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.

Problem Statement :

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.

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

Importing Libraries and dataset

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

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

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

Basic Cleaning and Exploration

```
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
```

```
data.describe()
```

	start_scan_to_end_scan	cutoff_factor	actual_distance_to_destination	actual_time	osrm_time	osrm_distance	fac
count	144867.000000	144867.000000	144867.000000	144867.000000	144867.000000	144867.000000	144867.000
mean	961.262986	232.926567	234.073372	416.927527	213.868272	284.771297	2.120
std	1037.012769	344.755577	344.990009	598.103621	308.011085	421.119294	1.715
min	20.000000	9.000000	9.000045	9.000000	6.000000	9.008200	0.144
25%	161.000000	22.000000	23.355874	51.000000	27.000000	29.914700	1.604
50%	449.000000	66.000000	66.126571	132.000000	64.000000	78.525800	1.857
75%	1634.000000	286.000000	286.708875	513.000000	257.000000	343.193250	2.213
max	7898.000000	1927.000000	1927.447705	4532.000000	1686.000000	2326.199100	77.387

```
data.nunique()
```

	0
data	2
trip_creation_time	14817
route_schedule_uuid	1504
route_type	2
trip_uuid	14817
source_center	1508
source_name	1498
destination_center	1481
destination_name	1468
od_start_time	26369
od_end_time	26369
start_scan_to_end_scan	1915
is_cutoff	2
cutoff_factor	501
cutoff_timestamp	93180
actual_distance_to_destination	144515
actual_time	3182
osrm_time	1531
osrm_distance	138046
factor	45641
segment_actual_time	747
segment_osrm_time	214
segment_osrm_distance	113799
segment_factor	5675

dtype: int64

```
pd.set_option('display.max_columns', None)
# to display all columns
```

```
data.head()
```

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_c
0	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
1	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
2	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
3	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
4	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886

```
data.shape
```

```
(144867, 24)
```

```
data.ndim
```

```
2
```

```
data.head(5)
```

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_c
0	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
1	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
2	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
3	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
4	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886

```
data.isna().sum()
```

	0
data	0
trip_creation_time	0
route_schedule_uuid	0
route_type	0
trip_uuid	0
source_center	0
source_name	293
destination_center	0
destination_name	261
od_start_time	0
od_end_time	0
start_scan_to_end_scan	0
is_cutoff	0
cutoff_factor	0
cutoff_timestamp	0
actual_distance_to_destination	0
actual_time	0
osrm_time	0
osrm_distance	0
factor	0
segment_actual_time	0
segment_osrm_time	0
segment_osrm_distance	0
segment_factor	0

dtype: int64

```
# Function to create a data frame with number and percentage of missing data in a data frame

def missing_values(data):
    # Number and percentage of missing data in data set for each column
    total_missing_data = data.isnull().sum().sort_values(ascending =False)
    percent_missing_data = (data.isnull().sum()/data.isnull().count()*100).sort_values(ascending=False)
    missing_values_data = pd.concat([total_missing_data, percent_missing_data], axis=1, keys=['Total', 'Percent'])
    return missing_values_data


missing_data=missing_values(data)
missing_data
```

	Total	Percent
source_name	293	0.202254
destination_name	261	0.180165
data	0	0.000000
cutoff_factor	0	0.000000
segment_osrm_distance	0	0.000000
segment_osrm_time	0	0.000000
segment_actual_time	0	0.000000
factor	0	0.000000
osrm_distance	0	0.000000
osrm_time	0	0.000000
actual_time	0	0.000000
actual_distance_to_destination	0	0.000000
cutoff_timestamp	0	0.000000
is_cutoff	0	0.000000
trip_creation_time	0	0.000000
start_scan_to_end_scan	0	0.000000
od_end_time	0	0.000000
od_start_time	0	0.000000
destination_center	0	0.000000
source_center	0	0.000000
trip_uuid	0	0.000000
route_type	0	0.000000
route_schedule_uuid	0	0.000000
segment_factor	0	0.000000

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

```
data.isnull().sum().sum()
```

```
0
```

Understanding the flow

```
data_copy=data.copy()
```

```
data_copy_grouped=data_copy.groupby(['trip_uuid','source_center','destination_center']).count().reset_index()
data_copy_grouped
```

	trip_uuid	source_center	destination_center	data	trip_creation_time	route_schedule_uuid	route_type	source_nam
0	trip-153671041653548748	IND209304AAA	IND000000ACB	18	18	18	18	1
1	trip-153671041653548748	IND462022AAA	IND209304AAA	21	21	21	21	2
2	trip-153671042288605164	IND561203AAB	IND562101AAA	3	3	3	3	
3	trip-153671042288605164	IND572101AAA	IND561203AAB	6	6	6	6	
4	trip-153671043369099517	IND000000ACB	IND160002AAC	12	12	12	12	1
...	...	...	...	...	...	...	...	
26217	trip-153861115439069069	IND628204AAA	IND627657AAA	4	4	4	4	
26218	trip-153861115439069069	IND628613AAA	IND627005AAA	4	4	4	4	
26219	trip-153861115439069069	IND628801AAA	IND628204AAA	2	2	2	2	
26220	trip-153861118270144424	IND583119AAA	IND583101AAA	2	2	2	2	
26221	trip-153861118270144424	IND583201AAA	IND583119AAA	2	2	2	2	

26222 rows × 24 columns

```
data_copy[data_copy['trip_uuid']=='trip-153671041653548748']
```

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destina
124981	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND462022AAA	Bhopal_Trnsport_H (Madhya Pradesh)	IN
124982	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND462022AAA	Bhopal_Trnsport_H (Madhya Pradesh)	IN
124983	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND462022AAA	Bhopal_Trnsport_H (Madhya Pradesh)	IN
124984	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND462022AAA	Bhopal_Trnsport_H (Madhya Pradesh)	IN
124985	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND462022AAA	Bhopal_Trnsport_H (Madhya Pradesh)	IN
124986	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND462022AAA	Bhopal_Trnsport_H (Madhya Pradesh)	IN
124987	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND462022AAA	Bhopal_Trnsport_H (Madhya Pradesh)	IN
124988	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND462022AAA	Bhopal_Trnsport_H (Madhya Pradesh)	IN
124989	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND462022AAA	Bhopal_Trnsport_H (Madhya Pradesh)	IN
124990	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND462022AAA	Bhopal_Trnsport_H (Madhya Pradesh)	IN
124991	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND462022AAA	Bhopal_Trnsport_H (Madhya Pradesh)	IN
124992	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND462022AAA	Bhopal_Trnsport_H (Madhya Pradesh)	IN
124993	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND462022AAA	Bhopal_Trnsport_H (Madhya Pradesh)	IN
124994	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND462022AAA	Bhopal_Trnsport_H (Madhya Pradesh)	IN
124995	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND462022AAA	Bhopal_Trnsport_H (Madhya Pradesh)	IN
124996	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND462022AAA	Bhopal_Trnsport_H (Madhya Pradesh)	IN
124997	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND462022AAA	Bhopal_Trnsport_H (Madhya Pradesh)	IN
124998	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND462022AAA	Bhopal_Trnsport_H (Madhya Pradesh)	IN
124999	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND462022AAA	Bhopal_Trnsport_H (Madhya Pradesh)	IN
125000	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND462022AAA	Bhopal_Trnsport_H (Madhya Pradesh)	IN
125001	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND462022AAA	Bhopal_Trnsport_H (Madhya Pradesh)	IN
125002	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND209304AAA	Kanpur_Central_H_6 (Uttar Pradesh)	IN
125003	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND209304AAA	Kanpur_Central_H_6 (Uttar Pradesh)	IN

125004	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND209304AAA	Kanpur_Central_H_6 (Uttar Pradesh)	IN
125005	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND209304AAA	Kanpur_Central_H_6 (Uttar Pradesh)	IN
125006	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND209304AAA	Kanpur_Central_H_6 (Uttar Pradesh)	IN
125007	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND209304AAA	Kanpur_Central_H_6 (Uttar Pradesh)	IN
125008	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND209304AAA	Kanpur_Central_H_6 (Uttar Pradesh)	IN
125009	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND209304AAA	Kanpur_Central_H_6 (Uttar Pradesh)	IN
125010	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND209304AAA	Kanpur_Central_H_6 (Uttar Pradesh)	IN
125011	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND209304AAA	Kanpur_Central_H_6 (Uttar Pradesh)	IN
125012	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND209304AAA	Kanpur_Central_H_6 (Uttar Pradesh)	IN
125013	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND209304AAA	Kanpur_Central_H_6 (Uttar Pradesh)	IN
125014	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND209304AAA	Kanpur_Central_H_6 (Uttar Pradesh)	IN
125015	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND209304AAA	Kanpur_Central_H_6 (Uttar Pradesh)	IN
125016	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND209304AAA	Kanpur_Central_H_6 (Uttar Pradesh)	IN
125017	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND209304AAA	Kanpur_Central_H_6 (Uttar Pradesh)	IN
125018	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND209304AAA	Kanpur_Central_H_6 (Uttar Pradesh)	IN
125019	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	trip-153671041653548748	IND209304AAA	Kanpur_Central_H_6 (Uttar Pradesh)	IN

Converting the datatype to datetime format

```
#changing datatype of date like columns from object to timestamp
data_copy[["od_start_time", "od_end_time",'trip_creation_time']] = data_copy[["od_start_time", "od_end_time",'trip_creation_time']].appl
data_copy.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  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  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), datetime64[ns](3), float64(10), int64(1), object(9)
memory usage: 26.6+ MB
```

