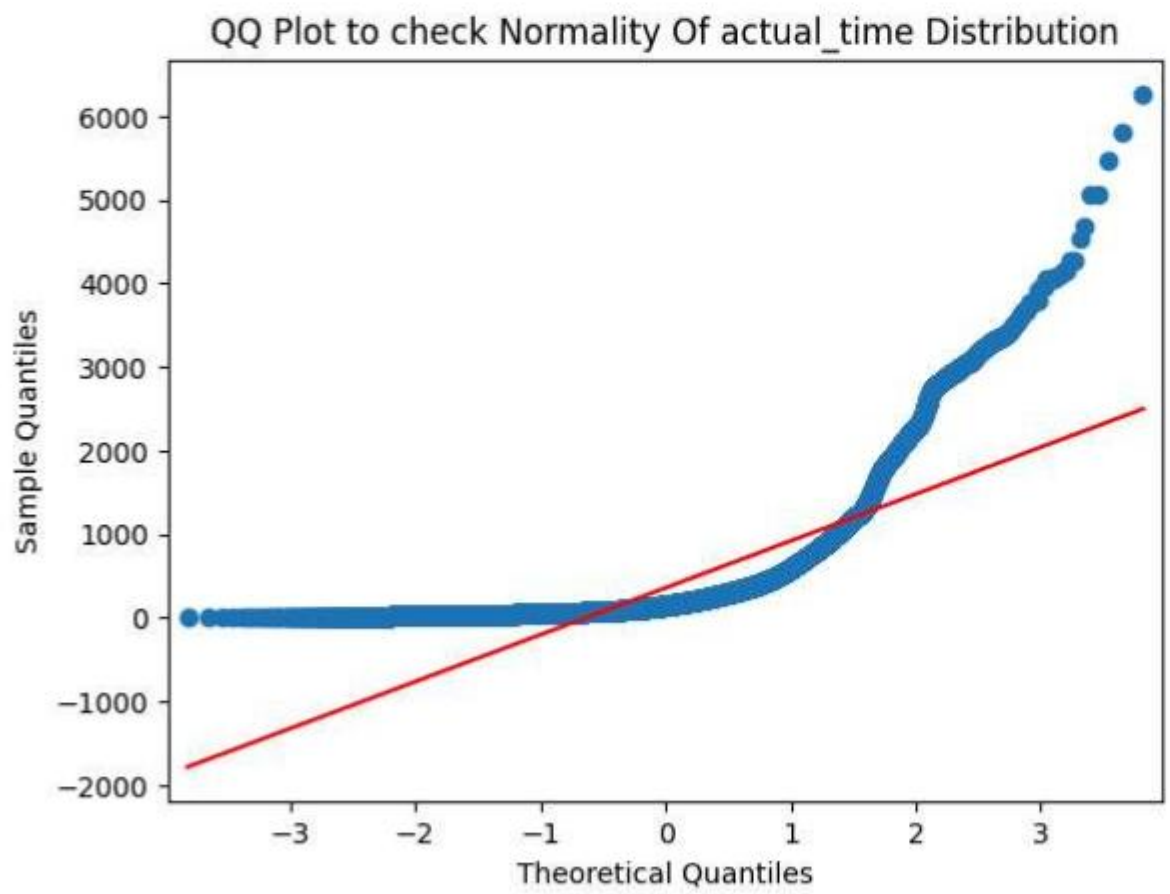
```
Text(0.5, 1.0, 'Distribution check')
```



Distribution Check With QQ Plot

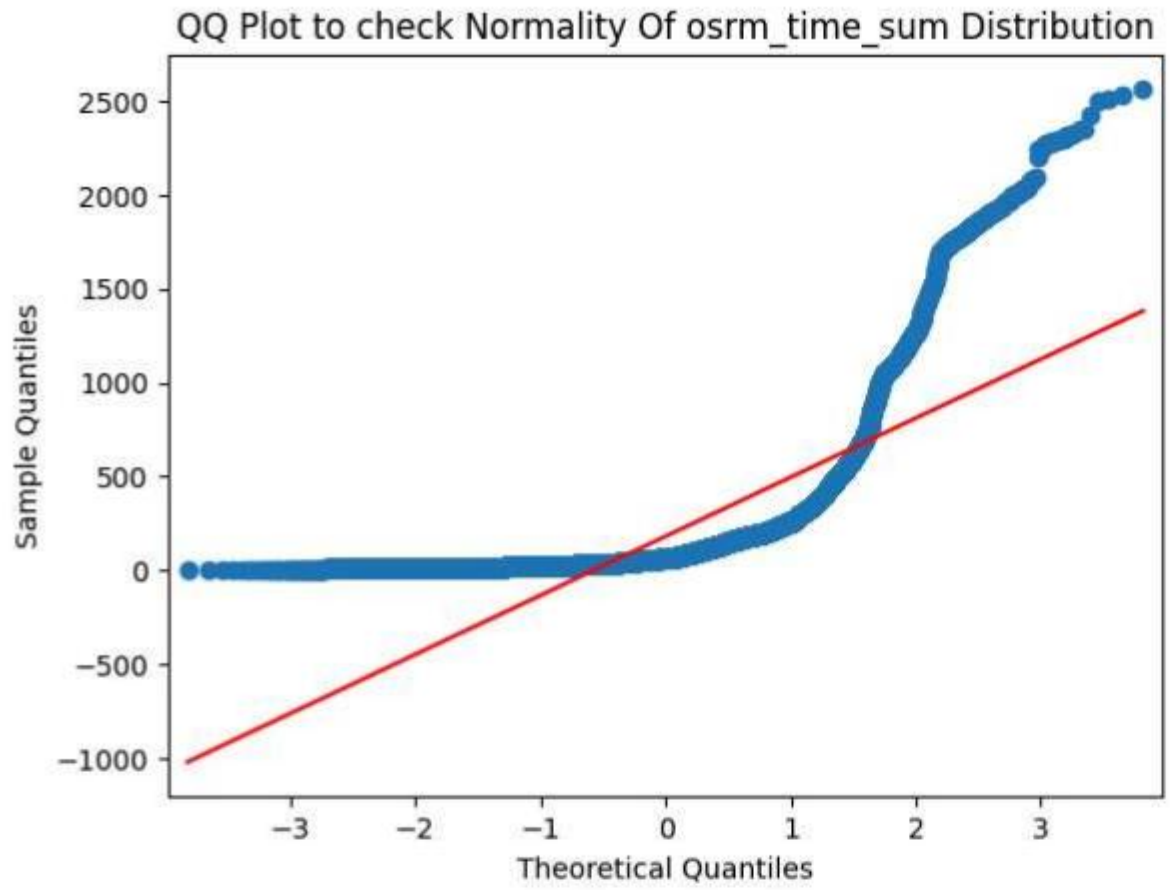
In [665…

```
qqplot(actual_time , line = 's')
plt.title("QQ Plot to check Normality Of actual_time Distribution")
plt.show()
```



In [666…

```
qqplot(osrm_time_sum , line = 's')
plt.title("QQ Plot to check Normality Of osrm_time_sum Distribution")
plt.show()
```



Insights 🔍

Both of the distribution doesn't follow Normal Distribution

Hypothesis Testing

Performing Kruskal-Wallis Test to check the difference between Medians

Significance level - 0.5

In [667…

```
stats,pvalue = kruskal(actual_time,osrm_time_sum)
if pvalue < 0.05:
  print("Reject Null Hypothesis : Median of actual_time is significantly different from median of OSRM time aggregated value")
else :
  print("Fail to reject Null Hypothesis :  Median of actual_time is similar with median of OSRM time aggregated value ")

print(f"Test Statistics = {stats} , pvalue = {pvalue}")
```

```
Reject Null Hypothesis : Median of actual_time is significantly different from median of OSRM time aggregated value
Test Statistics = 2783.2889404585285 , pvalue = 0.0
```

Note : Though both of the distribution does not follow normal distribution , Still we are going to perform Ttest.

