

```
In [3]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
import statsmodels.api as sm
sns.set(style="whitegrid")
sns.set(font_scale = 1.1)
```

Problem Statement

- **Define Problem Statement**
 - Definition of problem (as per given problem statement with additional views)
- **Primary Goal**
 - **Explore capabilities** using this data that helps to widen the gap between **the quality, efficiency, and profitability of their business versus their competitors.**
 - **Predicting delivery time segmented by route , source , destination**
 - **Clean, sanitize and manipulate data**
 - Recognizing **significant features** that will drive more orders.
 - How well those features describe the volume of orders
 - Recognizing **Demand pattern** based on **route type , trips booking time (days of week/month), source , destination , distance, time** etc.
 - How to **drive sales** , across route types and other factors mentioned above
 - Data driven discounting / offers among customer segments
- **Long term benefits : Sales growth , More market penetration** where (i.e. states, place, cities) there are less volume of orders, **Customer acquisition , Balance short and long trips** and **retention**

Basic Analysis

- **Exploratory Data Analysis** (10 points)
 - Observations on shape of data, data types of all the attributes, conversion of categorical attributes to 'category' (If required), missing value detection, statistical summary.
 - Visual Analysis (distribution plots of all the continuous variable(s), boxplots of all the categorical variables)

```
In [4]: df = pd.read_csv("delhivery_data.csv")
```

Data types - structure & characteristics of the dataset

```
In [5]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144867 entries, 0 to 144866
Data columns (total 24 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   data                                  144867 non-null  object
1   trip_creation_time                   144867 non-null  object
2   route_schedule_uuid                 144867 non-null  object
3   route_type                           144867 non-null  object
4   trip_uuid                            144867 non-null  object
5   source_center                       144867 non-null  object
6   source_name                         144574 non-null  object
7   destination_center                  144867 non-null  object
8   destination_name                    144606 non-null  object
9   od_start_time                       144867 non-null  object
10  od_end_time                         144867 non-null  object
11  start_scan_to_end_scan               144867 non-null  float64
12  is_cutoff                           144867 non-null  bool
13  cutoff_factor                       144867 non-null  int64
14  cutoff_timestamp                    144867 non-null  object
15  actual_distance_to_destination       144867 non-null  float64
16  actual_time                         144867 non-null  float64
17  osrm_time                           144867 non-null  float64
18  osrm_distance                       144867 non-null  float64
19  factor                              144867 non-null  float64
20  segment_actual_time                 144867 non-null  float64
21  segment_osrm_time                   144867 non-null  float64
22  segment_osrm_distance               144867 non-null  float64
23  segment_factor                      144867 non-null  float64
dtypes: bool(1), float64(10), int64(1), object(12)
memory usage: 25.6+ MB
```

Observations on shape of data

```
In [6]: df.shape
```

```
Out[6]: (144867, 24)
```

- **Observation** - Not a small size sample

Statistical summary

```
In [7]: df.describe()
```

```
Out[7]:
```

	start_scan_to_end_scan	cutoff_factor	actual_distance_to_destination	actual_time	osrm_time	osrm_c
count	144867.000000	144867.000000	144867.000000	144867.000000	144867.000000	144867
mean	961.262986	232.926567	234.073372	416.927527	213.868272	284
std	1037.012769	344.755577	344.990009	598.103621	308.011085	421
min	20.000000	9.000000	9.000045	9.000000	6.000000	9
25%	161.000000	22.000000	23.355874	51.000000	27.000000	29
50%	449.000000	66.000000	66.126571	132.000000	64.000000	78
75%	1634.000000	286.000000	286.708875	513.000000	257.000000	343
max	7898.000000	1927.000000	1927.447705	4532.000000	1686.000000	2326

```
In [8]: df.describe(include=object)
```

Out[8]:	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	
	count	144867	144867	144867	144867	144867	
	unique	2	14817	1504	2	14817	1508
	top	training	2018-09-28 05:23:15.359220	thanos::sroute:4029a8a2- 6c74-4b7e-a6d8- f9e069f...	FTL	trip- 153811219535896559	IND000000ACB Gurgi
	freq	104858	101	1812	99660	101	23347

Converting data type objects to datetime

```
In [9]: df["trip_creation_time"] = pd.to_datetime(df["trip_creation_time"])
df["od_start_time"] = pd.to_datetime(df["od_start_time"])
df["od_end_time"] = pd.to_datetime(df["od_end_time"])
df["cutoff_timestamp"] = pd.to_datetime(df["cutoff_timestamp"])
```

Non-Graphical Analysis (Part 1)

```
In [10]: df.head()
```

Out[10]:	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source
	0	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3...	Carting	trip- 153741093647649320	IND388121AAA Anand_VUN
	1	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3...	Carting	trip- 153741093647649320	IND388121AAA Anand_VUN
	2	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3...	Carting	trip- 153741093647649320	IND388121AAA Anand_VUN
	3	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3...	Carting	trip- 153741093647649320	IND388121AAA Anand_VUN
	4	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3...	Carting	trip- 153741093647649320	IND388121AAA Anand_VUN

5 rows × 24 columns

```
In [11]: df["data"].value_counts(normalize=True)*100
```

```
Out[11]: training    72.382254
test              27.617746
Name: data, dtype: float64
```

```
In [12]: df["route_type"].value_counts(normalize=True)*100
```

```
Out[12]: FTL          68.794135
Carting    31.205865
Name: route_type, dtype: float64
```

```
In [13]: df["source_name"].value_counts(normalize=True)*100
```

```
Out[13]: Gurgaon_Bilaspur_HB (Haryana)          16.148823
Bangalore_Nelmngla_H (Karnataka)          6.899581
Bhiwandi_Mankoli_HB (Maharashtra)         6.286054
Pune_Tathawde_H (Maharashtra)             2.808942
Hyderabad_Shamshbd_H (Telangana)          2.310236
...
Shahjhnpur_NavdaCln_D (Uttar Pradesh)     0.000692
Soro_UttarDPP_D (Orissa)                  0.000692
Kayamkulam_Bhrnikvu_D (Kerala)            0.000692
Krishnanagar_AnadiDPP_D (West Bengal)     0.000692
Faridabad_Old (Haryana)                   0.000692
Name: source_name, Length: 1498, dtype: float64
```

```
In [14]: df["destination_name"].value_counts(normalize=True)*100
```

```
Out[14]: Gurgaon_Bilaspur_HB (Haryana)          10.505788
Bangalore_Nelmngla_H (Karnataka)          7.620016
Bhiwandi_Mankoli_HB (Maharashtra)         3.797906
Hyderabad_Shamshbd_H (Telangana)          3.555869
Kolkata_Dankuni_HB (West Bengal)          3.382985
...
Hyd_Trimulgherry_Dc (Telangana)           0.000692
Vijayawada (Andhra Pradesh)              0.000692
Baghpat_Barout_D (Uttar Pradesh)          0.000692
Mumbai_Sanpada_CP (Maharashtra)           0.000692
Basta_Central_DPP_1 (Orissa)              0.000692
Name: destination_name, Length: 1468, dtype: float64
```

```
In [15]: df["segment_factor"].value_counts(normalize=True)*100
```

```
Out[15]: 2.000000    4.142420
1.500000    3.200867
1.000000    1.636674
1.666667    1.635983
-1.000000    1.620107
...
1.844444    0.000690
1.380000    0.000690
4.103448    0.000690
2.614458    0.000690
29.777778    0.000690
Name: segment_factor, Length: 5675, dtype: float64
```

- **Filtering Feature types by data type**

```
In [16]: continious_features = df.select_dtypes(include=['int64','float64']).columns
continious_features
```

```
Out[16]: Index(['start_scan_to_end_scan', 'cutoff_factor',
               'actual_distance_to_destination', 'actual_time', 'osrm_time',
               'osrm_distance', 'factor', 'segment_actual_time', 'segment_osrm_time',
               'segment_osrm_distance', 'segment_factor'],
              dtype='object')
```

```
In [17]: categorical_features = df.select_dtypes(include=['object']).columns
categorical_features
```

```
Out[17]: Index(['data', 'route_schedule_uuid', 'route_type', 'trip_uuid',  
      'source_center', 'source_name', 'destination_center',  
      'destination_name'],  
      dtype='object')
```

Missing Value Detection

```
In [18]: percent_missing = df.isnull().sum() * 100 / len(df)  
missing_value_df = pd.DataFrame({'column_name': df.columns,  
                                'percent_missing': percent_missing})  
missing_value_df.sort_values('percent_missing', ascending=False)
```

Out[18]:

	column_name	percent_missing
	source_name	0.202254
	destination_name	0.180165
	data	0.000000
	cutoff_factor	0.000000
	segment_osrm_distance	0.000000
	segment_osrm_time	0.000000
	segment_actual_time	0.000000
	factor	0.000000
	osrm_distance	0.000000
	osrm_time	0.000000
	actual_time	0.000000
	actual_distance_to_destination	0.000000
	cutoff_timestamp	0.000000
	is_cutoff	0.000000
	trip_creation_time	0.000000
	start_scan_to_end_scan	0.000000
	od_end_time	0.000000
	od_start_time	0.000000
	destination_center	0.000000
	source_center	0.000000
	trip_uuid	0.000000
	route_type	0.000000
	route_schedule_uuid	0.000000
	segment_factor	0.000000

- **Observations :**
 - **source_name (0.20%) and destination_name (0.18%)** have **missing values** and proportion is very less
 - **No missing values for rest of the features**

Missing values Treatment

```
In [19]: df["source_name"].fillna("Unknown", inplace=True)
df["destination_name"].fillna("Unknown", inplace=True)
```

```
In [20]: percent_missing = df.isnull().sum() * 100 / len(df)
missing_value_df = pd.DataFrame({'column_name': df.columns,
                                'percent_missing': percent_missing})
missing_value_df.sort_values('percent_missing', ascending=False)
```

```
Out[20]:
```

	column_name	percent_missing
	data	0.0
	trip_creation_time	0.0
	segment_osrm_distance	0.0
	segment_osrm_time	0.0
	segment_actual_time	0.0
	factor	0.0
	osrm_distance	0.0
	osrm_time	0.0
	actual_time	0.0
	actual_distance_to_destination	0.0
	cutoff_timestamp	0.0
	cutoff_factor	0.0
	is_cutoff	0.0
	start_scan_to_end_scan	0.0
	od_end_time	0.0
	od_start_time	0.0
	destination_name	0.0
	destination_center	0.0
	source_name	0.0
	source_center	0.0
	trip_uuid	0.0
	route_type	0.0
	route_schedule_uuid	0.0
	segment_factor	0.0

Visual Analysis (Part 1)

- Distribution plots of all the continuous variable(s), boxplots of all the categorical variables)

```
In [21]: continuous_features
```

```
Out[21]: Index(['start_scan_to_end_scan', 'cutoff_factor',  
      'actual_distance_to_destination', 'actual_time', 'osrm_time',  
      'osrm_distance', 'factor', 'segment_actual_time', 'segment_osrm_time',  
      'segment_osrm_distance', 'segment_factor'],  
      dtype='object')
```

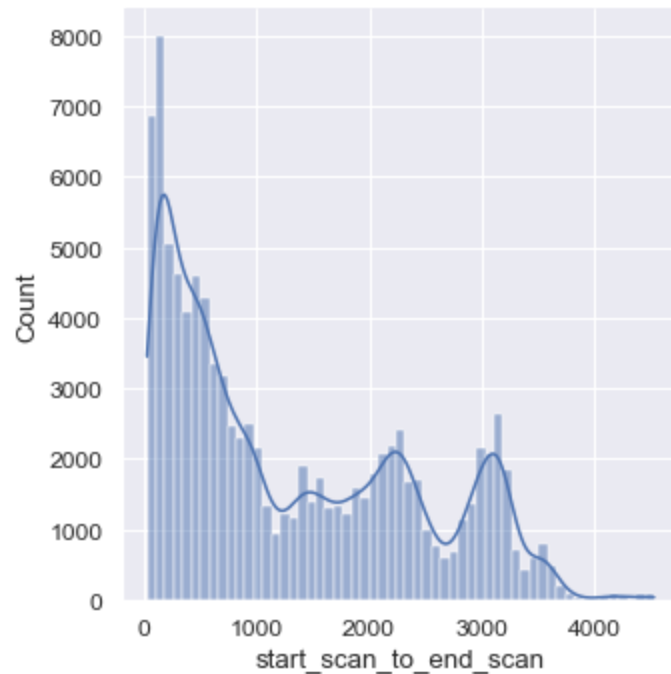
Seperating data by route type - Full truck load and Carting

```
In [22]: df_full_truck_load = df[df["route_type"] == 'FTL']  
df_carting = df[df["route_type"] == 'Carting']
```

Distribution plot of route type - Full truck load

```
In [23]: sns.displot(df_full_truck_load['start_scan_to_end_scan'], kde=True)
```

```
Out[23]: <seaborn.axisgrid.FacetGrid at 0x1a5c5e8d600>
```

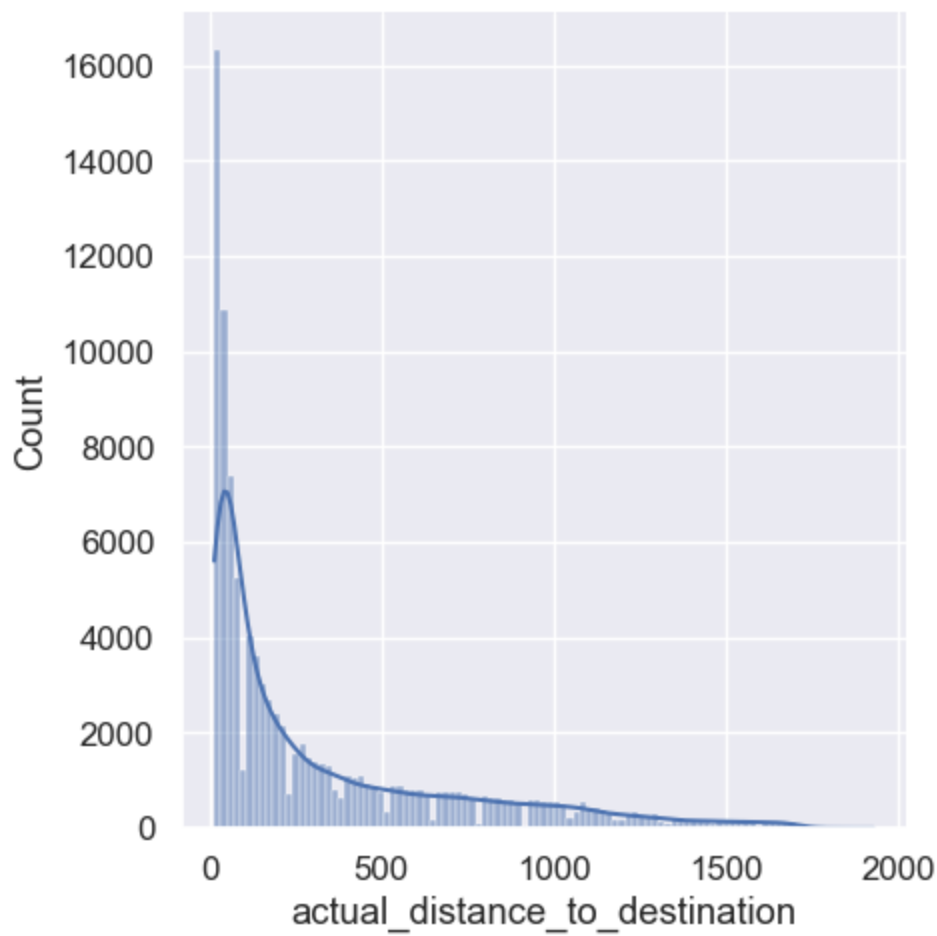


- **Observation :**

- Multi-modal distribution . Need to explore if "start_scan_to_end_scan i.e. Time taken to deliver from source to destination) can be categorized as sub categories such small time ,medium and large time (in consultation with domain experts)

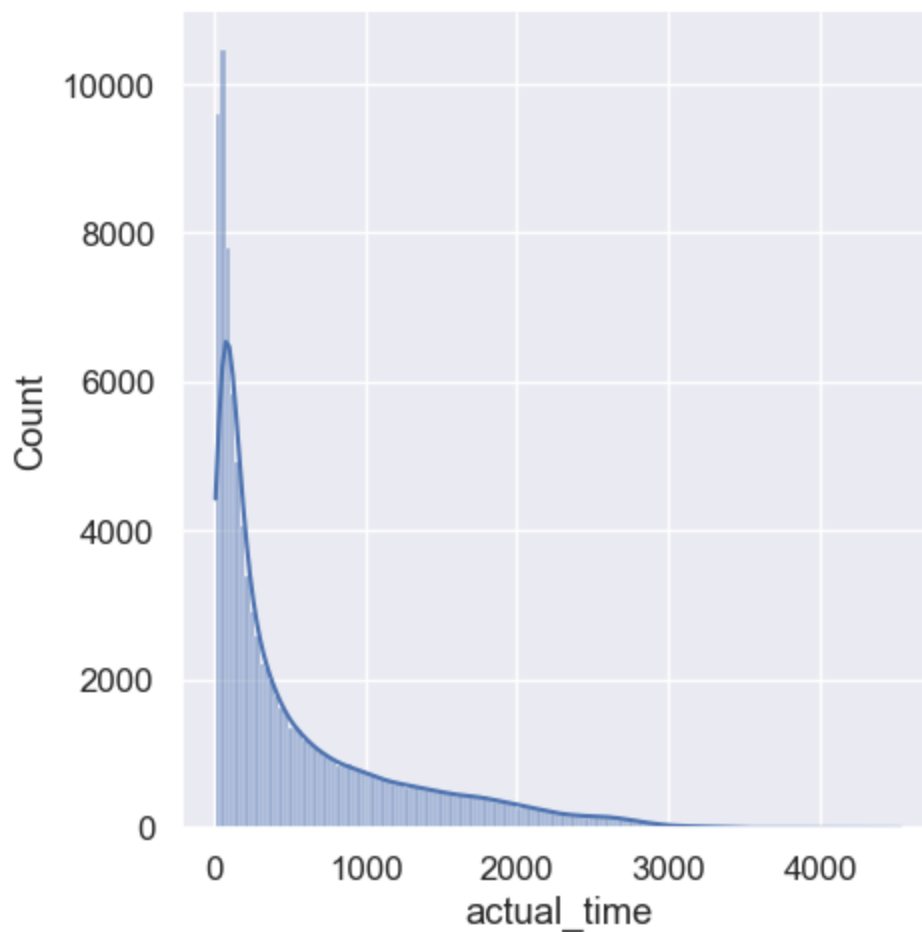
```
In [24]: sns.displot(df_full_truck_load['actual_distance_to_destination'], kde=True)
```

```
Out[24]: <seaborn.axisgrid.FacetGrid at 0x1a5c5e8da50>
```



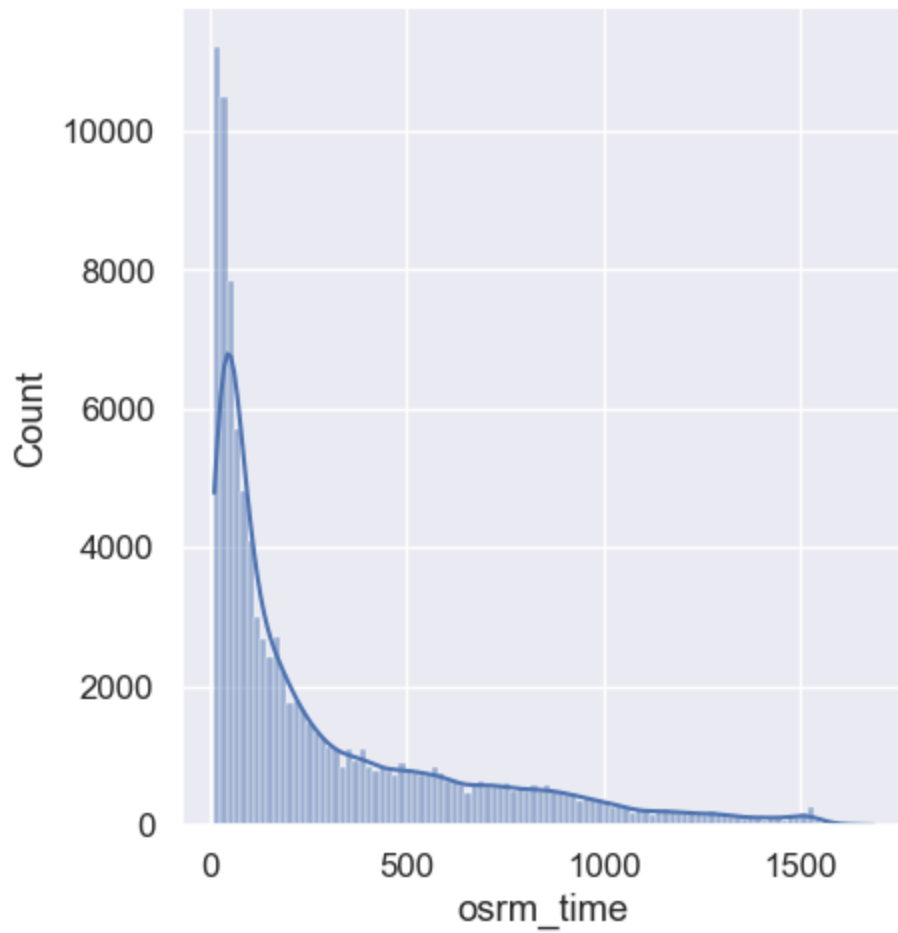
```
In [25]: sns.displot(df_full_truck_load['actual_time'], kde=True)
```

```
Out[25]: <seaborn.axisgrid.FacetGrid at 0x1a5ea2d0e50>
```



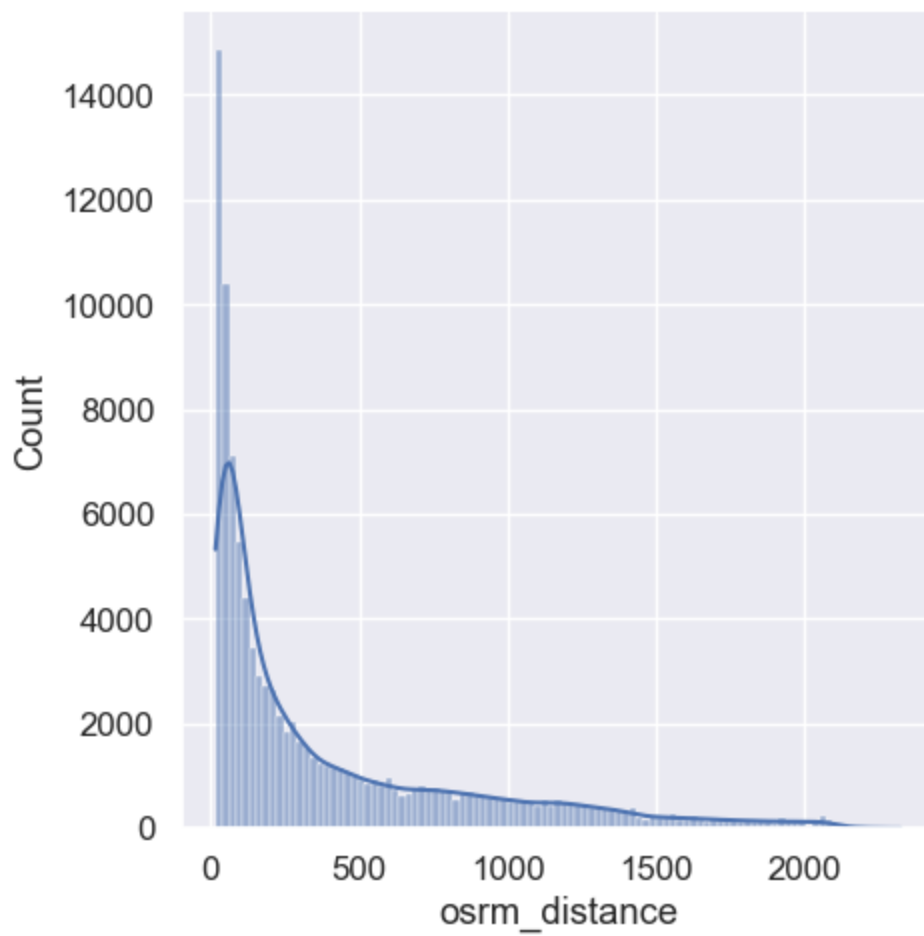

```
In [26]: sns.displot(df_full_truck_load['osrm_time'], kde=True)
```

```
Out[26]: <seaborn.axisgrid.FacetGrid at 0x1a5ea032c50>
```



```
In [27]: sns.displot(df_full_truck_load['osrm_distance'], kde=True)
```

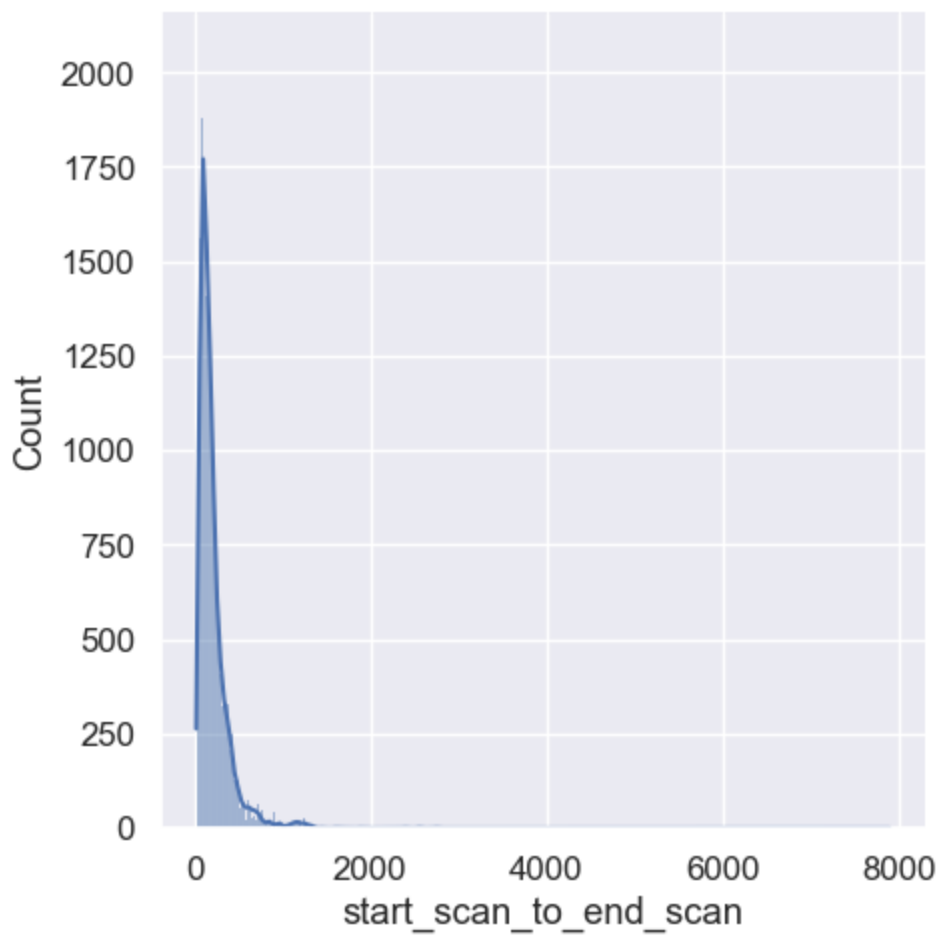
```
Out[27]: <seaborn.axisgrid.FacetGrid at 0x1a5e8560b20>
```



Distribution plot of route type - Carting

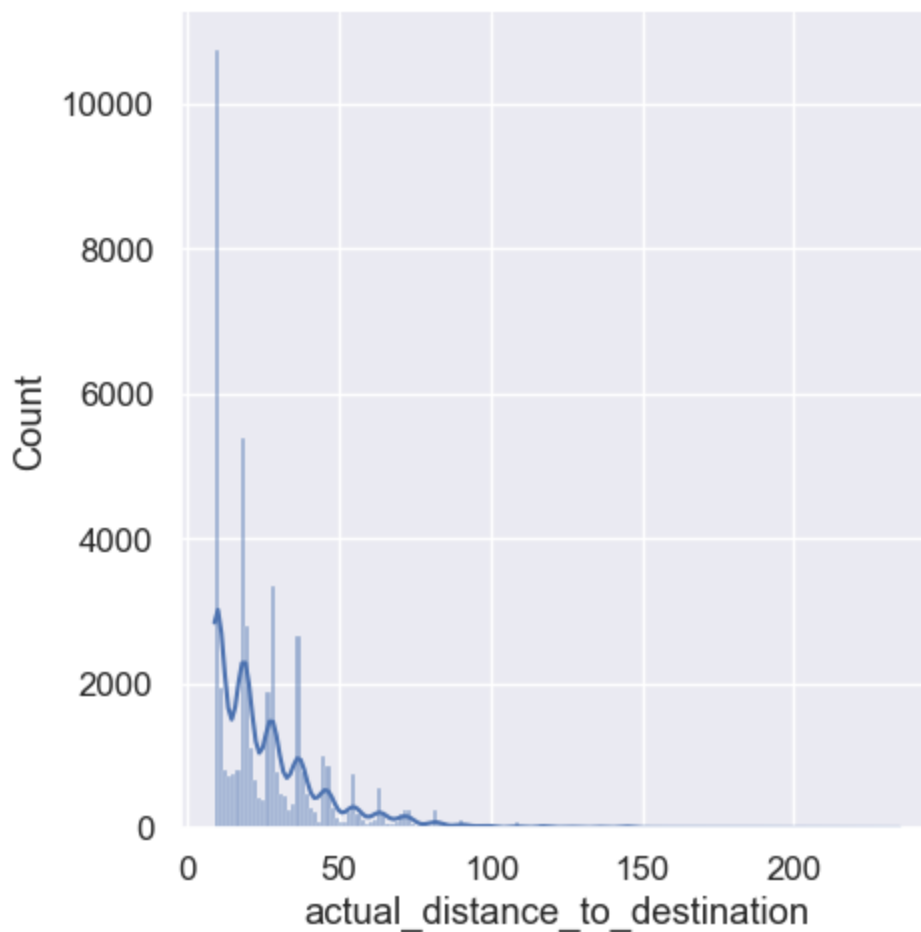
```
In [28]: sns.displot(df_carting['start_scan_to_end_scan'], kde=True)
```

```
Out[28]: <seaborn.axisgrid.FacetGrid at 0x1a5e9c95720>
```



```
In [29]: sns.displot(df_carting['actual_distance_to_destination'], kde=True)
```

```
Out[29]: <seaborn.axisgrid.FacetGrid at 0x1a5e82c4700>
```

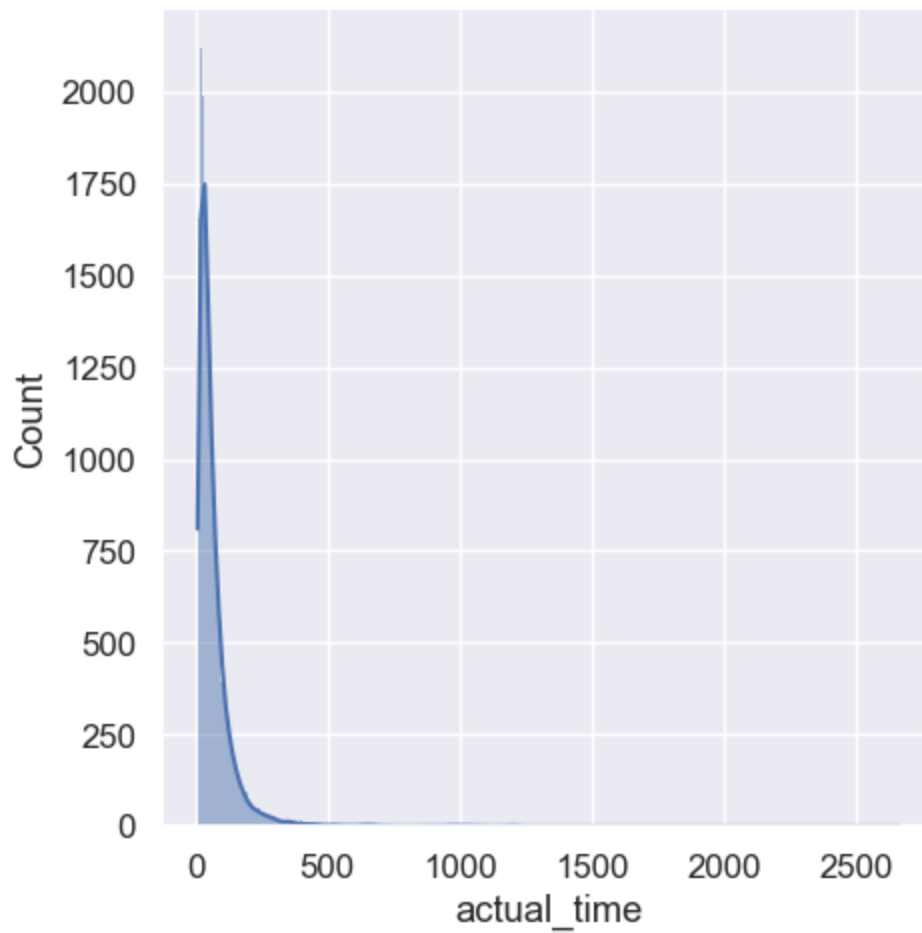


-Observations

- Multiple sub category of distances can be created by consulting with domain experts