Extracting and Creating New Columns

```
#extracting day, month & year from trip_creation_time
data_copy['trip_creation_month']=data_copy['trip_creation_time'].dt.month
data_copy['trip_creation_year']=data_copy['trip_creation_time'].dt.year
data_copy['trip_creation_day']=data_copy['trip_creation_time'].dt.day
data_copy.head(1)
```

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_c
0	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886

```
#difference between od_start & od_end time in hours
data_copy['Timediff_start_end_H']=round((data_copy['od_end_time']-data_copy['od_start_time'])/pd.Timedelta(minutes=1),2)
data_copy.head(1)
```

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_c
0	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886

Analyzing a single trip and its flow.

```
data_copy[data_copy['trip_uuid']=='trip-153741093647649320']
```

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destinatic
0	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3
1	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3
2	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3
3	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3
4	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3
5	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	IND3
6	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	IND3
7	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	IND3
8	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	IND3
9	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	IND3

Creating Features

```
#as below mentioned columns are comprising of segment related details we will do a cum. sum
data_copy['agg_segment_actual_time']=data_copy.groupby(['trip_uuid','source_center','destination_center'])['segment_actual_time'].transfo
data_copy['agg_segment_osrm_time']=data_copy.groupby(['trip_uuid','source_center','destination_center'])['segment_osrm_time'].transform('
data_copy['agg_segment_osrm_distance']=data_copy.groupby(['trip_uuid','source_center','destination_center'])['segment_osrm_distance'].tra

data_copy.head()
```

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_c
0	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
1	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
2	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
3	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
4	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886

```
#After finding out the cum. sum of above columns we will pick their max
data_copy['agg_segment_actual_time1']=data_copy.groupby(['trip_uuid','source_center','destination_center'])['agg_segment_actual_time'].tr
data_copy['agg_segment_osrm_time1']=data_copy.groupby(['trip_uuid','source_center','destination_center'])['agg_segment_osrm_time'].transf
data_copy['agg_segment_osrm_distance1']=data_copy.groupby(['trip_uuid','source_center','destination_center'])['agg_segment_osrm_distance'

data_copy.head()
```

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_c
0	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
1	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
2	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
3	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
4	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886

```
# aggregation of below mentioned based on their Trip_uuid, Source ID and Destination ID
# as they are mentioned as a cumsum in data dictionary we will take max
data_copy['agg_distance_to_destination']=data_copy.groupby(['trip_uuid','source_center','destination_center'])['actual_distance_to_destin
data_copy['agg_actual_time']=data_copy.groupby(['trip_uuid','source_center','destination_center'])['actual_time'].transform('max')
data_copy['agg_osrm_time']=data_copy.groupby(['trip_uuid','source_center','destination_center'])['osrm_time'].transform('max')
data_copy['agg_osrm_distance']=data_copy.groupby(['trip_uuid','source_center','destination_center'])['osrm_distance'].transform('max')
data_copy.head()
```

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_c
0	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
1	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
2	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
3	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
4	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886

```
#creating column with city, place, state from source centre & destination centre
data_copy[['Source_City','Source_Place','Source_Code/State']]=data_copy['source_name'].str.rsplit('_',n=2, expand=True)
data_copy.head()
```

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_c
0	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
1	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
2	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
3	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
4	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886

```
data_copy[['destination_City','destination_Place','destination_Code/State']]=data_copy['destination_name'].str.rsplit('_',n=2, expand=Tru
data_copy.head()
```

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_c
0	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
1	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
2	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
3	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
4	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886

```
#creating Source Code, Source state column, Destination Code, Destination state column from source centre & destination centre
data_copy[['Source_Code','Source_State']]=data_copy['Source_Code/State'].str.rsplit('(',n=2, expand=True)
data_copy[['destination_Code','destination_State']]=data_copy['destination_Code/State'].str.rsplit('(',n=2, expand=True)
data_copy.head()
```

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_c
0	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
1	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
2	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
3	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
4	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886

```
data_copy['Source_State'] = data_copy['Source_State'].str.rstrip(')')
data_copy['destination_State'] = data_copy['destination_State'].str.rstrip(')')
data_copy.head()
```

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_c
0	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
1	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
2	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
3	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886
4	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND3886

```
#dropping the existing columns as we have already got engineered features from them
data_copy.drop(columns=['od_end_time','od_start_time','trip_creation_time','source_name','destination_name'],axis=1,inplace=True)
```

```
print('Rows:', data_copy.shape[0],'\n' 'Columns: ',data_copy.shape[1])
```

```
Rows: 144316
Columns:  43
```

```
data_copy.drop(columns=['segment_factor','data','factor','is_cutoff', 'cutoff_factor','cutoff_timestamp',
                'route_schedule_uuid'],
       axis=1, inplace=True)
```

```
print('Rows:', data_copy.shape[0],'\n' 'Columns: ',data_copy.shape[1])
```

```
Rows: 144316
Columns:  36
```

```
data_copy.duplicated().sum()
```

```
0
```

The data's were not duplicated as the original columns have unique values. Lets create a new dataframe which includes the newly created features column.

```
data_copy.columns
```

```
Index(['route_type', 'trip_uuid', 'source_center', 'destination_center',
       'start_scan_to_end_scan', 'actual_distance_to_destination',
       'actual_time', 'osrm_time', 'osrm_distance', 'segment_actual_time',
       'segment_osrm_time', 'segment_osrm_distance', 'trip_creation_month',
       'trip_creation_year', 'trip_creation_day', 'Timediff_start_end_H',
       'agg_segment_actual_time', 'agg_segment_osrm_time',
       'agg_segment_osrm_distance', 'agg_segment_actual_time1',
       'agg_segment_osrm_time1', 'agg_segment_osrm_distance1',
       'agg_distance_to_destination', 'agg_actual_time', 'agg_osrm_time',
       'agg_osrm_distance', 'Source_City', 'Source_Place', 'Source_Code/State',
       'destination_City', 'destination_Place', 'destination_Code/State',
       'Source_Code', 'Source_State', 'destination_Code', 'destination_State'],
      dtype='object')
```

```
data_merged=data_copy.loc[:,['route_type', 'trip_uuid',
       'start_scan_to_end_scan',  'trip_creation_month',
       'trip_creation_year', 'trip_creation_day', 'Timediff_start_end_H', 'agg_segment_actual_time1',
       'agg_segment_osrm_time1', 'agg_segment_osrm_distance1',
       'agg_distance_to_destination', 'agg_actual_time', 'agg_osrm_time',
       'agg_osrm_distance', 'Source_City', 'Source_Place', 'Source_Code/State',
       'destination_City', 'destination_Place', 'destination_Code/State']]
```

```
data_merged.duplicated().sum()
```

```
118093
```

```
data_merged.head()
```

	route_type	trip_uuid	start_scan_to_end_scan	trip_creation_month	trip_creation_year	trip_creation_day	Timediff_sta
0	Carting	trip-153741093647649320	86.0	9	2018	20	
1	Carting	trip-153741093647649320	86.0	9	2018	20	
2	Carting	trip-153741093647649320	86.0	9	2018	20	
3	Carting	trip-153741093647649320	86.0	9	2018	20	
4	Carting	trip-153741093647649320	86.0	9	2018	20	

```
data_merged[data_merged['trip_uuid']=='trip-153741093647649320']
```

	route_type	trip_uuid	start_scan_to_end_scan	trip_creation_month	trip_creation_year	trip_creation_day	Timediff_sta
0	Carting	trip-153741093647649320	86.0	9	2018	20	
1	Carting	trip-153741093647649320	86.0	9	2018	20	
2	Carting	trip-153741093647649320	86.0	9	2018	20	
3	Carting	trip-153741093647649320	86.0	9	2018	20	
4	Carting	trip-153741093647649320	86.0	9	2018	20	
5	Carting	trip-153741093647649320	109.0	9	2018	20	
6	Carting	trip-153741093647649320	109.0	9	2018	20	
7	Carting	trip-153741093647649320	109.0	9	2018	20	
8	Carting	trip-153741093647649320	109.0	9	2018	20	
9	Carting	trip-153741093647649320	109.0	9	2018	20	

```
data_merged.shape
```

```
(144316, 20)
```

```
data_merged.duplicated().sum()
```

```
118093
```

```
data_merged.drop_duplicates(inplace=True)
data_merged.head()
```

	route_type	trip_uuid	start_scan_to_end_scan	trip_creation_month	trip_creation_year	trip_creation_day	Timediff_st
0	Carting	trip-153741093647649320	86.0	9	2018	20	
5	Carting	trip-153741093647649320	109.0	9	2018	20	
10	FTL	trip-153768492602129387	302.0	9	2018	23	
15	Carting	trip-153693976643699843	108.0	9	2018	14	
17	FTL	trip-153687145942424248	195.0	9	2018	13	

```
data_merged[data_merged['trip_uuid']=='trip-153741093647649320']
```

	route_type	trip_uuid	start_scan_to_end_scan	trip_creation_month	trip_creation_year	trip_creation_day	Timediff_sta
0	Carting	trip-153741093647649320	86.0	9	2018	20	
5	Carting	trip-153741093647649320	109.0	9	2018	20	

```
data_merged.duplicated().sum()
```

```
0
```

```
data_merged.shape
```

```
(26223, 20)
```

```
data_merged.columns
```

```
Index(['route_type', 'trip_uuid', 'start_scan_to_end_scan',
       'trip_creation_month', 'trip_creation_year', 'trip_creation_day',
       'Timediff_start_end_H', 'agg_segment_actual_time1',
       'agg_segment_osrm_time1', 'agg_segment_osrm_distance1',
       'agg_distance_to_destination', 'agg_actual_time', 'agg_osrm_time',
       'agg_osrm_distance', 'Source_City', 'Source_Place', 'Source_Code/State',
       'destination_City', 'destination_Place', 'destination_Code/State'],
      dtype='object')
```

```
data_merged.head()
```

	route_type	trip_uuid	start_scan_to_end_scan	trip_creation_month	trip_creation_year	trip_creation_day	Timediff_st
0	Carting	trip-153741093647649320	86.0	9	2018	20	
5	Carting	trip-153741093647649320	109.0	9	2018	20	
10	FTL	trip-153768492602129387	302.0	9	2018	23	
15	Carting	trip-153693976643699843	108.0	9	2018	14	
17	FTL	trip-153687145942424248	195.0	9	2018	13	