Performing Ttest independent

Significance level - 0.5

In [668…

```
stats,pvalue = ttest_ind(actual_time,osrm_time_sum)
if pvalue < 0.05:
  print("Reject Null Hypothesis : Mean of actual_time is significantly different from mean of OSRM time aggregated value")
else :
  print("Fail to reject Null Hypothesis :  Mean of actual_time is similar with mean of OSRM time aggregated value")

print(f"Test Statistics = {stats} , pvalue = {pvalue}")
```

```
Reject Null Hypothesis : Mean of actual_time is significantly different from mean of OSRM time aggregated value
Test Statistics = 33.21041532061086 , pvalue = 1.7694669370273323e-237
```

3. Analysis between actual_time aggregated value and segment actual time aggregated value

In [669…

```
trip_data[["actual_time","segment_actual_time_sum"]].describe()
```

Out[669…

	actual_time	segment_actual_time_sum
count	14787.000000	14787.000000
mean	356.306012	353.059174
std	561.517936	556.365911
min	9.000000	9.000000
25%	67.000000	66.000000
50%	148.000000	147.000000
75%	367.000000	364.000000
max	6265.000000	6230.000000

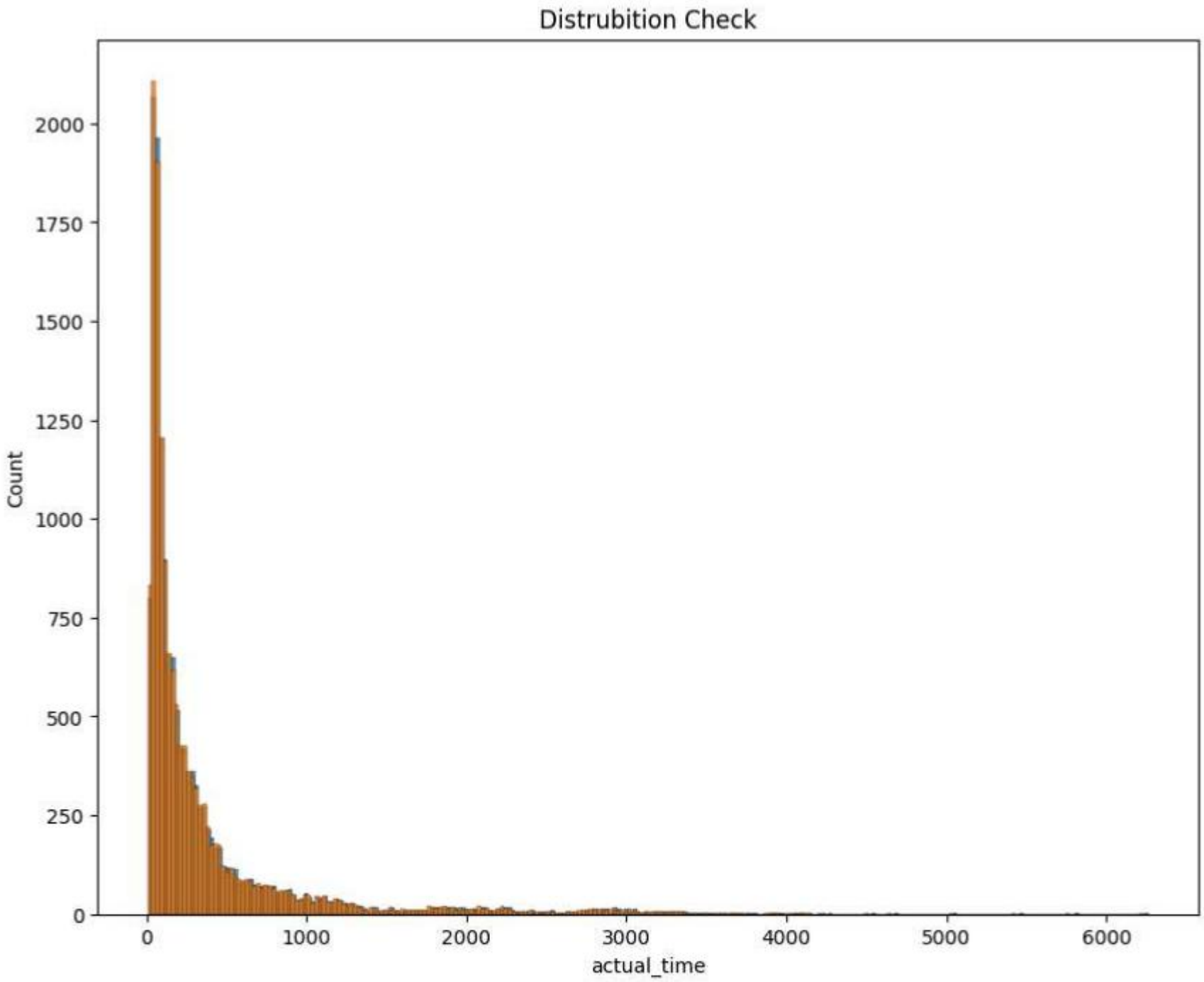
In [670…

```
segment_actual_time  = trip_data["segment_actual_time_sum"]
```

Visual Analysis

In [671…

```
plt.figure(figsize=(10,8))
sns.histplot(actual_time)
sns.histplot(segment_actual_time)
plt.title("Distrubition Check")
plt.show()
```

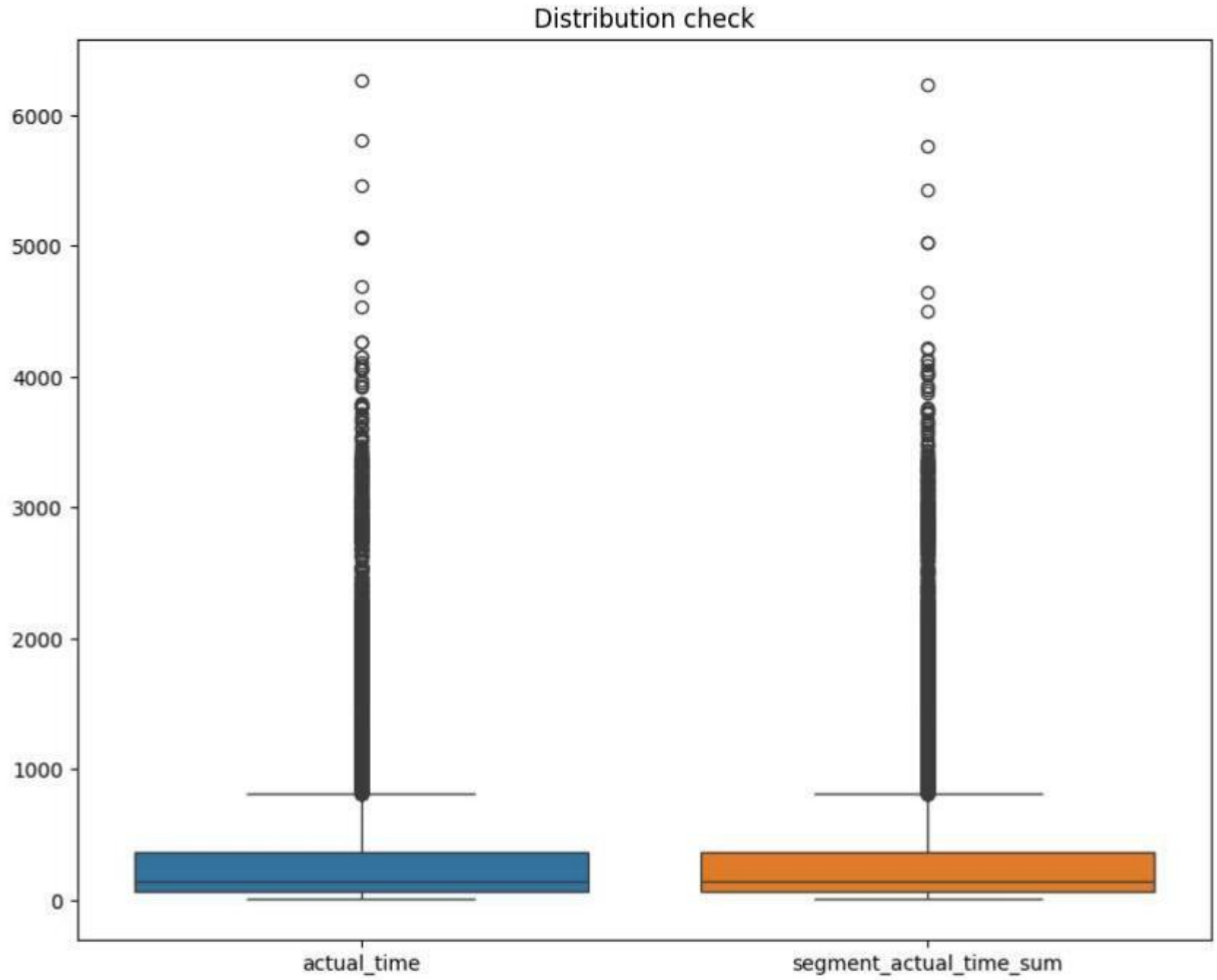


In [672…

```
plt.figure(figsize=(10,8))
sns.boxplot(trip_data[["actual_time","segment_actual_time_sum"]])
plt.title("Distribution check")
```