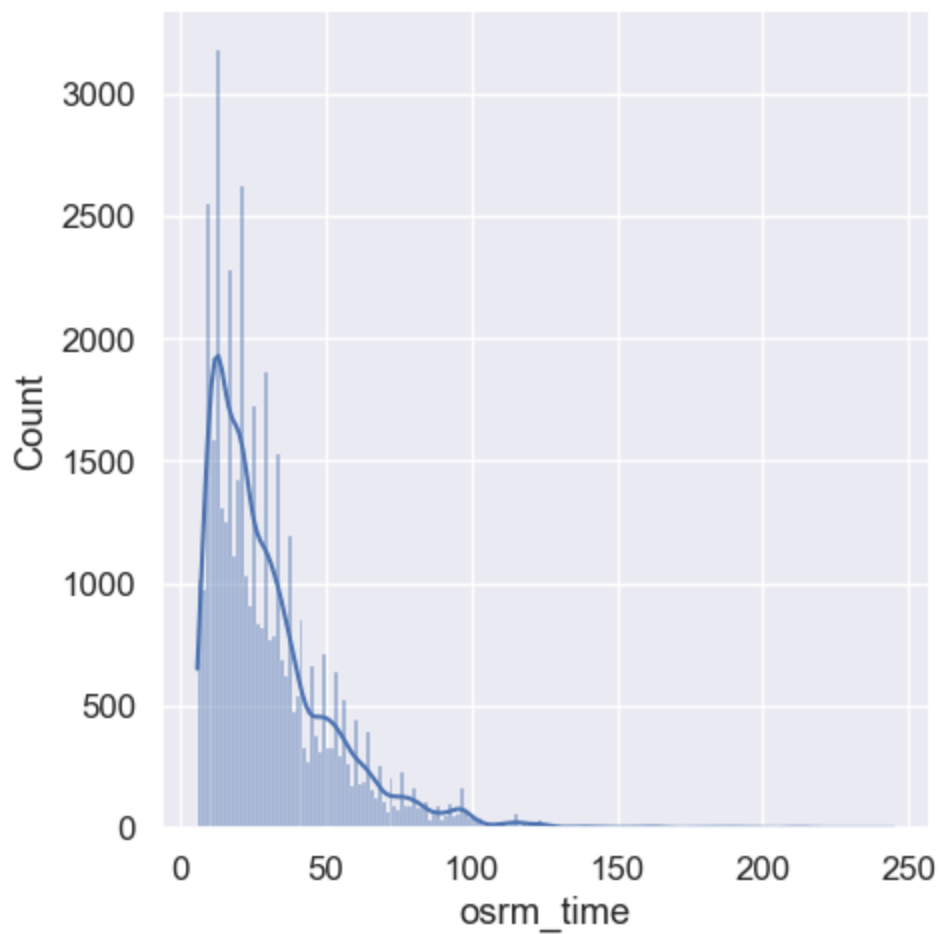
```
In [30]: sns.displot(df_carting['actual_time'], kde=True)
```

```
Out[30]: <seaborn.axisgrid.FacetGrid at 0x1a5e816afb0>
```



```
In [31]: sns.displot(df_carting['osrm_time'], kde=True)
```

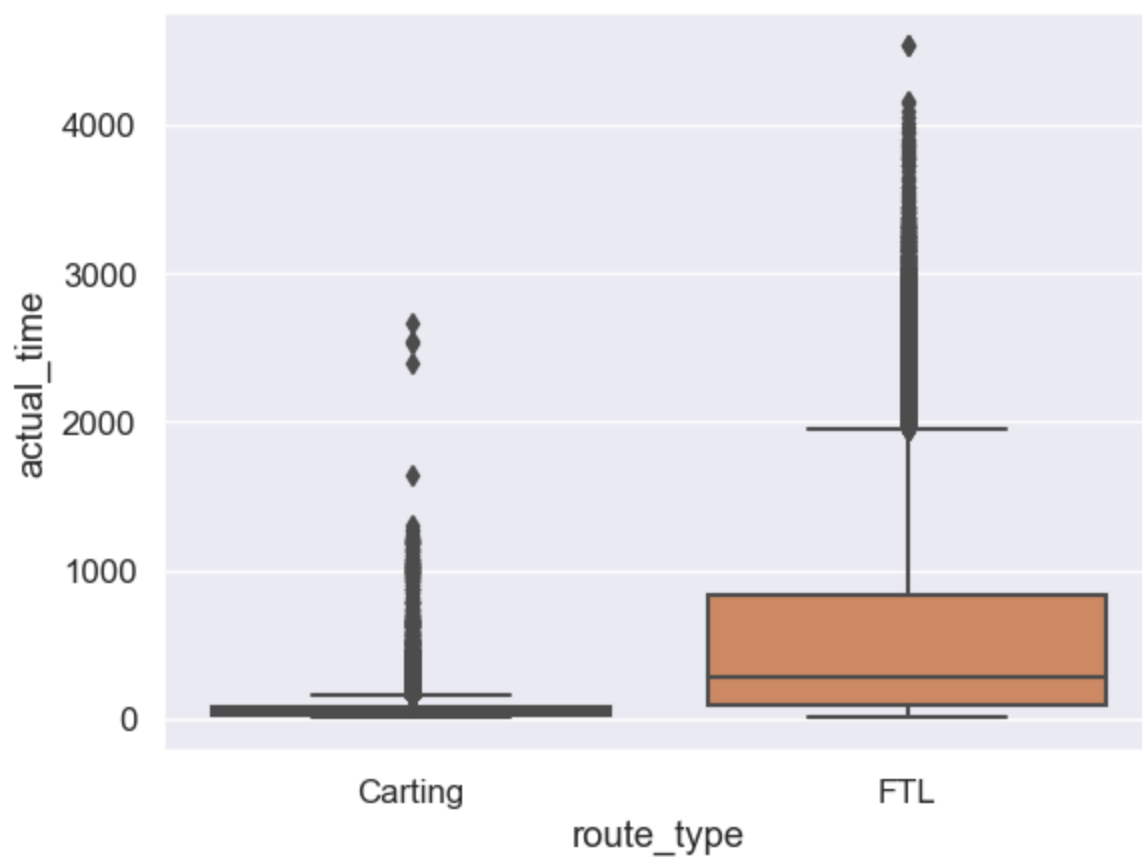
```
Out[31]: <seaborn.axisgrid.FacetGrid at 0x1a5ebdfd210>
```



Boxplot route type vs actual_time

```
In [32]: sns.boxplot(x="route_type", y="actual_time", data=df)
```

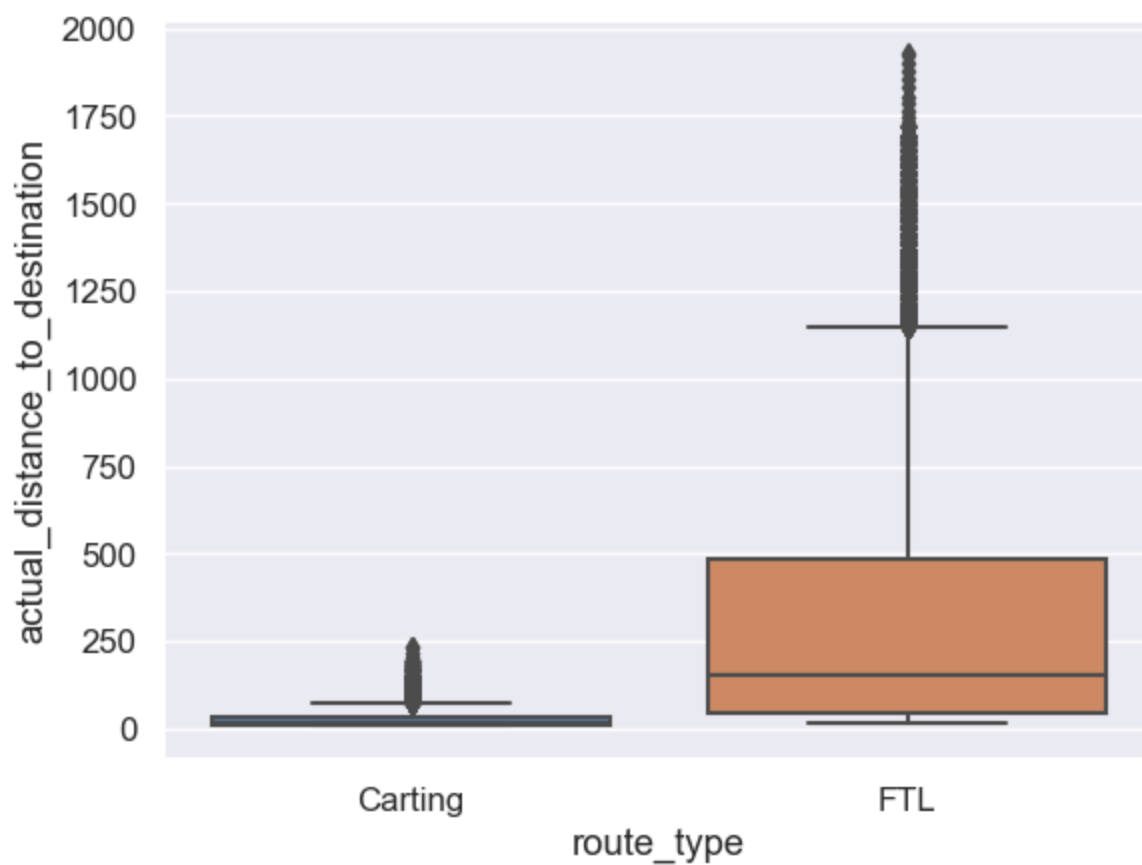
```
Out[32]: <AxesSubplot:xlabel='route_type', ylabel='actual_time'>
```



Boxplot route type vs actual_distance_to_destination

```
In [33]: sns.boxplot(x="route_type", y="actual_distance_to_destination", data=df)
```

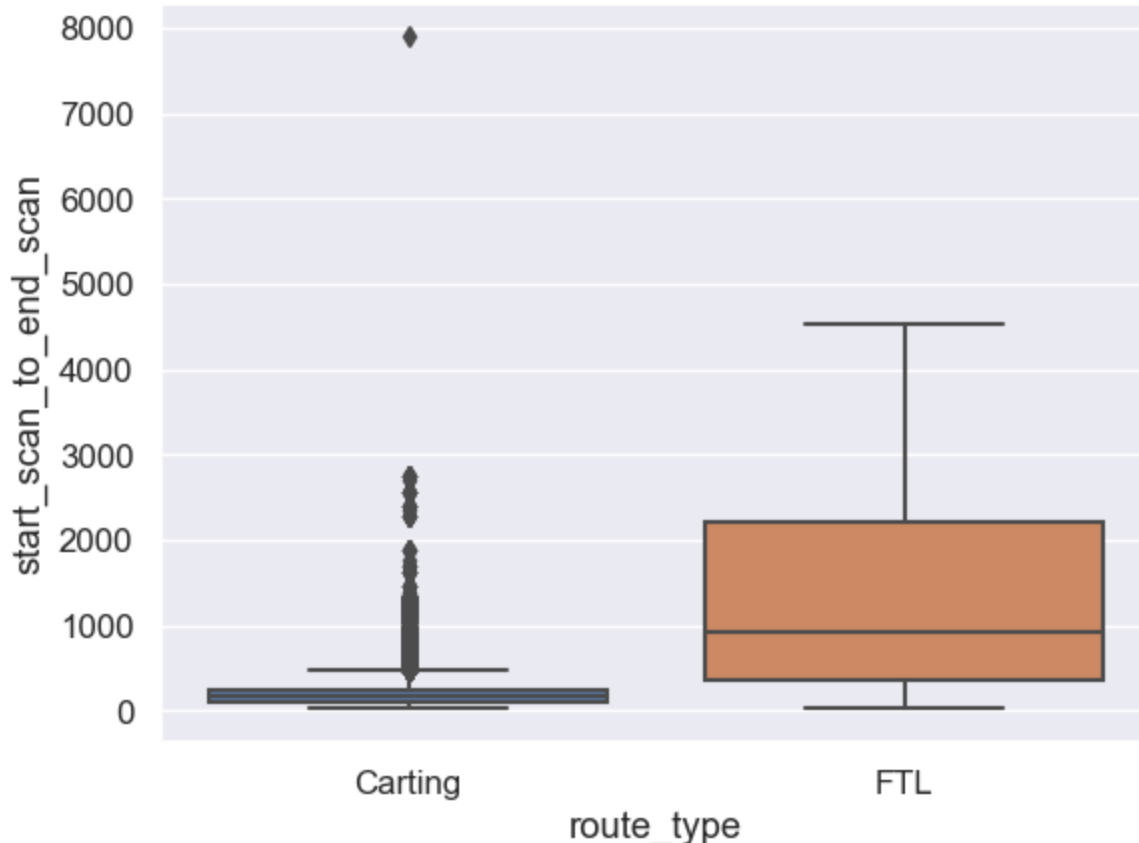
```
Out[33]: <AxesSubplot:xlabel='route_type', ylabel='actual_distance_to_destination'>
```



Boxplot route type vs start_scan_to_end_scan

```
In [34]: sns.boxplot(x="route_type", y="start_scan_to_end_scan", data=df)
```

```
Out[34]: <AxesSubplot:xlabel='route_type', ylabel='start_scan_to_end_scan'>
```



- **Insights**

- Insights based on EDA
 - **Outliers** - Most of the continuous features have outliers
 - **Distribution** - **None of the features follow Normal distribution** even for both route category i.e Full truck load and Carting
 - **start_scan_to_end_scan** follow **multi-modal distribution** , very likely it contains multiple sub-category in the distribution
 - **Other continuous variables follow Exponential distribution**

Feature Engineering (Part 1)

- **Trip_creation_time**: Extracting features like month, year and day from trip booking date

```
In [35]: df["trip_creation_time_year"] = df["trip_creation_time"].dt.year
df["trip_creation_time_month"] = df["trip_creation_time"].dt.month_name()
df["trip_creation_time_weekday"] = df["trip_creation_time"].dt.weekday
df["trip_creation_time_day"] = df["trip_creation_time"].dt.day
```

```
In [36]: df["od_start_time_year"] = df["od_start_time"].dt.year
df["od_start_time_month"] = df["od_start_time"].dt.month_name()
df["od_start_time_weekday"] = df["od_start_time"].dt.weekday
df["od_start_time_day"] = df["od_start_time"].dt.day
```

```
In [37]: df["od_end_time_year"] = df["od_end_time"].dt.year
df["od_end_time_month"] = df["od_end_time"].dt.month_name()
df["od_end_time_weekday"] = df["od_end_time"].dt.weekday
df["od_end_time_day"] = df["od_end_time"].dt.day
```

- Feature extraction from **"Source Name"** to **City, Place, Code and State**

```
In [38]: df[['source_name_city','source_name_place','source_name_code','source_name_state']] = df
```

```
In [39]: df[['source_name','source_name_city','source_name_place','source_name_code','source_name_state']] = df
```

Out[39]:

	source_name	source_name_city	source_name_place	source_name_code	source_name_state
0	Anand_VUNagar_DC (Gujarat)	Anand	VUNagar	DC	Gujarat
1	Anand_VUNagar_DC (Gujarat)	Anand	VUNagar	DC	Gujarat
2	Anand_VUNagar_DC (Gujarat)	Anand	VUNagar	DC	Gujarat
3	Anand_VUNagar_DC (Gujarat)	Anand	VUNagar	DC	Gujarat
4	Anand_VUNagar_DC (Gujarat)	Anand	VUNagar	DC	Gujarat
...
144862	Sonipat_Kundli_H (Haryana)	Sonipat	Kundli	H	Haryana
144863	Sonipat_Kundli_H (Haryana)	Sonipat	Kundli	H	Haryana
144864	Sonipat_Kundli_H (Haryana)	Sonipat	Kundli	H	Haryana
144865	Sonipat_Kundli_H (Haryana)	Sonipat	Kundli	H	Haryana
144866	Sonipat_Kundli_H (Haryana)	Sonipat	Kundli	H	Haryana

144867 rows × 5 columns

Data cleanup | source_name_city | Level Bangalore , Bengaluru to Bengaluru

```
In [40]: # Re-leveling source city from Bangalore to Bengaluru as both signifies same city
df["source_name_city"] = df["source_name_city"].str.replace("Bangalore", "Bengaluru", case=True)
df["source_name_city"] = df["source_name_city"].replace(to_replace=r'(^Del$)', value='Delhi', regex=True, inplace=True)
```

- Feature extraction from **"Destination Name"** to **City, Place, Code and State**

```
In [41]: df[['destination_name_city','destination_name_place','destination_name_code','destination_name_state']] = df
```

```
In [42]: df[['destination_name','destination_name_city','destination_name_place','destination_name_code','destination_name_state']] = df
```


Out[42]:

	destination_name_city	destination_name_place	destination_name_code	destination_name_state	
	0	Khambhat	MotvdDPP	D	Gujarat
	1	Khambhat	MotvdDPP	D	Gujarat
	2	Khambhat	MotvdDPP	D	Gujarat
	3	Khambhat	MotvdDPP	D	Gujarat
	4	Khambhat	MotvdDPP	D	Gujarat

	144862	Gurgaon	Bilaspur	HB	Haryana
	144863	Gurgaon	Bilaspur	HB	Haryana
	144864	Gurgaon	Bilaspur	HB	Haryana
	144865	Gurgaon	Bilaspur	HB	Haryana
	144866	Gurgaon	Bilaspur	HB	Haryana

144867 rows × 4 columns

Data cleanup | destination_name_city | Level Bangalore , Bengaluru to Bengaluru

In [43]:

```
# Re-leveling destination city from Bangalore to Bengaluru as both signifies same city
df["destination_name_city"] = df["destination_name_city"].str.replace("Bangalore", "Bengaluru")
```

Non-Graphical Analysis (Part 2)

In [44]:

```
df_full_truck_load = df[df["route_type"] == 'FTL']
df_carting = df[df["route_type"] == 'Carting']
```

In [45]:

```
# Viewing top proportion of orders based on source and destination states
source_destination_state_ct = pd.crosstab(df_full_truck_load["source_name_state"], df_full_truck_load["destination_name_state"],
source_destination_state_ct.sort_values('All', ascending=False).iloc[:5])
```

Out[45]:

destination_name_state	Assam	Bihar	Chandigarh	Chhattisgarh	Delhi	Gujarat	Haryana	Jharkhand	Karnataka
source_name_state									
All	0.59	4.05	0.1	0.25	2.79	1.88	21.45	0.89	23.26
Haryana	0.00	1.78	0.0	0.00	0.19	0.95	1.24	0.00	12.27
Maharashtra	0.00	0.00	0.0	0.00	2.38	0.00	7.23	0.00	3.91
Karnataka	0.00	0.00	0.0	0.00	0.00	0.00	8.37	0.00	4.89
Telangana	0.00	0.00	0.0	0.00	0.00	0.00	0.14	0.00	0.70

In [46]:

```
# Viewing top proportion of orders based on source and destination cities
source_destination_city_ct = pd.crosstab(df_full_truck_load["source_name_city"], df_full_truck_load["destination_name_city"],
source_destination_city_ct.sort_values('All', ascending=False).iloc[:5])
```

Out[46]:

destination_name_city	Achrol	Agartala	Aizawl	Ajmer	Akola	Almora	Aluva	Ambajogai	Amreli	AnandprShb
source_name_city										
All	0.03	0.01	0.02	0.01	1.06	0.05	0.67	0.03	0.15	0.09
Gurgaon	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Bhiwandi	0.00	0.00	0.00	0.00	1.03	0.00	0.00	0.00	0.00	0.00
Bengaluru	0.00	0.00	0.00	0.00	0.00	0.00	0.62	0.00	0.00	0.00
Pune	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

5 rows × 317 columns

In [47]:

```
# Viewing top proportion of orders based on source and destination place
source_destination_place_ct= pd.crosstab(df_full_truck_load["source_name_place"],df_full_truck_load["destination_name_place"],
source_destination_place_ct.sort_values(by = ['All', 'source_name_place'], ascending = True)
```

Out[47]:

destination_name_place	Adargchi	AdrshSt	AgrohDPP	Airport	AkkolRD	Alngjuri	AmbedDPP	AnugrDPP	Aravind
source_name_place									
All	0.72	0.0	0.05	2.79	0.05	0.06	0.01	0.02	0.0
Bilaspur	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.0
Mankoli	0.00	0.0	0.00	2.38	0.00	0.00	0.00	0.00	0.0
Nelmn gla	0.11	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.0
Tathawde	0.23	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.0

5 rows × 319 columns

Visual Analysis (Part 2) - Post Initial Feature engineering

In [515]:

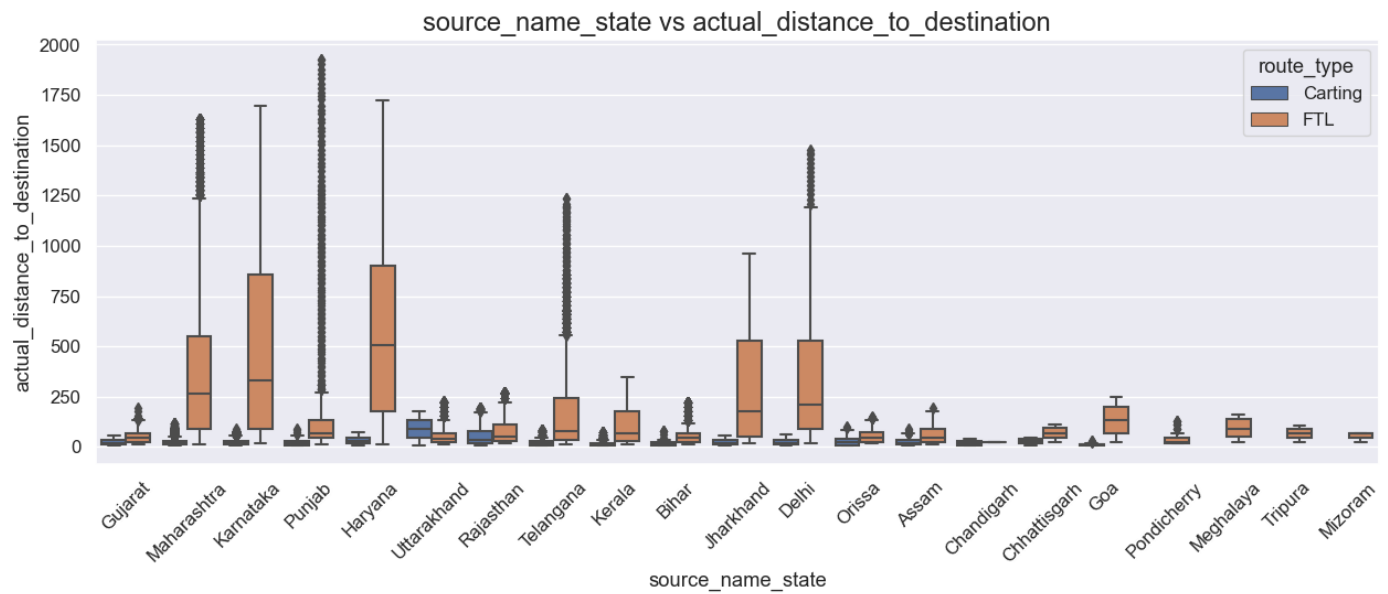
```
# selecting specific categorical features
selected_categorical_features = ['source_name_state','destination_name_state','trip_created','od_start_time_day','od_end_time_weekday', 'od_end_time_day']
```

In [516]:

```
# selecting specific numeric/continious features
selected_continious_features = ['start_scan_to_end_scan', 'actual_distance_to_destination','osrm_distance']
```

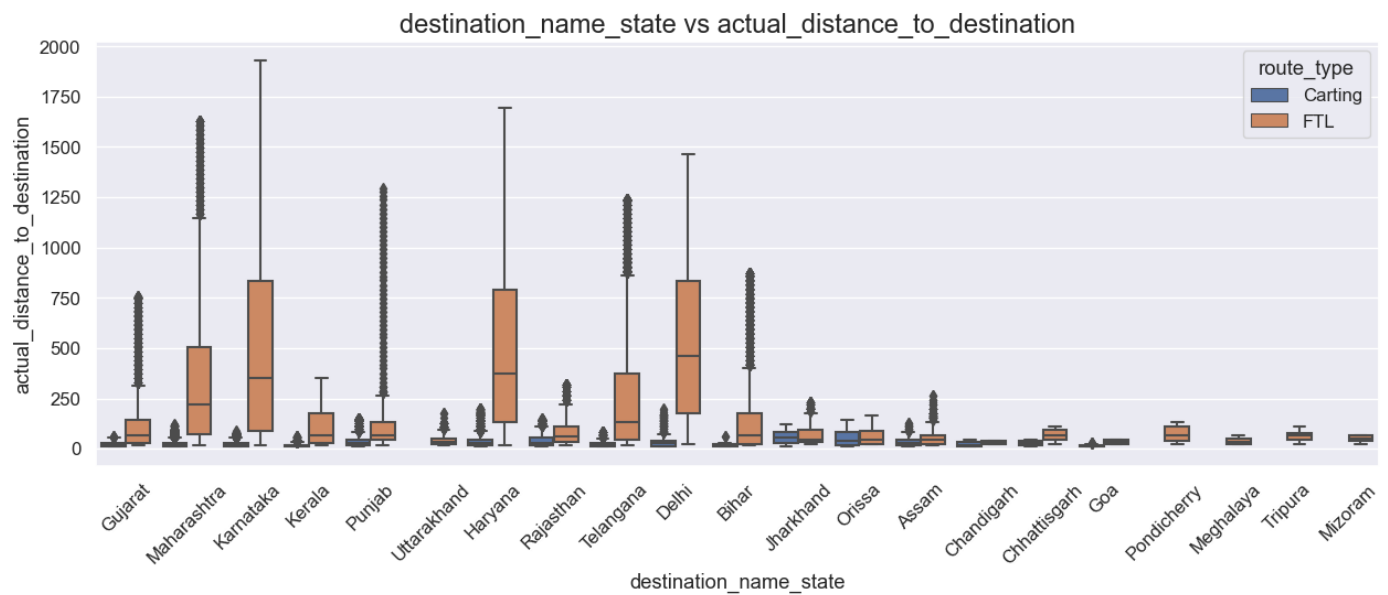
In [201]:

```
# plotting box plots and adding title , rotation for better visibility of levels i.e state
fig, axes = plt.subplots(figsize=(15,5))
plt.title("source_name_state vs actual_distance_to_destination",fontdict ={"fontsize": 14})
plt.xticks(rotation = 45)
sns.boxplot(x="source_name_state", y="actual_distance_to_destination", hue="route_type",
plt.show()
```



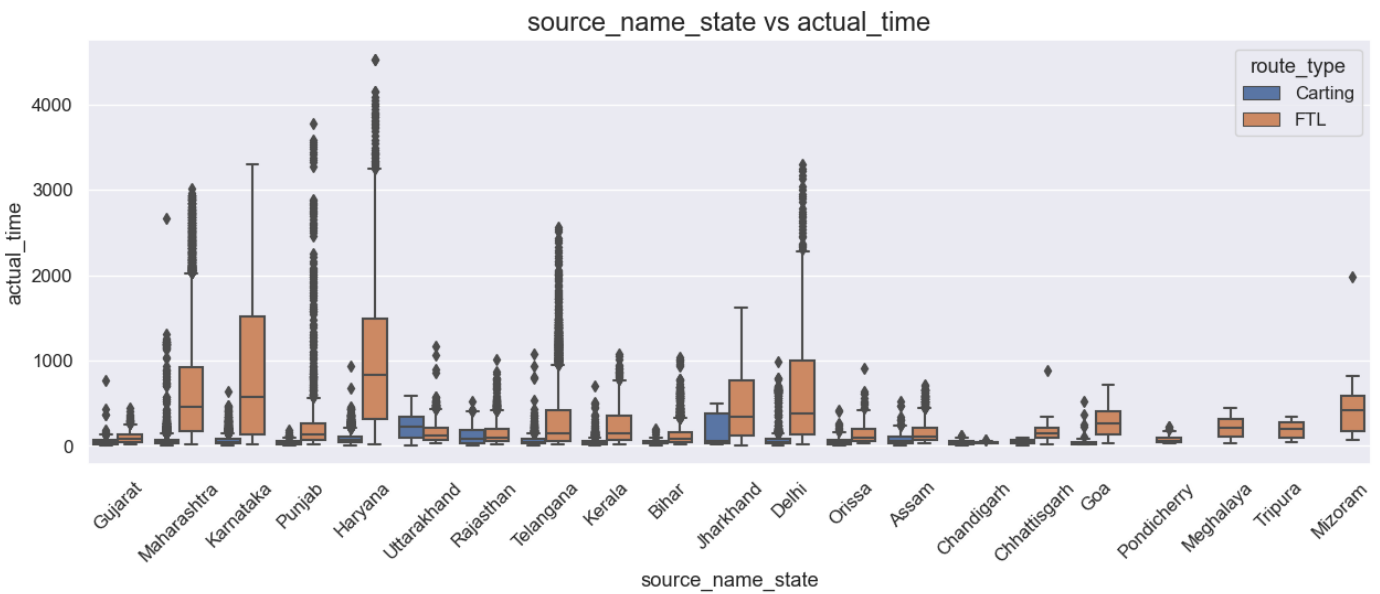
In [202...

```
fig, axes = plt.subplots(figsize=(15,5))
plt.title("destination_name_state vs actual_distance_to_destination",fontdict={"fontsize": 17})
plt.xticks(rotation = 45)
sns.boxplot(x="destination_name_state", y="actual_distance_to_destination", hue="route_type", data=df)
plt.show()
```



In [203...

```
fig, axes = plt.subplots(figsize=(15,5))
plt.title("source_name_state vs actual_time",fontdict={"fontsize": 17})
plt.xticks(rotation = 45)
sns.boxplot(x="source_name_state", y="actual_time", hue="route_type", data=df)
plt.show()
```

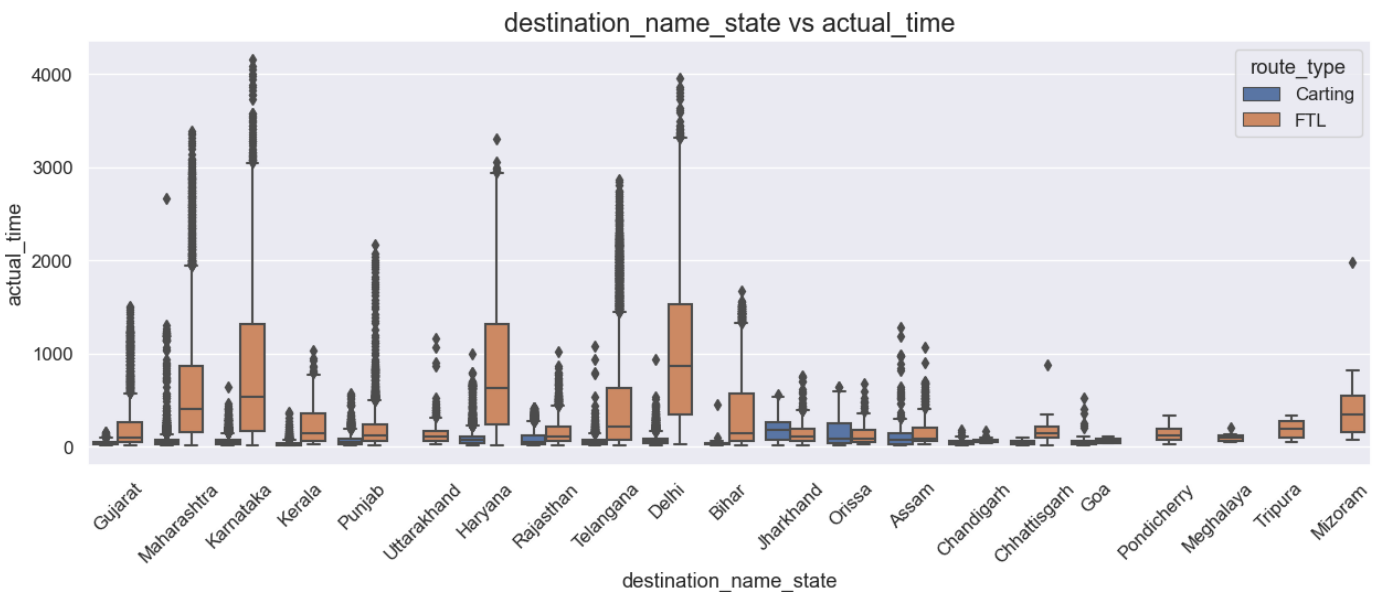


• **Observation :**

- Relatively **more Carting trips originated from "Uttarakhand" , "Rajasthan" , "Jharkhand"** etc.