Lets create a dataframe having unique rows for trips by combining, Summing the rows of subset package of the trips

```
data_uuid=data_merged.copy()
```

```
# aggregation of below mentioned based on their Trip_uuid, Source ID and Destination ID
# as they are mentioned as a cum. sum in data dictionary we will take max
data_uuid['start_scan_to_end_scan11']=data_uuid.groupby(['trip_uuid'])['start_scan_to_end_scan'].transform('sum')
data_uuid['Timediff_start_end_H11']=data_uuid.groupby(['trip_uuid'])['Timediff_start_end_H'].transform('sum')
data_uuid['agg_segment_actual_time11']=data_uuid.groupby(['trip_uuid'])['agg_segment_actual_time1'].transform('sum')
data_uuid['agg_segment_osrm_time11']=data_uuid.groupby(['trip_uuid'])['agg_segment_osrm_time1'].transform('sum')

data_uuid['agg_segment_osrm_distance11']=data_uuid.groupby(['trip_uuid'])['agg_segment_osrm_distance1'].transform('sum')
data_uuid['agg_distance_to_destination11']=data_uuid.groupby(['trip_uuid'])['agg_distance_to_destination'].transform('sum')
data_uuid['agg_actual_time11']=data_uuid.groupby(['trip_uuid'])['agg_actual_time'].transform('sum')
data_uuid['agg_osrm_time11']=data_uuid.groupby(['trip_uuid'])['agg_osrm_time'].transform('sum')
data_uuid['agg_osrm_distance11']=data_uuid.groupby(['trip_uuid'])['agg_osrm_distance'].transform('sum')
```

```
data_uuid.head()
```

	route_type	trip_uuid	start_scan_to_end_scan	trip_creation_month	trip_creation_year	trip_creation_day	Timediff_st
0	Carting	trip-153741093647649320	86.0	9	2018	20	
5	Carting	trip-153741093647649320	109.0	9	2018	20	
10	FTL	trip-153768492602129387	302.0	9	2018	23	
15	Carting	trip-153693976643699843	108.0	9	2018	14	
17	FTL	trip-153687145942424248	195.0	9	2018	13	

```
data_uuid['Source_City11']=data_uuid.groupby(['trip_uuid'])['Source_City'].transform('first')
data_uuid['Source_Place11']=data_uuid.groupby(['trip_uuid'])['Source_Place'].transform('first')
data_uuid['Source_Code/State11']=data_uuid.groupby(['trip_uuid'])['Source_Code/State'].transform('first')
data_uuid['destination_City11']=data_uuid.groupby(['trip_uuid'])['destination_City'].transform('last')
data_uuid['destination_Place11']=data_uuid.groupby(['trip_uuid'])['destination_Place'].transform('last')
data_uuid['destination_Code/State11']=data_uuid.groupby(['trip_uuid'])['destination_Code/State'].transform('last')
```

```
data_uuid.head()
```

	route_type	trip_uuid	start_scan_to_end_scan	trip_creation_month	trip_creation_year	trip_creation_day	Timediff_st
0	Carting	trip-153741093647649320	86.0	9	2018	20	
5	Carting	trip-153741093647649320	109.0	9	2018	20	
10	FTL	trip-153768492602129387	302.0	9	2018	23	
15	Carting	trip-153693976643699843	108.0	9	2018	14	
17	FTL	trip-153687145942424248	195.0	9	2018	13	

Creating a new DataFrame for eliminating the duplicates and having only one row detail for one trip which comprises all the details of the trip.

```
data_final=data_uuid.loc[:,['route_type', 'trip_uuid',
        'trip_creation_month', 'trip_creation_year', 'trip_creation_day',
       'start_scan_to_end_scan11', 'Timediff_start_end_H11',
       'agg_segment_actual_time11', 'agg_segment_osrm_time11',
       'agg_segment_osrm_distance11', 'agg_distance_to_destination11',
       'agg_actual_time11', 'agg_osrm_time11', 'agg_osrm_distance11',
       'Source_City11', 'Source_Place11', 'Source_Code/State11',
       'destination_City11', 'destination_Place11',
       'destination_Code/State11']]
```

```
data_final.duplicated().sum()
```

```
11436
```

```
data_final[data_final['trip_uuid']=='trip-153741093647649320']
```

	route_type	trip_uuid	trip_creation_month	trip_creation_year	trip_creation_day	start_scan_to_end_scan11	Timediff_s
0	Carting	trip-153741093647649320	9	2018	20	195.0	
5	Carting	trip-153741093647649320	9	2018	20	195.0	

```
data_final.drop_duplicates(inplace=True)
```

```
data_final.duplicated().sum()
```

```
0
```

```
data_final.shape
```

```
(14787, 20)
```

```
data_final[data_final['trip_uuid']=='trip-153741093647649320']
```

	route_type	trip_uuid	trip_creation_month	trip_creation_year	trip_creation_day	start_scan_to_end_scan11	Timediff_s
0	Carting	trip-153741093647649320	9	2018	20	195.0	

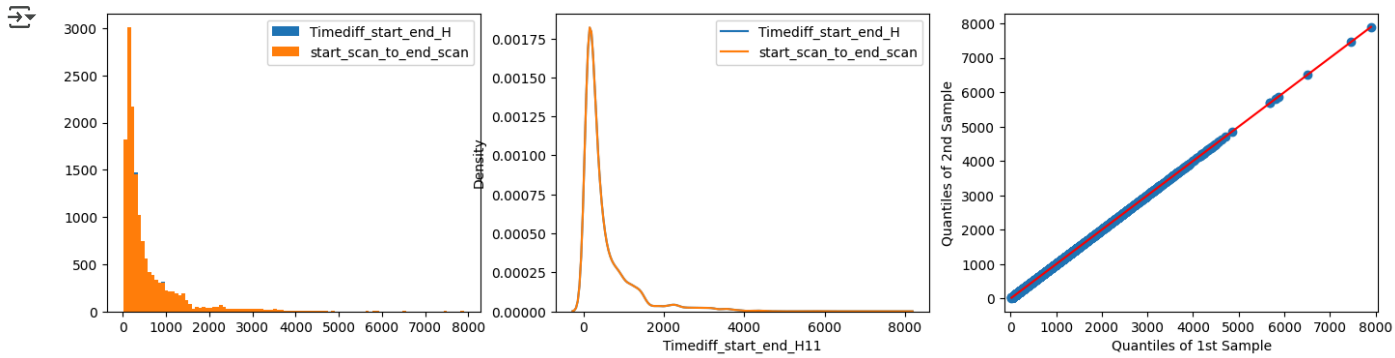
Hypothesis/ Visual Analysis

Comparison between Timediff_start_end_H11(od_start_time and od_end_time) and start_scan_to_end_scan

```
import pandas as pd
```

```
import numpy as np
from numpy import NaN, nan, NAN
import matplotlib.pyplot as plt
import seaborn as sns
import math, random
from scipy import stats
from statsmodels.stats.weightstats import ztest
from statsmodels.distributions.empirical_distribution import ECDF
from statsmodels.graphics.gofplots import qqplot, qqplot_2samples
import statsmodels.api as sm
import warnings
warnings.filterwarnings("ignore")
```

```
plt.figure(figsize=(17,4))
plt.subplot(131)
plt.hist(data_final['Timediff_start_end_H11'],bins=100,label='Timediff_start_end_H')
plt.hist(data_final['start_scan_to_end_scan11'],bins=100,label='start_scan_to_end_scan')
plt.legend()
plt.subplot(132)
sns.kdeplot(data_final['Timediff_start_end_H11'],label='Timediff_start_end_H')
sns.kdeplot(data_final['start_scan_to_end_scan11'],label='start_scan_to_end_scan')
plt.legend()
# Quantile-Quantile plot for 2samples
qqplot_2samples(data_final['Timediff_start_end_H11'], data_final['start_scan_to_end_scan11'], line="r", ax=plt.subplot(133))
plt.show()
```



Step-1: Defining Null & Alternate Hypothesis

H0 : The mean for Timediff_start_end_H & start_scan_to_end_scan are same

Ha : The mean for start_scan_to_end_scan and start_scan_to_end_scan are difference.