Out[672…

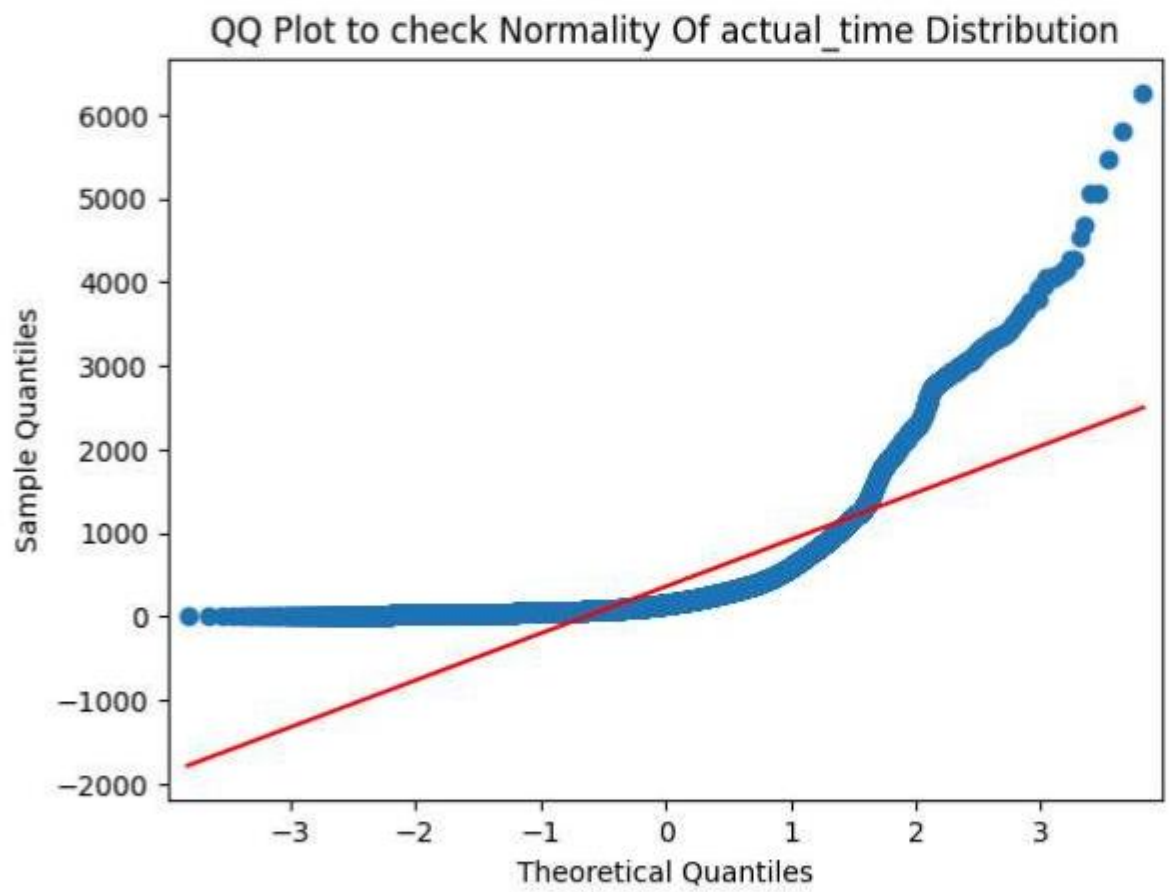
```
Text(0.5, 1.0, 'Distribution check')
```



Distribution Check with QQ Plot

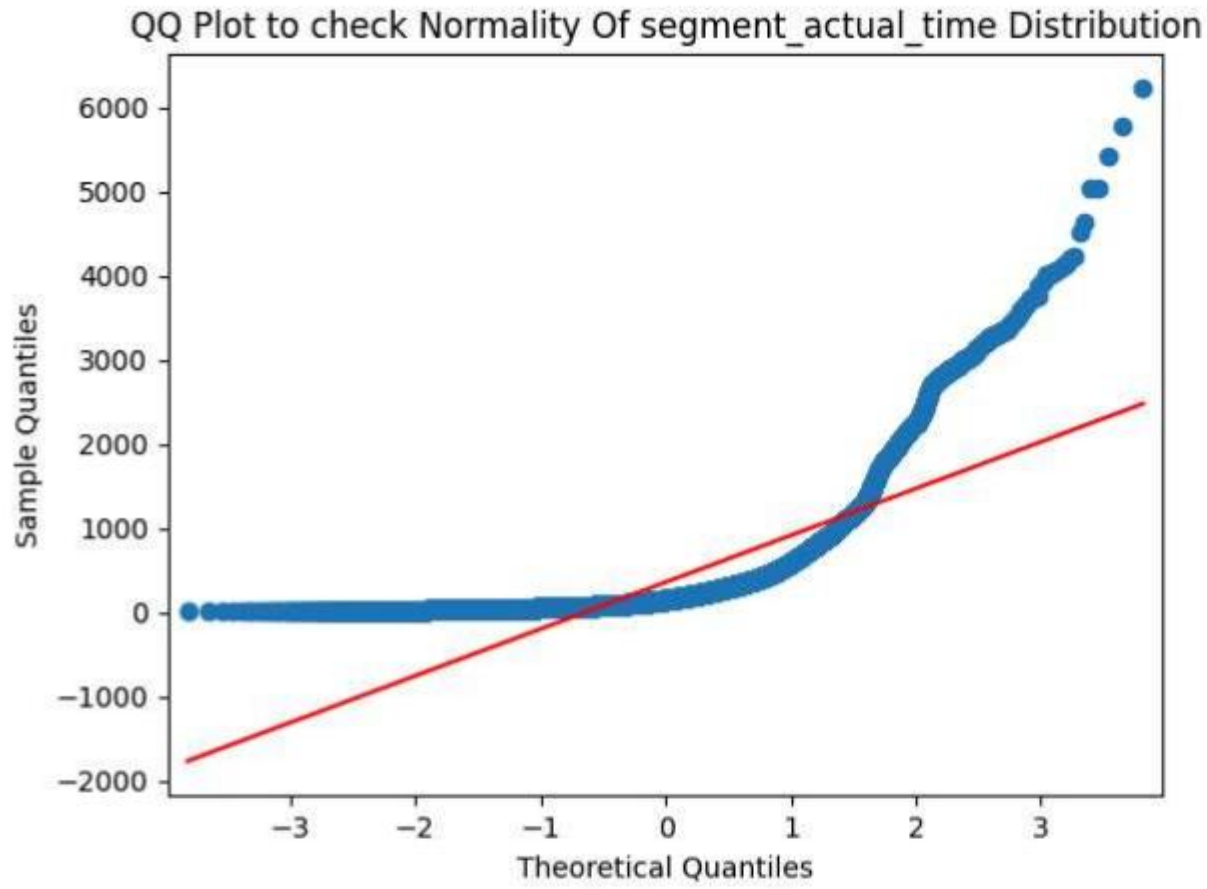
In [673…

```
qqplot(actual_time , line = 's')
plt.title("QQ Plot to check Normality Of actual_time Distribution")
plt.show()
```



In [674…

```
qqplot(segment_actual_time, line = 's')
plt.title("QQ Plot to check Normality Of segment_actual_time Distribution")
plt.show()
```



Insights 🔍

Both of the distribution doesn't follow Normal Distribution

Hypothesis Testing

Performing Kruskal-Wallis Test to check the difference between Medians

Significance level - 0.5

In [675…

```
stats,pvalue = kruskal(actual_time,segment_actual_time)
if pvalue < 0.05:
  print("Reject Null Hypothesis : Median of actual_time is significantly different from median of segment actual time aggregated value")
else :
  print("Fail to reject Null Hypothesis :  Median of actual_time is similar with median ofsegment actual time aggregated value ")

print(f"Test Statistics = {stats} , pvalue = {pvalue}")
```

```
Fail to reject Null Hypothesis :  Median of actual_time is similar with median ofsegment actual time aggregated value
Test Statistics = 0.6621963196958102 , pvalue = 0.4157856290406001
```

Note : Though both of the distribution does not follow normal distribution , Still we are going to perform Ttest.