In [204...

```
fig, axes = plt.subplots(figsize=(15,5))
plt.title("destination_name_state vs actual_time", fontdict = {"fontsize": 17})
plt.xticks(rotation = 45)
sns.boxplot(x="destination_name_state", y="actual_time", hue="route_type", data=df)
plt.show()
```

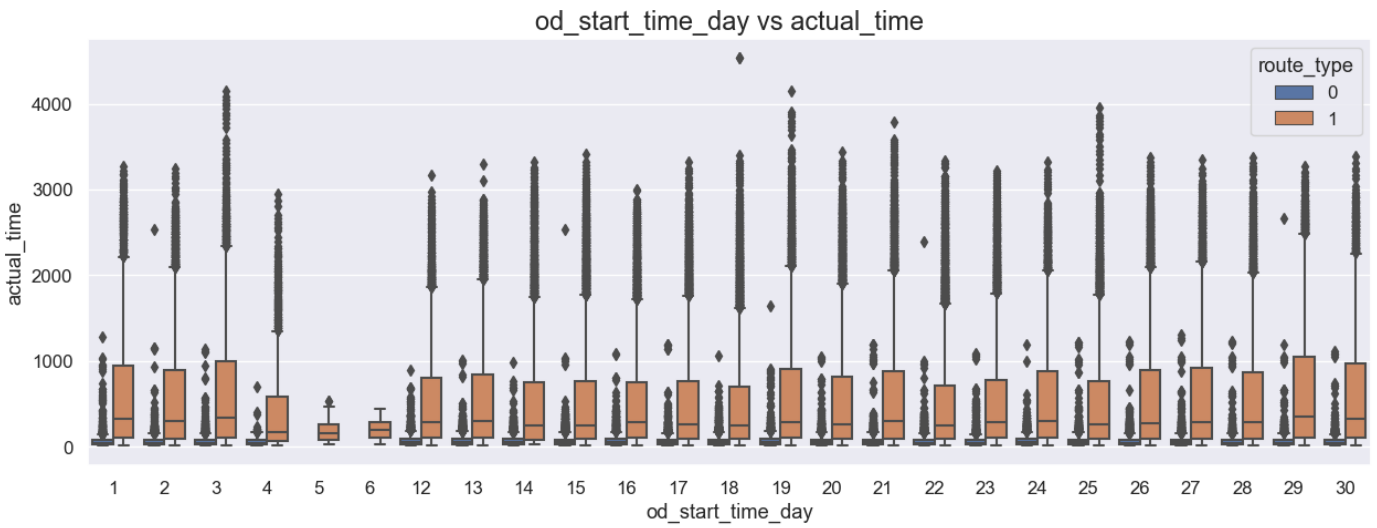


• **Observation :**

- Relatively more **Carting trips** booked for destination **"Jharkhand" , "Orissa" and Assam**

In [293...

```
fig, axes = plt.subplots(figsize=(15,5))
plt.title("od_start_time_day vs actual_time", fontdict = {"fontsize": 17})
sns.boxplot(x="od_start_time_day", y="actual_time", hue="route_type", data=df)
plt.show()
```

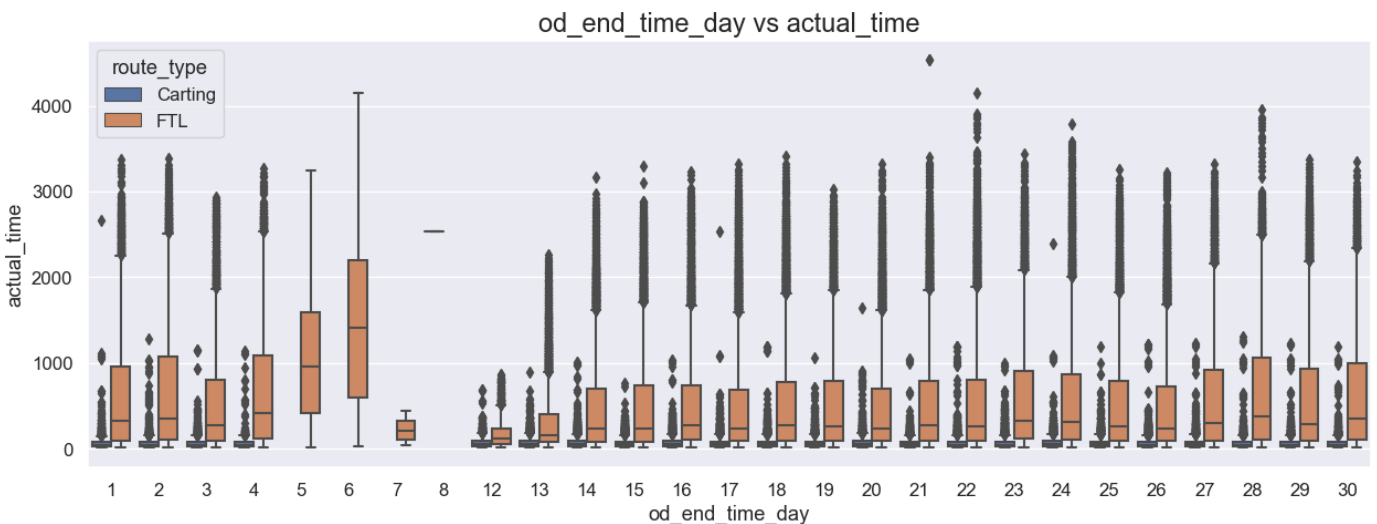


- **Observation :**

- Relatively less full truck loads trips starting on 5th or 6th day of the month

In [206...

```
fig, axes = plt.subplots(figsize=(15,5))
plt.title("od_end_time_day vs actual_time",fontdict={"fontsize": 17})
sns.boxplot(x="od_end_time_day", y="actual_time", hue="route_type", data=df)
plt.show()
```

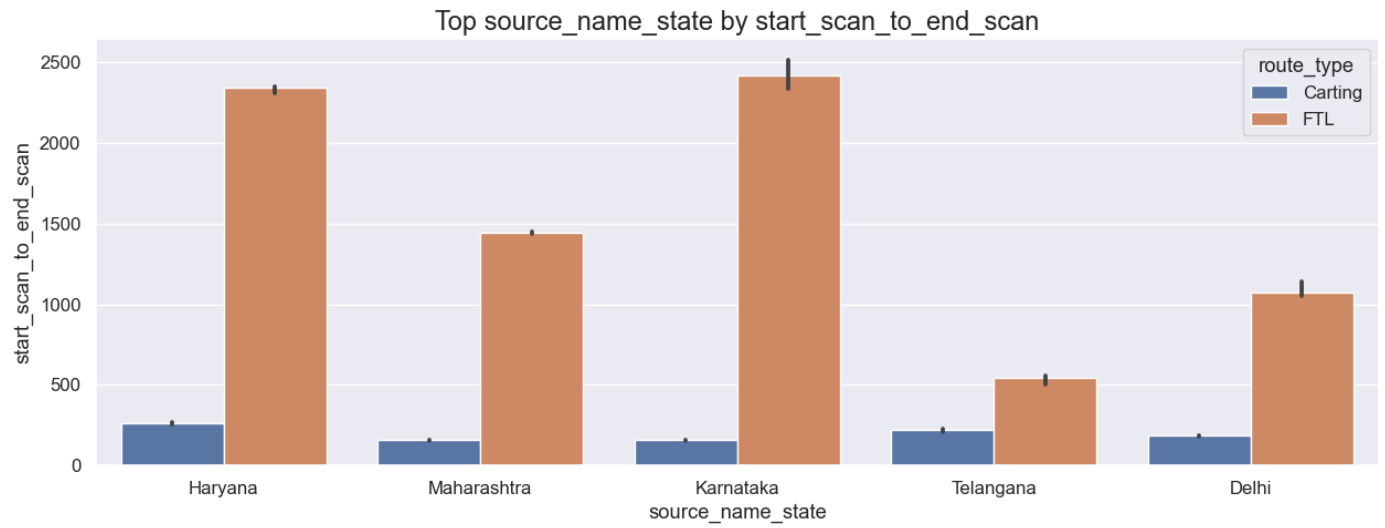


- **Observation :**

- Relatively **large full truck loads** trips **ending on 5th or 6th day of the month**
- Relatively **less full truck loads** trips **ending on 7th or 8th day of the month**

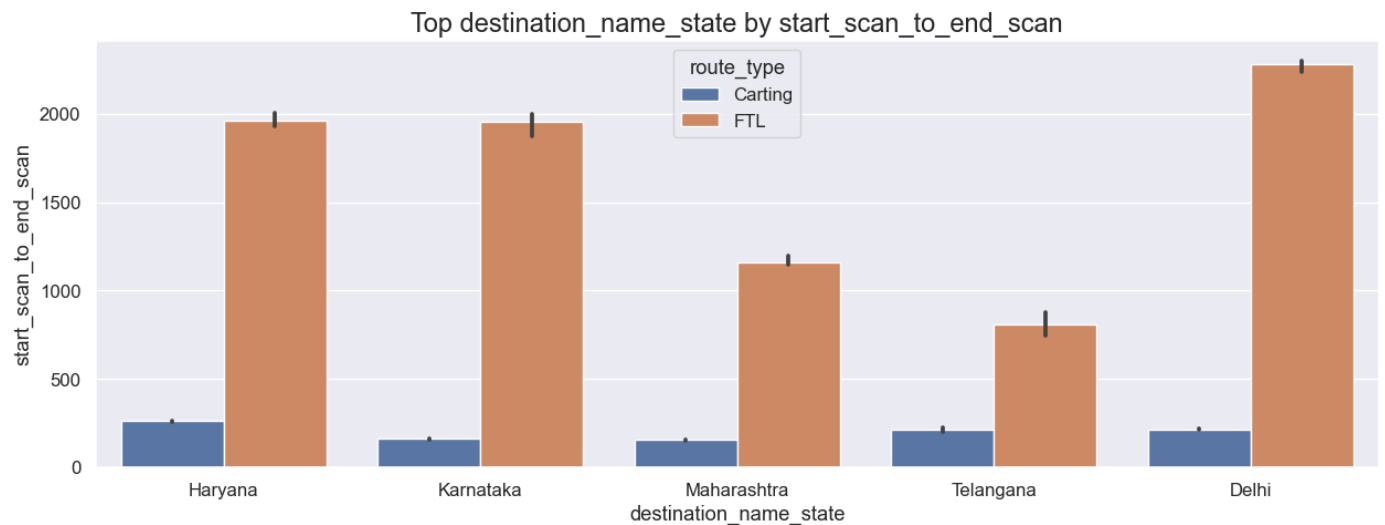
In [207...

```
# Showing top 5 source_names which registers max time of delivery
fig, axes = plt.subplots(figsize=(15,5))
plt.title("Top source_name_state by start_scan_to_end_scan",fontdict={"fontsize": 17})
sns.barplot(x="source_name_state", y="start_scan_to_end_scan", hue="route_type", data=df)
plt.show()
```



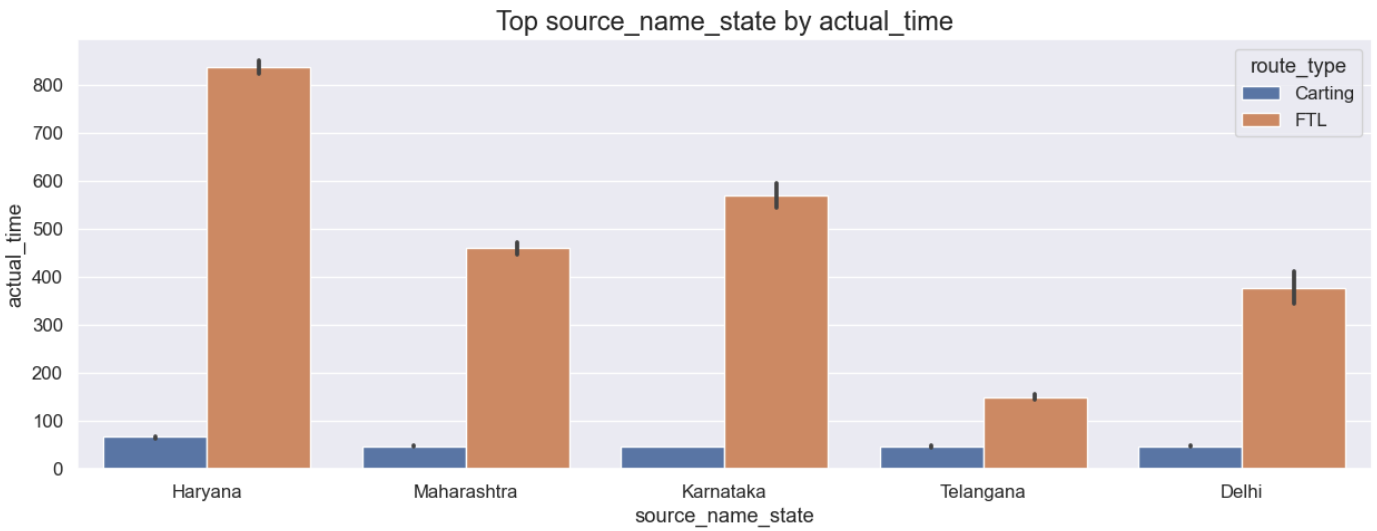
In [208...

```
# Showing top 5 destination_name_states which registers max time of delivery
fig, axes = plt.subplots(figsize=(15,5))
plt.title("Top destination_name_state by start_scan_to_end_scan",fontdict={"fontsize":
# estimator used as median as there are many outliers in the data
sns.barplot(x="destination_name_state", y="start_scan_to_end_scan", hue="route_type", da
plt.show()
```



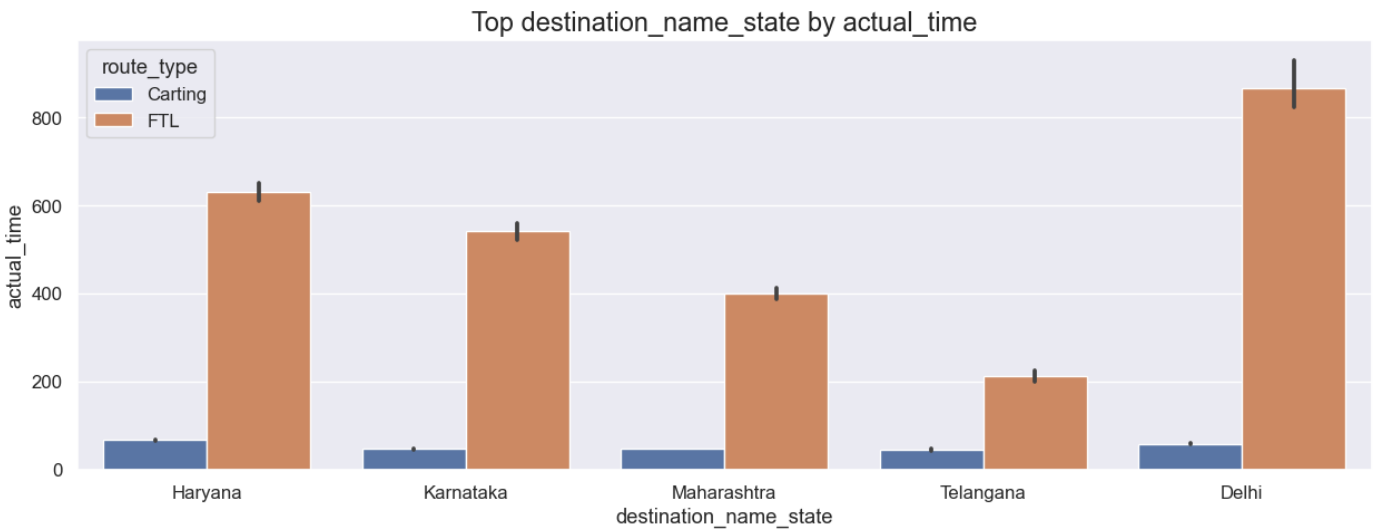
In [209...

```
# Showing top 5 source_name_states which registers max actual time of delivery
fig, axes = plt.subplots(figsize=(15,5))
plt.title("Top source_name_state by actual_time",fontdict={"fontsize": 17})
sns.barplot(x="source_name_state", y="actual_time", hue="route_type", data=df, order=df
plt.show()
```



In [210...

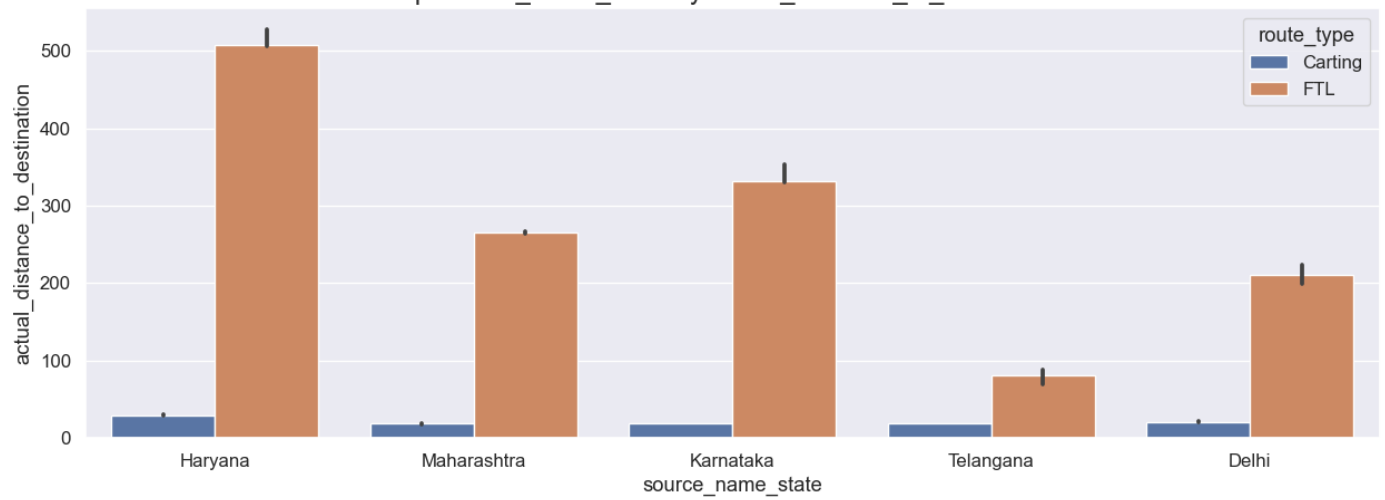
```
# Showing top 5 destination_name_states which registers max actual time of delivery
fig, axes = plt.subplots(figsize=(15,5))
plt.title("Top destination_name_state by actual_time",fontdict={"fontsize": 17})
sns.barplot(x="destination_name_state", y="actual_time", hue="route_type", data=df, order=
plt.show()
```



In [211...

```
# Showing top 5 source_name_states which registers max actual distance of delivery
fig, axes = plt.subplots(figsize=(15,5))
plt.title("Top source_name_state by actual_distance_to_destination ",fontdict={"fontsi:
sns.barplot(x="source_name_state", y="actual_distance_to_destination", hue="route_type",
plt.show()
```

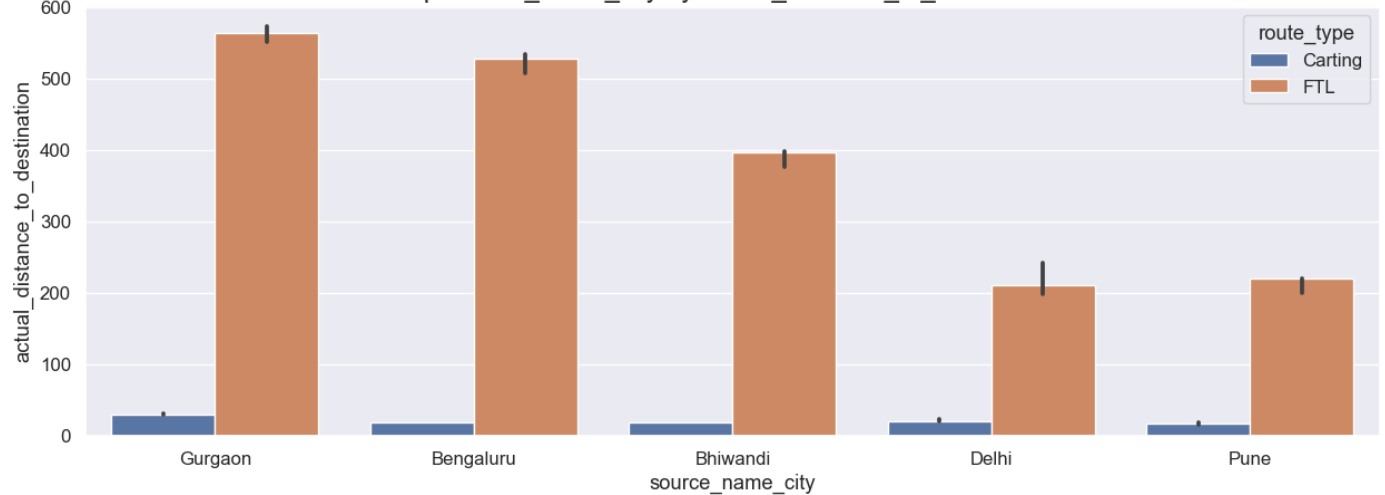
Top source_name_state by actual_distance_to_destination



In [212...

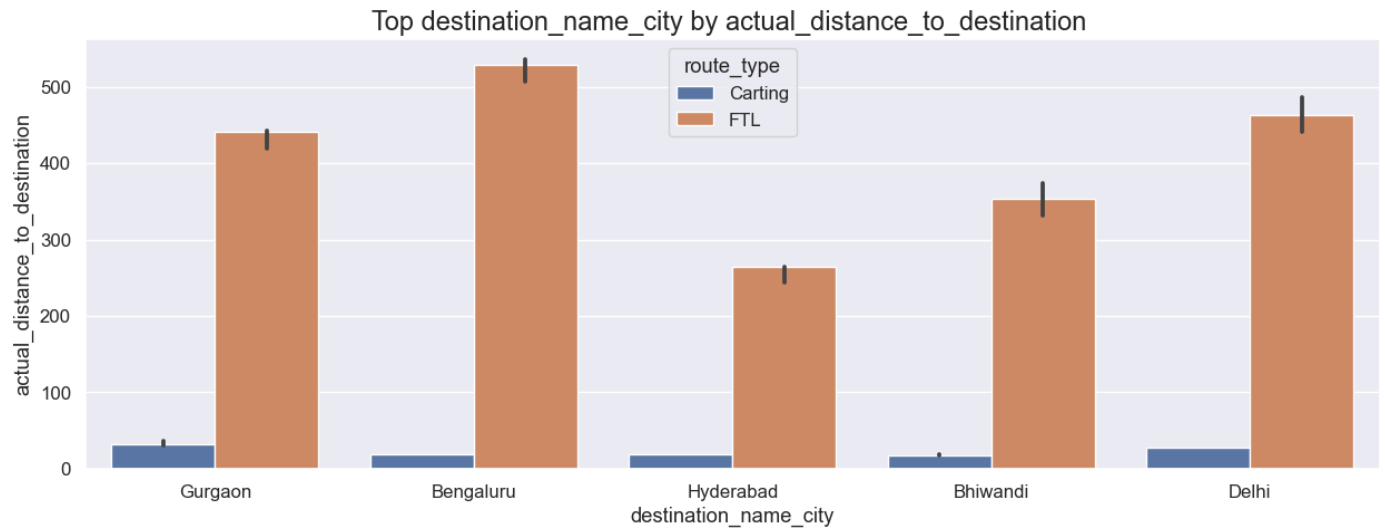
```
# Showing top 5 source_name_cities which registers max actual distance of delivery
fig, axes = plt.subplots(figsize=(15,5))
plt.title("Top source_name_city by actual_distance_to_destination ",fontdict={"fontsize":14})
sns.barplot(x="source_name_city", y="actual_distance_to_destination", hue="route_type",
plt.show()
```

Top source_name_city by actual_distance_to_destination



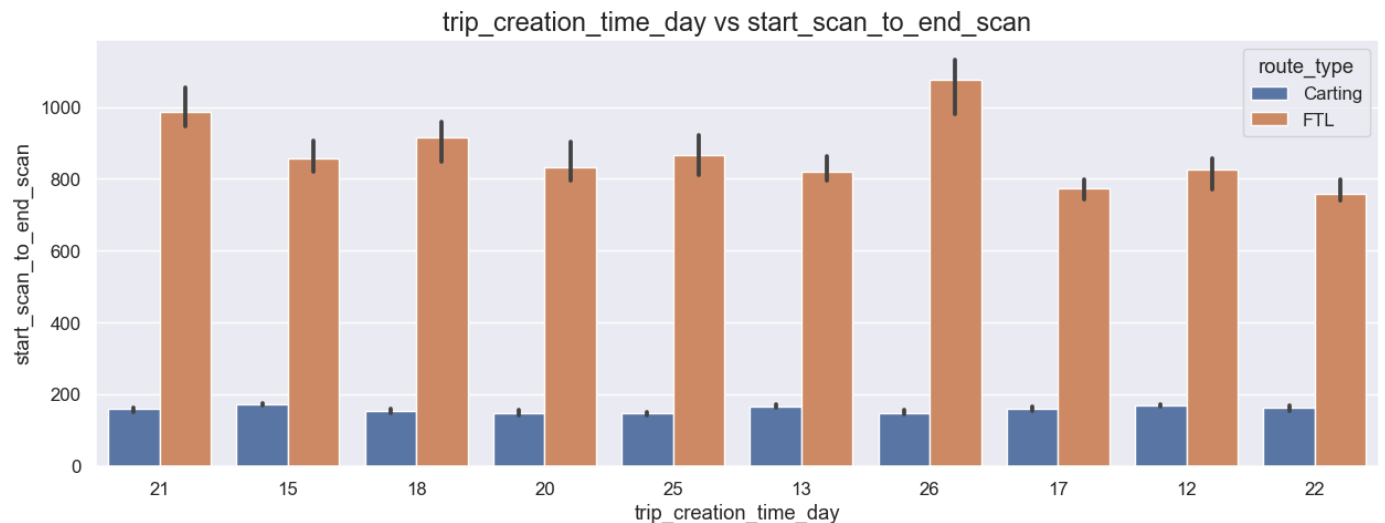
In [213...

```
# Showing top 5 destination_name_cities which registers max actual distance of delivery
fig, axes = plt.subplots(figsize=(15,5))
plt.title("Top destination_name_city by actual_distance_to_destination ",fontdict={"fontSize":14})
sns.barplot(x="destination_name_city", y="actual_distance_to_destination", hue="route_type",
plt.show()
```

In [214]...

```
# Showing top 10 trip creation days which registers max time of delivery
fig, axes = plt.subplots(figsize=(15,5))
plt.title("trip_creation_time_day vs start_scan_to_end_scan", fontdict={"fontsize": 17})
sns.barplot(x="trip_creation_time_day", y="start_scan_to_end_scan", hue="route_type", data=df)
plt.show()
```



Observations

- **Most Time taken**(i.e. for route type full truck load) to **deliver from source to destination** are from **Haryana , Karnataka , Maharashtra , Delhi , Telangana**
- **Actual time taken to complete the delivery** are high for source/destination **Haryana , Karnataka , Maharashtra , Delhi , Telangana**
- **Most distanced cities** for full truck deliveries are **Gurgaon , Bengaluru , Bhiwandi**
- **Most trips are being booked on 12,13,15,17,18,20,21,22,25,26** days of the month

Aggregation of fields and Merging of rows

Aggregation and Merge by trip_uid

In [48]:

```
# Aggregation by trip_uid
df_agg = df.groupby("trip_uid")[["actual_time", "actual_distance_to_destination", "osrm_distance"]].agg("sum")
df_agg.reset_index(inplace=True)
df_agg.rename(columns = {'actual_time':'actual_time_aggregated', 'actual_distance_to_destination':'actual_distance_to_destination_aggregated'})
df_agg.head()
```

Out[48]:

	trip_uuid	actual_time_aggregated	osrm_time_aggregated	segment_osrm_time_aggregated	segment_
0	trip-153671041653548748	15682.0	7787.0	1008.0	
1	trip-153671042288605164	399.0	210.0	65.0	
2	trip-153671043369099517	112225.0	65768.0	1941.0	
3	trip-153671046011330457	82.0	24.0	16.0	
4	trip-153671052974046625	556.0	207.0	115.0	

In [49]:

```
# Selecting specific features from non aggregated data , before merging
df_org = df[["trip_uuid","route_type","trip_creation_time_year","trip_creation_time_month","trip_creation_time_weekday"]]
df_org.shape
```

Out[49]: (144867, 6)

In [50]:

```
# Removing duplicate datas , keep first occurance of the data
df_org = df_org.drop_duplicates(keep='first')
df_org.shape
```

Out[50]: (14817, 6)

In [51]:

```
# viewing selected rows post removing duplicate rows
df_org.head()
```

Out[51]:

	trip_uuid	route_type	trip_creation_time_year	trip_creation_time_month	trip_creation_time_weekday
0	trip-153741093647649320	Carting	2018	September	3
10	trip-153768492602129387	FTL	2018	September	6
15	trip-153693976643699843	Carting	2018	September	4
17	trip-153687145942424248	FTL	2018	September	3
35	trip-153825970514894360	FTL	2018	September	5

In [52]:

```
# Removing duplicate records post aggregation
df_agg = df_agg.drop_duplicates(keep='first')
df_agg.shape
```

Out[52]: (14817, 7)

In [53]:

```
# Merging aggregated and raw features
df_agg = pd.merge(df_agg, df_org, how="inner", on="trip_uuid")
df_agg.shape
```

Out[53]: (14817, 12)

```
In [54]: df_agg.head()
```

Out[54]:

	trip_uuid	actual_time_aggregated	osrm_time_aggregated	segment_osrm_time_aggregated	segment_i
0	trip-153671041653548748	15682.0	7787.0	1008.0	
1	trip-153671042288605164	399.0	210.0	65.0	
2	trip-153671043369099517	112225.0	65768.0	1941.0	
3	trip-153671046011330457	82.0	24.0	16.0	
4	trip-153671052974046625	556.0	207.0	115.0	

Aggregation and Merge by 'trip_uuid','source_name', 'destination_name' - Select first and last

- Aggregation by 'trip_uuid','source_center', 'destination_center'

```
In [57]: # Aggregation by trip_uuid , source_center, destination_center
#df_agg_by_trip_src_dest= df.groupby(['trip_uuid','source_center', 'destination_center'])
df_agg_by_trip_src_dest_center= df.groupby(['trip_uuid','source_center', 'destination_center'])

# Unfolding grouped data to rows
df_agg_by_trip_src_dest_center.reset_index(inplace=True)
# Renaming grouped columns
df_agg_by_trip_src_dest_center.columns = ['_'.join(col) for col in df_agg_by_trip_src_dest_center.columns]
# Removing underscore from column names source_center_ and destination_center_
df_agg_by_trip_src_dest_center.rename(columns = {'trip_uuid_':'trip_uuid','source_center_':'source_center','destination_center_':'destination_center'})
# Merge by trip_uuid
df_agg_by_trip_src_dest_center_merged = pd.merge(df_agg_by_trip_src_dest_center, df_org, on='trip_uuid')
df_agg_by_trip_src_dest_center_merged.head()
```

Out[57]:

	trip_uuid	source_center	destination_center	actual_time_first	actual_time_last	osrm_time_first	osrm_time_last
0	trip-153671041653548748	IND209304AAA	IND000000ACB	50.0	732.0	33.0	
1	trip-153671041653548748	IND462022AAA	IND209304AAA	43.0	830.0	39.0	
2	trip-153671042288605164	IND561203AAB	IND562101AAA	18.0	47.0	10.0	
3	trip-153671042288605164	IND572101AAA	IND561203AAB	14.0	96.0	8.0	
4	trip-153671043369099517	IND000000ACB	IND160002AAC	36.0	611.0	19.0	

- Aggregation by 'trip_uuid','source_name', 'destination_name'

```
In [524... # Aggregation by trip_uuid , source_name, destination_name
df_agg_by_trip_src_dest= df.groupby(['trip_uuid','source_name', 'destination_name'])[['actual_time_first', 'actual_time_last', 'osrm_time_first', 'osrm_time_last']]
```

```
# Unfolding grouped data to rows
df_agg_by_trip_src_dest.reset_index(inplace=True)
# Renaming grouped columns
df_agg_by_trip_src_dest.columns = ['_'.join(col) for col in df_agg_by_trip_src_dest.columns]
# Removing underscore from column names source_center_ and destination_center_
df_agg_by_trip_src_dest.rename(columns = {'trip_uuid_': 'trip_uuid', 'source_name_': 'source_name', 'destination_name_': 'destination_name', 'actual_time_first_': 'actual_time_first', 'actual_time_last_': 'actual_time_last', 'osrm_time_': 'osrm_time'})
df_agg_by_trip_src_dest.head()
```

```
Out[524]:
```

	trip_uuid	source_name	destination_name	actual_time_first	actual_time_last	osrm_time
0	trip-153671041653548748	Bhopal_Trnsport_H (Madhya Pradesh)	Kanpur_Central_H_6 (Uttar Pradesh)	43.0	830.0	
1	trip-153671041653548748	Kanpur_Central_H_6 (Uttar Pradesh)	Gurgaon_Bilaspur_HB (Haryana)	50.0	732.0	
2	trip-153671042288605164	Doddablpur_ChikaDPP_D (Karnataka)	Chikblapur_ShntiSgr_D (Karnataka)	18.0	47.0	
3	trip-153671042288605164	Tumkur_Veersagr_I (Karnataka)	Doddablpur_ChikaDPP_D (Karnataka)	14.0	96.0	
4	trip-153671043369099517	Bangalore_Nelmngla_H (Karnataka)	Gurgaon_Bilaspur_HB (Haryana)	60.0	2736.0	

```
In [525... df_agg_by_trip_src_dest.shape
```

```
Out[525]: (26368, 15)
```