Step-2: Choosing Appropriate test

Here we are using Two Sample T-Test

Step-3: Choosing Significance level

Here we are aiming for 95% confidence, hence alpha=0.05

Step-4: Perform the test and determine the pvalue

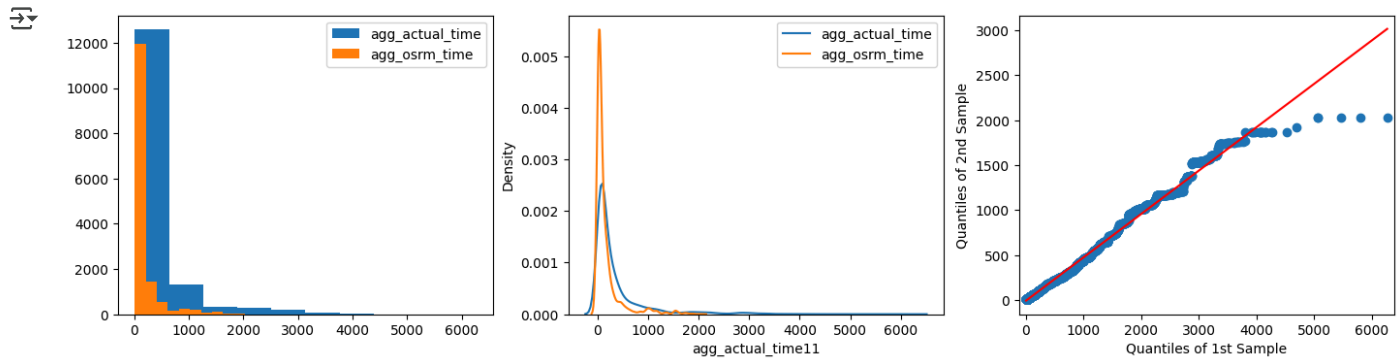
```
import scipy.stats as stats
t_stat,p_value = stats.ttest_ind(data_final['Timediff_start_end_H11'],data_final['start_scan_to_end_scan11'],alternative="two-sided")
print("t_stat : ",t_stat)
print("p_value : ",p_value)
print('P_value One_side :',(p_value/2))

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

```
t_stat :  0.11551867533202027
p_value :  0.9080348031420551
P_value One_side : 0.45401740157102755
Fail to Reject NULL HYPOTHESIS
```

The pvalue is not less than alpha, hence the mean between Timediff_start_end_H11 and start_scan_to_end_scan11 are same.

Comparision Between Aggregate Actual time & Aggregate OSRM Time

```
plt.figure(figsize=(17,4))
plt.subplot(131)
plt.hist(data_final['agg_actual_time11'],bins=10,label='agg_actual_time')
plt.hist(data_final['agg_osrm_time11'],bins=10,label='agg_osrm_time')
plt.legend()
plt.subplot(132)
sns.kdeplot(data_final['agg_actual_time11'],label='agg_actual_time')
sns.kdeplot(data_final['agg_osrm_time11'],label='agg_osrm_time')
plt.legend()
# Quantile-Quantile plot for 2samples
qqplot_2samples(data_final['agg_actual_time11'],data_final['agg_osrm_time11'], line="r", ax=plt.subplot(133))
plt.show()
```



Step-1: Defining Null & Alternate Hypothesis

H0 : The mean for agg_actual_time & agg_osrm_time are same

Ha : The mean for agg_actual_time and agg_osrm_time are difference.

Step-2: Choosing Appropriate test

Here we are using Two Sample T-Test

Step-3: Choosing Significance level

Here we are aiming for 95% confidence, hence alpha=0.05

Step-4: Perform the test and determine the pvalue

```
import scipy.stats as stats
t_stat,p_value = stats.ttest_ind(data_final['agg_actual_time11'],data_final['agg_osrm_time11'])
print('t_stat :', t_stat)
print('P-value :', p_value)
if p_value < 0.05:
    print('Reject NULL HYPOTHESIS')
else:
    print('Fail to Reject NULL HYPOTHESIS')
```

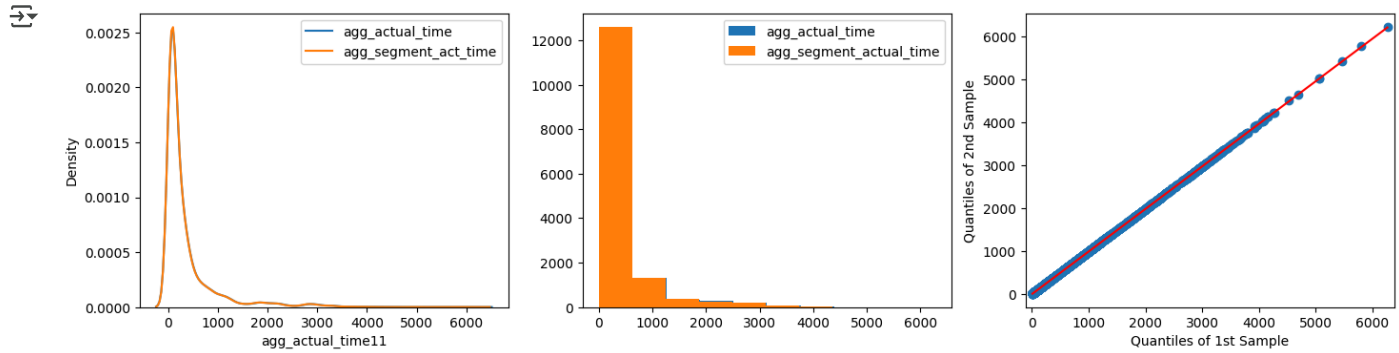
```
t_stat : 37.924611689639825
P-value : 2.358932823082838e-307
Reject NULL HYPOTHESIS
```

The pvalue is less than alpha, hence the mean between agg_actual_time11 and agg_osrm_time11 are not same.

```
#####################################################################
```

Comparision Between Aggregate Actual time & Aggregate segment_actual_time

```
plt.figure(figsize=(17,4))
plt.subplot(131)
sns.kdeplot(data_final['agg_actual_time11'],label='agg_actual_time')
sns.kdeplot(data_final['agg_segment_actual_time11'],label='agg_segment_act_time')
plt.legend()
plt.subplot(132)
plt.hist(data_final['agg_actual_time11'],bins=10,label='agg_actual_time')
plt.hist(data_final['agg_segment_actual_time11'],bins=10,label='agg_segment_actual_time')
plt.legend()
# Quantile-Quantile plot for 2samples
qqplot_2samples(data_final['agg_actual_time11'],data_final['agg_segment_actual_time11'], line="r", ax=plt.subplot(133))
plt.show()
```



Step-1: Defining Null & Alternate Hypothesis

H0 : The mean for agg_Actual_time & agg_segment_actual_time are same

Ha : The mean for agg_Actual_time and agg_segment_actual_time are difference.

Step-2: Choosing Appropriate test

Here we are using Two Sample T-Test

Step-3: Choosing Significance level

Here we are aiming for 95% confidence, hence alpha=0.05

Step-4: Perform the test and determine the pvalue

```
t_stat,p_value = stats.ttest_ind(data_final['agg_actual_time11'],data_final['agg_segment_actual_time11'])
print('t_stat :', t_stat)
print('P-value :',(p_value))

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

```
t_stat : 0.4978641813349065
P-value : 0.6185834771383849
Fail to Reject NULL HYPOTHESIS
```

The pvalue is not less than alpha, hence the mean between agg_actual_time11 and agg_segment_actual_time11 are same.

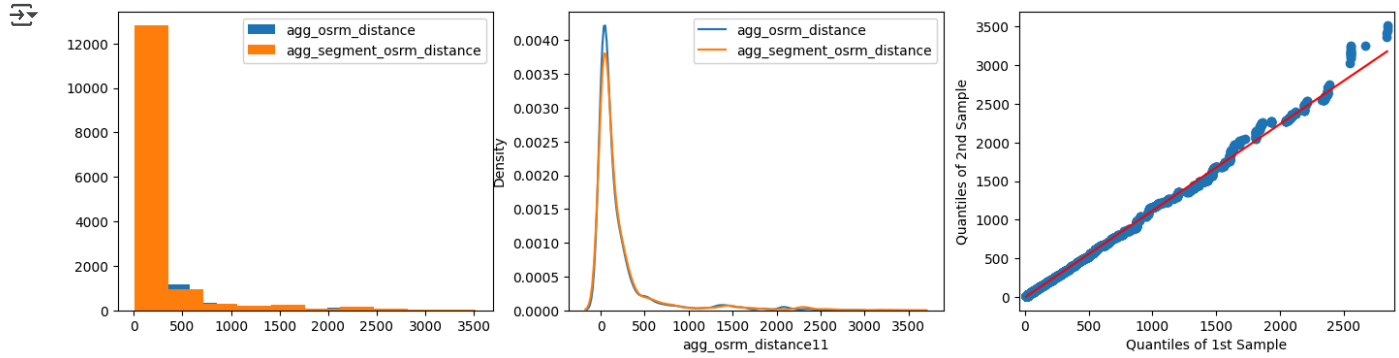
```
##########################################################################################################
```

Double-click (or enter) to edit

Comparision Between Aggregate OSRM distance & Aggregate Segment osrm distance

```
plt.figure(figsize=(17,4))
plt.subplot(1,3,1)
plt.hist(data_final['agg_osrm_distance11'],bins=10,label='agg_osrm_distance')
plt.hist(data_final['agg_segment_osrm_distance11'],bins=10,label='agg_segment_osrm_distance')
plt.legend()
```

```
plt.subplot(1,3,2)
sns.kdeplot(data_final['agg_osrm_distance11'],label='agg_osrm_distance')
sns.kdeplot(data_final['agg_segment_osrm_distance11'],label='agg_segment_osrm_distance')
plt.legend()
# Quantile-Quantile plot for 2samples
qqplot_2samples(data_final['agg_osrm_distance11'],data_final['agg_segment_osrm_distance11'], line="r", ax=plt.subplot(133))
plt.show()
```



Step-1: Defining Null & Alternate Hypothesis

H0 : The mean for Agg_osrm_distance & agg_segment_osrm_distance are same

Ha : The mean for Agg_osrm_distance and agg_segment_osrm_distance are difference.