Performing Ttest independent

Significance level - 0.5

In [676…

```
stats,pvalue = ttest_ind(actual_time,segment_actual_time)
if pvalue < 0.05:
  print("Reject Null Hypothesis : Mean of actual_time is significantly different from mean of segment actual time aggregated value")
else :
  print("Fail to reject Null Hypothesis :  Mean of actual_time is similar with mean of segment actual time aggregated value")

print(f"Test Statistics = {stats} , pvalue = {pvalue}")
```

```
Fail to reject Null Hypothesis :  Mean of actual_time is similar with mean of segment actual time aggregated value
Test Statistics = 0.499475764573994 , pvalue = 0.6174479719707524
```

4. Analysis between osrm distance aggregated value and segment osrm distance aggregated value

In [677…

```
trip_data[["osrm_distance","segment_osrm_distance_sum"]].describe()
```

Out[677…

	osrm_distance	segment_osrm_distance_sum
count	14787.000000	14787.000000
mean	203.887411	222.705466
std	370.565564	416.846279
min	9.072900	9.072900
25%	30.756900	32.578850
50%	65.302800	69.784200
75%	206.644200	216.560600
max	2840.081000	3523.632400

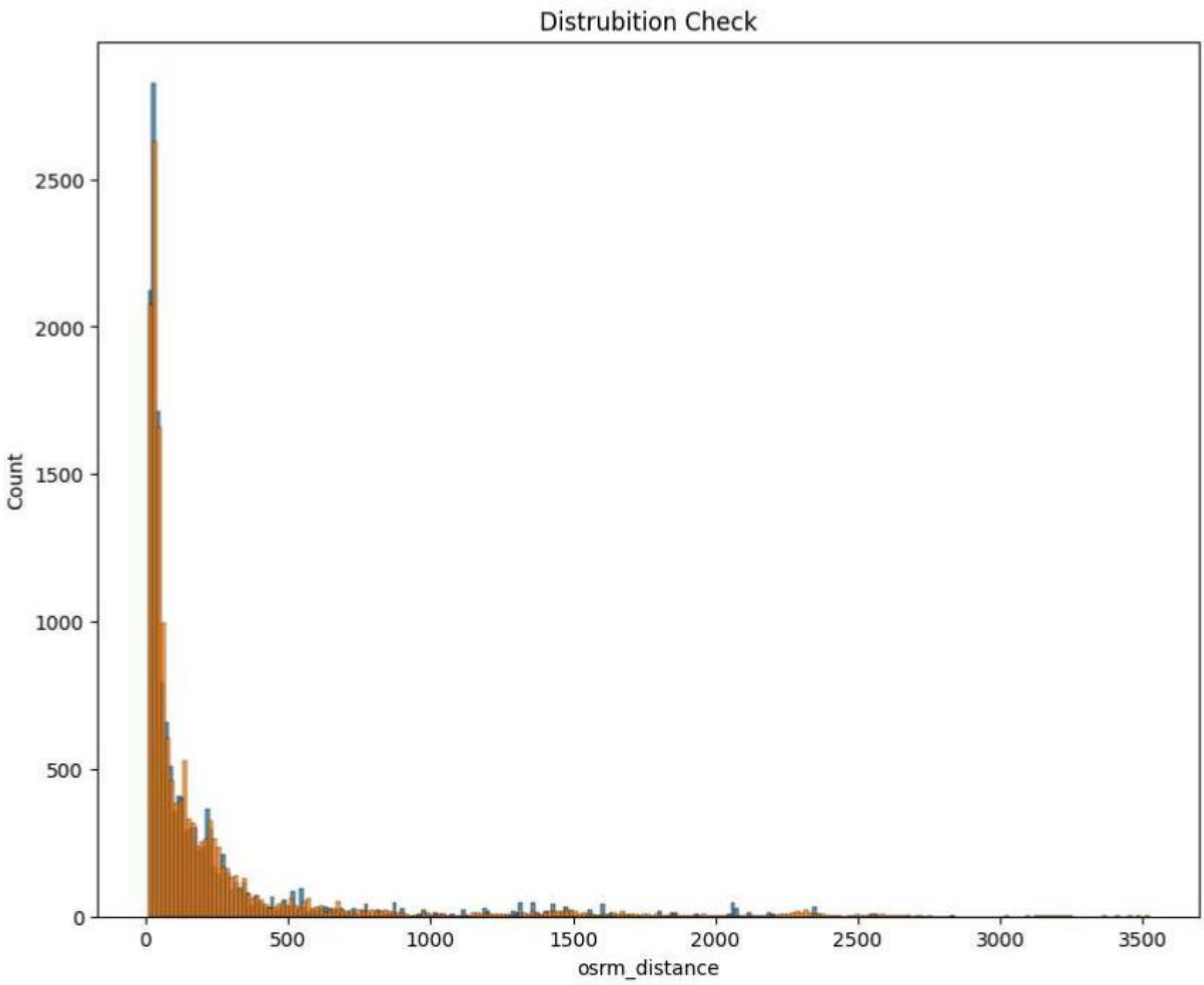
In [678…

```
osrm_distance = trip_data["osrm_distance"]
segment_osrm_distance = trip_data["segment_osrm_distance_sum"]
```

Visual Analysis

In [679…

```
plt.figure(figsize=(10,8))
sns.histplot(osrm_distance)
sns.histplot(segment_osrm_distance)
plt.title("Distrubition Check")
plt.show()
```

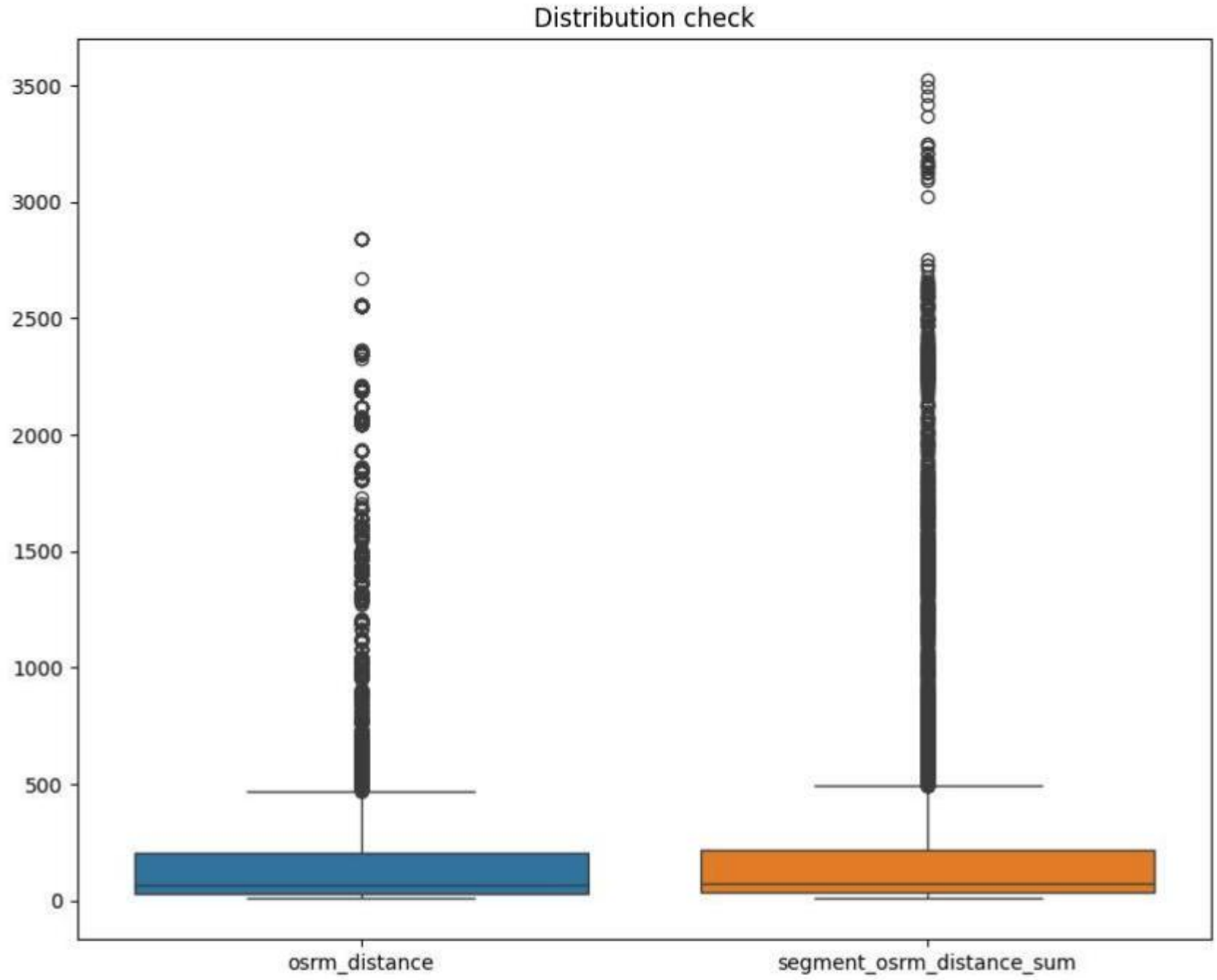


In [680…

```
plt.figure(figsize=(10,8))
sns.boxplot(trip_data[["osrm_distance","segment_osrm_distance_sum"]])
plt.title("Distribution check")
```