• Merge by 'trip_uuid'

```
In [526... df_agg_by_trip_src_dest_merged = pd.merge(df_agg_by_trip_src_dest, df_org, how="inner",
df_agg_by_trip_src_dest_merged.shape
```

```
Out[526]: (26368, 20)
```

```
In [527... df_agg_by_trip_src_dest_merged.head()
```

```
Out[527]:
```

	trip_uuid	source_name	destination_name	actual_time_first	actual_time_last	osrm_time
0	trip-153671041653548748	Bhopal_Trnsport_H (Madhya Pradesh)	Kanpur_Central_H_6 (Uttar Pradesh)	43.0	830.0	
1	trip-153671041653548748	Kanpur_Central_H_6 (Uttar Pradesh)	Gurgaon_Bilaspur_HB (Haryana)	50.0	732.0	
2	trip-153671042288605164	Doddablpur_ChikaDPP_D (Karnataka)	Chikblapur_ShntiSgr_D (Karnataka)	18.0	47.0	
3	trip-153671042288605164	Tumkur_Veersagr_I (Karnataka)	Doddablpur_ChikaDPP_D (Karnataka)	14.0	96.0	
4	trip-153671043369099517	Bangalore_Nelmngla_H (Karnataka)	Gurgaon_Bilaspur_HB (Haryana)	60.0	2736.0	

```
In [528... df_agg_by_trip_src_dest_merged.head()
```

Out[528]:

	trip_uuid	source_name	destination_name	actual_time_first	actual_time_last	osrm_ti
0	trip-153671041653548748	Bhopal_Trnsport_H (Madhya Pradesh)	Kanpur_Central_H_6 (Uttar Pradesh)	43.0	830.0	
1	trip-153671041653548748	Kanpur_Central_H_6 (Uttar Pradesh)	Gurgaon_Bilaspur_HB (Haryana)	50.0	732.0	
2	trip-153671042288605164	Doddablpur_ChikaDPP_D (Karnataka)	Chikblapur_ShntiSgr_D (Karnataka)	18.0	47.0	
3	trip-153671042288605164	Tumkur_Veersagr_I (Karnataka)	Doddablpur_ChikaDPP_D (Karnataka)	14.0	96.0	
4	trip-153671043369099517	Bangalore_Nelmngla_H (Karnataka)	Gurgaon_Bilaspur_HB (Haryana)	60.0	2736.0	

In [529...

```
# Applying feature engineering part 1 on aggregated data
# Extraction of city , place , code , state
df_agg_by_trip_src_dest_merged[['source_name_city','source_name_place','source_name_code']]
# Data cleanup
df_agg_by_trip_src_dest_merged["source_name_city"]= df_agg_by_trip_src_dest_merged["source_name_city"].replace(to_replace=r'(^Del$)', value='')
df_agg_by_trip_src_dest_merged["source_name_city"].replace(to_replace=r'(^Del$)', value='')

# Above steps on destination name column
df_agg_by_trip_src_dest_merged[['destination_name_city','destination_name_place','destination_name_code']]
df_agg_by_trip_src_dest_merged["destination_name_city"]= df_agg_by_trip_src_dest_merged["destination_name_city"].replace(to_replace=r'(^Del$)', value='')
df_agg_by_trip_src_dest_merged["destination_name_city"].replace(to_replace=r'(^Del$)', value='')
```

In [530...

```
df_agg_by_trip_src_dest_merged.head()
```

Out[530]:

	trip_uuid	source_name	destination_name	actual_time_first	actual_time_last	osrm_ti
0	trip-153671041653548748	Bhopal_Trnsport_H (Madhya Pradesh)	Kanpur_Central_H_6 (Uttar Pradesh)	43.0	830.0	
1	trip-153671041653548748	Kanpur_Central_H_6 (Uttar Pradesh)	Gurgaon_Bilaspur_HB (Haryana)	50.0	732.0	
2	trip-153671042288605164	Doddablpur_ChikaDPP_D (Karnataka)	Chikblapur_ShntiSgr_D (Karnataka)	18.0	47.0	
3	trip-153671042288605164	Tumkur_Veersagr_I (Karnataka)	Doddablpur_ChikaDPP_D (Karnataka)	14.0	96.0	
4	trip-153671043369099517	Bangalore_Nelmngla_H (Karnataka)	Gurgaon_Bilaspur_HB (Haryana)	60.0	2736.0	

5 rows × 28 columns

In-depth analysis and Feature engineering (Part 2)

- Calculate the **time taken between od_start_time and od_end_time** and keep it as a feature. Drop the original columns, if required

In [227...

```
df['time_taken_between_od_start_and_od_end_time'] = df['od_end_time'] - df['od_start_time']
df['time_taken_between_od_start_and_od_end_time'] = df['time_taken_between_od_start_and_od_end_time'].astype(int)
df['time_taken_between_od_start_and_od_end_time'] = df['time_taken_between_od_start_and_od_end_time'].fillna(0)
```

In [228...

```
df[['time_taken_between_od_start_and_od_end_time', 'od_end_time', 'od_start_time']]
```

Out[228]:

	time_taken_between_od_start_and_od_end_time	od_end_time	od_start_time
0	1.437	2018-09-20 04:47:45.236797	2018-09-20 03:21:32.418600
1	1.437	2018-09-20 04:47:45.236797	2018-09-20 03:21:32.418600
2	1.437	2018-09-20 04:47:45.236797	2018-09-20 03:21:32.418600
3	1.437	2018-09-20 04:47:45.236797	2018-09-20 03:21:32.418600
4	1.437	2018-09-20 04:47:45.236797	2018-09-20 03:21:32.418600
...
144862	7.128	2018-09-20 23:32:09.618069	2018-09-20 16:24:28.436231
144863	7.128	2018-09-20 23:32:09.618069	2018-09-20 16:24:28.436231
144864	7.128	2018-09-20 23:32:09.618069	2018-09-20 16:24:28.436231
144865	7.128	2018-09-20 23:32:09.618069	2018-09-20 16:24:28.436231
144866	7.128	2018-09-20 23:32:09.618069	2018-09-20 16:24:28.436231

144867 rows × 3 columns

- **Aggregated data (by trip_uuid, source and destination)**
 - Calculate the **time difference between first and last actual_time**

In [58]:

```
df_agg_by_trip_src_dest_center_merged['actual_time_diff'] = df_agg_by_trip_src_dest_center_merged['actual_time_diff']
```

- Calculate the **time difference between first and last osrm_time**

In [60]:

```
df_agg_by_trip_src_dest_center_merged['osrm_time_diff'] = df_agg_by_trip_src_dest_center_merged['osrm_time_diff']
```

Compare the difference between "time_taken_between_od_start_and_od_end_time" and "start_scan_to_end_scan". Do hypothesis testing/ Visual analysis to check.

In [229]:

```
df['start_scan_to_end_scan_in_hrs'] = df['start_scan_to_end_scan'] / 60  
df['start_scan_to_end_scan_in_hrs'] = df['start_scan_to_end_scan_in_hrs'].round(3)
```

In [230]:

```
df[['time_taken_between_od_start_and_od_end_time', 'start_scan_to_end_scan_in_hrs']]
```

Out[230]:

	time_taken_between_od_start_and_od_end_time	start_scan_to_end_scan_in_hrs
0	1.437	1.433
1	1.437	1.433
2	1.437	1.433
3	1.437	1.433
4	1.437	1.433
...
144862	7.128	7.117
144863	7.128	7.117
144864	7.128	7.117
144865	7.128	7.117
144866	7.128	7.117

144867 rows × 2 columns

- **Sample T-Test** to check if difference between "time_taken_between_od_start_and_od_end_time" and "start_scan_to_end_scan"
 - **Define H0 and Ha**
 - **Null hypothesis (H0)** : **Group means** of "time_taken_between_od_start_and_od_end_time" and "start_scan_to_end_scan" are **equal**
 - **Alternate hypothesis (Ha)** : **Group means** of "time_taken_between_od_start_and_od_end_time" and "start_scan_to_end_scan" are **NOT equal**
 - **Define experiment and "sensible" (i.e. distribution of test under H0) test statistics**
 - **Two sample T-test (Independent)** .
 - Note : Could have used z-test as well because sample size is more than 30. However , T-test will be turnout to Z-Test as sample size is large (i.e. more than 10k)
 - Independent T-Test : Two diffrent random variable (i.e. "time_taken_between_od_start_and_od_end_time" and "start_scan_to_end_scan") being tested
 - **Decide One sided / two-sided tail test**
 - Two-sided as in Ha the measure is "not equal", we're neither checking greater nor lesser
 - **Define alfa (significance level)**
 - Let's assume significance level(alpha value) as 5%
 - **Calculate p-value**

In [231]...

```
stats.ttest_ind(df["time_taken_between_od_start_and_od_end_time"],df["start_scan_to_end_scan"])
```

Out[231]:

```
Ttest_indResult(statistic=0.12870351906903685, pvalue=0.8975923400909249)
```

- **T-Test Analysis**
 - **Conclusion**
 - Failed to Reject Null hupothesis as p value is 0.8975923400909249 i.e. greater than alpha value .05

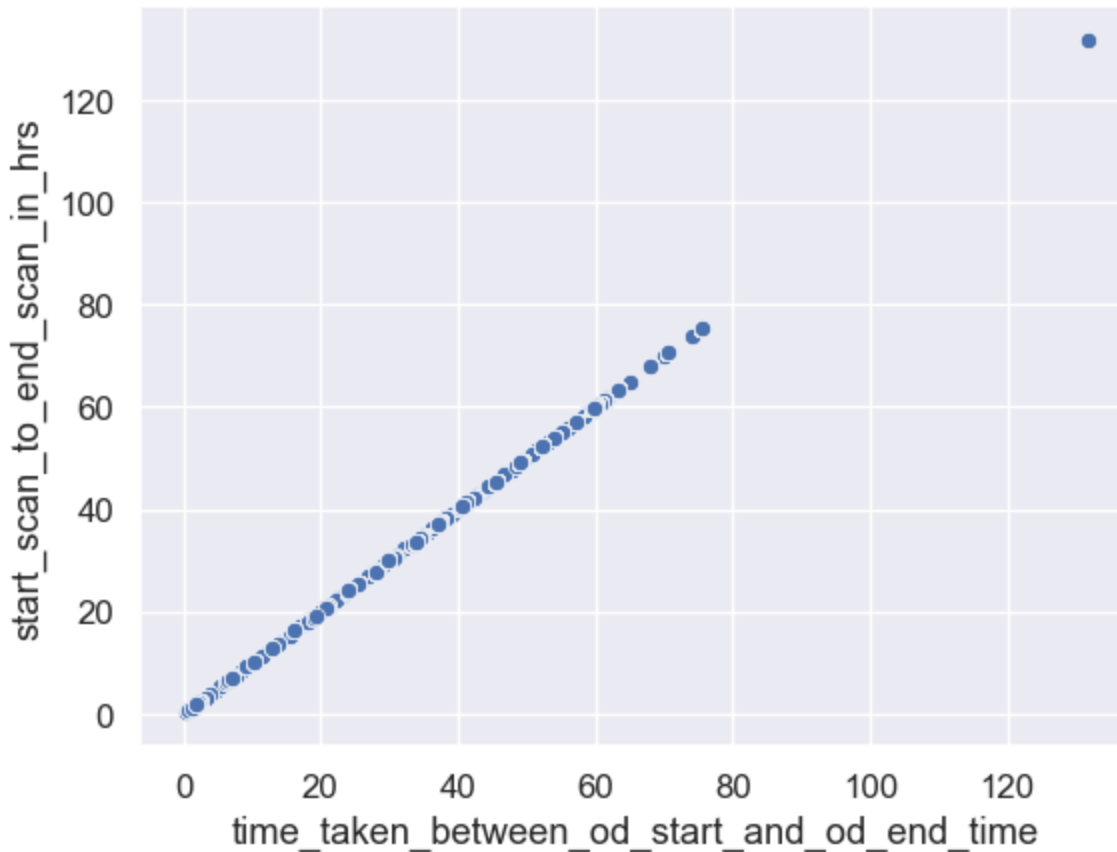
- Can't reject that "time_taken_between_od_start_and_od_end_time" and "start_scan_to_end_scan" are equal

In [232]:

```
sns.scatterplot(x="time_taken_between_od_start_and_od_end_time", y="start_scan_to_end_scan_in_hrs")
```

Out[232]:

```
<AxesSubplot:xlabel='time_taken_between_od_start_and_od_end_time', ylabel='start_scan_to_end_scan_in_hrs'>
```



- Overall **conclusion on the difference between "time_taken_between_od_start_and_od_end_time" and "start_scan_to_end_scan"**
 - Based on both statistical and visual analysis both features "time_taken_between_od_start_and_od_end_time" and "start_scan_to_end_scan" are same
 - We can drop new feature "time_taken_between_od_start_and_od_end_time"

Hypothesis testing/ visual analysis between "actual_time_aggregated" and "osrm_time_aggregated" value (aggregated values are the values you'll get after merging the rows on the basis of trip_uid)

- **Sample T-Test** to check if there is a difference between "actual_time_aggregated" and "osrm_time_aggregated"
 - **Define H0 and Ha**
 - **Null hypothesis (H0)** : Group means of "actual_time_aggregated" and "osrm_time_aggregated" are **equal**
 - **Alternate hypothesis (Ha)** : Group means of "actual_time_aggregated" and "osrm_time_aggregated" are **NOT equal**
 - **Define experiment and "sensible" (i.e. distribution of test under H0) test statistics**
 - **Two sample T-test (Independent)** .

- Note : Could have used z-test as well because sample size is more than 30. However , T-test will be turnout to Z-Test as sample size is large (i.e. more than 10k)
- Independent T-Test : Two diffrent random variable (i.e. "actual_time_aggregated" and "osrm_time_aggregated") being tested
- **Decide One sided / two-sided tail test**
 - Two-sided as in Ha the measure is "not equal", we're neither checking greater nor lesser
- **Define alfa (significance level)**
 - Let's assume significance level(alpha value) as 5%
- **Calculate p-value**

In [233...

```
stats.ttest_ind(df_agg["actual_time_aggregated"], df_agg["osrm_time_aggregated"])
```

Out[233]:

```
Ttest_indResult(statistic=14.073444960610715, pvalue=7.714905383019579e-45)
```

• T-Test Analysis

▪ Conclusion

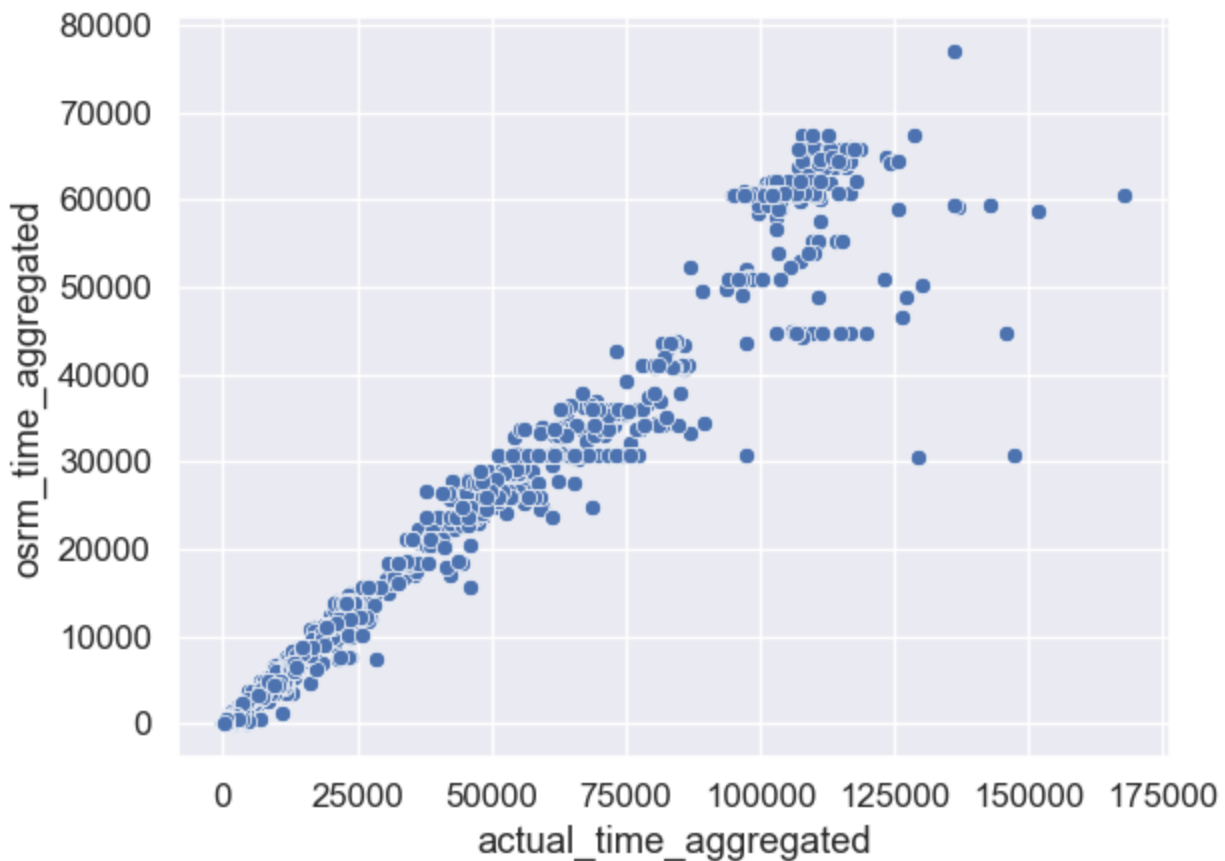
- Reject Null hupthesis as p value is 7.714905383019579e-45 i.e. less than alpha value .05
- **"actual_time_aggregated" and "osrm_time_aggregated" are two different features**
- **Need to reatin both features i.e. "actual_time_aggregated" and "osrm_time_aggregated"**

In [234...

```
sns.scatterplot(x="actual_time_aggregated", y="osrm_time_aggregated", data=df_agg)
```

Out[234]:

```
<AxesSubplot:xlabel='actual_time_aggregated', ylabel='osrm_time_aggregated'>
```



Compare feature **actual_time** vs **segment_actual_time**

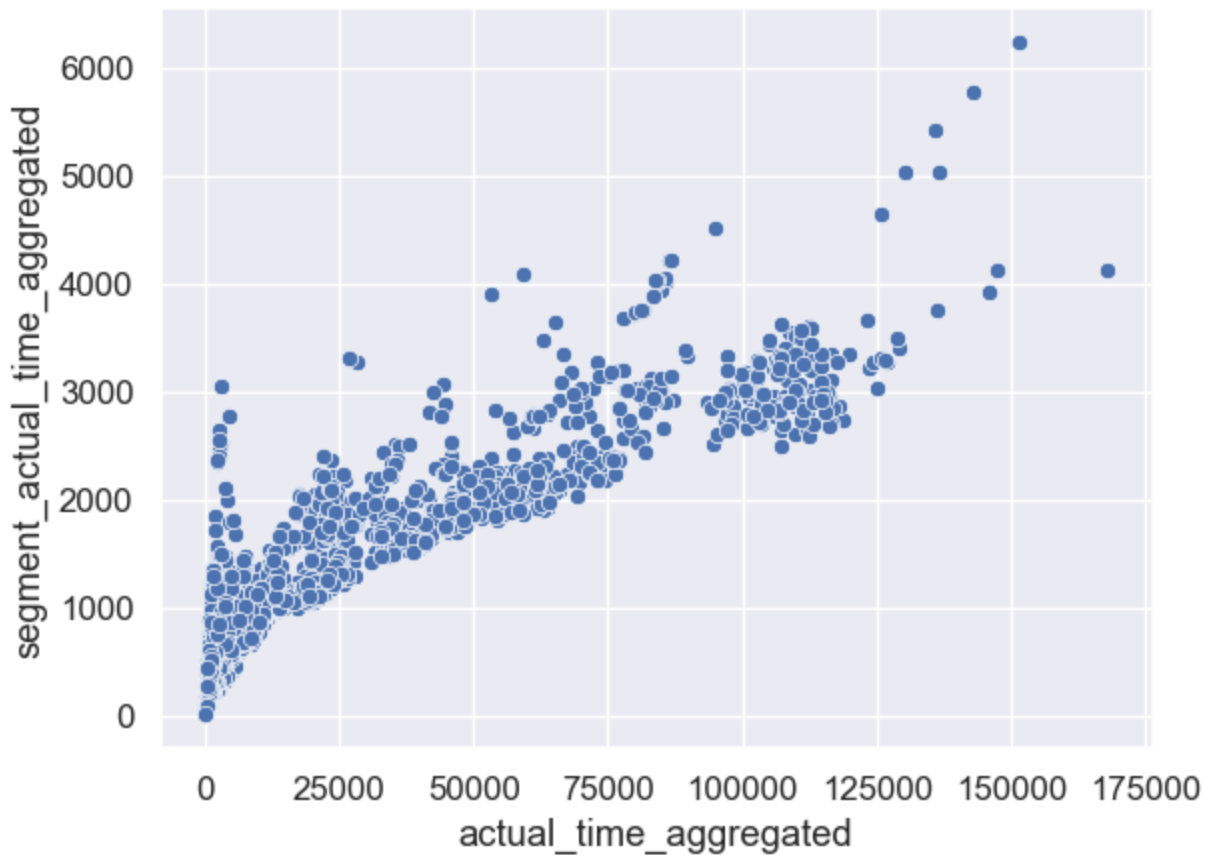
In [235...

```
stats.ttest_ind(df_agg["actual_time_aggregated"], df_agg["segment_actual_time_aggregated"])
```

Out[235]: Ttest_indResult(statistic=29.75724632324628, pvalue=9.305532733717133e-192)

In [236... `sns.scatterplot(x="actual_time_aggregated", y="segment_actual_time_aggregated", data=df_`

Out[236]: <AxesSubplot:xlabel='actual_time_aggregated', ylabel='segment_actual_time_aggregated'>



- **T-Test Analysis**

- **Conclusion**

- Reject Null hypothesis as p value is 9.305532733717133e-192 i.e. less than alpha value .05
 - **"actual_time_aggregated" and "segment_actual_time_aggregated" are two different features**
 - **Need to retain both features i.e. "actual_time_aggregated" and "segment_actual_time_aggregated"**

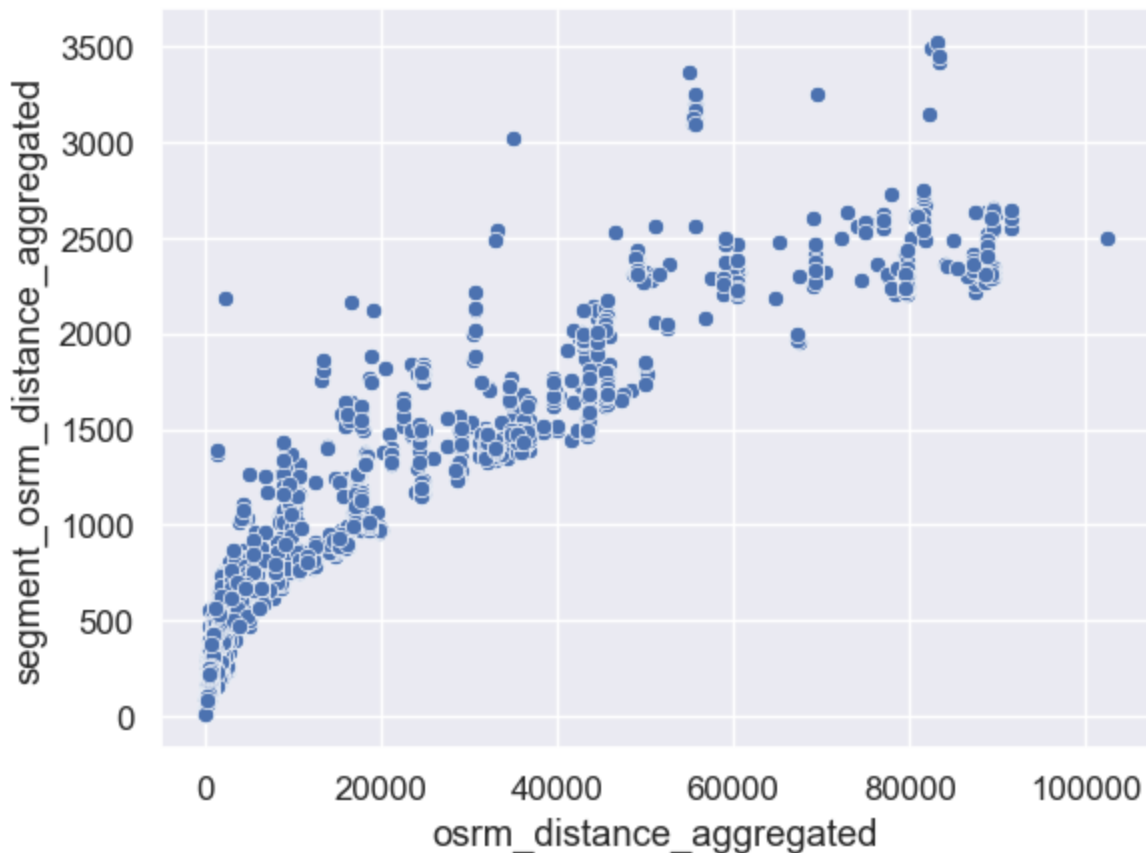
Compare feature **osrm_distance** vs **segment_osrm_distance**

In [237... `stats.ttest_ind(df_agg["osrm_distance_aggregated"], df_agg["segment_osrm_distance_aggregated"],`

Out[237]: Ttest_indResult(statistic=28.952997899197353, pvalue=8.78329034932333e-182)

In [238... `sns.scatterplot(x="osrm_distance_aggregated", y="segment_osrm_distance_aggregated", data=df_`

Out[238]: <AxesSubplot:xlabel='osrm_distance_aggregated', ylabel='segment_osrm_distance_aggregated'>



- **T-Test Analysis**

- **Conclusion**

- Reject Null hypothesis as p value is $8.78329034932333e-182$ i.e. less than alpha value .05
 - **"osrm_distance_aggregated" and "segment_osrm_distance_aggregated" are two different features**
 - **Need to retain both features i.e. "osrm_distance_aggregated" and "segment_osrm_distance_aggregated"**

Compare feature **osrm_time** vs **segment_osrm_time**

```
In [239]: stats.ttest_ind(df_agg["osrm_time_aggregated"], df_agg["segment_osrm_time_aggregated"])
```

```
Out[239]: Ttest_indResult(statistic=29.19742674380395, pvalue=8.695112641096768e-185)
```

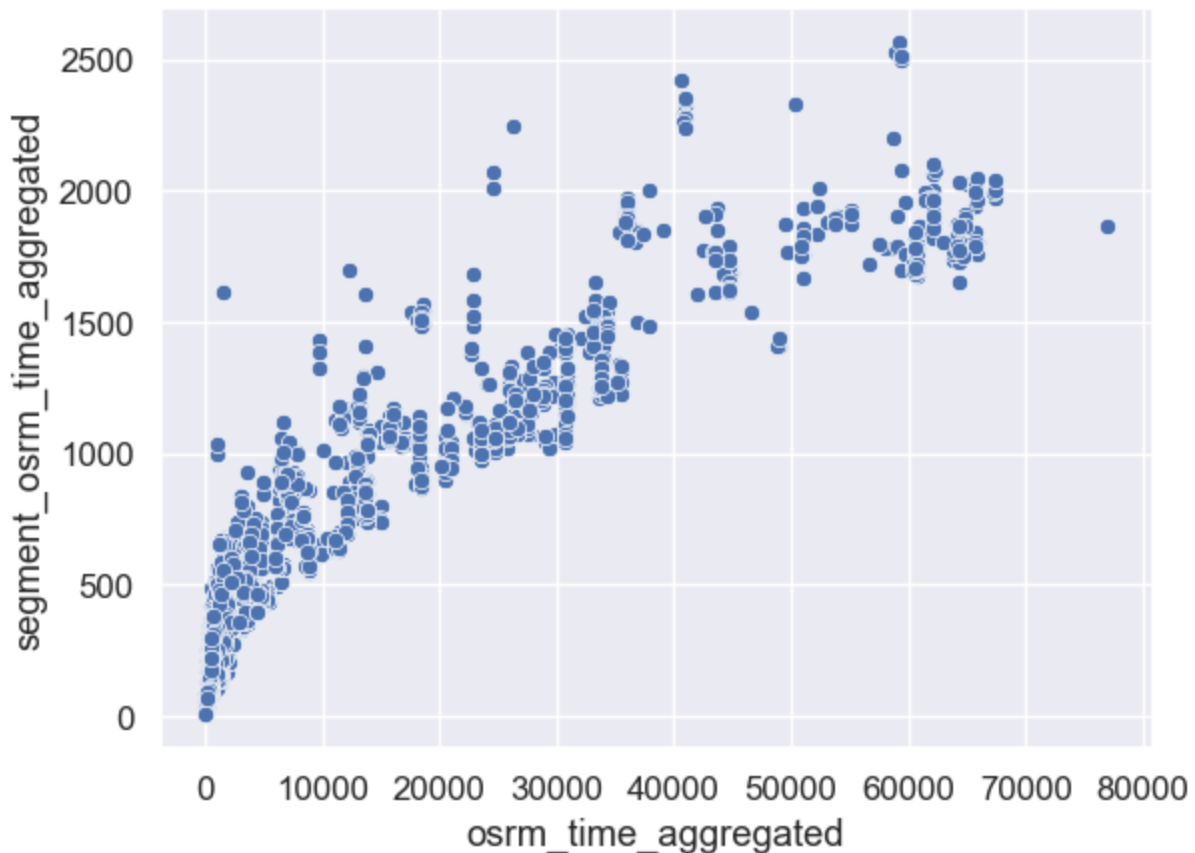
- **T-Test Analysis**

- **Conclusion**

- Reject Null hypothesis as p value is $8.695112641096768e-185$ i.e. less than alpha value .05
 - **"osrm_time_aggregated" and "segment_osrm_time_aggregated" are two different features**
 - **Need to retain both features i.e. "osrm_time_aggregated" and "segment_osrm_time_aggregated"**

```
In [240]: sns.scatterplot(x="osrm_time_aggregated", y="segment_osrm_time_aggregated", data=df_agg)
```

```
Out[240]: <AxesSubplot:xlabel='osrm_time_aggregated', ylabel='segment_osrm_time_aggregated'>
```



- **Visual Analysis**

- **Conclusion**

- Follows close linear relationship to some time range
 - Beyond that range , "**actual_time_aggregated**" and "**osrm_time_aggregated**" **varies differently**