Step-2: Choosing Appropriate test

Here we are using Two Sample T-Test

Step-3: Choosing Significance level

Here we are aiming for 95% confidence, hence alpha=0.05

Step-4: Perform the test and determine the pvalue

```
import scipy.stats as stats
t_stat,p_value = stats.ttest_ind(data_final['agg_osrm_distance11'],data_final['agg_segment_osrm_distance11'])
print('t_stat :', t_stat)
print('P-value :',(p_value))

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

```
t_stat : -3.9379741183399783
P-value : 8.236076174381012e-05
Reject NULL HYPOTHESIS
```

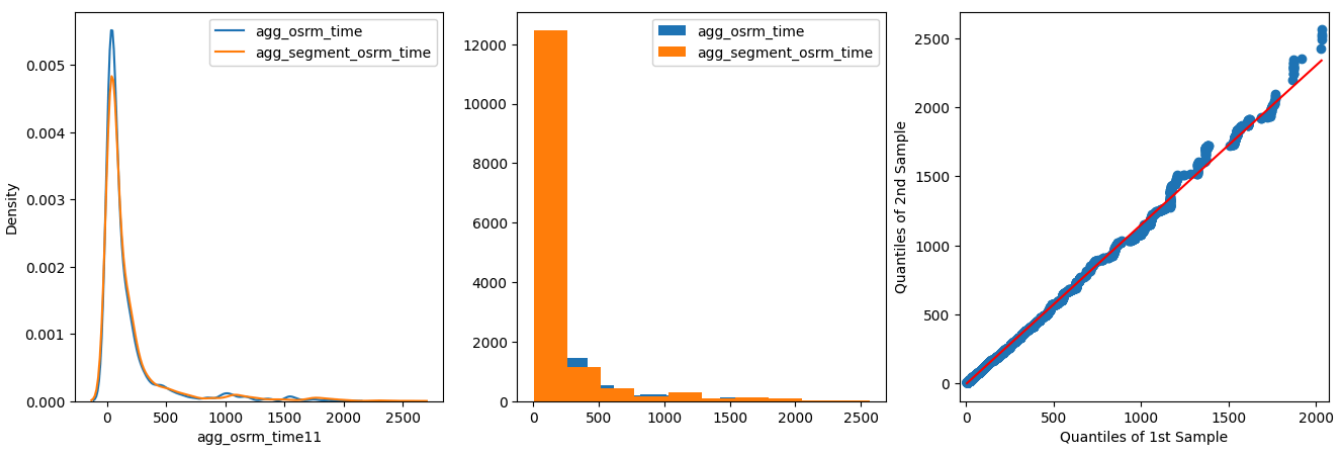
The pvalue is less than alpha, hence the mean between agg_osrm_distance11 and agg_segment_osrm_distance11 are not same.

```
#############################################################################################3
```

Comparision Between Aggregate OSRM time & Aggregate Segment OSRM Time

```
plt.figure(figsize=(16,5))
plt.subplot(131)
sns.kdeplot(data_final['agg_osrm_time11'],label='agg_osrm_time')
sns.kdeplot(data_final['agg_segment_osrm_time11'],label='agg_segment_osrm_time')
plt.legend()
plt.subplot(132)
plt.hist(data_final['agg_osrm_time11'],bins=10,label='agg_osrm_time')
plt.hist(data_final['agg_segment_osrm_time11'],bins=10,label='agg_segment_osrm_time')
plt.legend()
# Quantile-Quantile plot for 2samples
```

```
qqplot_2samples(data_final['agg_osrm_time11'],data_final['agg_segment_osrm_time11'], line="r", ax=plt.subplot(133))
plt.show()
```



Step-1: Defining Null & Alternate Hypothesis

H0 : The mean for Agg_osrm_distance & agg_segment_osrm_distance are same

Ha : The mean for Agg_osrm_distance and agg_segment_osrm_distance are difference.

Step-2: Choosing Appropriate test

Here we are using Two Sample T-Test

Step-3: Choosing Significance level

Here we are aiming for 95% confidence, hence alpha=0.05

Step-4: Perform the test and determine the pvalue

```
import scipy.stats as stats
t_stat,p_value = stats.ttest_ind(data_final['agg_osrm_time11'],data_final['agg_segment_osrm_time11'])
print('t_stat :', t_stat)
print('P-value :', p_value)
if p_value < 0.05:
    print('Reject NULL HYPOTHESIS')
else:
    print('Fail to Reject NULL HYPOTHESIS')
```

```
t_stat : -5.505522067054686
P-value : 3.711314386305602e-08
Reject NULL HYPOTHESIS
```

The pvalue is less than alpha, hence the mean between agg_osrm_time11 and agg_segment_osrm_time11 are not same.

```
#########################################################3
```

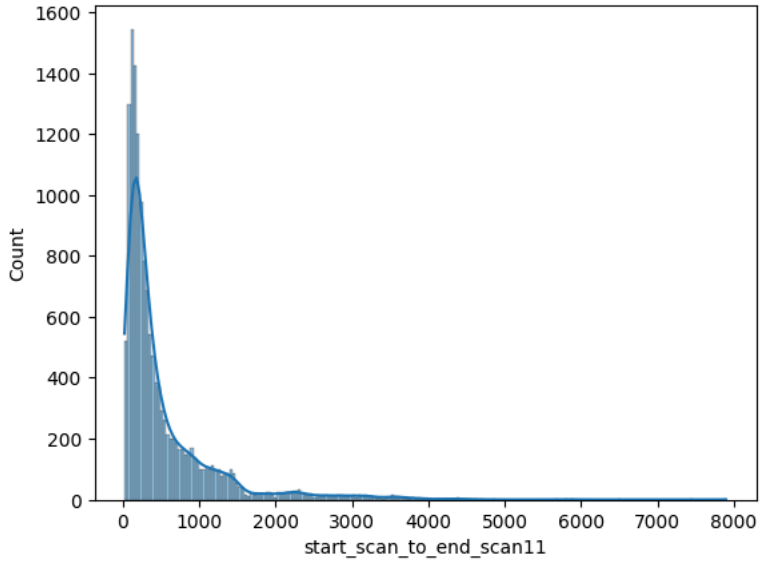
Exploratory Data Analysis

Univariate Data Analysis

```
num_cols = data_final.select_dtypes('float64').columns.values
cat_cols = data_final.select_dtypes('object').columns.values
```

```
for i in num_cols:
    print('###############')
    print(data_final[i].value_counts())
    sns.histplot(data_final[i],kde=True)
    plt.show()
```

```
###############
start_scan_to_end_scan11
148.0     51
115.0     51
87.0      50
113.0     49
128.0     49
          ..
1895.0     1
1634.0     1
1199.0     1
1205.0     1
2429.0     1
Name: count, Length: 2203, dtype: int64
```




```
###############
Timediff_start_end_H11
319.61     4
286.63     4
122.43     4
147.10     4
86.20      4
          ..
227.87     1
924.06     1
658.28     1
3732.37    1
427.69     1
Name: count, Length: 13573, dtype: int64
```

- The data's are heavily right skewed.

```
for i in cat_cols:
    print('###############')
    print(data_final[i].value_counts())
```

```
###############
route_type
Carting    8906
FTL        5881
Name: count, dtype: int64
###############
trip_uuid
trip-153741093647649320    1
trip-153836648611826977    1
trip-153681920064110379    1
trip-153744931166370622    1
trip-153764628243892763    1
                          ..
trip-153741177166786003    1
trip-153801210039247977    1
trip-153737819969505360    1
trip-153739632610417618    1
trip-153746066843555182    1
Name: count, Length: 14787, dtype: int64
###############
Source_City11
Bengaluru               1014
Gurgaon                 1011
Bhiwandi                 811
```

```
Bangalore                731
Delhi                    617
                        ...
Parvathipuram_Central      1
Koraput                    1
Jasai                      1
Baripada                   1
Ashta                      1
Name: count, Length: 706, dtype: int64
###############
Source_Place11
Bilaspur            959
Mankoli             811
Nelmngla            732
H                   643
I                   571
                   ...
Ymunpurm              1
Shahdara (Delhi)      1
KalikDPP              1
PuranDPP              1
ShantiNg              1
Name: count, Length: 672, dtype: int64
###############
Source_Code/State11
HB (Haryana)          937
HB (Maharashtra)      811
HB (Karnataka)        757
H (Karnataka)         751
H (Punjab)            370
                     ...
2 (Andhra Pradesh)      1
1 (Andhra Pradesh)      1
2 (Karnataka)           1
         ...
```

Busiest Route

```
1189.0      1
```

```
data_copy_grouped.head()
```

	trip_uuid	source_center	destination_center	data	trip_creation_time	route_schedule_uuid	route_type	source_name	de
0	trip-153671041653548748	IND209304AAA	IND000000ACB	18	18	18	18	18	
1	trip-153671041653548748	IND462022AAA	IND209304AAA	21	21	21	21	21	
2	trip-153671042288605164	IND561203AAB	IND562101AAA	3	3	3	3	3	
3	trip-153671042288605164	IND572101AAA	IND561203AAB	6	6	6	6	6	
4	trip-153671043369099517	IND000000ACB	IND160002AAC	12	12	12	12	12	

```
data_copy_grouped.route_type.max()
```

```
81
```

```
agg_segment_osrm_time11
```

```
# find trip uuid of max count
data_copy_grouped[data_copy_grouped['route_type']==81]
```

	trip_uuid	source_center	destination_center	data	trip_creation_time	route_schedule_uuid	route_type	source_nam
12201	trip-153755502932196495	IND160002AAC	IND562132AAA	81	81	81	81	8