Out[680…

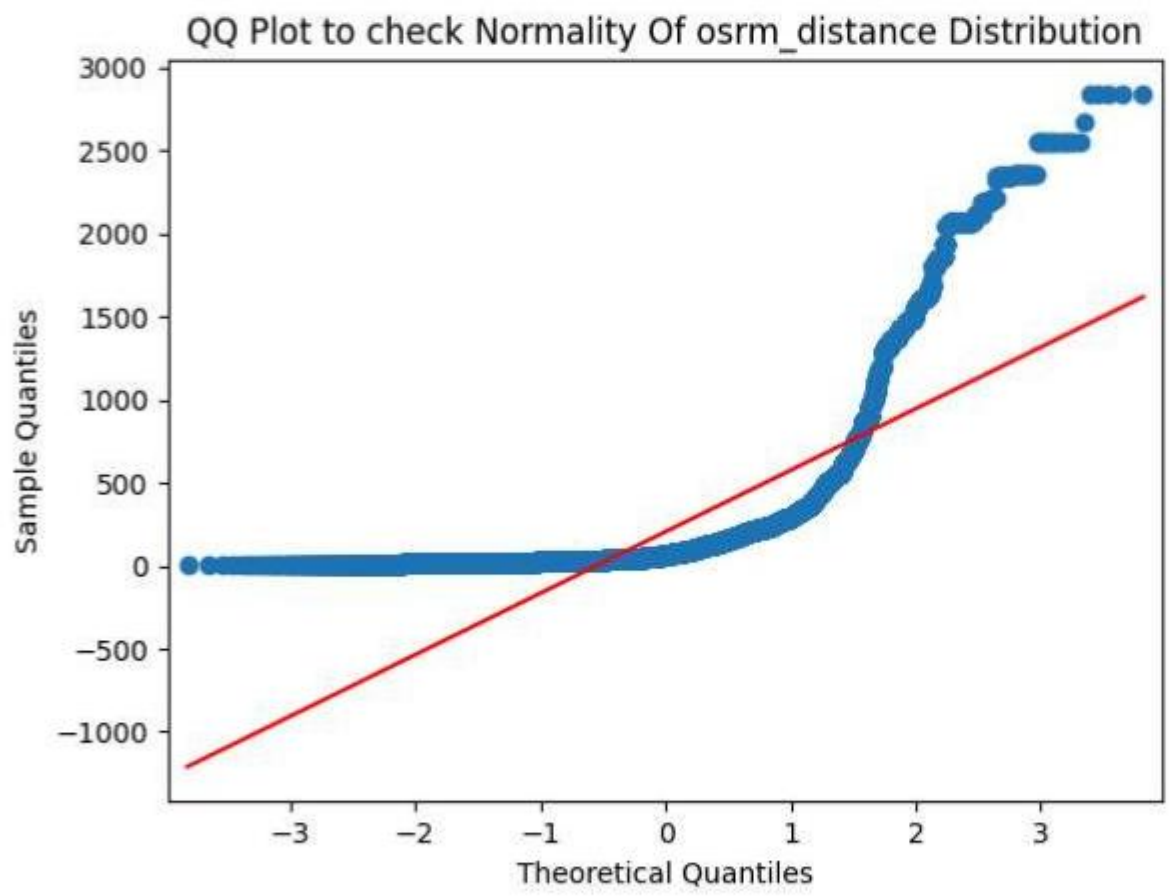
```
Text(0.5, 1.0, 'Distribution check')
```



Distribution Check with QQ Plot

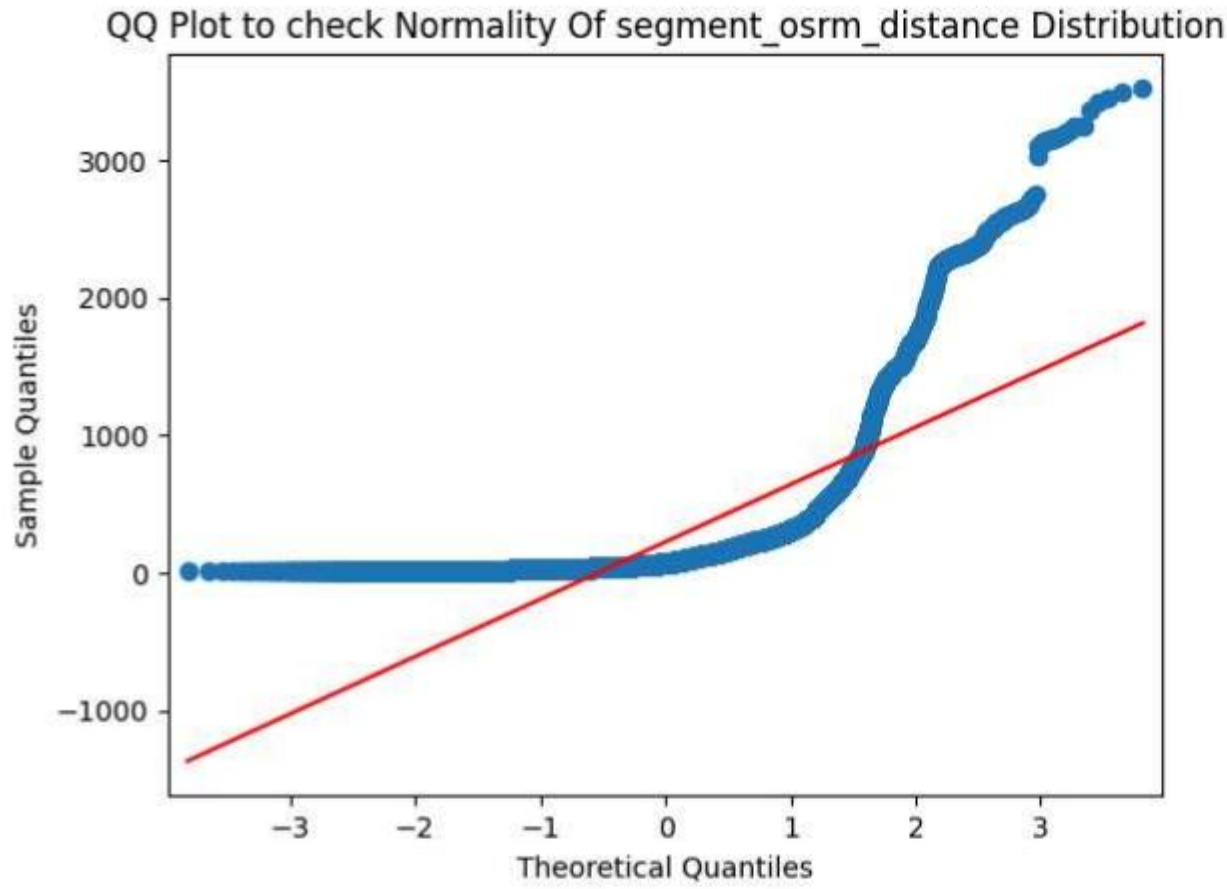
In [681…

```
qqplot(osrm_distance, line = 's')
plt.title("QQ Plot to check Normality Of osrm_distance Distribution")
plt.show()
```



In [682…

```
qqplot(segment_osrm_distance, line = 's')
plt.title("QQ Plot to check Normality Of segment_osrm_distance Distribution")
plt.show()
```



Insights 🔍

Both of the distribution doesn't follow Normal Distribution

Hypothesis Testing

Performing Kruskal-Wallis Test to check the difference between Medians

Significance level - 0.5

In [683…

```
stats,pvalue = kruskal(osrm_distance,segment_osrm_distance)
if pvalue < 0.05:
  print("Reject Null Hypothesis : Median of osrm distance aggregated value is significantly different from median of segment osrm distance a
else :
  print("Fail to reject Null Hypothesis :  Median of osrm distance aggregated value is similar with median of segment osrm distance aggregat

print(f"Test Statistics = {stats} , pvalue = {pvalue}")
```

```
Reject Null Hypothesis : Median of osrm distance aggregated value is significantly different from median of segment osrm distance aggregated
value
Test Statistics = 23.92792425802056 , pvalue = 1.0001053043133998e-06
```

Note : Though both of the distribution does not follow normal distribution , Still we are going to perform Ttest.