Compare feature **osrm_time_diff** vs **actual_time_diff**

- **Hypothesis**

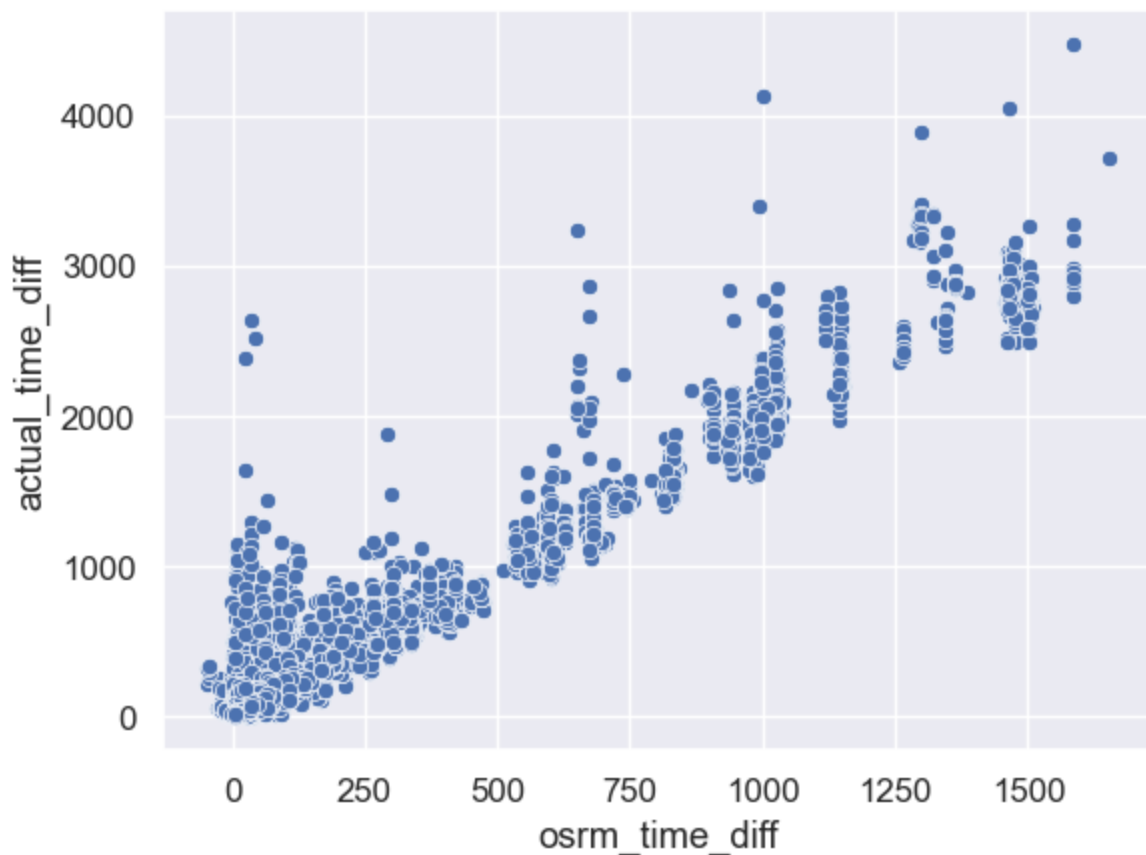
- Null hypothesis - Mean of **osrm_time_diff** time and **actual_time_diff** have no difference
 - Alternate hypothesis - Mean of **osrm_time_diff** time and **actual_time_diff** have difference

```
In [63]: stats.ttest_ind(df_agg_by_trip_src_dest_center_merged["osrm_time_diff"],df_agg_by_trip_s
```

```
Out[63]: Ttest_indResult(statistic=-33.067911482916315, pvalue=2.3296445482665114e-237)
```

```
In [64]: sns.scatterplot(x="osrm_time_diff", y="actual_time_diff", data=df_agg_by_trip_src_dest_c
```

```
Out[64]: <AxesSubplot:xlabel='osrm_time_diff', ylabel='actual_time_diff'>
```



- **Visual Analysis**

- **Conclusion**

- Follows random linear relationship to some time range
 - Beyond that range , "**osrm_time_diff**" and "**actual_time_diff**" **varies differently**
 - **More accurate predictions required for better estimate of time**
 - Need to observe orders which are following accurate relationship and take more such orders

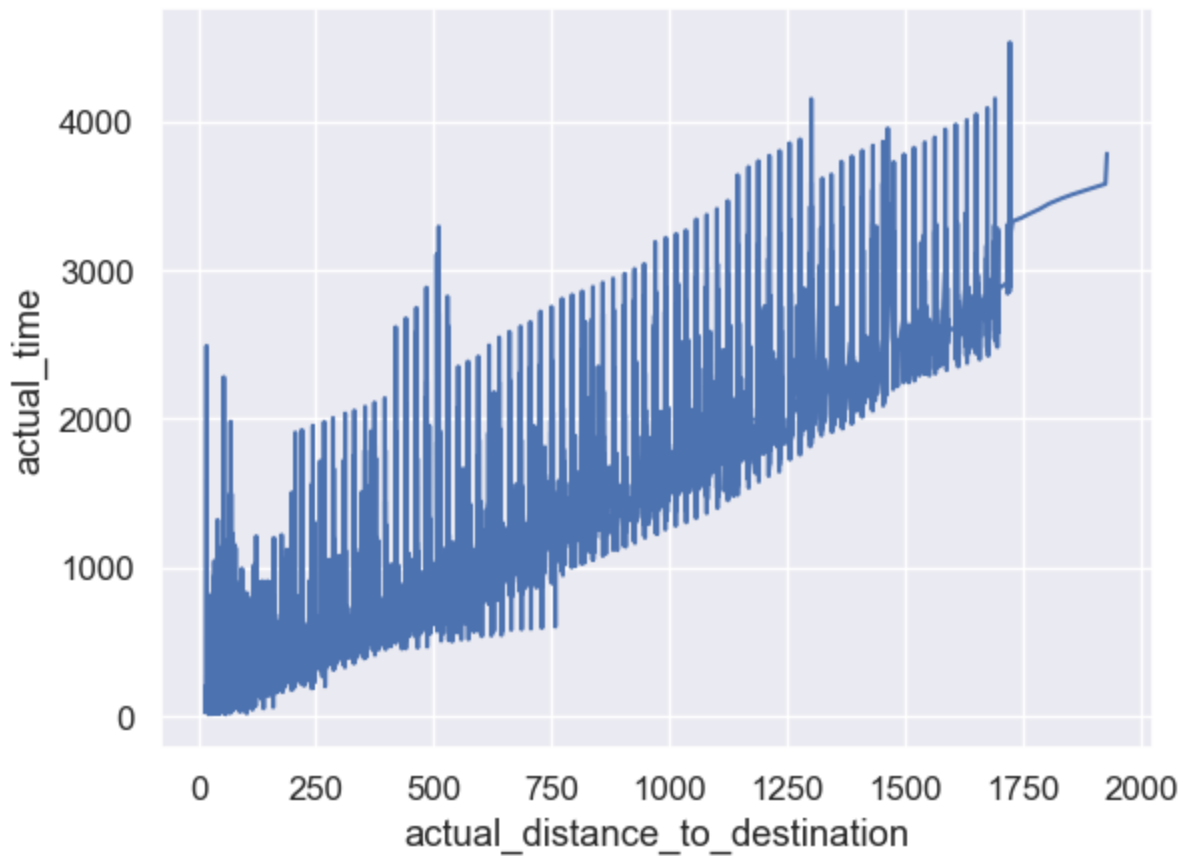
Comparison & Visualization of time and distance fields

```
In [241... distance_feature_list = [ "start_scan_to_end_scan", "actual_distance_to_destination", "osrm_distance_to_destination" ]
time_feature_list = [ "actual_time", "osrm_time", "segment_actual_time", "segment_osrm_time" ]
```

Full truck load

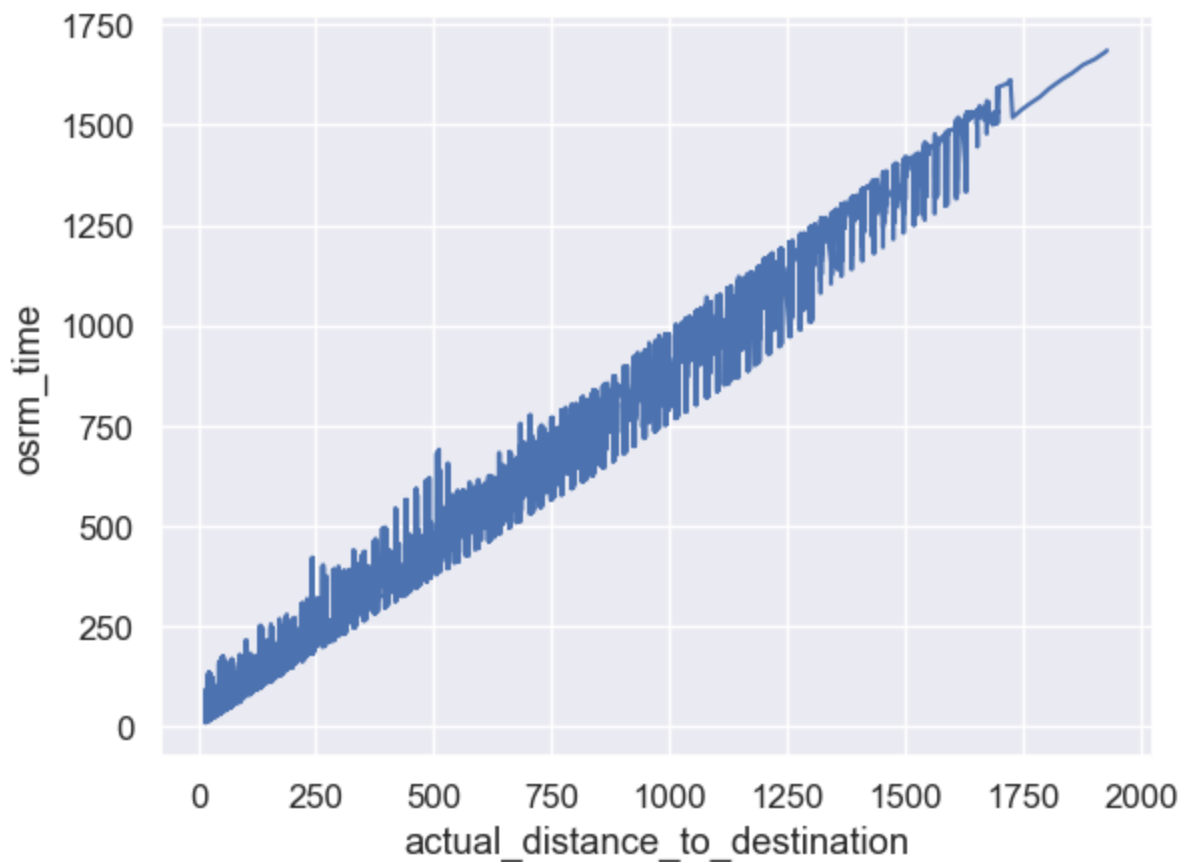
```
In [242... sns.lineplot(x="actual_distance_to_destination", y="actual_time", data = df_full_truck_load)
```

```
Out[242]: <AxesSubplot:xlabel='actual_distance_to_destination', ylabel='actual_time'>
```



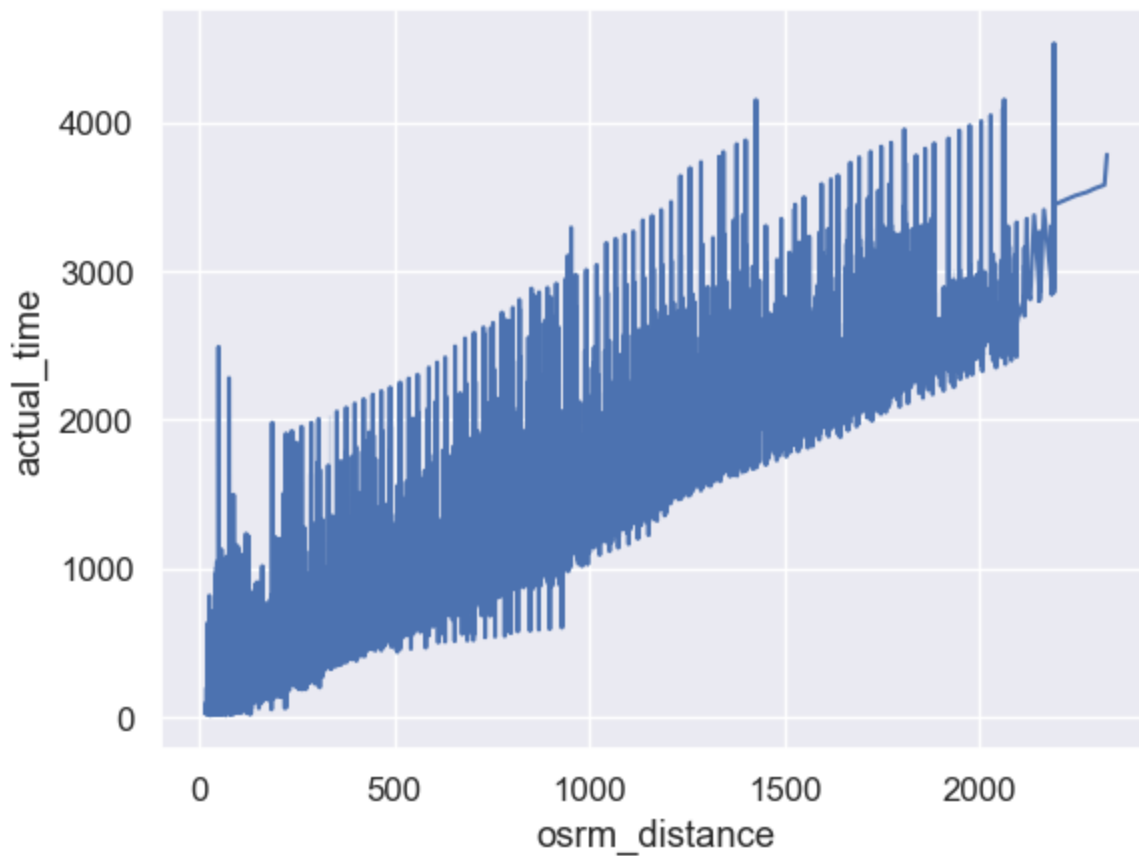
In [243]: `sns.lineplot(x="actual_distance_to_destination", y="osrm_time", data = df_full_truck_load)`

Out[243]: `<AxesSubplot:xlabel='actual_distance_to_destination', ylabel='osrm_time'>`



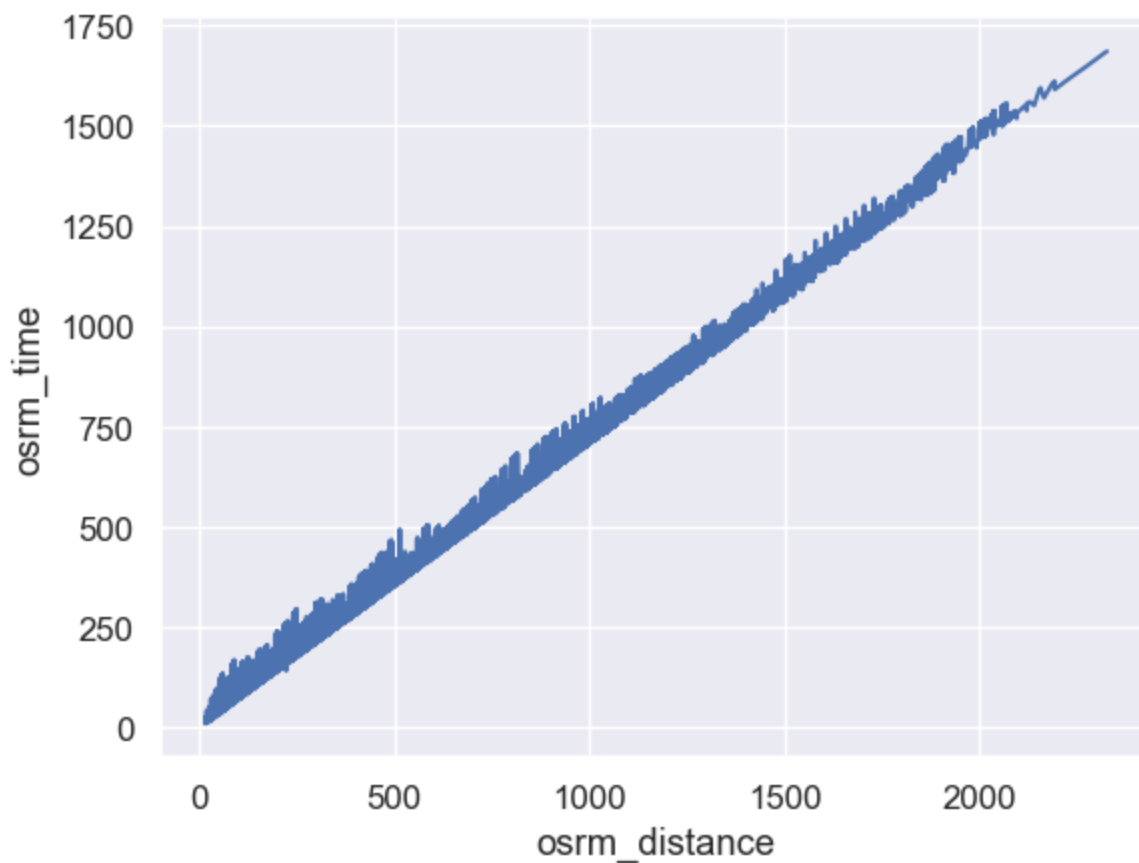
In [244]: `sns.lineplot(x="osrm_distance", y="actual_time", data = df_full_truck_load)`

Out[244]: <AxesSubplot: xlabel='osrm_distance', ylabel='actual_time'>



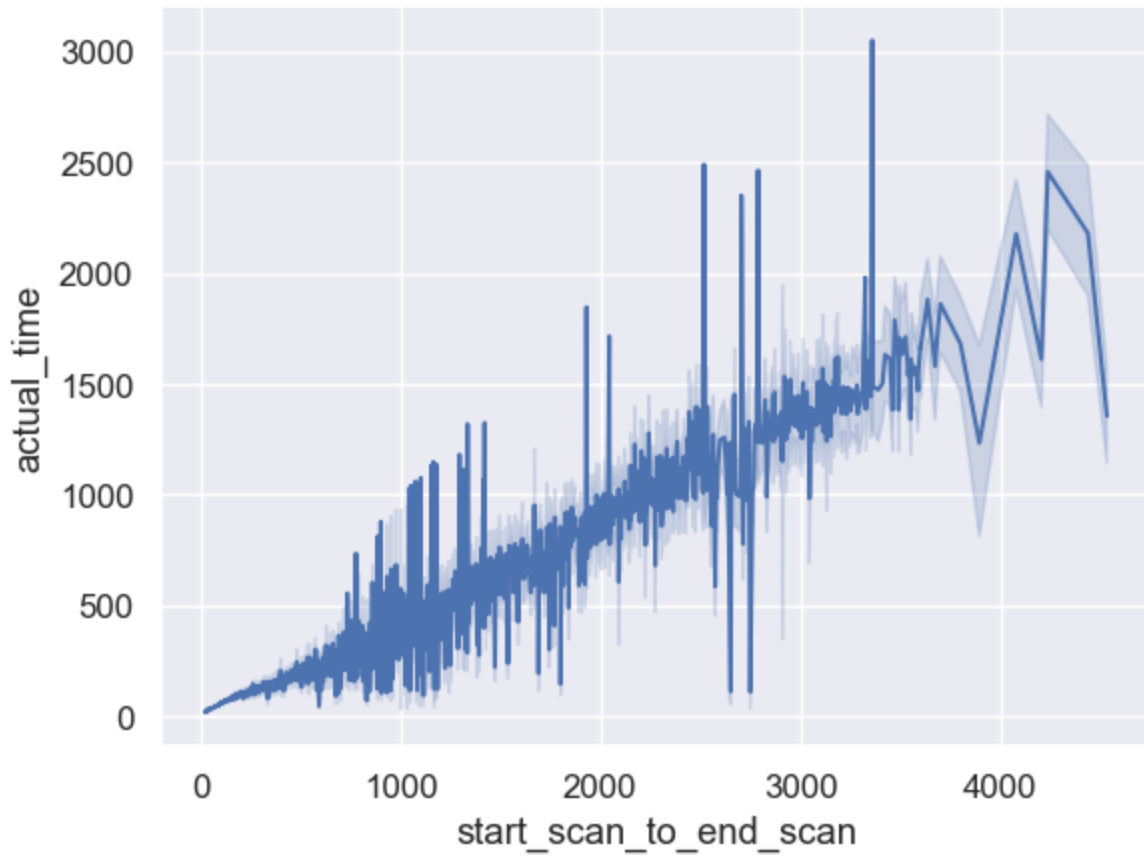
In [245... `sns.lineplot(x="osrm_distance", y="osrm_time", data = df_full_truck_load)`

Out[245]: <AxesSubplot: xlabel='osrm_distance', ylabel='osrm_time'>



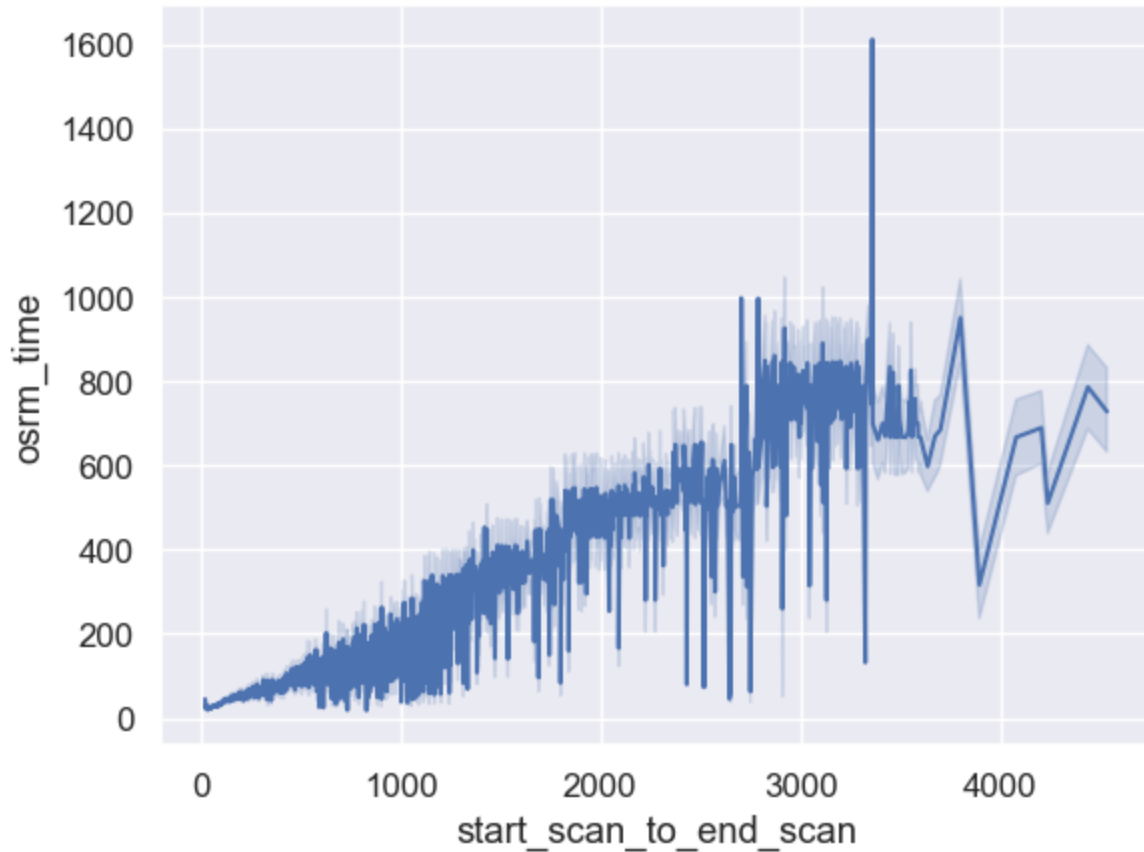
In [246... `sns.lineplot(x="start_scan_to_end_scan", y="actual_time", data = df_full_truck_load)`

Out[246]: <AxesSubplot:xlabel='start_scan_to_end_scan', ylabel='actual_time'>



In [247... `sns.lineplot(x="start_scan_to_end_scan", y="osrm_time", data = df_full_truck_load)`

Out[247]: <AxesSubplot:xlabel='start_scan_to_end_scan', ylabel='osrm_time'>



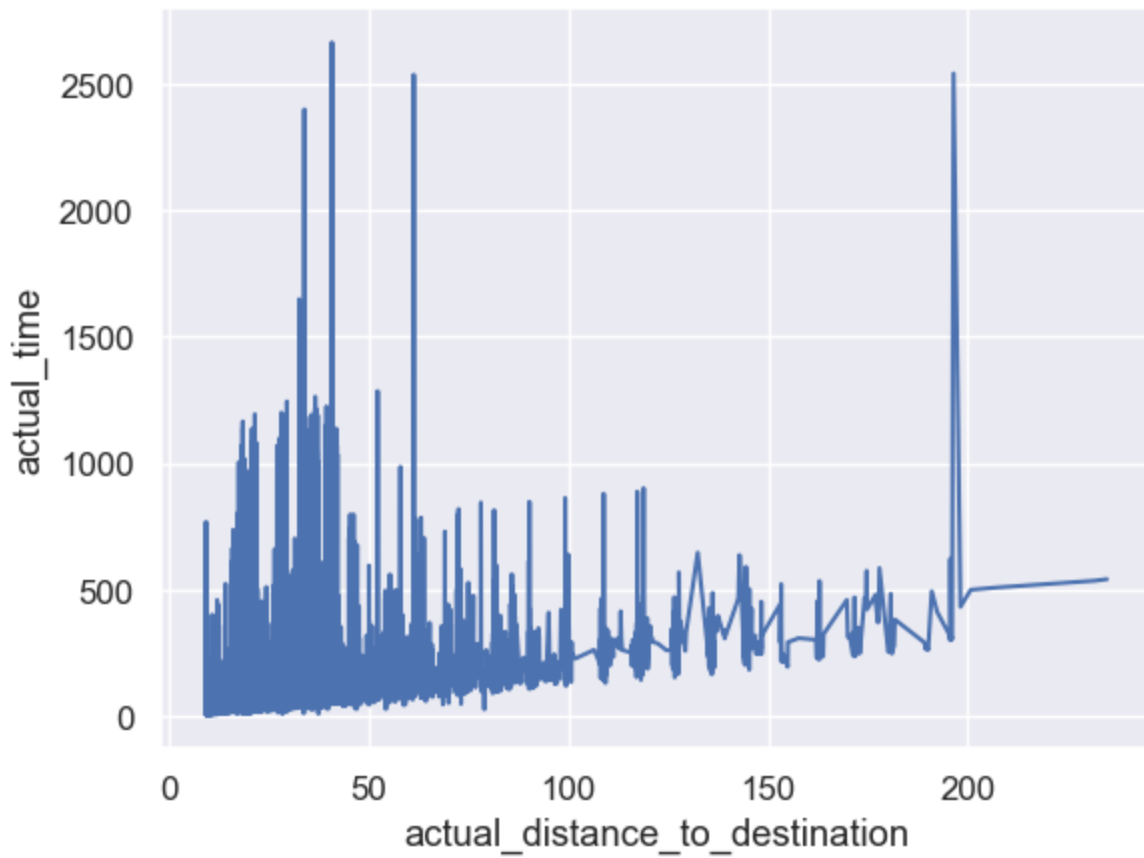
Carting

In [248...

```
sns.lineplot(x="actual_distance_to_destination", y="actual_time", data = df_carting)
```

Out[248]:

```
<AxesSubplot:xlabel='actual_distance_to_destination', ylabel='actual_time'>
```

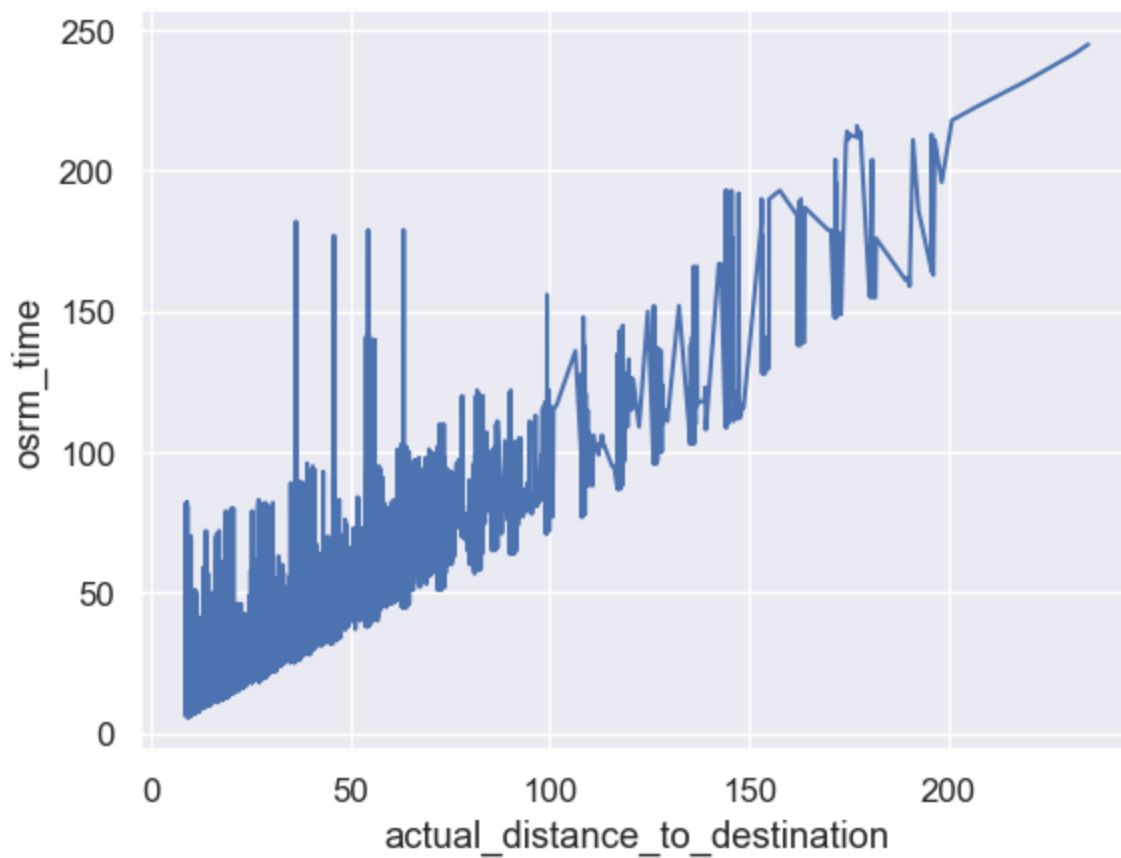


In [249...

```
sns.lineplot(x="actual_distance_to_destination", y="osrm_time", data = df_carting)
```

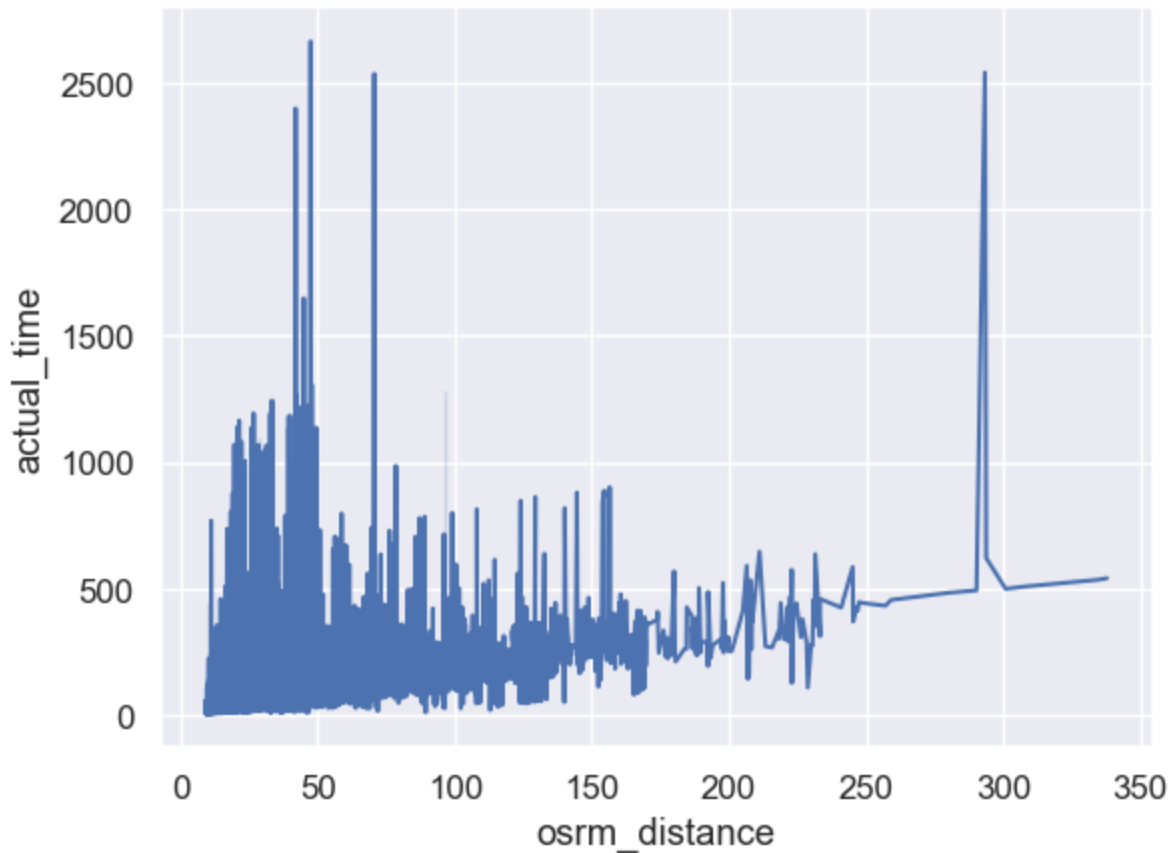
Out[249]:

```
<AxesSubplot:xlabel='actual_distance_to_destination', ylabel='osrm_time'>
```