```
120.2104    1
```

```
data[data['trip_uuid']=='trip-153755502932196495']
```

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	dest
61008	training	2018-09-21 18:37:09.322207	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	trip-153755502932196495	IND160002AAC	Chandigarh_Mehmdpur_H (Punjab)	
61009	training	2018-09-21 18:37:09.322207	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	trip-153755502932196495	IND160002AAC	Chandigarh_Mehmdpur_H (Punjab)	
61010	training	2018-09-21 18:37:09.322207	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	trip-153755502932196495	IND160002AAC	Chandigarh_Mehmdpur_H (Punjab)	
61011	training	2018-09-21 18:37:09.322207	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	trip-153755502932196495	IND160002AAC	Chandigarh_Mehmdpur_H (Punjab)	
61012	training	2018-09-21 18:37:09.322207	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	trip-153755502932196495	IND160002AAC	Chandigarh_Mehmdpur_H (Punjab)	
...	...	...	...	...	...	...	...	
61084	training	2018-09-21 18:37:09.322207	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	trip-153755502932196495	IND160002AAC	Chandigarh_Mehmdpur_H (Punjab)	
61085	training	2018-09-21 18:37:09.322207	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	trip-153755502932196495	IND160002AAC	Chandigarh_Mehmdpur_H (Punjab)	
61086	training	2018-09-21 18:37:09.322207	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	trip-153755502932196495	IND160002AAC	Chandigarh_Mehmdpur_H (Punjab)	
61087	training	2018-09-21 18:37:09.322207	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	trip-153755502932196495	IND160002AAC	Chandigarh_Mehmdpur_H (Punjab)	
61088	training	2018-09-21 18:37:09.322207	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	trip-153755502932196495	IND160002AAC	Chandigarh_Mehmdpur_H (Punjab)	

81 rows × 24 columns

```
data_final[data_final['trip_uuid']=='trip-153755502932196495'][['agg_segment_actual_time11',
       'agg_segment_osrm_time11', 'agg_segment_osrm_distance11',
       'agg_distance_to_destination11', 'agg_actual_time11', 'agg_osrm_time11']]
```

	agg_segment_actual_time11	agg_segment_osrm_time11	agg_segment_osrm_distance11	agg_distance_to_destination11	agg_actual_t
61008	3751.0	1864.0	2500.2145	1927.447705	3

60.0 134

Bussiest Route is from source Chandigarh_Mehmdpur_H (Punjab) to Bangalore_Nelmngla_H (Karnataka) Average_distance between them is 1927 kms & average time taken is 3784 mins

966.0 1

```
temp=['start_scan_to_end_scan11',
       'trip_creation_day', 'Timediff_start_end_H11', 'agg_segment_actual_time11',
       'agg_segment_osrm_time11', 'agg_segment_osrm_distance11',
       'agg_distance_to_destination11', 'agg_actual_time11', 'agg_osrm_time11',
       'agg_osrm_distance11']
```

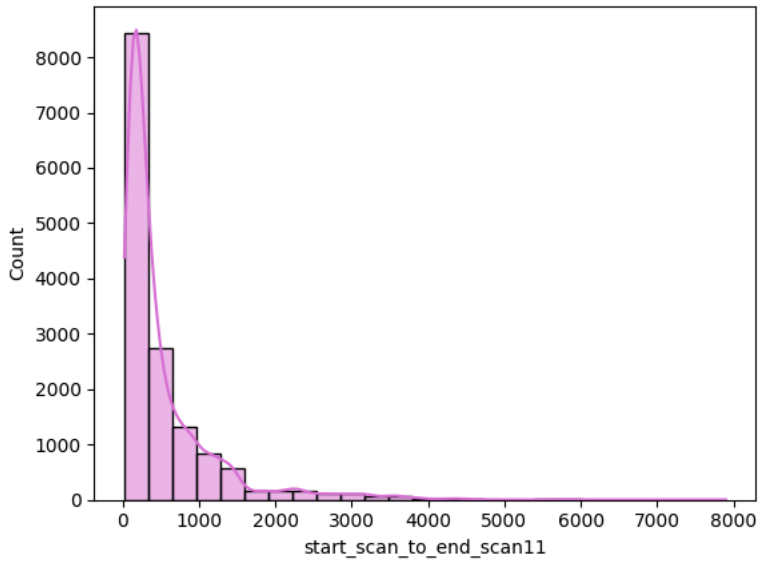
```
temp
```

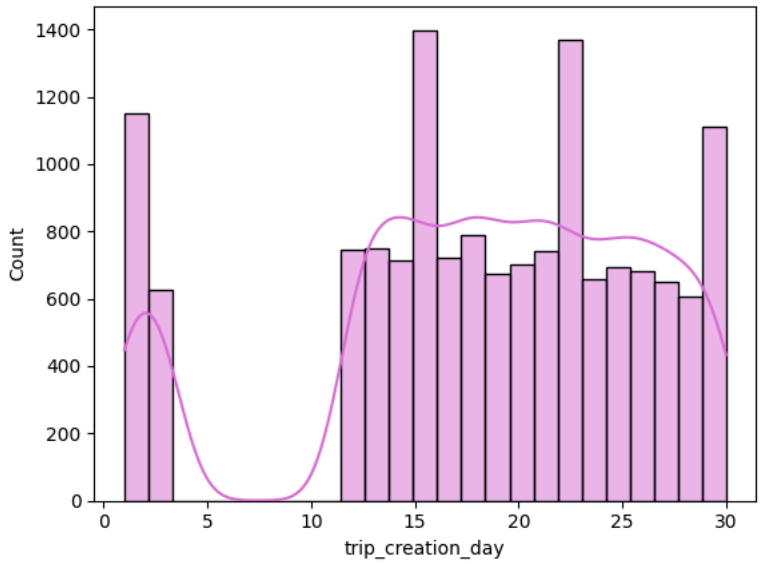
```
['start_scan_to_end_scan11',
 'trip_creation_day',
 'Timediff_start_end_H11',
 'agg_segment_actual_time11',
 'agg_segment_osrm_time11',
 'agg_segment_osrm_distance11',
 'agg_distance_to_destination11',
 'agg_actual_time11',
 'agg_osrm_time11',
 'agg_osrm_distance11']
```

Data Visualization

```
for i in temp:
  sns.histplot(data_final[i], bins=25, kde=True, color='orchid')
```

```
plt.show()
```



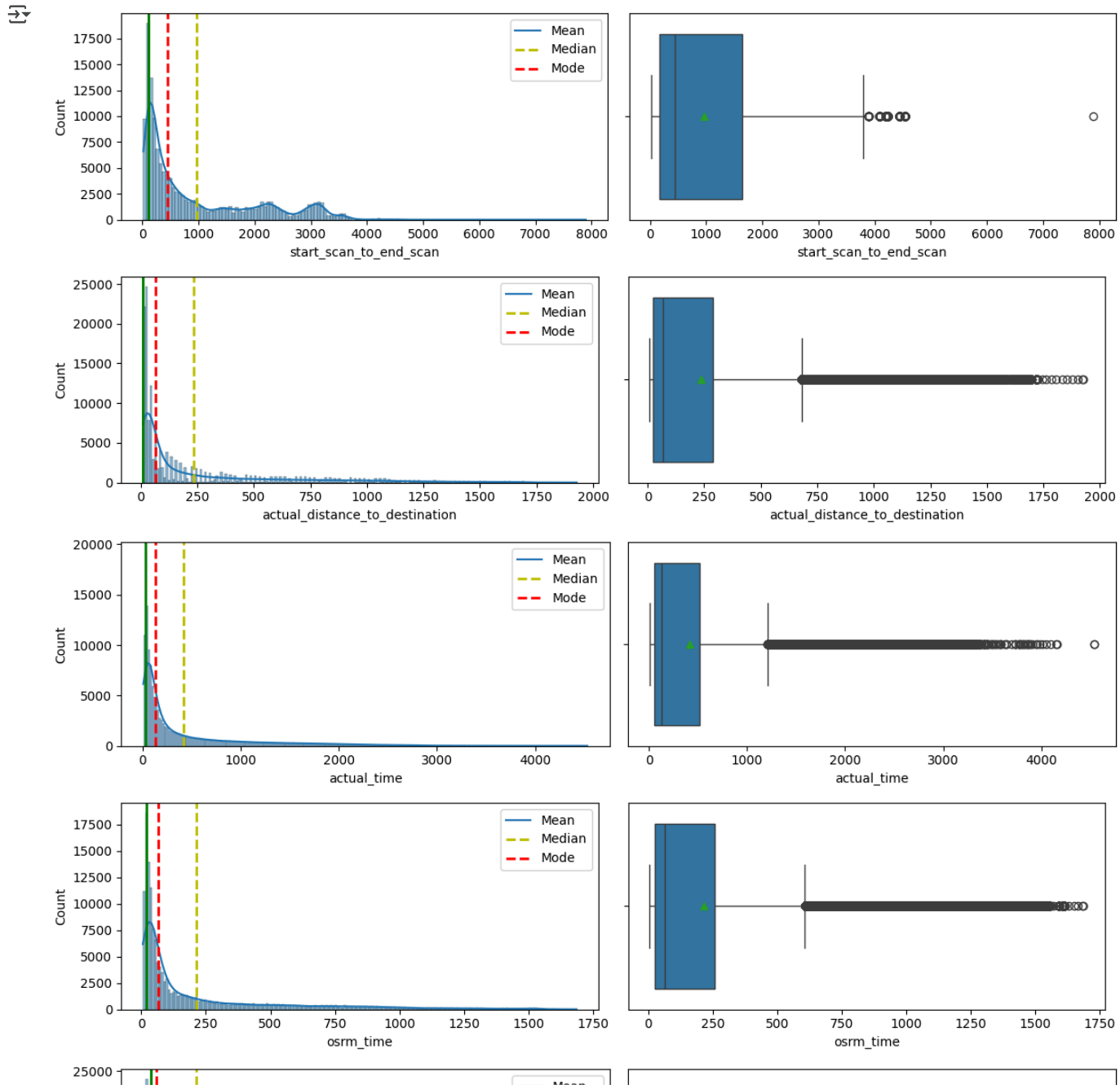


Outlier Detection & their Treatment