Performing Ttest independent

Significance level - 0.5

In [684…

```
stats,pvalue = ttest_ind(osrm_distance,segment_osrm_distance)
if pvalue < 0.05:
  print("Reject Null Hypothesis : Mean of osrm distance aggregated value  is significantly different from mean of segment osrm distance aggr
else :
  print("Fail to reject Null Hypothesis :  Mean of osrm distance aggregated is similar with mean of segment osrm distance aggregated value"

print(f"Test Statistics = {stats} , pvalue = {pvalue}")
```

```
Reject Null Hypothesis : Mean of osrm distance aggregated value  is significantly different from mean of segment osrm distance aggregated va
lue
Test Statistics = -4.102786976805513 , pvalue = 4.0929578191203324e-05
```

5. Analysis between osrm time aggregated value and segment osrm time aggregated value

In [685…

```
trip_data[["osrm_time","segment_osrm_time_sum"]].describe()
```

Out[685…

	osrm_time	segment_osrm_time_sum
count	14787.000000	14787.000000
mean	160.990938	180.511598
std	271.459495	314.679279
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

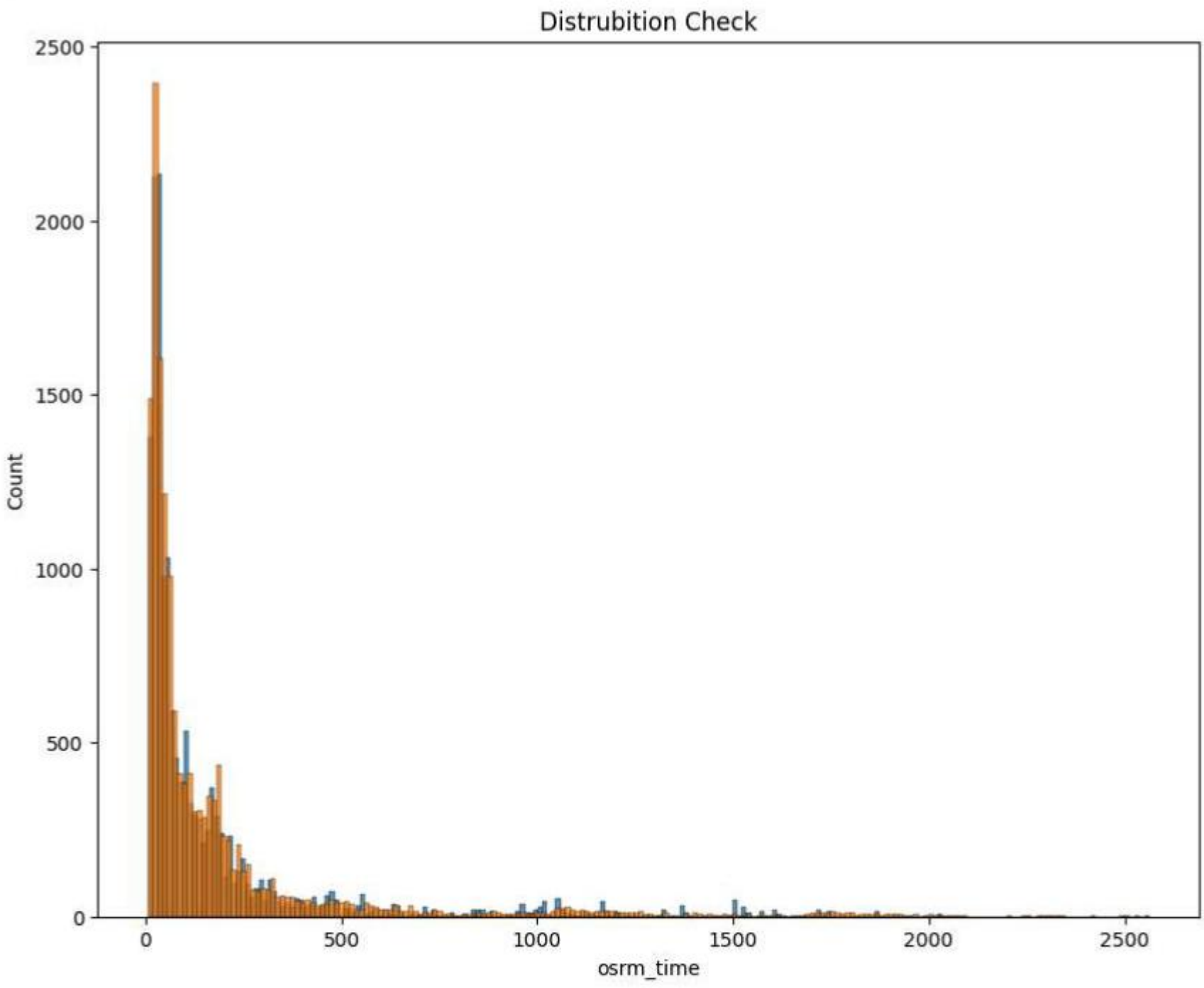
In [686…

```
osrm_time = trip_data["osrm_time"]
segment_osrm_time = trip_data["segment_osrm_time_sum"]
```

Visual Analysis

In [687…

```
plt.figure(figsize=(10,8))
sns.histplot(osrm_time)
sns.histplot(segment_osrm_time)
plt.title("Distrubition Check")
plt.show()
```

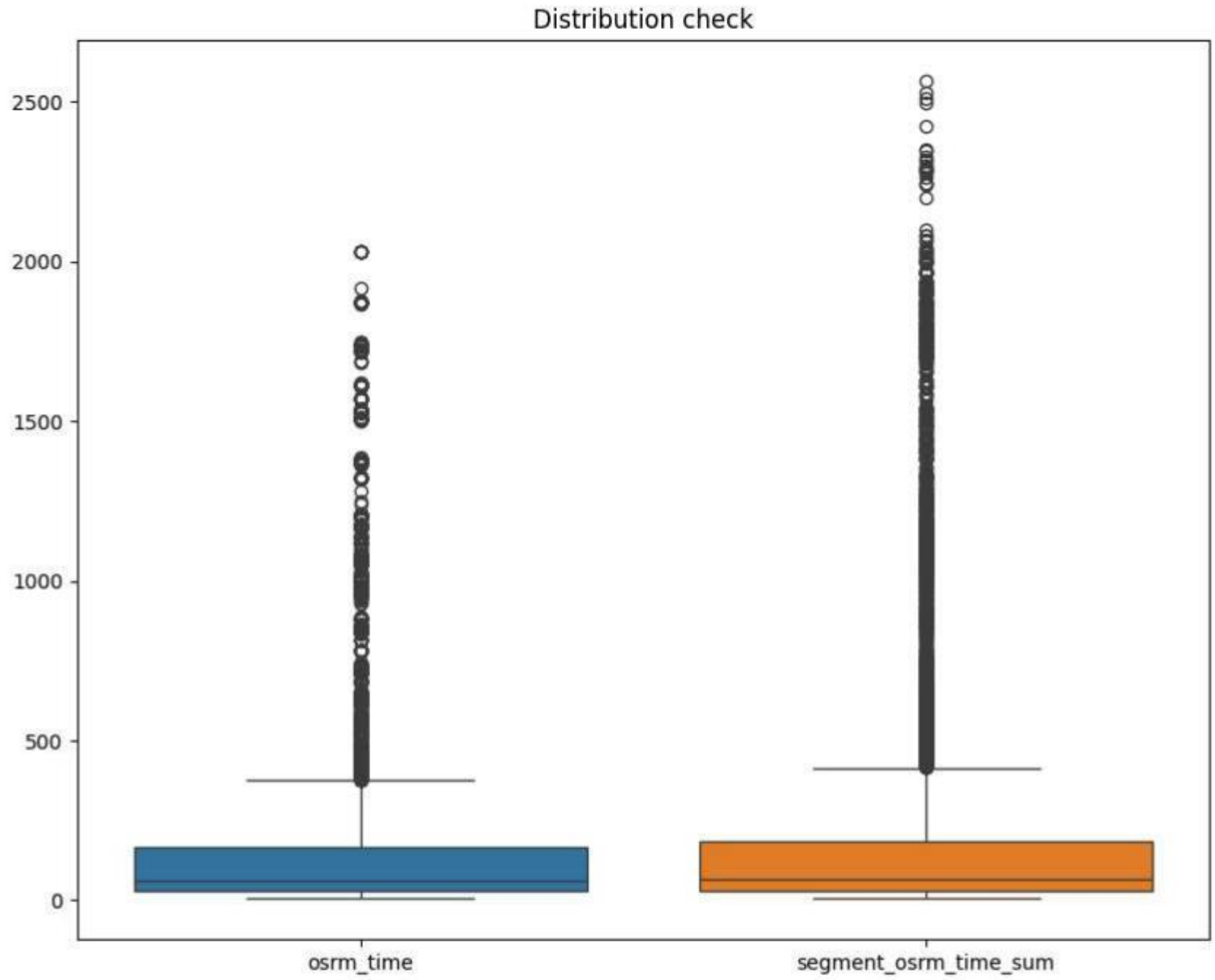


In [688…

```
plt.figure(figsize=(10,8))
sns.boxplot(trip_data[["osrm_time","segment_osrm_time_sum"]])
plt.title("Distribution check")
```