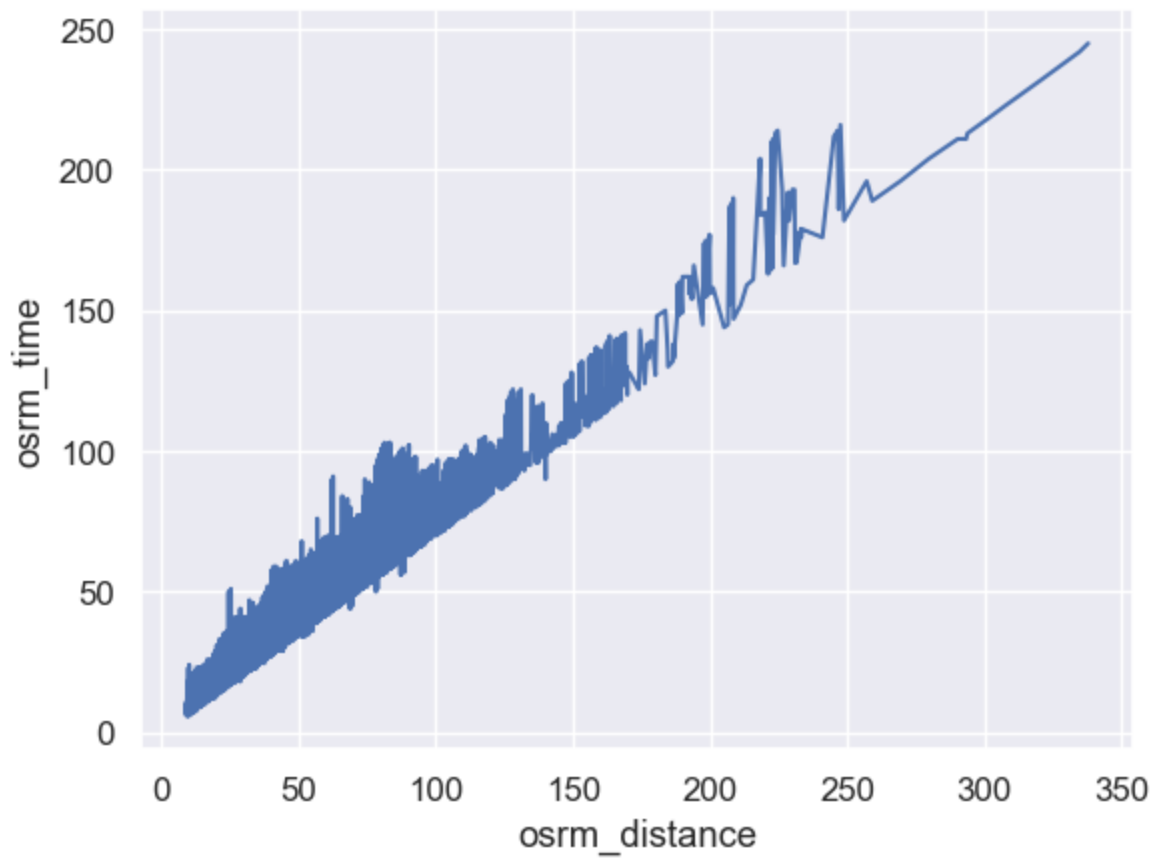
```
In [250]: sns.lineplot(x="osrm_distance", y="actual_time", data = df_carting)
```

```
Out[250]: <AxesSubplot:xlabel='osrm_distance', ylabel='actual_time'>
```



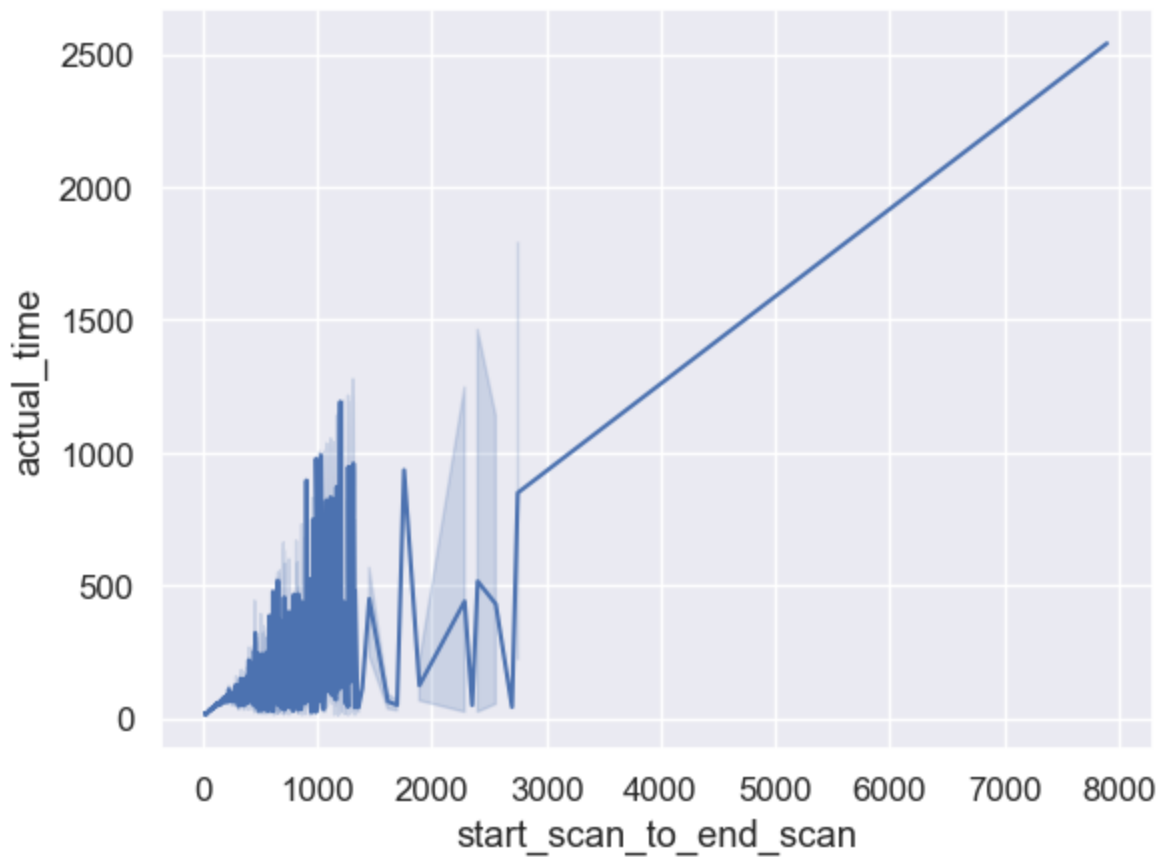
```
In [251]: sns.lineplot(x="osrm_distance", y="osrm_time", data = df_carting)
```

Out[251]: <AxesSubplot: xlabel='osrm_distance', ylabel='osrm_time'>



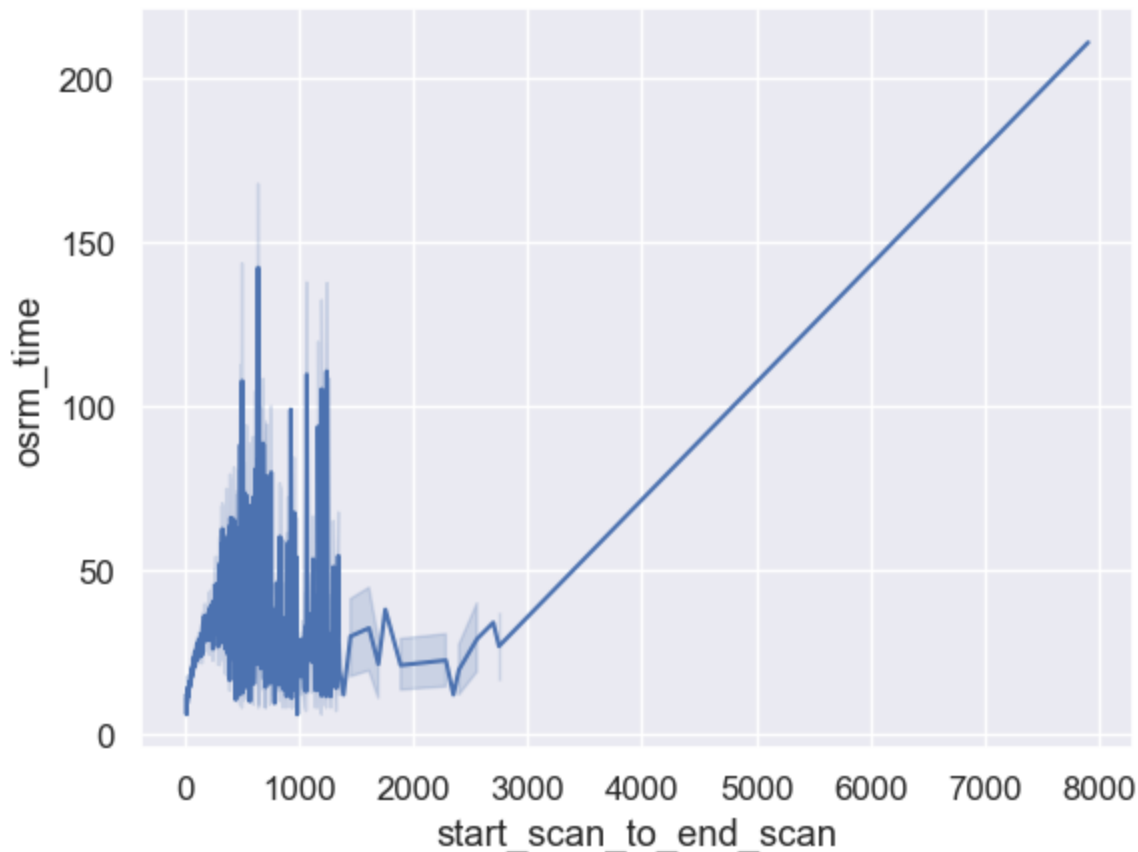
In [252... `sns.lineplot(x="start_scan_to_end_scan", y="actual_time", data = df_carting)`

Out[252]: <AxesSubplot: xlabel='start_scan_to_end_scan', ylabel='actual_time'>



In [253... `sns.lineplot(x="start_scan_to_end_scan", y="osrm_time", data = df_carting)`

```
Out[253]: <AxesSubplot:xlabel='start_scan_to_end_scan', ylabel='osrm_time'>
```



- **Conclusion**

- **Approximate Linear relationship observed** between following **distance and time features**
 - "actual_distance_to_destination" vs "osrm_time"
 - "osrm_distance" vs "osrm_time"
 - "start_scan_to_end_scan" vs "actual_time"
 - "osrm_distance" vs "osrm_time"

Outlier Detection and treatment

- Find outliers in the numerical variables and check it using visual analysis

```
In [254... continuous_features = df.select_dtypes(include=['int64','float64']).columns
continuous_features
```

```
Out[254]: Index(['start_scan_to_end_scan', 'cutoff_factor',
      'actual_distance_to_destination', 'actual_time', 'osrm_time',
      'osrm_distance', 'factor', 'segment_actual_time', 'segment_osrm_time',
      'segment_osrm_distance', 'segment_factor', 'trip_creation_time_year',
      'trip_creation_time_weekday', 'trip_creation_time_day',
      'od_start_time_year', 'od_start_time_weekday', 'od_start_time_day',
      'od_end_time_year', 'od_end_time_weekday', 'od_end_time_day',
      'time_taken_between_od_start_and_od_end_time',
      'start_scan_to_end_scan_in_hrs'],
      dtype='object')
```

```
In [255... def find_outliers_IQR(column_name):
    print("Outliers by feature name --> ",column_name)
    # calculating quartiles
    Q1=df[column_name].quantile(0.25)
```

```
Q3=df[column_name].quantile(0.75)
# calculating inter quartile range
IQR=Q3-Q1
lower = Q1 - 1.5*IQR
upper = Q3 + 1.5*IQR
# filtering data that is outside inter quartile range
outliers = df[((df[column_name]<lower) | (df[column_name]>upper)))]

return outliers
```

In [256...

```
for feature_name in continuous_features:
    print(find_outliers_IQR(feature_name))
```

Outliers by feature name --> start_scan_to_end_scan

	data	trip_creation_time	\
32950	training	2018-09-13 01:28:45.326644	
32951	training	2018-09-13 01:28:45.326644	
32952	training	2018-09-13 01:28:45.326644	
32953	training	2018-09-13 01:28:45.326644	
32954	training	2018-09-13 01:28:45.326644	
...	
79524	training	2018-09-19 13:44:58.665210	
79525	training	2018-09-19 13:44:58.665210	
79526	training	2018-09-19 13:44:58.665210	
79527	training	2018-09-19 13:44:58.665210	
123196	test	2018-10-01 23:35:54.432745	

	route_schedule_uuid	route_type	\
32950	thanos::sroute:6b87651c-fdf4-432f-bf80-0e394f3...	FTL	
32951	thanos::sroute:6b87651c-fdf4-432f-bf80-0e394f3...	FTL	
32952	thanos::sroute:6b87651c-fdf4-432f-bf80-0e394f3...	FTL	
32953	thanos::sroute:6b87651c-fdf4-432f-bf80-0e394f3...	FTL	
32954	thanos::sroute:6b87651c-fdf4-432f-bf80-0e394f3...	FTL	
...	
79524	thanos::sroute:bc7dbb1d-9379-4674-b8d3-f9c3b96...	FTL	
79525	thanos::sroute:bc7dbb1d-9379-4674-b8d3-f9c3b96...	FTL	
79526	thanos::sroute:bc7dbb1d-9379-4674-b8d3-f9c3b96...	FTL	
79527	thanos::sroute:bc7dbb1d-9379-4674-b8d3-f9c3b96...	FTL	
123196	thanos::sroute:4316e05f-b4cc-4ea7-b801-62a93ae...	Carting	

	trip_uuid	source_center	\
32950	trip-153680212532637033	IND712311AAA	
32951	trip-153680212532637033	IND712311AAA	
32952	trip-153680212532637033	IND712311AAA	
32953	trip-153680212532637033	IND712311AAA	
32954	trip-153680212532637033	IND712311AAA	
...	
79524	trip-153736469866480991	IND000000ACB	
79525	trip-153736469866480991	IND000000ACB	
79526	trip-153736469866480991	IND000000ACB	
79527	trip-153736469866480991	IND000000ACB	
123196	trip-153843695443252828	IND764071AAB	

	source_name	destination_center	\
32950	Kolkata_Dankuni_HB (West Bengal)	IND781018AAB	
32951	Kolkata_Dankuni_HB (West Bengal)	IND781018AAB	
32952	Kolkata_Dankuni_HB (West Bengal)	IND781018AAB	
32953	Kolkata_Dankuni_HB (West Bengal)	IND781018AAB	
32954	Kolkata_Dankuni_HB (West Bengal)	IND781018AAB	
...	
79524	Gurgaon_Bilaspur_HB (Haryana)	IND712311AAA	
79525	Gurgaon_Bilaspur_HB (Haryana)	IND712311AAA	
79526	Gurgaon_Bilaspur_HB (Haryana)	IND712311AAA	
79527	Gurgaon_Bilaspur_HB (Haryana)	IND712311AAA	
123196	Pappadahandi_Central_DPP_2 (Orissa)	IND530012AAA	

	destination_name	od_start_time	\
32950	Guwahati_Hub (Assam)	2018-09-13 01:28:45.326644	
32951	Guwahati_Hub (Assam)	2018-09-13 01:28:45.326644	
32952	Guwahati_Hub (Assam)	2018-09-13 01:28:45.326644	
32953	Guwahati_Hub (Assam)	2018-09-13 01:28:45.326644	
32954	Guwahati_Hub (Assam)	2018-09-13 01:28:45.326644	
...	
79524	Kolkata_Dankuni_HB (West Bengal)	2018-09-19 13:44:58.665210	
79525	Kolkata_Dankuni_HB (West Bengal)	2018-09-19 13:44:58.665210	
79526	Kolkata_Dankuni_HB (West Bengal)	2018-09-19 13:44:58.665210	
79527	Kolkata_Dankuni_HB (West Bengal)	2018-09-19 13:44:58.665210	
123196	Visakhapatnam_Gajuwaka_IP (Andhra Pradesh)	2018-10-02 15:21:51.236205	

	...	source_name_city	source_name_place	source_name_code	\
32950	...	NaN	NaN	NaN	
32951	...	NaN	NaN	NaN	
32952	...	NaN	NaN	NaN	
32953	...	NaN	NaN	NaN	
32954	...	NaN	NaN	NaN	
...	
79524	...	Gurgaon	Bilaspur	HB	
79525	...	Gurgaon	Bilaspur	HB	
79526	...	Gurgaon	Bilaspur	HB	
79527	...	Gurgaon	Bilaspur	HB	
123196	...	NaN	NaN	NaN	

	source_name_state	destination_name_city	destination_name_place	\
32950	NaN	NaN	NaN	
32951	NaN	NaN	NaN	
32952	NaN	NaN	NaN	
32953	NaN	NaN	NaN	
32954	NaN	NaN	NaN	
...	
79524	Haryana	NaN	NaN	
79525	Haryana	NaN	NaN	
79526	Haryana	NaN	NaN	
79527	Haryana	NaN	NaN	
123196	NaN	NaN	NaN	

	destination_name_code	destination_name_state	\
32950	NaN	NaN	
32951	NaN	NaN	
32952	NaN	NaN	
32953	NaN	NaN	
32954	NaN	NaN	
...	
79524	NaN	NaN	
79525	NaN	NaN	
79526	NaN	NaN	
79527	NaN	NaN	
123196	NaN	NaN	

	time_taken_between_od_start_and_od_end_time	\
32950	64.959	
32951	64.959	
32952	64.959	
32953	64.959	
32954	64.959	
...	...	
79524	70.658	
79525	70.658	
79526	70.658	
79527	70.658	
123196	131.643	

	start_scan_to_end_scan_in_hrs	
32950	64.950	
32951	64.950	
32952	64.950	
32953	64.950	
32954	64.950	
...	...	
79524	70.650	
79525	70.650	
79526	70.650	
79527	70.650	
123196	131.633	

[373 rows x 46 columns]

Outliers by feature name -->	cutoff_factor
data	trip_creation_time \
402	training 2018-09-25 15:06:59.975279
403	training 2018-09-25 15:06:59.975279
404	training 2018-09-25 15:06:59.975279
405	training 2018-09-25 15:06:59.975279
406	training 2018-09-25 15:06:59.975279
...	...
144796	test 2018-10-01 18:17:37.047270
144797	test 2018-10-01 18:17:37.047270
144798	test 2018-10-01 18:17:37.047270
144799	test 2018-10-01 18:17:37.047270
144800	test 2018-10-01 18:17:37.047270

	route_schedule_uuid	route_type \
402	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL
403	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL
404	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL
405	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL
406	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL
...
144796	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL
144797	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL
144798	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL
144799	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL
144800	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL

	trip_uuid	source_center \
402	trip-153788801997503817	IND825409AAA
403	trip-153788801997503817	IND825409AAA
404	trip-153788801997503817	IND825409AAA
405	trip-153788801997503817	IND825409AAA
406	trip-153788801997503817	IND825409AAA
...
144796	trip-153841785704702048	IND000000ACB
144797	trip-153841785704702048	IND000000ACB
144798	trip-153841785704702048	IND000000ACB
144799	trip-153841785704702048	IND000000ACB
144800	trip-153841785704702048	IND000000ACB

	source_name	destination_center \
402	JhumriTlya_RadhaCpx_D (Jharkhand)	IND000000ACB
403	JhumriTlya_RadhaCpx_D (Jharkhand)	IND000000ACB
404	JhumriTlya_RadhaCpx_D (Jharkhand)	IND000000ACB
405	JhumriTlya_RadhaCpx_D (Jharkhand)	IND000000ACB
406	JhumriTlya_RadhaCpx_D (Jharkhand)	IND000000ACB
...
144796	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA
144797	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA
144798	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA
144799	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA
144800	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA

	destination_name	od_start_time	...	\
402	Gurgaon_Bilaspur_HB (Haryana)	2018-09-26 03:15:43.970231	...	
403	Gurgaon_Bilaspur_HB (Haryana)	2018-09-26 03:15:43.970231	...	
404	Gurgaon_Bilaspur_HB (Haryana)	2018-09-26 03:15:43.970231	...	
405	Gurgaon_Bilaspur_HB (Haryana)	2018-09-26 03:15:43.970231	...	
406	Gurgaon_Bilaspur_HB (Haryana)	2018-09-26 03:15:43.970231	...	
...	
144796	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	
144797	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	
144798	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	
144799	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	
144800	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	

	source_name_city	source_name_place	source_name_code	\
402	JhumriTlya	RadhaCpx	D	
403	JhumriTlya	RadhaCpx	D	
404	JhumriTlya	RadhaCpx	D	
405	JhumriTlya	RadhaCpx	D	
406	JhumriTlya	RadhaCpx	D	
...	
144796	Gurgaon	Bilaspur	HB	
144797	Gurgaon	Bilaspur	HB	
144798	Gurgaon	Bilaspur	HB	
144799	Gurgaon	Bilaspur	HB	
144800	Gurgaon	Bilaspur	HB	

	source_name_state	destination_name_city	destination_name_place	\
402	Jharkhand	Gurgaon	Bilaspur	
403	Jharkhand	Gurgaon	Bilaspur	
404	Jharkhand	Gurgaon	Bilaspur	
405	Jharkhand	Gurgaon	Bilaspur	
406	Jharkhand	Gurgaon	Bilaspur	
...	
144796	Haryana	Bengaluru	Nelmngla	
144797	Haryana	Bengaluru	Nelmngla	
144798	Haryana	Bengaluru	Nelmngla	
144799	Haryana	Bengaluru	Nelmngla	
144800	Haryana	Bengaluru	Nelmngla	

	destination_name_code	destination_name_state	\
402	HB	Haryana	
403	HB	Haryana	
404	HB	Haryana	
405	HB	Haryana	
406	HB	Haryana	
...	
144796	H	Karnataka	
144797	H	Karnataka	
144798	H	Karnataka	
144799	H	Karnataka	
144800	H	Karnataka	

	time_taken_between_od_start_and_od_end_time	\
402	25.852	
403	25.852	
404	25.852	
405	25.852	
406	25.852	
...	...	
144796	49.162	
144797	49.162	
144798	49.162	
144799	49.162	
144800	49.162	

	start_scan_to_end_scan_in_hrs
402	25.85
403	25.85
404	25.85
405	25.85
406	25.85
...	...
144796	49.15
144797	49.15
144798	49.15
144799	49.15
144800	49.15

[17246 rows x 46 columns]

Outliers by feature name --> actual_distance to_destination

	data	trip_creation_time	\
401	training	2018-09-25 15:06:59.975279	
402	training	2018-09-25 15:06:59.975279	
403	training	2018-09-25 15:06:59.975279	
404	training	2018-09-25 15:06:59.975279	
405	training	2018-09-25 15:06:59.975279	
...	
144796	test	2018-10-01 18:17:37.047270	
144797	test	2018-10-01 18:17:37.047270	
144798	test	2018-10-01 18:17:37.047270	
144799	test	2018-10-01 18:17:37.047270	
144800	test	2018-10-01 18:17:37.047270	

	route_schedule_uuid	route_type	\
401	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	
402	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	
403	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	
404	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	
405	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	
...	
144796	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	
144797	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	
144798	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	
144799	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	
144800	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	

	trip_uuid	source_center	\
401	trip-153788801997503817	IND825409AAA	
402	trip-153788801997503817	IND825409AAA	
403	trip-153788801997503817	IND825409AAA	
404	trip-153788801997503817	IND825409AAA	
405	trip-153788801997503817	IND825409AAA	
...	
144796	trip-153841785704702048	IND000000ACB	
144797	trip-153841785704702048	IND000000ACB	
144798	trip-153841785704702048	IND000000ACB	
144799	trip-153841785704702048	IND000000ACB	
144800	trip-153841785704702048	IND000000ACB	

	source_name	destination_center	\
401	JhumriTlya_RadhaCpx_D (Jharkhand)	IND000000ACB	
402	JhumriTlya_RadhaCpx_D (Jharkhand)	IND000000ACB	
403	JhumriTlya_RadhaCpx_D (Jharkhand)	IND000000ACB	
404	JhumriTlya_RadhaCpx_D (Jharkhand)	IND000000ACB	
405	JhumriTlya_RadhaCpx_D (Jharkhand)	IND000000ACB	
...	
144796	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA	
144797	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA	
144798	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA	
144799	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA	
144800	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA	

	destination_name	od_start_time	...	\
401	Gurgaon_Bilaspur_HB (Haryana)	2018-09-26 03:15:43.970231	...	
402	Gurgaon_Bilaspur_HB (Haryana)	2018-09-26 03:15:43.970231	...	
403	Gurgaon_Bilaspur_HB (Haryana)	2018-09-26 03:15:43.970231	...	
404	Gurgaon_Bilaspur_HB (Haryana)	2018-09-26 03:15:43.970231	...	
405	Gurgaon_Bilaspur_HB (Haryana)	2018-09-26 03:15:43.970231	...	
...	
144796	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	
144797	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	
144798	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	
144799	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	
144800	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	

	source_name_city	source_name_place	source_name_code	\
401	JhumriTlya	RadhaCpx	D	
402	JhumriTlya	RadhaCpx	D	
403	JhumriTlya	RadhaCpx	D	
404	JhumriTlya	RadhaCpx	D	
405	JhumriTlya	RadhaCpx	D	
...	
144796	Gurgaon	Bilaspur	HB	
144797	Gurgaon	Bilaspur	HB	
144798	Gurgaon	Bilaspur	HB	
144799	Gurgaon	Bilaspur	HB	
144800	Gurgaon	Bilaspur	HB	

	source_name_state	destination_name_city	destination_name_place	\
401	Jharkhand	Gurgaon	Bilaspur	
402	Jharkhand	Gurgaon	Bilaspur	
403	Jharkhand	Gurgaon	Bilaspur	
404	Jharkhand	Gurgaon	Bilaspur	
405	Jharkhand	Gurgaon	Bilaspur	
...	
144796	Haryana	Bengaluru	Nelmngla	
144797	Haryana	Bengaluru	Nelmngla	
144798	Haryana	Bengaluru	Nelmngla	
144799	Haryana	Bengaluru	Nelmngla	
144800	Haryana	Bengaluru	Nelmngla	

	destination_name_code	destination_name_state	\
401	HB	Haryana	
402	HB	Haryana	
403	HB	Haryana	
404	HB	Haryana	
405	HB	Haryana	
...	
144796	H	Karnataka	
144797	H	Karnataka	
144798	H	Karnataka	
144799	H	Karnataka	
144800	H	Karnataka	

	time_taken_between_od_start_and_od_end_time	\
401	25.852	
402	25.852	
403	25.852	
404	25.852	
405	25.852	
...	...	
144796	49.162	
144797	49.162	
144798	49.162	
144799	49.162	
144800	49.162	

	start_scan_to_end_scan_in_hrs
401	25.85
402	25.85
403	25.85
404	25.85
405	25.85
...	...
144796	49.15
144797	49.15
144798	49.15
144799	49.15
144800	49.15

[17992 rows x 46 columns]

Outliers by feature name --> actual_time			
	data	trip_creation_time	\
406	training	2018-09-25 15:06:59.975279	
407	training	2018-09-25 15:06:59.975279	
408	training	2018-09-25 15:06:59.975279	
409	training	2018-09-25 15:06:59.975279	
410	training	2018-09-25 15:06:59.975279	
...	
144796	test	2018-10-01 18:17:37.047270	
144797	test	2018-10-01 18:17:37.047270	
144798	test	2018-10-01 18:17:37.047270	
144799	test	2018-10-01 18:17:37.047270	
144800	test	2018-10-01 18:17:37.047270	

	route_schedule_uuid	route_type	\
406	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	
407	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	
408	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	
409	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	
410	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	
...	
144796	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	
144797	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	
144798	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	
144799	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	
144800	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	

	trip_uuid	source_center	\
406	trip-153788801997503817	IND825409AAA	
407	trip-153788801997503817	IND825409AAA	
408	trip-153788801997503817	IND825409AAA	
409	trip-153788801997503817	IND825409AAA	
410	trip-153788801997503817	IND825409AAA	
...	
144796	trip-153841785704702048	IND000000ACB	
144797	trip-153841785704702048	IND000000ACB	
144798	trip-153841785704702048	IND000000ACB	
144799	trip-153841785704702048	IND000000ACB	
144800	trip-153841785704702048	IND000000ACB	

	source_name	destination_center	\
406	JhumriTlya_RadhaCpx_D (Jharkhand)	IND000000ACB	
407	JhumriTlya_RadhaCpx_D (Jharkhand)	IND000000ACB	
408	JhumriTlya_RadhaCpx_D (Jharkhand)	IND000000ACB	
409	JhumriTlya_RadhaCpx_D (Jharkhand)	IND000000ACB	
410	JhumriTlya_RadhaCpx_D (Jharkhand)	IND000000ACB	
...	
144796	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA	
144797	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA	
144798	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA	
144799	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA	
144800	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA	

	destination_name	od_start_time	...	\
406	Gurgaon_Bilaspur_HB (Haryana)	2018-09-26 03:15:43.970231	...	
407	Gurgaon_Bilaspur_HB (Haryana)	2018-09-26 03:15:43.970231	...	
408	Gurgaon_Bilaspur_HB (Haryana)	2018-09-26 03:15:43.970231	...	
409	Gurgaon_Bilaspur_HB (Haryana)	2018-09-26 03:15:43.970231	...	
410	Gurgaon_Bilaspur_HB (Haryana)	2018-09-26 03:15:43.970231	...	
...	
144796	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	
144797	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	
144798	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	
144799	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	
144800	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	

	source_name_city	source_name_place	source_name_code	\
406	JhumriTlya	RadhaCpx	D	
407	JhumriTlya	RadhaCpx	D	
408	JhumriTlya	RadhaCpx	D	
409	JhumriTlya	RadhaCpx	D	
410	JhumriTlya	RadhaCpx	D	
...	
144796	Gurgaon	Bilaspur	HB	
144797	Gurgaon	Bilaspur	HB	
144798	Gurgaon	Bilaspur	HB	
144799	Gurgaon	Bilaspur	HB	
144800	Gurgaon	Bilaspur	HB	

	source_name_state	destination_name_city	destination_name_place	\
406	Jharkhand	Gurgaon	Bilaspur	
407	Jharkhand	Gurgaon	Bilaspur	
408	Jharkhand	Gurgaon	Bilaspur	
409	Jharkhand	Gurgaon	Bilaspur	
410	Jharkhand	Gurgaon	Bilaspur	
...	
144796	Haryana	Bengaluru	Nelmngla	
144797	Haryana	Bengaluru	Nelmngla	
144798	Haryana	Bengaluru	Nelmngla	
144799	Haryana	Bengaluru	Nelmngla	
144800	Haryana	Bengaluru	Nelmngla	

	destination_name_code	destination_name_state	\
406	HB	Haryana	
407	HB	Haryana	
408	HB	Haryana	
409	HB	Haryana	
410	HB	Haryana	
...	
144796	H	Karnataka	
144797	H	Karnataka	
144798	H	Karnataka	
144799	H	Karnataka	
144800	H	Karnataka	

	time_taken_between_od_start_and_od_end_time	\
406	25.852	
407	25.852	
408	25.852	
409	25.852	
410	25.852	
...	...	
144796	49.162	
144797	49.162	
144798	49.162	
144799	49.162	
144800	49.162	

	start_scan_to_end_scan_in_hrs
406	25.85
407	25.85
408	25.85
409	25.85
410	25.85
...	...
144796	49.15
144797	49.15
144798	49.15
144799	49.15
144800	49.15

[16633 rows x 46 columns]