```
def uni(d):
    f,ax = plt.subplots(nrows=1,ncols=2,figsize=(12,3))
    sns.histplot(d, kde=True, ax=ax[0])
    ax[0].axvline(d.mean(), color='y', linestyle='--',linewidth=2)
    ax[0].axvline(d.median(), color='r', linestyle='dashed', linewidth=2)
    ax[0].axvline(d.mode()[0],color='g',linestyle='solid',linewidth=2)
    ax[0].legend({'Mean':d.mean(),'Median':d.median(),'Mode':d.mode()})

    sns.boxplot(x=d, showmeans=True, ax=ax[1])
    plt.tight_layout()
```

```
num_cols = data.select_dtypes('float64').columns.values
```

```
for f in num_cols:
    uni(data[f])
plt.show()
```

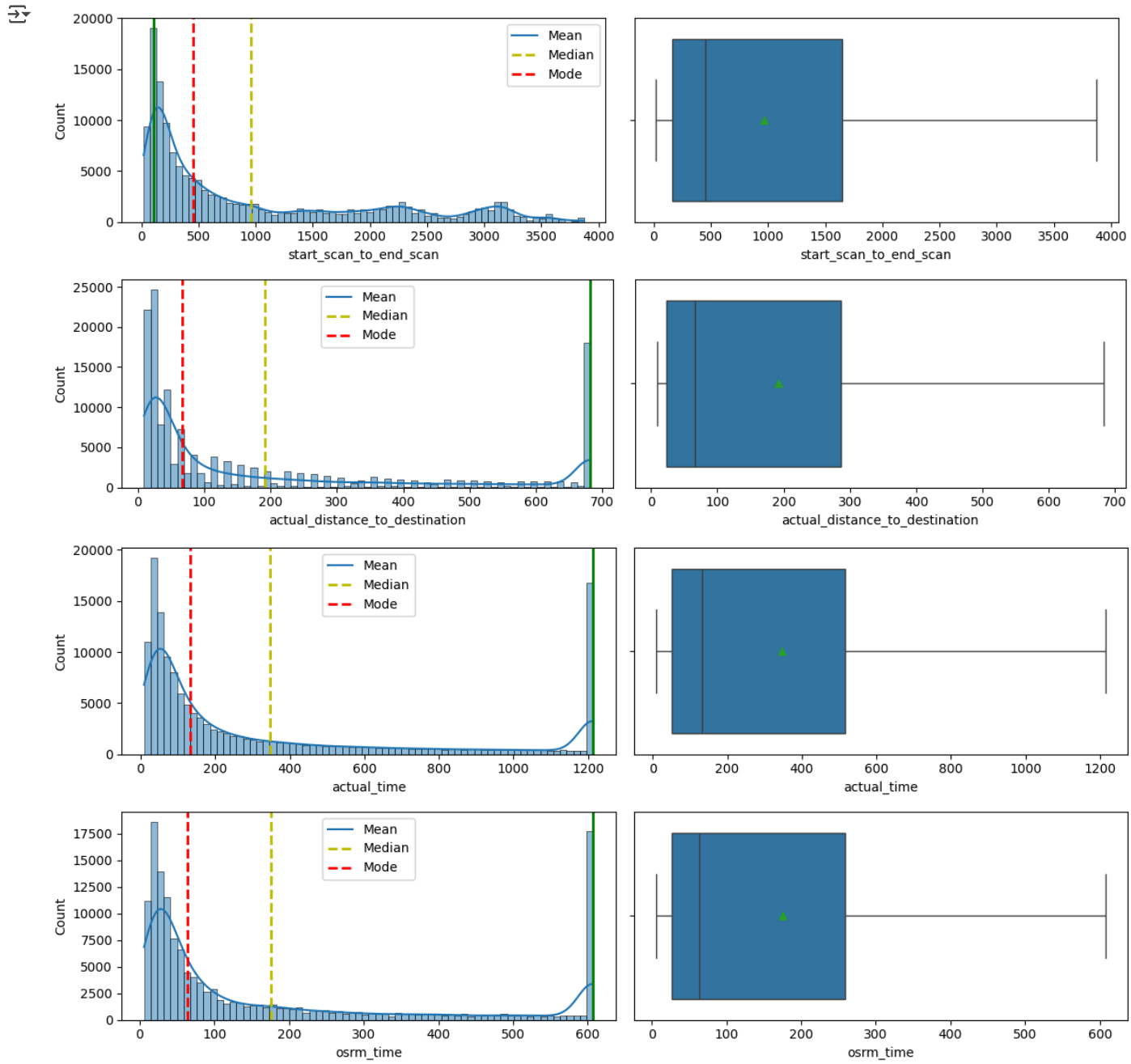



```
#treating outliers:
def treat_outlier(variable):
    #Takes two parameters: dataframe & variable of interest as string
    q1,q3=np.percentile(variable,[25,75])
    iqr = q3-q1
    lo_range = q1-(1.5*iqr)
    up_range = q3+(1.5*iqr)
    return lo_range,up_range
```

```
for col in num_cols:
    ir,ur=treat_outlier(data[col])
    data[col]=np.where(data[col]>ur,ur,data[col])
    data[col]=np.where(data[col]<ir,ir,data[col])
```

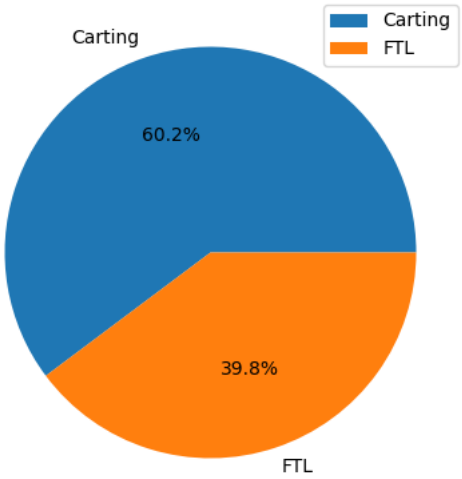
Here I have found the outliers and replaced them with max and min of whisker's value.

```
#Lets check where outliers are removed or not:
for f in num_cols:
    uni(data[f])
plt.show()
```



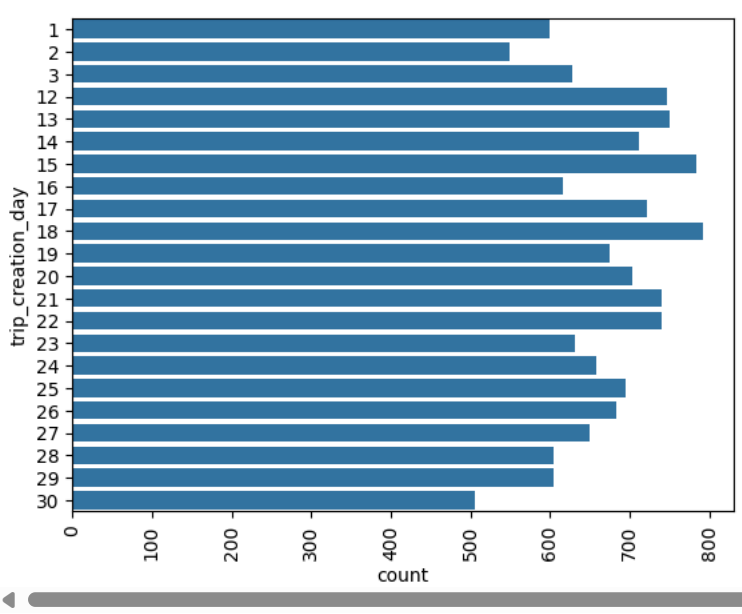
- **The outliers are removed**