Out[688…

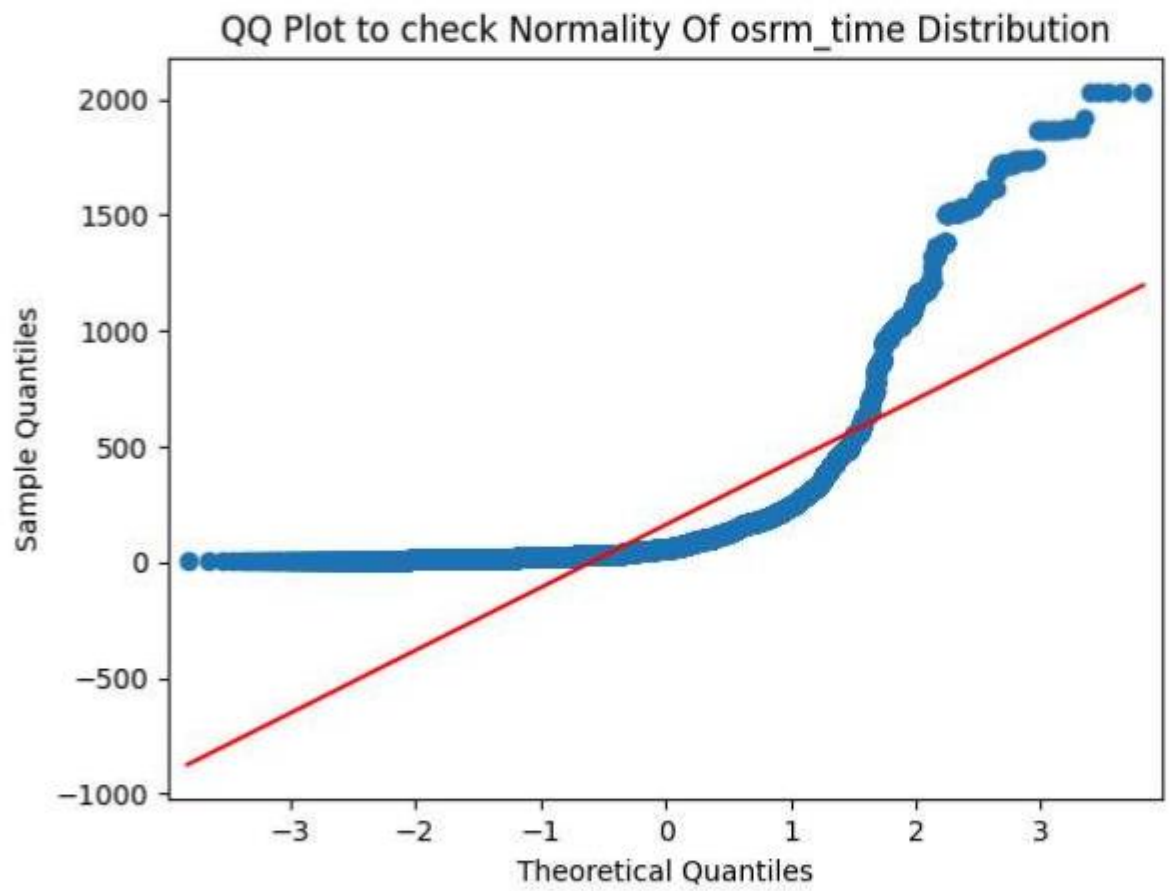
```
Text(0.5, 1.0, 'Distribution check')
```



Distribution Check with QQ Plot

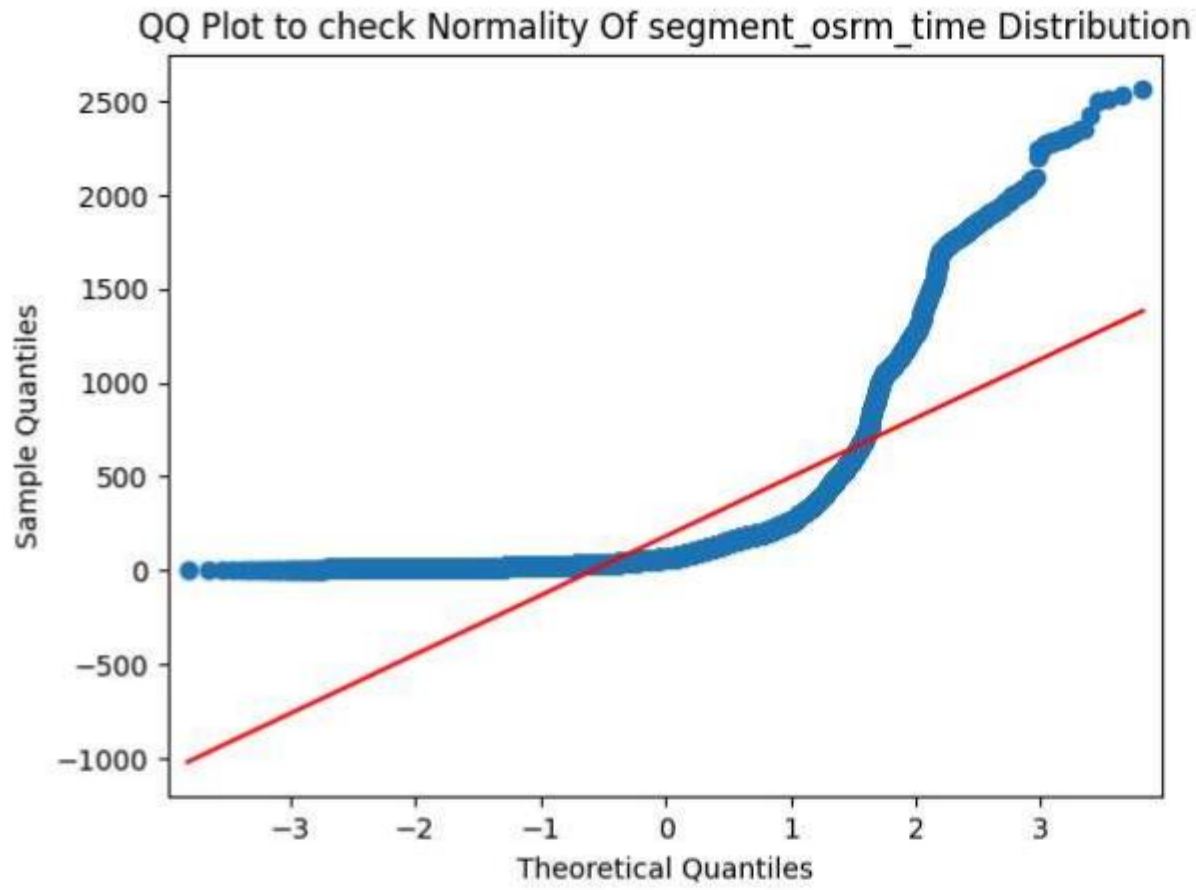
In [689…

```
qqplot(osrm_time, line = 's')
plt.title("QQ Plot to check Normality Of osrm_time Distribution")
plt.show()
```



In [690…

```
qqplot(segment_osrm_time, line = 's')
plt.title("QQ Plot to check Normality Of segment_osrm_time Distribution")
plt.show()
```



Insights 🔍

Both of the distribution doesn't follow Normal Distribution

Hypothesis Testing

Performing Kruskal-Wallis Test to check the difference between Medians

Significance level - 0.5

In [691…
```
stats,pvalue = kruskal(osrm_time,segment_osrm_time)
if pvalue < 0.05:
  print("Reject Null Hypothesis : Median of osrm time aggregated value is significantly different from median of segment osrm time aggregate
else :
  print("Fail to reject Null Hypothesis :  Median of osrm time aggregated value is similar with median of segment osrm time aggregated value

print(f"Test Statistics = {stats} , pvalue = {pvalue}")
```

```
Reject Null Hypothesis : Median of osrm time aggregated value is significantly different from median of segment osrm time aggregated value
Test Statistics = 31.06964278714758 , pvalue = 2.48934342075211e-08
```

Note : Though both of the distribution does not follow normal distribution , Still we are going to perform Ttest.

Performing Ttest independent

Significance level - 0.5

In [692…
```
stats,pvalue = ttest_ind(osrm_time,segment_osrm_time)
if pvalue < 0.05:
  print("Reject Null Hypothesis : Mean of osrm time aggregated value  is significantly different from mean of segmentosrm time aggregated va
else :
  print("Fail to reject Null Hypothesis :  Mean of osrm time aggregated value is similar with mean of segment osrm time aggregated value")

print(f"Test Statistics = {stats} , pvalue = {pvalue}")
```

```
Reject Null Hypothesis : Mean of osrm time aggregated value  is significantly different from mean of segmentosrm time aggregated value
Test Statistics = -5.711782161676085 , pvalue = 1.128703468644937e-08
```

Do one-hot encoding of categorical variables

In [770…
```
from sklearn.preprocessing import StandardScaler,MinMaxScaler,OneHotEncoder
```

In [771…
```
encoded_data = trip_data.copy()
```

Performing One Hot Encoding

In [772…
```
cat_col = ["data","route_type"]
```

In [773…
```
encoded_data.head(3)
```

Out[773…

	data	trip_creation_time	route_type	trip_uuid	source_center	destination_center	od_timetotal_hour	start_scan_to_end_scan	actual_dista
0	training	2018-09-12 00:00:16.535741	FTL	trip-153671041653548748	IND209304AAA	IND209304AAA	37.668497	2259.0	
1	training	2018-09-12 00:00:22.886430	Carting	trip-153671042288605164	IND561203AAB	IND561203AAB	3.026865	180.0	
2	training	2018-09-12 00:00:33.691250	FTL	trip-153671043369099517	IND000000ACB	IND000000ACB	65.572709	3933.0	