Outliers by feature name --> osrm_time \			
	data	trip_creation_time	
404	training	2018-09-25 15:06:59.975279	
405	training	2018-09-25 15:06:59.975279	
406	training	2018-09-25 15:06:59.975279	
407	training	2018-09-25 15:06:59.975279	
408	training	2018-09-25 15:06:59.975279	
...	
144796	test	2018-10-01 18:17:37.047270	
144797	test	2018-10-01 18:17:37.047270	
144798	test	2018-10-01 18:17:37.047270	
144799	test	2018-10-01 18:17:37.047270	
144800	test	2018-10-01 18:17:37.047270	

	route_schedule_uuid	route_type	\
404	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	
405	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	
406	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	
407	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	
408	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	
...	
144796	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	
144797	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	
144798	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	
144799	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	
144800	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	

	trip_uuid	source_center	\
404	trip-153788801997503817	IND825409AAA	
405	trip-153788801997503817	IND825409AAA	
406	trip-153788801997503817	IND825409AAA	
407	trip-153788801997503817	IND825409AAA	
408	trip-153788801997503817	IND825409AAA	
...	
144796	trip-153841785704702048	IND000000ACB	
144797	trip-153841785704702048	IND000000ACB	
144798	trip-153841785704702048	IND000000ACB	
144799	trip-153841785704702048	IND000000ACB	
144800	trip-153841785704702048	IND000000ACB	

	source_name	destination_center	\
404	JhumriTlya_RadhaCpx_D (Jharkhand)	IND000000ACB	
405	JhumriTlya_RadhaCpx_D (Jharkhand)	IND000000ACB	
406	JhumriTlya_RadhaCpx_D (Jharkhand)	IND000000ACB	
407	JhumriTlya_RadhaCpx_D (Jharkhand)	IND000000ACB	
408	JhumriTlya_RadhaCpx_D (Jharkhand)	IND000000ACB	
...	
144796	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA	
144797	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA	
144798	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA	
144799	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA	
144800	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA	

	destination_name	od_start_time	...	\
404	Gurgaon_Bilaspur_HB (Haryana)	2018-09-26 03:15:43.970231	...	
405	Gurgaon_Bilaspur_HB (Haryana)	2018-09-26 03:15:43.970231	...	
406	Gurgaon_Bilaspur_HB (Haryana)	2018-09-26 03:15:43.970231	...	
407	Gurgaon_Bilaspur_HB (Haryana)	2018-09-26 03:15:43.970231	...	
408	Gurgaon_Bilaspur_HB (Haryana)	2018-09-26 03:15:43.970231	...	
...	
144796	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	
144797	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	
144798	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	
144799	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	
144800	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	

	source_name_city	source_name_place	source_name_code	\
404	JhumriTlya	RadhaCpx	D	
405	JhumriTlya	RadhaCpx	D	
406	JhumriTlya	RadhaCpx	D	
407	JhumriTlya	RadhaCpx	D	
408	JhumriTlya	RadhaCpx	D	
...	
144796	Gurgaon	Bilaspur	HB	
144797	Gurgaon	Bilaspur	HB	
144798	Gurgaon	Bilaspur	HB	
144799	Gurgaon	Bilaspur	HB	
144800	Gurgaon	Bilaspur	HB	

	source_name_state	destination_name_city	destination_name_place	\
404	Jharkhand	Gurgaon	Bilaspur	
405	Jharkhand	Gurgaon	Bilaspur	
406	Jharkhand	Gurgaon	Bilaspur	
407	Jharkhand	Gurgaon	Bilaspur	
408	Jharkhand	Gurgaon	Bilaspur	
...	
144796	Haryana	Bengaluru	Nelmngla	
144797	Haryana	Bengaluru	Nelmngla	
144798	Haryana	Bengaluru	Nelmngla	
144799	Haryana	Bengaluru	Nelmngla	
144800	Haryana	Bengaluru	Nelmngla	

	destination_name_code	destination_name_state	\
404	HB	Haryana	
405	HB	Haryana	
406	HB	Haryana	
407	HB	Haryana	
408	HB	Haryana	
...	
144796	H	Karnataka	
144797	H	Karnataka	
144798	H	Karnataka	
144799	H	Karnataka	
144800	H	Karnataka	

	time_taken_between_od_start_and_od_end_time	\
404	25.852	
405	25.852	
406	25.852	
407	25.852	
408	25.852	
...	...	
144796	49.162	
144797	49.162	
144798	49.162	
144799	49.162	
144800	49.162	

	start_scan_to_end_scan_in_hrs
404	25.85
405	25.85
406	25.85
407	25.85
408	25.85
...	...
144796	49.15
144797	49.15
144798	49.15
144799	49.15
144800	49.15

[17603 rows x 46 columns]

Outliers by feature name --> osrm_distance			
	data	trip_creation_time	\
404	training	2018-09-25 15:06:59.975279	
405	training	2018-09-25 15:06:59.975279	
406	training	2018-09-25 15:06:59.975279	
407	training	2018-09-25 15:06:59.975279	
408	training	2018-09-25 15:06:59.975279	
...	
144796	test	2018-10-01 18:17:37.047270	
144797	test	2018-10-01 18:17:37.047270	
144798	test	2018-10-01 18:17:37.047270	
144799	test	2018-10-01 18:17:37.047270	
144800	test	2018-10-01 18:17:37.047270	

	route_schedule_uuid	route_type	\
404	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	
405	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	
406	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	
407	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	
408	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	
...	
144796	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	
144797	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	
144798	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	
144799	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	
144800	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	

	trip_uuid	source_center	\
404	trip-153788801997503817	IND825409AAA	
405	trip-153788801997503817	IND825409AAA	
406	trip-153788801997503817	IND825409AAA	
407	trip-153788801997503817	IND825409AAA	
408	trip-153788801997503817	IND825409AAA	
...	
144796	trip-153841785704702048	IND000000ACB	
144797	trip-153841785704702048	IND000000ACB	
144798	trip-153841785704702048	IND000000ACB	
144799	trip-153841785704702048	IND000000ACB	
144800	trip-153841785704702048	IND000000ACB	

	source_name	destination_center	\
404	JhumriTlya_RadhaCpx_D (Jharkhand)	IND000000ACB	
405	JhumriTlya_RadhaCpx_D (Jharkhand)	IND000000ACB	
406	JhumriTlya_RadhaCpx_D (Jharkhand)	IND000000ACB	
407	JhumriTlya_RadhaCpx_D (Jharkhand)	IND000000ACB	
408	JhumriTlya_RadhaCpx_D (Jharkhand)	IND000000ACB	
...	
144796	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA	
144797	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA	
144798	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA	
144799	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA	
144800	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA	

	destination_name	od_start_time	...	\
404	Gurgaon_Bilaspur_HB (Haryana)	2018-09-26 03:15:43.970231	...	
405	Gurgaon_Bilaspur_HB (Haryana)	2018-09-26 03:15:43.970231	...	
406	Gurgaon_Bilaspur_HB (Haryana)	2018-09-26 03:15:43.970231	...	
407	Gurgaon_Bilaspur_HB (Haryana)	2018-09-26 03:15:43.970231	...	
408	Gurgaon_Bilaspur_HB (Haryana)	2018-09-26 03:15:43.970231	...	
...	
144796	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	
144797	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	
144798	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	
144799	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	
144800	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	

	source_name_city	source_name_place	source_name_code	\
404	JhumriTlya	RadhaCpx	D	
405	JhumriTlya	RadhaCpx	D	
406	JhumriTlya	RadhaCpx	D	
407	JhumriTlya	RadhaCpx	D	
408	JhumriTlya	RadhaCpx	D	
...	
144796	Gurgaon	Bilaspur	HB	
144797	Gurgaon	Bilaspur	HB	
144798	Gurgaon	Bilaspur	HB	
144799	Gurgaon	Bilaspur	HB	
144800	Gurgaon	Bilaspur	HB	

	source_name_state	destination_name_city	destination_name_place	\
404	Jharkhand	Gurgaon	Bilaspur	
405	Jharkhand	Gurgaon	Bilaspur	
406	Jharkhand	Gurgaon	Bilaspur	
407	Jharkhand	Gurgaon	Bilaspur	
408	Jharkhand	Gurgaon	Bilaspur	
...	
144796	Haryana	Bengaluru	Nelmngla	
144797	Haryana	Bengaluru	Nelmngla	
144798	Haryana	Bengaluru	Nelmngla	
144799	Haryana	Bengaluru	Nelmngla	
144800	Haryana	Bengaluru	Nelmngla	

	destination_name_code	destination_name_state	\
404	HB	Haryana	
405	HB	Haryana	
406	HB	Haryana	
407	HB	Haryana	
408	HB	Haryana	
...	
144796	H	Karnataka	
144797	H	Karnataka	
144798	H	Karnataka	
144799	H	Karnataka	
144800	H	Karnataka	

	time_taken_between_od_start_and_od_end_time	\
404	25.852	
405	25.852	
406	25.852	
407	25.852	
408	25.852	
...	...	
144796	49.162	
144797	49.162	
144798	49.162	
144799	49.162	
144800	49.162	

	start_scan_to_end_scan_in_hrs
404	25.85
405	25.85
406	25.85
407	25.85
408	25.85
...	...
144796	49.15
144797	49.15
144798	49.15
144799	49.15
144800	49.15

[17816 rows x 46 columns]

Outliers by feature name --> factor			
	data	trip_creation_time	\
15	training	2018-09-14 15:42:46.437249	
16	training	2018-09-14 15:42:46.437249	
76	test	2018-09-27 14:16:14.819357	
77	test	2018-09-27 14:16:14.819357	
78	test	2018-09-27 14:16:14.819357	
...	
144634	training	2018-09-18 00:34:51.206487	
144658	training	2018-09-12 00:14:49.629525	
144848	training	2018-09-14 18:45:34.164734	
144854	training	2018-09-17 11:35:28.838714	
144866	training	2018-09-20 16:24:28.436231	

	route_schedule_uuid	route_type	\
15	thanos::sroute:a16bfa03-3462-4bce-9c82-5784c7d...	Carting	
16	thanos::sroute:a16bfa03-3462-4bce-9c82-5784c7d...	Carting	
76	thanos::sroute:1283977c-889a-4e96-b632-5bala69...	Carting	
77	thanos::sroute:1283977c-889a-4e96-b632-5bala69...	Carting	
78	thanos::sroute:1283977c-889a-4e96-b632-5bala69...	Carting	
...	
144634	thanos::sroute:387e7ab9-2237-48b1-af49-2508ce2...	FTL	
144658	thanos::sroute:b62ab3ed-c60b-47d2-8c91-fe62135...	Carting	
144848	thanos::sroute:40b6dc9c-faa1-4753-8bc8-ac8c3e0...	Carting	
144854	thanos::sroute:d8f74492-4484-412a-887a-61c8e6b...	Carting	
144866	thanos::sroute:f0569d2f-4e20-4c31-8542-67b86d5...	Carting	

	trip_uuid	source_center	\
15	trip-153693976643699843	IND400011AAA	
16	trip-153693976643699843	IND400011AAA	
76	trip-153805777481903807	IND600056AAB	
77	trip-153805777481903807	IND600056AAB	
78	trip-153805777481903807	IND600056AAB	
...	
144634	trip-153723089120625505	IND151001AAA	
144658	trip-153671128962918389	IND302014AAB	
144848	trip-153695073416451616	IND400102AAB	
144854	trip-153718412883843340	IND600056AAB	
144866	trip-153746066843555182	IND131028AAB	

	source_name	destination_center	\
15	LowerParel_CP (Maharashtra)	IND400072AAD	
16	LowerParel_CP (Maharashtra)	IND400072AAD	
76	MAA_Poonamallee_HB (Tamil Nadu)	IND600032AAB	
77	MAA_Poonamallee_HB (Tamil Nadu)	IND600032AAB	
78	MAA_Poonamallee_HB (Tamil Nadu)	IND600032AAB	
...	
144634	Bhatinda_DPC (Punjab)	IND151302AAA	
144658	Jaipur_Central_I_7 (Rajasthan)	IND302026AAA	
144848	Mumbai_Jogeshwri_L (Maharashtra)	IND421302AAG	
144854	MAA_Poonamallee_HB (Tamil Nadu)	IND600032AAB	
144866	Sonipat_Kundli_H (Haryana)	IND000000ACB	

	destination_name	od_start_time	...	\
15	Mumbai_Chndivli_PC (Maharashtra)	2018-09-14 15:42:46.437249	...	
16	Mumbai_Chndivli_PC (Maharashtra)	2018-09-14 15:42:46.437249	...	
76	Chennai_Hub (Tamil Nadu)	2018-09-27 14:16:14.819357	...	
77	Chennai_Hub (Tamil Nadu)	2018-09-27 14:16:14.819357	...	
78	Chennai_Hub (Tamil Nadu)	2018-09-27 14:16:14.819357	...	
...	
144634	TalwandiSabo_Wardno3_D (Punjab)	2018-09-18 00:34:51.206487	...	
144658	Jaipur_Bhankrot_DC (Rajasthan)	2018-09-12 00:14:49.629525	...	
144848	Bhiwandi_Mankoli_HB (Maharashtra)	2018-09-14 18:45:34.164734	...	
144854	Chennai_Hub (Tamil Nadu)	2018-09-17 11:35:28.838714	...	
144866	Gurgaon_Bilaspur_HB (Haryana)	2018-09-20 16:24:28.436231	...	

	source_name_city	source_name_place	source_name_code	\
15	NaN	NaN	NaN	
16	NaN	NaN	NaN	
76	NaN	NaN	NaN	
77	NaN	NaN	NaN	
78	NaN	NaN	NaN	
...	
144634	NaN	NaN	NaN	
144658	NaN	NaN	NaN	
144848	Mumbai	Jogeshwri	L	
144854	NaN	NaN	NaN	
144866	Sonipat	Kundli	H	

	source_name_state	destination_name_city	destination_name_place	\
15	NaN	Mumbai	Chndivli	
16	NaN	Mumbai	Chndivli	
76	NaN	NaN	NaN	
77	NaN	NaN	NaN	
78	NaN	NaN	NaN	
...	
144634	NaN	NaN	NaN	
144658	NaN	Jaipur	Bhankrot	
144848	Maharashtra	Bhiwandi	Mankoli	
144854	NaN	NaN	NaN	
144866	Haryana	Gurgaon	Bilaspur	

	destination_name_code	destination_name_state	\
15	PC	Maharashtra	
16	PC	Maharashtra	
76	NaN	NaN	
77	NaN	NaN	
78	NaN	NaN	
...	
144634	NaN	NaN	
144658	DC	Rajasthan	
144848	HB	Maharashtra	
144854	NaN	NaN	
144866	HB	Haryana	

	time_taken_between_od_start_and_od_end_time	\
15	1.816	
16	1.816	
76	2.999	
77	2.999	
78	2.999	
...	...	
144634	1.639	
144658	1.843	
144848	6.565	
144854	1.948	
144866	7.128	

	start_scan_to_end_scan_in_hrs
15	1.800
16	1.800
76	2.983
77	2.983
78	2.983
...	...
144634	1.633
144658	1.833
144848	6.550
144854	1.933
144866	7.117

[11429 rows x 46 columns]

Outliers by feature name --> segment_actual_time			
	data	trip_creation_time	\
21	training	2018-09-13 20:44:19.424489	
34	training	2018-09-13 20:44:19.424489	
72	test	2018-10-01 16:00:45.719099	
73	test	2018-10-01 16:00:45.719099	
106	training	2018-09-25 08:53:04.377810	
...	
144790	test	2018-10-01 18:17:37.047270	
144819	training	2018-09-26 14:05:52.096792	
144848	training	2018-09-14 18:45:34.164734	
144853	training	2018-09-22 11:30:41.399439	
144866	training	2018-09-20 16:24:28.436231	

	route_schedule_uuid	route_type	\
21	thanos::sroute:76951383-1608-44e4-a284-46d92e8...	FTL	
34	thanos::sroute:76951383-1608-44e4-a284-46d92e8...	FTL	
72	thanos::sroute:182fdad4-dc74-4c7d-ada4-0a76d4c...	FTL	
73	thanos::sroute:182fdad4-dc74-4c7d-ada4-0a76d4c...	FTL	
106	thanos::sroute:4460a38d-ab9b-484e-bd4e-f4201d0...	FTL	
...	
144790	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	
144819	thanos::sroute:f7de4133-6bd9-4367-a7f7-ab190b6...	FTL	
144848	thanos::sroute:40b6dc9c-faa1-4753-8bc8-ac8c3e0...	Carting	
144853	thanos::sroute:d81088e2-9ccd-43e9-9260-3e85633...	FTL	
144866	thanos::sroute:f0569d2f-4e20-4c31-8542-67b86d5...	Carting	

	trip_uuid	source_center	\
21	trip-153687145942424248	IND560099AAB	
34	trip-153687145942424248	IND560099AAB	
72	trip-153840964571880594	IND131028AAB	
73	trip-153840964571880594	IND247667AAB	
106	trip-153786558437756691	IND306401AAB	
...	
144790	trip-153841785704702048	IND000000ACB	
144819	trip-153797075209653066	IND413401AAA	
144848	trip-153695073416451616	IND400102AAB	
144853	trip-153761584139918815	IND421302AAG	
144866	trip-153746066843555182	IND131028AAB	

	source_name	destination_center	\
21	Bengaluru_Bomsndra_HB (Karnataka)	IND683511AAA	
34	Bengaluru_Bomsndra_HB (Karnataka)	IND683511AAA	
72	Sonipat_Kundli_H (Haryana)	IND247667AAB	
73	Roorkee_IOTCEncl_L (Uttarakhand)	IND249407AAA	
106	Pali_Nayagaon_I (Rajasthan)	IND342005AAD	
...	
144790	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA	
144819	Barshi_Kurduwadi_D (Maharashtra)	IND411033AAA	
144848	Mumbai_Jogeshwari_L (Maharashtra)	IND421302AAG	
144853	Bhiwandi_Mankoli_HB (Maharashtra)	IND411033AAA	
144866	Sonipat_Kundli_H (Haryana)	IND000000ACB	

	destination_name	od_start_time	...	\
21	Aluva_Peedika_H (Kerala)	2018-09-13 23:59:56.061158	...	
34	Aluva_Peedika_H (Kerala)	2018-09-13 23:59:56.061158	...	
72	Roorkee_IOTCEncl_L (Uttarakhand)	2018-10-01 16:00:45.719099	...	
73	Haridwar (Uttarakhand)	2018-10-01 23:55:44.909377	...	
106	Jodhpur_Basni_I (Rajasthan)	2018-09-25 21:31:00.741991	...	
...	
144790	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	
144819	Pune_Tathawde_H (Maharashtra)	2018-09-27 02:21:39.762995	...	
144848	Bhiwandi_Mankoli_HB (Maharashtra)	2018-09-14 18:45:34.164734	...	
144853	Pune_Tathawde_H (Maharashtra)	2018-09-22 11:30:41.399439	...	
144866	Gurgaon_Bilaspur_HB (Haryana)	2018-09-20 16:24:28.436231	...	

	source_name_city	source_name_place	source_name_code	\
21	Bengaluru	Bomsndra	HB	
34	Bengaluru	Bomsndra	HB	
72	Sonipat	Kundli	H	
73	Roorkee	IOTCEncl	L	
106	Pali	Nayagaon	I	
...	
144790	Gurgaon	Bilaspur	HB	
144819	Barshi	Kurduwdi	D	
144848	Mumbai	Jogeshwri	L	
144853	Bhiwandi	Mankoli	HB	
144866	Sonipat	Kundli	H	

	source_name_state	destination_name_city	destination_name_place	\
21	Karnataka	Aluva	Peedika	
34	Karnataka	Aluva	Peedika	
72	Haryana	Roorkee	IOTCEncl	
73	Uttarakhand	NaN	NaN	
106	Rajasthan	Jodhpur	Basni	
...	
144790	Haryana	Bengaluru	Nelmngla	
144819	Maharashtra	Pune	Tathawde	
144848	Maharashtra	Bhiwandi	Mankoli	
144853	Maharashtra	Pune	Tathawde	
144866	Haryana	Gurgaon	Bilaspur	

	destination_name_code	destination_name_state	\
21	H	Kerala	
34	H	Kerala	
72	L	Uttarakhand	
73	NaN	NaN	
106	I	Rajasthan	
...	
144790	H	Karnataka	
144819	H	Maharashtra	
144848	HB	Maharashtra	
144853	H	Maharashtra	
144866	HB	Haryana	

	time_taken_between_od_start_and_od_end_time	\
21	13.934	
34	13.934	
72	7.719	
73	1.871	
106	2.849	
...	...	
144790	49.162	
144819	6.224	
144848	6.565	
144853	10.240	
144866	7.128	

	start_scan_to_end_scan_in_hrs
21	13.933
34	13.933
72	7.717
73	1.867
106	2.833
...	...
144790	49.150
144819	6.217
144848	6.550
144853	10.233
144866	7.117

[9298 rows x 46 columns]

Outliers by feature name --> segment_osrm_time

		data	trip_creation_time	\
34		training	2018-09-13 20:44:19.424489	
38		test	2018-09-29 22:21:45.149226	
157		training	2018-09-15 23:58:16.827101	
158		training	2018-09-15 23:58:16.827101	
214		training	2018-09-17 00:14:20.789064	
...		
144802		training	2018-09-26 14:05:52.096792	
144829		training	2018-09-26 19:50:29.657378	
144837		training	2018-09-26 19:50:29.657378	
144843		training	2018-09-26 19:50:29.657378	
144845		training	2018-09-26 19:50:29.657378	

		route_schedule_uuid	route_type	\
34		thanos::sroute:76951383-1608-44e4-a284-46d92e8...	FTL	
38		thanos::sroute:0904e75c-b3ac-4278-96cf-802835a...	FTL	
157		thanos::sroute:fb308c0f-ea3a-48ef-a6c3-4776341...	FTL	
158		thanos::sroute:fb308c0f-ea3a-48ef-a6c3-4776341...	FTL	
214		thanos::sroute:d0cd2cb2-ce42-4103-b999-f8899e9...	FTL	
...		
144802		thanos::sroute:f7de4133-6bd9-4367-a7f7-ab190b6...	FTL	
144829		thanos::sroute:f6dlba62-76a2-4dba-83ec-3ac0803...	FTL	
144837		thanos::sroute:f6dlba62-76a2-4dba-83ec-3ac0803...	FTL	
144843		thanos::sroute:f6dlba62-76a2-4dba-83ec-3ac0803...	FTL	
144845		thanos::sroute:f6dlba62-76a2-4dba-83ec-3ac0803...	FTL	

		trip_uuid	source_center	\
34		trip-153687145942424248	IND560099AAB	
38		trip-153825970514894360	IND141109AAA	
157		trip-153705589682687518	IND206001AAA	
158		trip-153705589682687518	IND206001AAA	
214		trip-153714326609873773	IND431517AAB	
...		
144802		trip-153797075209653066	IND411033AAA	
144829		trip-153799142965708367	IND454001AAA	
144837		trip-153799142965708367	IND457226AAA	
144843		trip-153799142965708367	IND457226AAA	
144845		trip-153799142965708367	IND457226AAA	

		source_name	destination_center	\
34		Bengaluru_Bomsndra_HB (Karnataka)	IND683511AAA	
38		Raikot_DC (Punjab)	IND000000ACA	
157		Etawah_MhraChng_D (Uttar Pradesh)	IND000000ACB	
158		Etawah_MhraChng_D (Uttar Pradesh)	IND000000ACB	
214		Ambajogai_BnsllNgr_D (Maharashtra)	IND411033AAA	
...		
144802		Pune_Tathawde_H (Maharashtra)	IND413002AAA	
144829		Dhar_Trimurti_D (Madhya Pradesh)	IND457001AAA	
144837		Jaora_RtlamNka_D (Madhya Pradesh)	IND382430AAB	
144843		Jaora_RtlamNka_D (Madhya Pradesh)	IND382430AAB	
144845		Jaora_RtlamNka_D (Madhya Pradesh)	IND382430AAB	

		destination_name	od_start_time	...	\
34		Aluva_Peedika_H (Kerala)	2018-09-13 23:59:56.061158	...	
38		Ludhiana_MilrGanj_HB (Punjab)	2018-09-30 05:12:34.503322	...	
157		Gurgaon_Bilaspur_HB (Haryana)	2018-09-17 02:46:57.274441	...	
158		Gurgaon_Bilaspur_HB (Haryana)	2018-09-17 02:46:57.274441	...	
214		Pune_Tathawde_H (Maharashtra)	2018-09-17 05:21:32.158856	...	
...		
144802		Solapur_Central_I_2 (Maharashtra)	2018-09-26 14:05:52.096792	...	
144829		Ratlam_Khjwli_DC (Madhya Pradesh)	2018-09-27 02:48:14.315366	...	
144837		Ahmedabad_East_H_1 (Gujarat)	2018-09-27 06:55:50.265761	...	
144843		Ahmedabad_East_H_1 (Gujarat)	2018-09-27 06:55:50.265761	...	
144845		Ahmedabad_East_H_1 (Gujarat)	2018-09-27 06:55:50.265761	...	

	source_name_city	source_name_place	source_name_code	\
34	Bengaluru	Bomsndra	HB	
38	NaN	NaN	NaN	
157	NaN	NaN	NaN	
158	NaN	NaN	NaN	
214	Ambajogai	BnsllNgr	D	
...	
144802	Pune	Tathawde	H	
144829	NaN	NaN	NaN	
144837	NaN	NaN	NaN	
144843	NaN	NaN	NaN	
144845	NaN	NaN	NaN	

	source_name_state	destination_name_city	destination_name_place	\
34	Karnataka	Aluva	Peedika	
38	NaN	Ludhiana	MilrGanj	
157	NaN	Gurgaon	Bilaspur	
158	NaN	Gurgaon	Bilaspur	
214	Maharashtra	Pune	Tathawde	
...	
144802	Maharashtra	NaN	NaN	
144829	NaN	NaN	NaN	
144837	NaN	NaN	NaN	
144843	NaN	NaN	NaN	
144845	NaN	NaN	NaN	

	destination_name_code	destination_name_state	\
34	H	Kerala	
38	HB	Punjab	
157	HB	Haryana	
158	HB	Haryana	
214	H	Maharashtra	
...	
144802	NaN	NaN	
144829	NaN	NaN	
144837	NaN	NaN	
144843	NaN	NaN	
144845	NaN	NaN	

	time_taken_between_od_start_and_od_end_time	\
34	13.934	
38	1.536	
157	8.350	
158	8.350	
214	10.954	
...	...	
144802	9.260	
144829	2.303	
144837	10.379	
144843	10.379	
144845	10.379	

	start_scan_to_end_scan_in_hrs
34	13.933
38	1.533
157	8.350
158	8.350
214	10.950
...	...
144802	9.250
144829	2.300
144837	10.367
144843	10.367
144845	10.367

[6378 rows x 46 columns]

Outliers by feature name --> segment_osrm_distance

	data	trip_creation_time	\
34	training	2018-09-13 20:44:19.424489	
157	training	2018-09-15 23:58:16.827101	
158	training	2018-09-15 23:58:16.827101	
214	training	2018-09-17 00:14:20.789064	
316	training	2018-09-24 02:57:00.372087	
...	
144774	test	2018-10-01 18:17:37.047270	
144802	training	2018-09-26 14:05:52.096792	
144829	training	2018-09-26 19:50:29.657378	
144837	training	2018-09-26 19:50:29.657378	
144845	training	2018-09-26 19:50:29.657378	

	route_schedule_uuid	route_type	\
34	thanos::sroute:76951383-1608-44e4-a284-46d92e8...	FTL	
157	thanos::sroute:fb308c0f-ea3a-48ef-a6c3-4776341...	FTL	
158	thanos::sroute:fb308c0f-ea3a-48ef-a6c3-4776341...	FTL	
214	thanos::sroute:d0cd2cb2-ce42-4103-b999-f8899e9...	FTL	
316	thanos::sroute:8f136f2a-7552-4c91-acfa-ff555d1...	FTL	
...	
144774	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	
144802	thanos::sroute:f7de4133-6bd9-4367-a7f7-ab190b6...	FTL	
144829	thanos::sroute:f6dlba62-76a2-4dba-83ec-3ac0803...	FTL	
144837	thanos::sroute:f6dlba62-76a2-4dba-83ec-3ac0803...	FTL	
144845	thanos::sroute:f6dlba62-76a2-4dba-83ec-3ac0803...	FTL	

	trip_uuid	source_center	\
34	trip-153687145942424248	IND560099AAB	
157	trip-153705589682687518	IND206001AAA	
158	trip-153705589682687518	IND206001AAA	
214	trip-153714326609873773	IND431517AAB	
316	trip-153775782037183132	IND413002AAA	
...	
144774	trip-153841785704702048	IND000000ACB	
144802	trip-153797075209653066	IND411033AAA	
144829	trip-153799142965708367	IND454001AAA	
144837	trip-153799142965708367	IND457226AAA	
144845	trip-153799142965708367	IND457226AAA	

	source_name	destination_center	\
34	Bengaluru_Bomsndra_HB (Karnataka)	IND683511AAA	
157	Etawah_MhraChng_D (Uttar Pradesh)	IND000000ACB	
158	Etawah_MhraChng_D (Uttar Pradesh)	IND000000ACB	
214	Ambajogai_BnsllNgr_D (Maharashtra)	IND411033AAA	
316	Solapur_Central_I_2 (Maharashtra)	IND501359AAE	
...	
144774	Gurgaon_Bilaspur_HB (Haryana)	IND562132AAA	
144802	Pune_Tathawde_H (Maharashtra)	IND413002AAA	
144829	Dhar_Trimurti_D (Madhya Pradesh)	IND457001AAA	
144837	Jaora_RtlamNka_D (Madhya Pradesh)	IND382430AAB	
144845	Jaora_RtlamNka_D (Madhya Pradesh)	IND382430AAB	

	destination_name	od_start_time	...	\
34	Aluva_Peedika_H (Kerala)	2018-09-13 23:59:56.061158	...	
157	Gurgaon_Bilaspur_HB (Haryana)	2018-09-17 02:46:57.274441	...	
158	Gurgaon_Bilaspur_HB (Haryana)	2018-09-17 02:46:57.274441	...	
214	Pune_Tathawde_H (Maharashtra)	2018-09-17 05:21:32.158856	...	
316	Hyderabad_Shamshbd_H (Telangana)	2018-09-24 12:46:04.801166	...	
...	
144774	Bangalore_Nelmngla_H (Karnataka)	2018-10-02 09:02:19.284969	...	
144802	Solapur_Central_I_2 (Maharashtra)	2018-09-26 14:05:52.096792	...	
144829	Ratlam_Khjurwli_DC (Madhya Pradesh)	2018-09-27 02:48:14.315366	...	
144837	Ahmedabad_East_H_1 (Gujarat)	2018-09-27 06:55:50.265761	...	
144845	Ahmedabad_East_H_1 (Gujarat)	2018-09-27 06:55:50.265761	...	

	source_name_city	source_name_place	source_name_code	\
34	Bengaluru	Bomsndra	HB	
157	NaN	NaN	NaN	
158	NaN	NaN	NaN	
214	Ambajogai	BnsllNgr	D	
316	NaN	NaN	NaN	
...	
144774	Gurgaon	Bilaspur	HB	
144802	Pune	Tathawde	H	
144829	NaN	NaN	NaN	
144837	NaN	NaN	NaN	
144845	NaN	NaN	NaN	

	source_name_state	destination_name_city	destination_name_place	\
34	Karnataka	Aluva	Peedika	
157	NaN	Gurgaon	Bilaspur	
158	NaN	Gurgaon	Bilaspur	
214	Maharashtra	Pune	Tathawde	
316	NaN	Hyderabad	Shamshbd	
...	
144774	Haryana	Bengaluru	Nelmngla	
144802	Maharashtra	NaN	NaN	
144829	NaN	NaN	NaN	
144837	NaN	NaN	NaN	
144845	NaN	NaN	NaN	

	destination_name_code	destination_name_state	\
34	H	Kerala	
157	HB	Haryana	
158	HB	Haryana	
214	H	Maharashtra	
316	H	Telangana	
...	
144774	H	Karnataka	
144802	NaN	NaN	
144829	NaN	NaN	
144837	NaN	NaN	
144845	NaN	NaN	

	time_taken_between_od_start_and_od_end_time	\
34	13.934	
157	8.350	
158	8.350	
214	10.954	
316	10.822	
...	...	
144774	49.162	
144802	9.260	
144829	2.303	
144837	10.379	
144845	10.379	

	start_scan_to_end_scan_in_hrs
34	13.933
157	8.350
158	8.350
214	10.950
316	10.817
...	...
144774	49.150
144802	9.250
144829	2.300
144837	10.367
144845	10.367

[4315 rows x 46 columns]

Outliers by feature name -->	segment_factor
data	trip_creation_time \
6	training 2018-09-20 02:35:36.476840
9	training 2018-09-20 02:35:36.476840
15	training 2018-09-14 15:42:46.437249
47	training 2018-09-12 01:33:48.711350
54	training 2018-09-12 01:33:48.711350
...	...
144846	training 2018-09-26 19:50:29.657378
144848	training 2018-09-14 18:45:34.164734
144852	training 2018-09-22 11:30:41.399439
144853	training 2018-09-22 11:30:41.399439
144866	training 2018-09-20 16:24:28.436231

	route_schedule_uuid	route_type \
6	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting
9	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting
15	thanos::sroute:a16bfa03-3462-4bce-9c82-5784c7d...	Carting
47	thanos::sroute:5f7d8d49-ae14-430e-9333-37361e1...	Carting
54	thanos::sroute:5f7d8d49-ae14-430e-9333-37361e1...	Carting
...
144846	thanos::sroute:f6dlba62-76a2-4dba-83ec-3ac0803...	FTL
144848	thanos::sroute:40b6dc9c-faa1-4753-8bc8-ac8c3e0...	Carting
144852	thanos::sroute:d81088e2-9ccd-43e9-9260-3e85633...	FTL
144853	thanos::sroute:d81088e2-9ccd-43e9-9260-3e85633...	FTL
144866	thanos::sroute:f0569d2f-4e20-4c31-8542-67b86d5...	Carting

	trip_uuid	source_center \
6	trip-153741093647649320	IND388620AAB
9	trip-153741093647649320	IND388620AAB
15	trip-153693976643699843	IND400011AAA
47	trip-153671602871109556	IND362001AAA
54	trip-153671602871109556	IND362720AAA
...
144846	trip-153799142965708367	IND457226AAA
144848	trip-153695073416451616	IND400102AAB
144852	trip-153761584139918815	IND421302AAG
144853	trip-153761584139918815	IND421302AAG
144866	trip-153746066843555182	IND131028AAB

	source_name	destination_center \
6	Khambhat_MotvdDPP_D (Gujarat)	IND388320AAA
9	Khambhat_MotvdDPP_D (Gujarat)	IND388320AAA
15	LowerParel_CP (Maharashtra)	IND400072AAD
47	Junagadh_DPC (Gujarat)	IND362220AAA
54	Kodinar_NCplxDPP_D (Gujarat)	IND362560AAA
...
144846	Jaora_RtlamNka_D (Madhya Pradesh)	IND382430AAB
144848	Mumbai_Jogeshwri_L (Maharashtra)	IND421302AAG
144852	Bhiwandi_Mankoli_HB (Maharashtra)	IND411033AAA
144853	Bhiwandi_Mankoli_HB (Maharashtra)	IND411033AAA
144866	Sonipat_Kundli_H (Haryana)	IND000000ACB

	destination_name	od_start_time	...	\
6	Anand_Vaghasi_IP (Gujarat)	2018-09-20 04:47:45.236797	...	
9	Anand_Vaghasi_IP (Gujarat)	2018-09-20 04:47:45.236797	...	
15	Mumbai_Chndivli_PC (Maharashtra)	2018-09-14 15:42:46.437249	...	
47	Junagadh_keshod_DC (Gujarat)	2018-09-12 01:33:48.711350	...	
54	Una_Mamlatdr_DC (Gujarat)	2018-09-12 06:12:09.579013	...	
...	
144846	Ahmedabad_East_H_1 (Gujarat)	2018-09-27 06:55:50.265761	...	
144848	Bhiwandi_Mankoli_HB (Maharashtra)	2018-09-14 18:45:34.164734	...	
144852	Pune_Tathawde_H (Maharashtra)	2018-09-22 11:30:41.399439	...	
144853	Pune_Tathawde_H (Maharashtra)	2018-09-22 11:30:41.399439	...	
144866	Gurgaon_Bilaspur_HB (Haryana)	2018-09-20 16:24:28.436231	...	