```
fig1, ax1 = plt.subplots(figsize=(10,5))
ax1.pie(data_final['route_type'].value_counts(), labels=data_final['route_type'].unique(), autopct='%1.1f%%')
plt.legend()
plt.show()
```



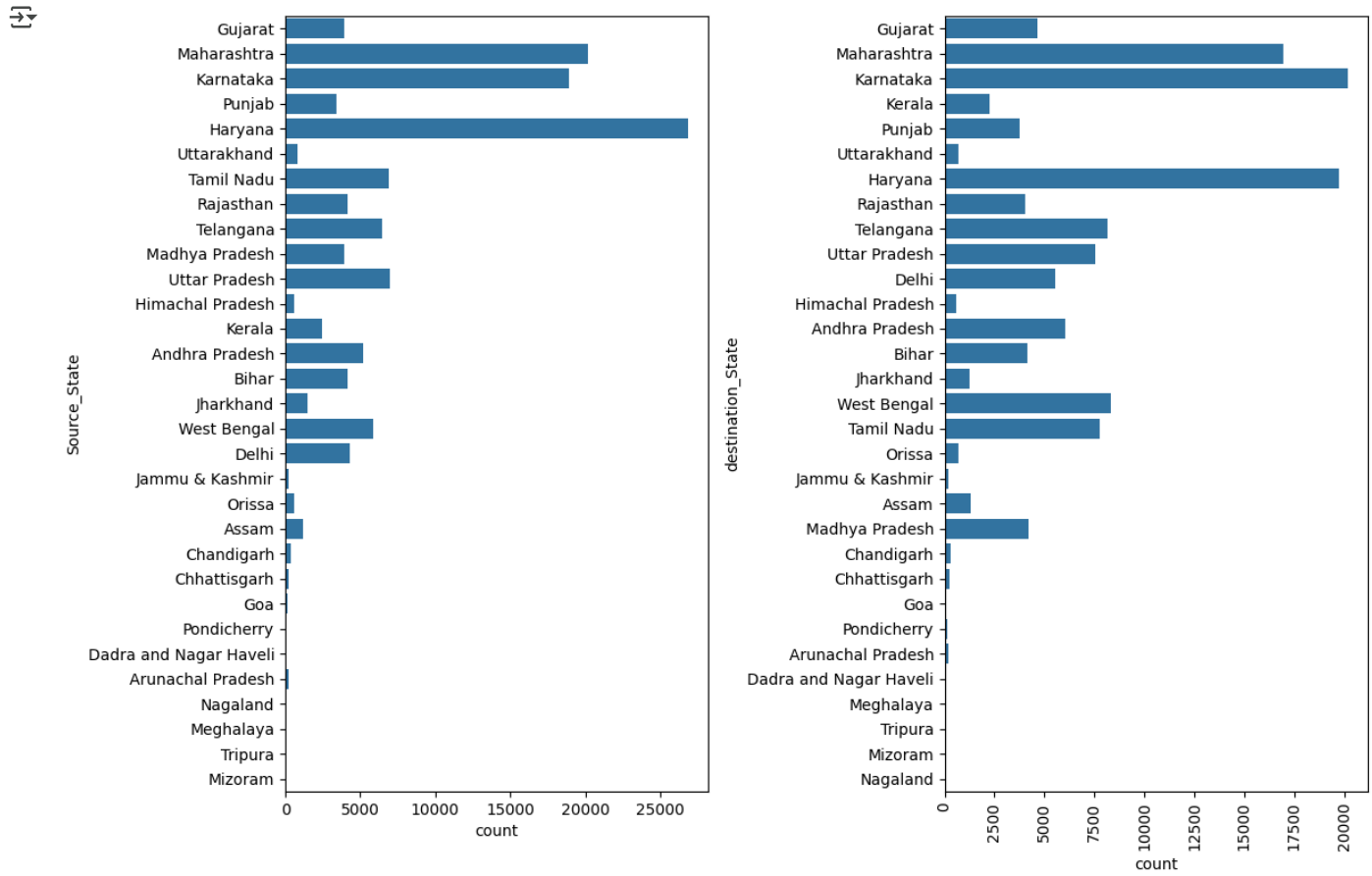
- **Therefore by analyzing the given data, it has been found that 60% of the route type used for delivery were Carting and the remaining were FTL.**

```
sns.countplot(y=data_final['trip_creation_day'])
plt.xticks(rotation=90)
plt.show()
```



- The start and end date of the months the trips were lesser.
- More trips were during mid of the month, but there is not huge diiference. The trips were similar across the month.
- No trips were found from 4th till 11th of the month.

```
f,ax = plt.subplots(nrows=1,ncols=2,figsize=(12,8))
sns.countplot(y=data_copy['Source_State'],ax=ax[0])
sns.countplot(y=data_copy['destination_State'],ax=ax[1])

plt.xticks(rotation=90)
plt.tight_layout()
plt.show()
```



- The top 3 states that contributes to overall trips were Haryana, Maharastra and Karnataka.

Bivariate Analysis

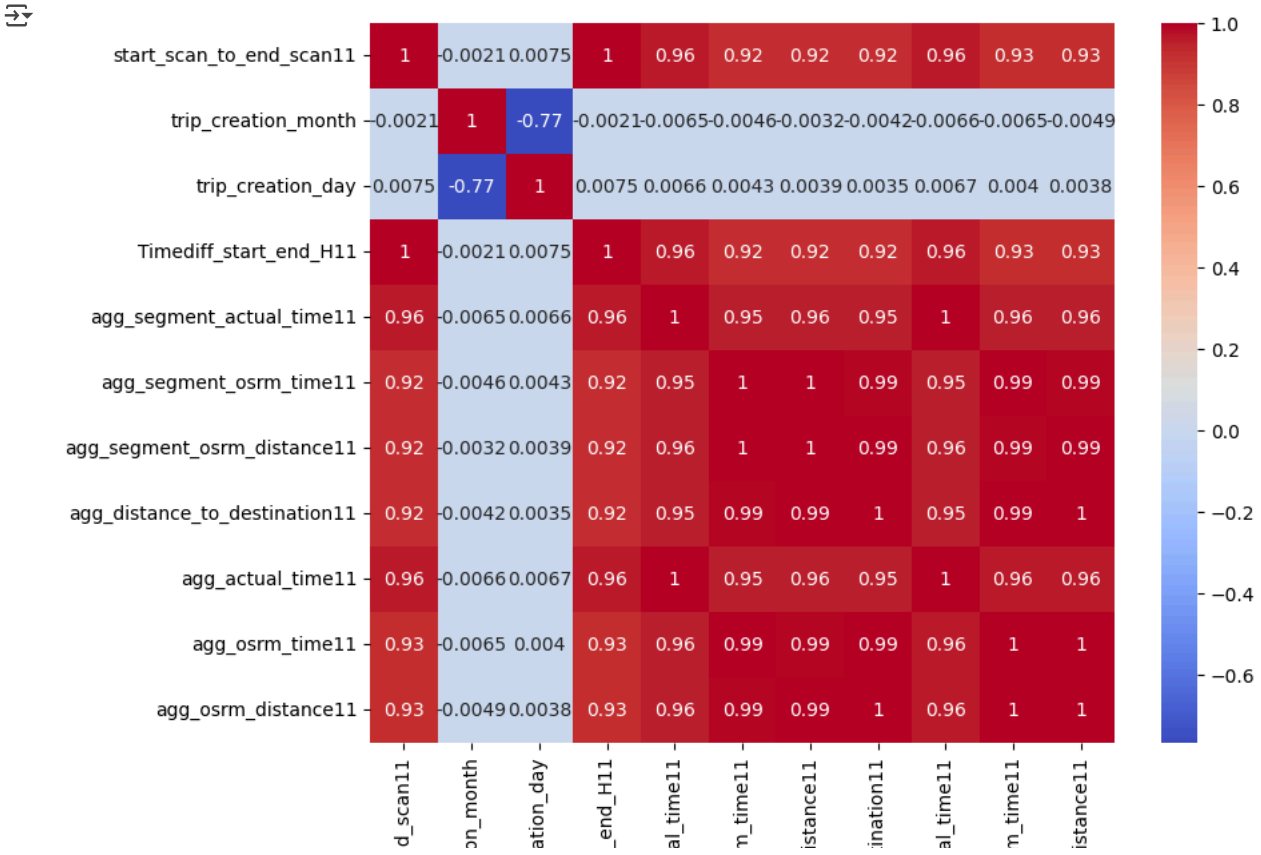
Since most of the features were numerical, instead of using other plots I have used heatmap to know the overall relation between each features

```
rel=data_final.loc[:,['route_type', 'trip_uuid',
       'start_scan_to_end_scan11', 'trip_creation_month',
       'trip_creation_day', 'Timediff_start_end_H11', 'agg_segment_actual_time11',
       'agg_segment_osrm_time11', 'agg_segment_osrm_distance11',
       'agg_distance_to_destination11', 'agg_actual_time11', 'agg_osrm_time11',
       'agg_osrm_distance11', 'Source_City11', 'Source_Place11', 'Source_Code/State11',
       'destination_City11', 'destination_Place11', 'destination_Code/State11']]
```

```
rel.columns
```

```
Index(['route_type', 'trip_uuid', 'start_scan_to_end_scan11',
       'trip_creation_month', 'trip_creation_day', 'Timediff_start_end_H11',
       'agg_segment_actual_time11', 'agg_segment_osrm_time11',
       'agg_segment_osrm_distance11', 'agg_distance_to_destination11',
       'agg_actual_time11', 'agg_osrm_time11', 'agg_osrm_distance11',
       'Source_City11', 'Source_Place11', 'Source_Code/State11',
       'destination_City11', 'destination_Place11',
       'destination_Code/State11'],
      dtype='object')
```

```
# Select only numerical features for correlation analysis
numerical_features = rel.select_dtypes(include=['number'])

# Calculate the correlation matrix for numerical features
plt.figure(figsize=(9, 7))
sns.heatmap(numerical_features.corr(), annot=True, cmap='coolwarm')
plt.show()
```


start_scan_to_end_scan11
trip_creation_month
trip_creation_day
Timediff_start_end_H11
agg_segment_actual_time11
agg_segment_osrm_time11
agg_segment_osrm_distance11
agg_distance_to_destination11
agg_actual_time11
agg_osrm_time11
agg_osrm_distance11
1 -0.0021 0.0075 1 0.96 0.92 0.92 0.92 0.96 0.93 0.93
-0.0021 1 -0.77 -0.0021 -0.0065 -0.0046 -0.0032 -0.0042 -0.0066 -0.0065 -0.0049
0.0075 -0.77 1 0.0075 0.0066 0.0043 0.0039 0.0035 0.0067 0.004 0.0038
1 -0.0021 0.0075 1 0.96 0.92 0.92 0.92 0.96 0.93 0.93
0.96 -0.0065 0.0066 0.96 1 0.95 0.96 0.95 1 0.96 0.96
0.92 -0.0046 0.0043 0.92 0.95 1 1 0.99 0.95 0.99 0.99
0.92 -0.0032 0.0039 0.92 0.96 1 1 0.99 0.96 0.99 0.99
0.92 -0.0042 0.0035 0.92 0.95 0.99 0.99 1 0.95 0.99 1
0.96 -0.0066 0.0067 0.96 1 0.95 0.96 0.95 1 0.96 0.96
0.93 -0.0065 0.004 0.93 0.96 0.99 0.99 0.99 0.96 1 1
0.93 -0.0049 0.0038 0.93 0.96 0.99 0.99 1 0.96 1 1
d_scan11
on_month
ation_day
_end_H11
al_time11
m_time11
istance11
ination11
al_time11
m_time11
istance11
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6