In [774…
```
one_hot = OneHotEncoder(sparse = False)
```

In [775…
```
one_hot.fit(trip_data[cat_col])
```

Out[775…
```
▾ OneHotEncoder
OneHotEncoder(sparse=False, sparse_output=False)
```

In [776…
```
transformed_data = one_hot.transform(encoded_data[cat_col])
```

In [777…
```
transformed_df = pd.DataFrame(transformed_data, columns=one_hot.get_feature_names_out(cat_col))
transformed_df.index = encoded_data.index
```

In [778…
```
encoded_data = encoded_data.drop(columns=cat_col)
```

In [779…
```
encoded_data = pd.concat([transformed_df,encoded_data], axis=1)
```

In [780…
```
encoded_data.sample(10) # OneHotEncoded Data
```

Out[780…

	data_test	data_training	route_type_Carting	route_type_FTL	trip_creation_time	trip_uuid	source_center	destination_center	od_timet
14409	1.0	0.0	0.0	1.0	2018-10-03 11:04:40.851381	trip-153856468085110066	IND382430AAB	IND384205AAA	
8668	0.0	1.0	0.0	1.0	2018-09-24 01:47:30.550981	trip-153775365055073872	IND570020AAA	IND571430AAA	
8995	0.0	1.0	0.0	1.0	2018-09-24 18:16:54.909822	trip-153781301490956343	IND431136AAC	IND411033AAA	
10805	1.0	0.0	1.0	0.0	2018-09-27 04:18:37.965599	trip-153802191796534285	IND411033AAA	IND411021AAA	
14010	1.0	0.0	0.0	1.0	2018-10-02 20:39:14.658000	trip-153851275465767815	IND625008AAA	IND626117AAA	
12587	1.0	0.0	0.0	1.0	2018-09-30 02:33:17.115026	trip-153827479711474961	IND700053AAA	IND700053AAA	
3606	0.0	1.0	1.0	0.0	2018-09-16 23:55:35.631778	trip-153714213563153043	IND686507AAA	IND686513AAA	
12581	1.0	0.0	1.0	0.0	2018-09-30 02:15:31.485797	trip-153827373148555770	IND362001AAA	IND360575AAA	
6110	0.0	1.0	1.0	0.0	2018-09-20 09:29:09.120247	trip-153743574911996941	IND121001AAA	IND121004AAB	
214	0.0	1.0	1.0	0.0	2018-09-12 05:41:23.812308	trip-153673088381201691	IND401104AAA	IND400072AAB	

Normalize/ Standardize the numerical features using MinMaxScaler or StandardScaler.

MinMaxScaler

In [754…
```
encoded_data2 = encoded_data.copy()
```

In [756…
```
minmax = MinMaxScaler()
```

In [757…
```
Scaled_data = minmax.fit_transform(encoded_data[num_col])
```

In [759…
```
encoded_data2[num_col] = Scaled_data
```

In [789…
```
encoded_data2[num_col].sample(10) #Normalized Data
```

Out[789…

	od_timetotal_hour	start_scan_to_end_scan	actual_distance_to_destination	actual_time	osrm_time	osrm_distance	segment_actual_time_sum	segme
11480	0.050885	0.050794	0.079545	0.053389	0.077986	0.072040	0.052885	
12161	0.000828	0.000762	0.000004	0.000799	0.001974	0.000697	0.000804	
4283	0.026060	0.025905	0.040952	0.030531	0.045903	0.041539	0.030542	
1574	0.226038	0.225905	0.405092	0.245684	0.356861	0.357958	0.244494	
11470	0.009371	0.009397	0.001694	0.007992	0.005923	0.003694	0.008037	
11191	0.040782	0.040762	0.005163	0.005275	0.006417	0.005543	0.005305	
7338	0.057593	0.057651	0.085757	0.050352	0.080454	0.075063	0.049992	
13825	0.019711	0.019683	0.000366	0.003676	0.006417	0.002081	0.003697	
14651	0.172118	0.171937	0.078110	0.080563	0.113031	0.095771	0.080051	
8718	0.016871	0.016889	0.001798	0.005435	0.005429	0.004009	0.005465	

🔍 **Insights :**

- High Consistency in Short Trips: Normalized data for short trips shows minimal deviation between actual and predicted metrics, with values staying close to each other, indicating efficient prediction models for shorter routes.
- Larger Deviations in Longer Trips: For longer trips, the normalized data highlights significant discrepancies between actual and predicted values, suggesting room for optimization in handling extended journeys, especially in time and distance estimations.

StandardScaler

In [781…
```
sscaler = StandardScaler()
```

In [782…
```
scaled_data = sscaler.fit_transform(encoded_data[num_col])
```

In [783…
```
encoded_data[num_col] = scaled_data
```

In [790…
```
encoded_data[num_col].sample(10) #Standardized Data
```

Out[790…

	od_timetotal_hour	start_scan_to_end_scan	actual_distance_to_destination	actual_time	osrm_time	osrm_distance	segment_actual_time_sum	segme
2727	-0.578113	-0.577955	-0.442079	-0.552639	-0.467824	-0.447932	-0.551920	
3737	-0.602876	-0.602263	-0.441229	-0.515239	-0.456772	-0.447254	-0.515971	
6922	0.567334	0.569056	0.239051	0.052883	0.261591	0.250711	0.052019	
4364	-0.197286	-0.196631	-0.261560	-0.216040	-0.283628	-0.260332	-0.219394	
11667	0.548379	0.544748	0.056977	0.241664	0.309482	0.128259	0.235358	
5411	2.529012	2.531887	2.992528	2.638819	2.954534	3.019706	2.634939	
6071	-0.213278	-0.213343	-0.208050	-0.226725	-0.243105	-0.203238	-0.228381	
579	0.613980	0.613113	0.032998	0.279064	0.014769	0.063510	0.280294	
343	0.157408	0.155828	-0.057637	0.238102	0.114235	0.067872	0.242548	
7842	1.168235	1.167628	0.702758	1.538193	0.921012	0.985283	1.518730	

Insights 🔍

- High Variation for Outliers: Some trips display extreme positive values (e.g., over 2 standard deviations above the mean), indicating significantly longer actual times and distances than predicted, suggesting outliers or unusually lengthy trips.
- Negative Standardized Values Indicate Shorter Trips: Several negative standardized values reflect trips where the actual time and distance were consistently lower than expected, hinting at either shorter routes or more efficient deliveries for these cases.

🔍 Combined Insights & Recommendations

1. Route Type Efficiency – Carting vs. FTL:

- Carting routes dominate the trips, yet they show higher inefficiencies in terms of travel time and distance compared to FTL routes, which are fewer but more efficient.
- Recommendation: Shifting more shipments to FTL routes when possible can optimize both cost and time, especially for longer distances.

2. Impact of Key Centers:

- The central hub, frequently used as both a source and destination, shows signs of congestion, which could be contributing to delays in travel time and completion.
- Recommendation: Rethink routing through this hub by either staggering dispatch times or diverting some traffic to alternative centers to improve overall efficiency.

3. Time of Day & Trip Duration:

- Early morning trips tend to be more efficient, with shorter travel durations, while trips initiated around mid-day tend to encounter more delays.
- Recommendation: Reschedule trips to maximize early morning and night shifts, reducing delays caused by mid-day congestion, especially for time-sensitive deliveries.

4. Geographic Focus – State-Level Patterns:

- Regions like Maharashtra and Bengaluru consistently show higher traffic and inefficiency, indicating potential bottlenecks.
- Recommendation: Introduce region-specific strategies, such as traffic monitoring and predictive models, to improve routing and delivery speed in these areas.

5. Day of the Week Trends:

- Wednesdays are particularly busy, leading to a drop in efficiency. Spreading the workload more evenly throughout the week could help smooth operations.
- Recommendation: Shift some mid-week trips to lighter days like Tuesday or Thursday to balance out the workload and avoid bottlenecks.

6. Deviation from Predictions:

- Significant differences between predicted and actual travel times suggest inefficiencies in the routing system's accuracy.
- Recommendation: Update the routing models with more real-world data, like traffic and road conditions, to better align predicted times with actual outcomes.

7. Standardization of Trip Durations:

- Trip durations show considerable variability, leading to unpredictable delivery times, particularly on longer routes.
- Recommendation: Focus on reducing this variability by employing better route optimization and dynamic traffic re-routing to make delivery times more consistent.

These insights suggest that optimizing routing, rethinking traffic-heavy areas, and adjusting scheduling patterns could significantly reduce delivery inefficiencies and improve overall performance.