	source_name_city	source_name_place	source_name_code	\
6	Khambhat	MotvdDPP	D	
9	Khambhat	MotvdDPP	D	
15	NaN	NaN	NaN	
47	NaN	NaN	NaN	
54	Kodinar	NCplxDPP	D	
...	
144846	NaN	NaN	NaN	
144848	Mumbai	Jogeshwri	L	
144852	Bhiwandi	Mankoli	HB	
144853	Bhiwandi	Mankoli	HB	
144866	Sonipat	Kundli	H	

	source_name_state	destination_name_city	destination_name_place	\
6	Gujarat	Anand	Vaghasi	
9	Gujarat	Anand	Vaghasi	
15	NaN	Mumbai	Chndivli	
47	NaN	Junagadh	keshod	
54	Gujarat	Una	Mamlatdr	
...	
144846	NaN	NaN	NaN	
144848	Maharashtra	Bhiwandi	Mankoli	
144852	Maharashtra	Pune	Tathawde	
144853	Maharashtra	Pune	Tathawde	
144866	Haryana	Gurgaon	Bilaspur	

	destination_name_code	destination_name_state	\
6	IP	Gujarat	
9	IP	Gujarat	
15	PC	Maharashtra	
47	DC	Gujarat	
54	DC	Gujarat	
...	
144846	NaN	NaN	
144848	HB	Maharashtra	
144852	H	Maharashtra	
144853	H	Maharashtra	
144866	HB	Haryana	

	time_taken_between_od_start_and_od_end_time	\
6	1.820	
9	1.820	
15	1.816	
47	1.143	
54	1.121	
...	...	
144846	10.379	
144848	6.565	
144852	10.240	
144853	10.240	
144866	7.128	

	start_scan_to_end_scan_in_hrs
6	1.817
9	1.817
15	1.800
47	1.133
54	1.117
...	...
144846	10.367
144848	6.550
144852	10.233
144853	10.233
144866	7.117

[13976 rows x 46 columns]

Outliers by feature name --> trip_creation_time_year

Empty DataFrame

Columns: [data, trip_creation_time, route_schedule_uuid, route_type, trip_uuid, source_center, source_name, destination_center, destination_name, od_start_time, od_end_time, start_scan_to_end_scan, is_cutoff, cutoff_factor, cutoff_timestamp, actual_distance_to_destination, actual_time, osrm_time, osrm_distance, factor, segment_actual_time, segment_osrm_time, segment_osrm_distance, segment_factor, trip_creation_time_year, trip_creation_time_month, trip_creation_time_weekday, trip_creation_time_day, od_start_time_year, od_start_time_month, od_start_time_weekday, od_start_time_day, od_end_time_year, od_end_time_month, od_end_time_weekday, od_end_time_day, source_name_city, source_name_place, source_name_code, source_name_state, destination_name_city, destination_name_place, destination_name_code, destination_name_state, time_taken_between_od_start_and_od_end_time, start_scan_to_end_scan_in_hrs]

Index: []

[0 rows x 46 columns]

Outliers by feature name --> trip_creation_time_weekday

Empty DataFrame

Columns: [data, trip_creation_time, route_schedule_uuid, route_type, trip_uuid, source_center, source_name, destination_center, destination_name, od_start_time, od_end_time, start_scan_to_end_scan, is_cutoff, cutoff_factor, cutoff_timestamp, actual_distance_to_destination, actual_time, osrm_time, osrm_distance, factor, segment_actual_time, segment_osrm_time, segment_osrm_distance, segment_factor, trip_creation_time_year, trip_creation_time_month, trip_creation_time_weekday, trip_creation_time_day, od_start_time_year, od_start_time_month, od_start_time_weekday, od_start_time_day, od_end_time_year, od_end_time_month, od_end_time_weekday, od_end_time_day, source_name_city, source_name_place, source_name_code, source_name_state, destination_name_city, destination_name_place, destination_name_code, destination_name_state, time_taken_between_od_start_and_od_end_time, start_scan_to_end_scan_in_hrs]

Index: []

[0 rows x 46 columns]

Outliers by feature name --> trip_creation_time_day

Empty DataFrame

Columns: [data, trip_creation_time, route_schedule_uuid, route_type, trip_uuid, source_center, source_name, destination_center, destination_name, od_start_time, od_end_time, start_scan_to_end_scan, is_cutoff, cutoff_factor, cutoff_timestamp, actual_distance_to_destination, actual_time, osrm_time, osrm_distance, factor, segment_actual_time, segment_osrm_time, segment_osrm_distance, segment_factor, trip_creation_time_year, trip_creation_time_month, trip_creation_time_weekday, trip_creation_time_day, od_start_time_year, od_start_time_month, od_start_time_weekday, od_start_time_day, od_end_time_year, od_end_time_month, od_end_time_weekday, od_end_time_day, source_name_city, source_name_place, source_name_code, source_name_state, destination_name_city, destination_name_place, destination_name_code, destination_name_state, time_taken_between_od_start_and_od_end_time, start_scan_to_end_scan_in_hrs]

Index: []

[0 rows x 46 columns]

Outliers by feature name --> od_start_time_year

Empty DataFrame

Columns: [data, trip_creation_time, route_schedule_uuid, route_type, trip_uuid, source_center, source_name, destination_center, destination_name, od_start_time, od_end_time, start_scan_to_end_scan, is_cutoff, cutoff_factor, cutoff_timestamp, actual_distance_to_destination, actual_time, osrm_time, osrm_distance, factor, segment_actual_time, segment_osrm_time, segment_osrm_distance, segment_factor, trip_creation_time_year, trip_creation_time_month, trip_creation_time_weekday, trip_creation_time_day, od_start_time_year, od_start_time_month, od_start_time_weekday, od_start_time_day, od_end_time_year, od_end_time_month, od_end_time_weekday, od_end_time_day, source_name_city, source_name_place, source_name_code, source_name_state, destination_name_city, destination_name_place, destination_name_code, destination_name_state, time_taken_between_od_start_and_od_end_time, start_scan_to_end_scan_in_hrs]

Index: []

[0 rows x 46 columns]

Outliers by feature name --> od_start_time_weekday

Empty DataFrame


```

art_scan_to_end_scan, is_cutoff, cutoff_factor, cutoff_timestamp, actual_distance_to_des
tination, actual_time, osrm_time, osrm_distance, factor, segment_actual_time, segment_os
rm_time, segment_osrm_distance, segment_factor, trip_creation_time_year, trip_creation_t
ime_month, trip_creation_time_weekday, trip_creation_time_day, od_start_time_year, od_st
art_time_month, od_start_time_weekday, od_start_time_day, od_end_time_year, od_end_time
month, od_end_time_weekday, od_end_time_day, source_name_city, source_name_place, source
_name_code, source_name_state, destination_name_city, destination_name_place, destinatio
n_name_code, destination_name_state, time_taken_between_od_start_and_od_end_time, start_
scan_to_end_scan_in_hrs]
Index: []

```

[0 rows x 46 columns]

Outliers by feature name --> time_taken_between_od_start_and_od_end_time

```

      data      trip_creation_time \
32950  training 2018-09-13 01:28:45.326644
32951  training 2018-09-13 01:28:45.326644
32952  training 2018-09-13 01:28:45.326644
32953  training 2018-09-13 01:28:45.326644
32954  training 2018-09-13 01:28:45.326644
...
79524  training 2018-09-19 13:44:58.665210
79525  training 2018-09-19 13:44:58.665210
79526  training 2018-09-19 13:44:58.665210
79527  training 2018-09-19 13:44:58.665210
123196  test    2018-10-01 23:35:54.432745

```

```

                                route_schedule_uuid route_type \
32950  thanos::sroute:6b87651c-fdf4-432f-bf80-0e394f3...      FTL
32951  thanos::sroute:6b87651c-fdf4-432f-bf80-0e394f3...      FTL
32952  thanos::sroute:6b87651c-fdf4-432f-bf80-0e394f3...      FTL
32953  thanos::sroute:6b87651c-fdf4-432f-bf80-0e394f3...      FTL
32954  thanos::sroute:6b87651c-fdf4-432f-bf80-0e394f3...      FTL
...
79524  thanos::sroute:bc7dbb1d-9379-4674-b8d3-f9c3b96...      FTL
79525  thanos::sroute:bc7dbb1d-9379-4674-b8d3-f9c3b96...      FTL
79526  thanos::sroute:bc7dbb1d-9379-4674-b8d3-f9c3b96...      FTL
79527  thanos::sroute:bc7dbb1d-9379-4674-b8d3-f9c3b96...      FTL
123196  thanos::sroute:4316e05f-b4cc-4ea7-b801-62a93ae...  Carting

```

```

      trip_uuid source_center \
32950  trip-153680212532637033  IND712311AAA
32951  trip-153680212532637033  IND712311AAA
32952  trip-153680212532637033  IND712311AAA
32953  trip-153680212532637033  IND712311AAA
32954  trip-153680212532637033  IND712311AAA
...
79524  trip-153736469866480991  IND000000ACB
79525  trip-153736469866480991  IND000000ACB
79526  trip-153736469866480991  IND000000ACB
79527  trip-153736469866480991  IND000000ACB
123196  trip-153843695443252828  IND764071AAB

```

```

      source_name destination_center \
32950  Kolkata_Dankuni_HB (West Bengal)  IND781018AAB
32951  Kolkata_Dankuni_HB (West Bengal)  IND781018AAB
32952  Kolkata_Dankuni_HB (West Bengal)  IND781018AAB
32953  Kolkata_Dankuni_HB (West Bengal)  IND781018AAB
32954  Kolkata_Dankuni_HB (West Bengal)  IND781018AAB
...
79524  Gurgaon_Bilaspur_HB (Haryana)  IND712311AAA
79525  Gurgaon_Bilaspur_HB (Haryana)  IND712311AAA
79526  Gurgaon_Bilaspur_HB (Haryana)  IND712311AAA
79527  Gurgaon_Bilaspur_HB (Haryana)  IND712311AAA
123196  Pappadahandi_Central_DPP_2 (Orissa)  IND530012AAA

```

```

destination_name      od_start_time \

```

32950		Guwahati_Hub	(Assam)	2018-09-13	01:28:45.326644
32951		Guwahati_Hub	(Assam)	2018-09-13	01:28:45.326644
32952		Guwahati_Hub	(Assam)	2018-09-13	01:28:45.326644
32953		Guwahati_Hub	(Assam)	2018-09-13	01:28:45.326644
32954		Guwahati_Hub	(Assam)	2018-09-13	01:28:45.326644
...					
79524	Kolkata_Dankuni_HB	(West Bengal)	2018-09-19	13:44:58.665210	
79525	Kolkata_Dankuni_HB	(West Bengal)	2018-09-19	13:44:58.665210	
79526	Kolkata_Dankuni_HB	(West Bengal)	2018-09-19	13:44:58.665210	
79527	Kolkata_Dankuni_HB	(West Bengal)	2018-09-19	13:44:58.665210	
123196	Visakhapatnam_Gajuwaka_IP	(Andhra Pradesh)	2018-10-02	15:21:51.236205	

	...	source_name_city	source_name_place	source_name_code	\
32950	...	NaN	NaN	NaN	
32951	...	NaN	NaN	NaN	
32952	...	NaN	NaN	NaN	
32953	...	NaN	NaN	NaN	
32954	...	NaN	NaN	NaN	
...	
79524	...	Gurgaon	Bilaspur	HB	
79525	...	Gurgaon	Bilaspur	HB	
79526	...	Gurgaon	Bilaspur	HB	
79527	...	Gurgaon	Bilaspur	HB	
123196	...	NaN	NaN	NaN	

		source_name_state	destination_name_city	destination_name_place	\
32950		NaN	NaN	NaN	
32951		NaN	NaN	NaN	
32952		NaN	NaN	NaN	
32953		NaN	NaN	NaN	
32954		NaN	NaN	NaN	
...		
79524		Haryana	NaN	NaN	
79525		Haryana	NaN	NaN	
79526		Haryana	NaN	NaN	
79527		Haryana	NaN	NaN	
123196		NaN	NaN	NaN	

		destination_name_code	destination_name_state	\
32950		NaN	NaN	
32951		NaN	NaN	
32952		NaN	NaN	
32953		NaN	NaN	
32954		NaN	NaN	
...		
79524		NaN	NaN	
79525		NaN	NaN	
79526		NaN	NaN	
79527		NaN	NaN	
123196		NaN	NaN	

		time_taken_between_od_start_and_od_end_time	\
32950		64.959	
32951		64.959	
32952		64.959	
32953		64.959	
32954		64.959	
...		...	
79524		70.658	
79525		70.658	
79526		70.658	
79527		70.658	
123196		131.643	

		start_scan_to_end_scan_in_hrs
32950		64.950

32951	64.950
32952	64.950
32953	64.950
32954	64.950
...	...
79524	70.650
79525	70.650
79526	70.650
79527	70.650
123196	131.633

[373 rows x 46 columns]

Outliers by feature name --> start_scan_to_end_scan_in_hrs

	data	trip_creation_time \
32950	training	2018-09-13 01:28:45.326644
32951	training	2018-09-13 01:28:45.326644
32952	training	2018-09-13 01:28:45.326644
32953	training	2018-09-13 01:28:45.326644
32954	training	2018-09-13 01:28:45.326644
...
79524	training	2018-09-19 13:44:58.665210
79525	training	2018-09-19 13:44:58.665210
79526	training	2018-09-19 13:44:58.665210
79527	training	2018-09-19 13:44:58.665210
123196	test	2018-10-01 23:35:54.432745

	route_schedule_uuid	route_type \
32950	thanos::sroute:6b87651c-fdf4-432f-bf80-0e394f3...	FTL
32951	thanos::sroute:6b87651c-fdf4-432f-bf80-0e394f3...	FTL
32952	thanos::sroute:6b87651c-fdf4-432f-bf80-0e394f3...	FTL
32953	thanos::sroute:6b87651c-fdf4-432f-bf80-0e394f3...	FTL
32954	thanos::sroute:6b87651c-fdf4-432f-bf80-0e394f3...	FTL
...
79524	thanos::sroute:bc7dbb1d-9379-4674-b8d3-f9c3b96...	FTL
79525	thanos::sroute:bc7dbb1d-9379-4674-b8d3-f9c3b96...	FTL
79526	thanos::sroute:bc7dbb1d-9379-4674-b8d3-f9c3b96...	FTL
79527	thanos::sroute:bc7dbb1d-9379-4674-b8d3-f9c3b96...	FTL
123196	thanos::sroute:4316e05f-b4cc-4ea7-b801-62a93ae...	Carting

	trip_uuid	source_center \
32950	trip-153680212532637033	IND712311AAA
32951	trip-153680212532637033	IND712311AAA
32952	trip-153680212532637033	IND712311AAA
32953	trip-153680212532637033	IND712311AAA
32954	trip-153680212532637033	IND712311AAA
...
79524	trip-153736469866480991	IND000000ACB
79525	trip-153736469866480991	IND000000ACB
79526	trip-153736469866480991	IND000000ACB
79527	trip-153736469866480991	IND000000ACB
123196	trip-153843695443252828	IND764071AAB

	source_name	destination_center \
32950	Kolkata_Dankuni_HB (West Bengal)	IND781018AAB
32951	Kolkata_Dankuni_HB (West Bengal)	IND781018AAB
32952	Kolkata_Dankuni_HB (West Bengal)	IND781018AAB
32953	Kolkata_Dankuni_HB (West Bengal)	IND781018AAB
32954	Kolkata_Dankuni_HB (West Bengal)	IND781018AAB
...
79524	Gurgaon_Bilaspur_HB (Haryana)	IND712311AAA
79525	Gurgaon_Bilaspur_HB (Haryana)	IND712311AAA
79526	Gurgaon_Bilaspur_HB (Haryana)	IND712311AAA
79527	Gurgaon_Bilaspur_HB (Haryana)	IND712311AAA
123196	Pappadahandi_Central_DPP_2 (Orissa)	IND530012AAA

destination_name

od_start_time \

32950		Guwahati_Hub	(Assam)	2018-09-13	01:28:45.326644
32951		Guwahati_Hub	(Assam)	2018-09-13	01:28:45.326644
32952		Guwahati_Hub	(Assam)	2018-09-13	01:28:45.326644
32953		Guwahati_Hub	(Assam)	2018-09-13	01:28:45.326644
32954		Guwahati_Hub	(Assam)	2018-09-13	01:28:45.326644
...	
79524	Kolkata_Dankuni_HB	(West Bengal)	2018-09-19	13:44:58.665210	
79525	Kolkata_Dankuni_HB	(West Bengal)	2018-09-19	13:44:58.665210	
79526	Kolkata_Dankuni_HB	(West Bengal)	2018-09-19	13:44:58.665210	
79527	Kolkata_Dankuni_HB	(West Bengal)	2018-09-19	13:44:58.665210	
123196	Visakhapatnam_Gajuwaka_IP	(Andhra Pradesh)	2018-10-02	15:21:51.236205	

	source_name_city	source_name_place	source_name_code	\
32950	...	NaN	NaN	NaN
32951	...	NaN	NaN	NaN
32952	...	NaN	NaN	NaN
32953	...	NaN	NaN	NaN
32954	...	NaN	NaN	NaN
...
79524	...	Gurgaon	Bilaspur	HB
79525	...	Gurgaon	Bilaspur	HB
79526	...	Gurgaon	Bilaspur	HB
79527	...	Gurgaon	Bilaspur	HB
123196	...	NaN	NaN	NaN

	source_name_state	destination_name_city	destination_name_place	\
32950	NaN	NaN	NaN	
32951	NaN	NaN	NaN	
32952	NaN	NaN	NaN	
32953	NaN	NaN	NaN	
32954	NaN	NaN	NaN	
...
79524	Haryana	NaN	NaN	
79525	Haryana	NaN	NaN	
79526	Haryana	NaN	NaN	
79527	Haryana	NaN	NaN	
123196	NaN	NaN	NaN	

	destination_name_code	destination_name_state	\
32950	NaN	NaN	
32951	NaN	NaN	
32952	NaN	NaN	
32953	NaN	NaN	
32954	NaN	NaN	
...
79524	NaN	NaN	
79525	NaN	NaN	
79526	NaN	NaN	
79527	NaN	NaN	
123196	NaN	NaN	

	time_taken_between_od_start_and_od_end_time	\
32950	64.959	
32951	64.959	
32952	64.959	
32953	64.959	
32954	64.959	
...
79524	70.658	
79525	70.658	
79526	70.658	
79527	70.658	
123196	131.643	

	start_scan_to_end_scan_in_hrs
32950	64.950

32951	64.950
32952	64.950
32953	64.950
32954	64.950
...	...
79524	70.650
79525	70.650
79526	70.650
79527	70.650
123196	131.633

[373 rows x 46 columns]

In [257...

```
continious_features
```

Out[257]:

```
Index(['start_scan_to_end_scan', 'cutoff_factor',
      'actual_distance_to_destination', 'actual_time', 'osrm_time',
      'osrm_distance', 'factor', 'segment_actual_time', 'segment_osrm_time',
      'segment_osrm_distance', 'segment_factor', 'trip_creation_time_year',
      'trip_creation_time_weekday', 'trip_creation_time_day',
      'od_start_time_year', 'od_start_time_weekday', 'od_start_time_day',
      'od_end_time_year', 'od_end_time_weekday', 'od_end_time_day',
      'time_taken_between_od_start_and_od_end_time',
      'start_scan_to_end_scan_in_hrs'],
      dtype='object')
```

In [258...

```
find_outliers_IQR("actual_time")
```

Outliers by feature name --> actual_time

Out[258]:

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center		
	406	training	2018-09-25 15:06:59.975279	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	trip-153788801997503817	IND825409AAA	Jhur
	407	training	2018-09-25 15:06:59.975279	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	trip-153788801997503817	IND825409AAA	Jhur
	408	training	2018-09-25 15:06:59.975279	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	trip-153788801997503817	IND825409AAA	Jhur
	409	training	2018-09-25 15:06:59.975279	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	trip-153788801997503817	IND825409AAA	Jhur
	410	training	2018-09-25 15:06:59.975279	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	trip-153788801997503817	IND825409AAA	Jhur

	144796	test	2018-10-01 18:17:37.047270	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	trip-153841785704702048	IND000000ACB	G
	144797	test	2018-10-01 18:17:37.047270	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	trip-153841785704702048	IND000000ACB	G
	144798	test	2018-10-01 18:17:37.047270	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	trip-153841785704702048	IND000000ACB	G
	144799	test	2018-10-01 18:17:37.047270	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	trip-153841785704702048	IND000000ACB	G
	144800	test	2018-10-01 18:17:37.047270	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	trip-153841785704702048	IND000000ACB	G

16633 rows × 46 columns

In [259...

```
find_outliers_IQR("segment_actual_time")
```

Outliers by feature name --> segment_actual_time

Out[259]:

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center		
	21	training	2018-09-13 20:44:19.424489	thanos::sroute:76951383-1608-44e4-a284-46d92e8...	FTL	trip-153687145942424248	IND560099AAB	Ben
	34	training	2018-09-13 20:44:19.424489	thanos::sroute:76951383-1608-44e4-a284-46d92e8...	FTL	trip-153687145942424248	IND560099AAB	Ben
	72	test	2018-10-01 16:00:45.719099	thanos::sroute:182fdad4-dc74-4c7d-ada4-0a76d4c...	FTL	trip-153840964571880594	IND131028AAB	
	73	test	2018-10-01 16:00:45.719099	thanos::sroute:182fdad4-dc74-4c7d-ada4-0a76d4c...	FTL	trip-153840964571880594	IND247667AAB	
	106	training	2018-09-25 08:53:04.377810	thanos::sroute:4460a38d-ab9b-484e-bd4e-f4201d0...	FTL	trip-153786558437756691	IND306401AAB	
	
	144790	test	2018-10-01 18:17:37.047270	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	trip-153841785704702048	IND000000ACB	(
	144819	training	2018-09-26 14:05:52.096792	thanos::sroute:f7de4133-6bd9-4367-a7f7-ab190b6...	FTL	trip-153797075209653066	IND413401AAA	
	144848	training	2018-09-14 18:45:34.164734	thanos::sroute:40b6dc9c-faa1-4753-8bc8-ac8c3e0...	Carting	trip-153695073416451616	IND400102AAB	
	144853	training	2018-09-22 11:30:41.399439	thanos::sroute:d81088e2-9ccd-43e9-9260-3e85633...	FTL	trip-153761584139918815	IND421302AAG	E
	144866	training	2018-09-20 16:24:28.436231	thanos::sroute:f0569d2f-4e20-4c31-8542-67b86d5...	Carting	trip-153746066843555182	IND131028AAB	

9298 rows × 46 columns

In [260...

```
find_outliers_IQR("actual_time")
```

Outliers by feature name --> actual_time

Out[260]:

	data	trip_creation_time	route_schedule_uuid	route_type		trip_uuid	source_center	
	406	training	2018-09-25 15:06:59.975279	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	153788801997503817	trip-IND825409AAA	Jhun
	407	training	2018-09-25 15:06:59.975279	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	153788801997503817	trip-IND825409AAA	Jhun
	408	training	2018-09-25 15:06:59.975279	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	153788801997503817	trip-IND825409AAA	Jhun
	409	training	2018-09-25 15:06:59.975279	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	153788801997503817	trip-IND825409AAA	Jhun
	410	training	2018-09-25 15:06:59.975279	thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...	FTL	153788801997503817	trip-IND825409AAA	Jhun

	144796	test	2018-10-01 18:17:37.047270	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	153841785704702048	trip-IND000000ACB	G
	144797	test	2018-10-01 18:17:37.047270	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	153841785704702048	trip-IND000000ACB	G
	144798	test	2018-10-01 18:17:37.047270	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	153841785704702048	trip-IND000000ACB	G
	144799	test	2018-10-01 18:17:37.047270	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	153841785704702048	trip-IND000000ACB	G
	144800	test	2018-10-01 18:17:37.047270	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	153841785704702048	trip-IND000000ACB	G

16633 rows × 46 columns

- **Conclusion**

- **Outliers impacts mean based statistical methods**
- **Observation during outlier removal**
- **There are outliers in almost every features**
- **Removing those outliers iteratively , can result loss of significant feature**
- **Need domain expert consultation** before removing independent feature based outliers
- Hence **proceeding with Baseline analysis with outliers**
- Moreover, certain deep learning model can work without outliers , hence skipping outlier removal

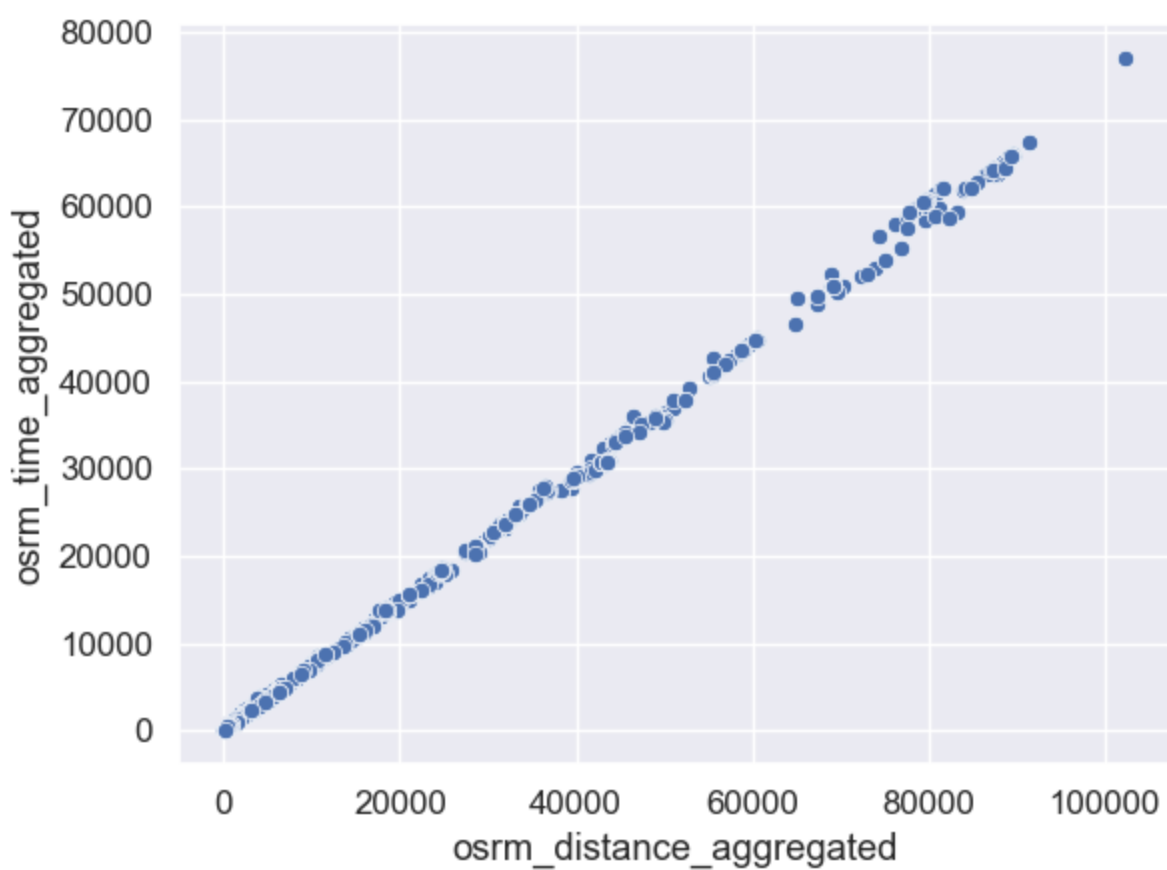
Checking relationship between aggregated fields

In [261]:

```
sns.scatterplot(x="osrm_distance_aggregated", y="osrm_time_aggregated", data=df_agg)
```

Out[261]:

```
<AxesSubplot:xlabel='osrm_distance_aggregated', ylabel='osrm_time_aggregated'>
```

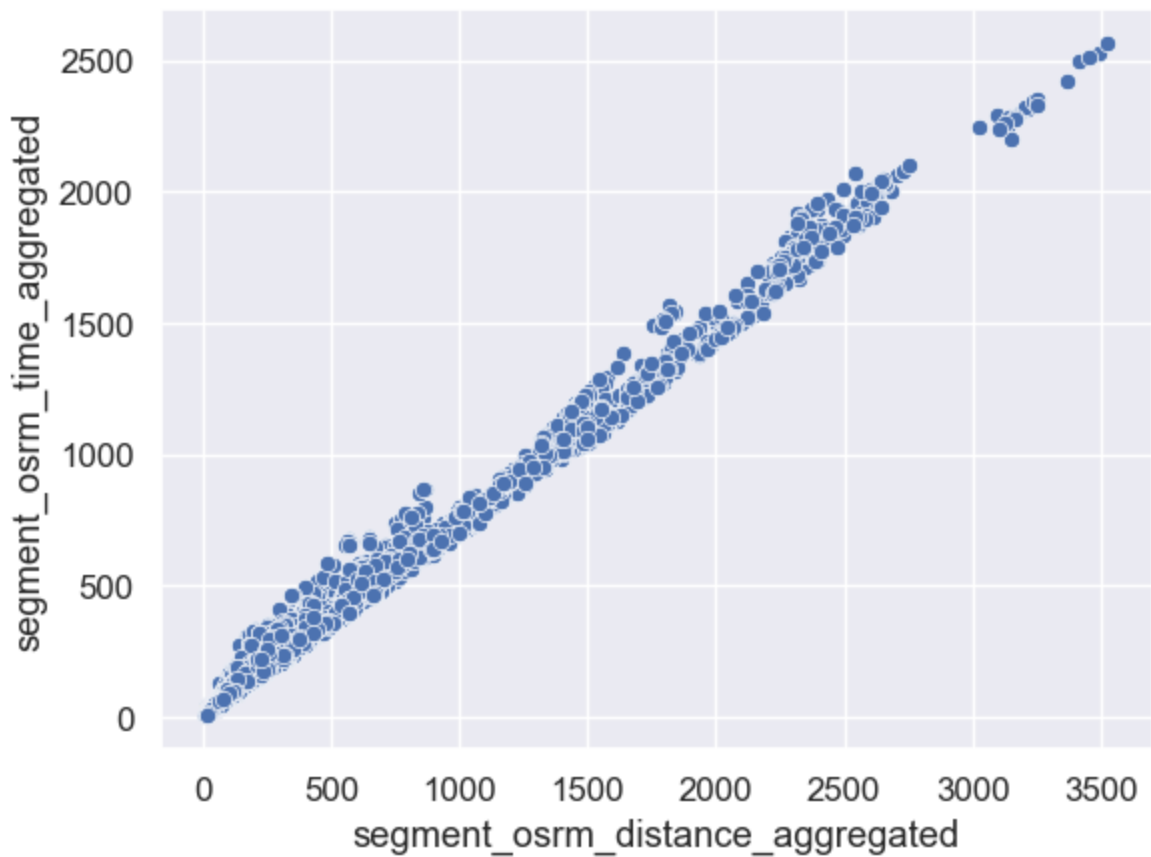


In [262]...

```
sns.scatterplot(x="segment_osrm_distance_aggregated", y="segment_osrm_time_aggregated",
```

Out[262]:

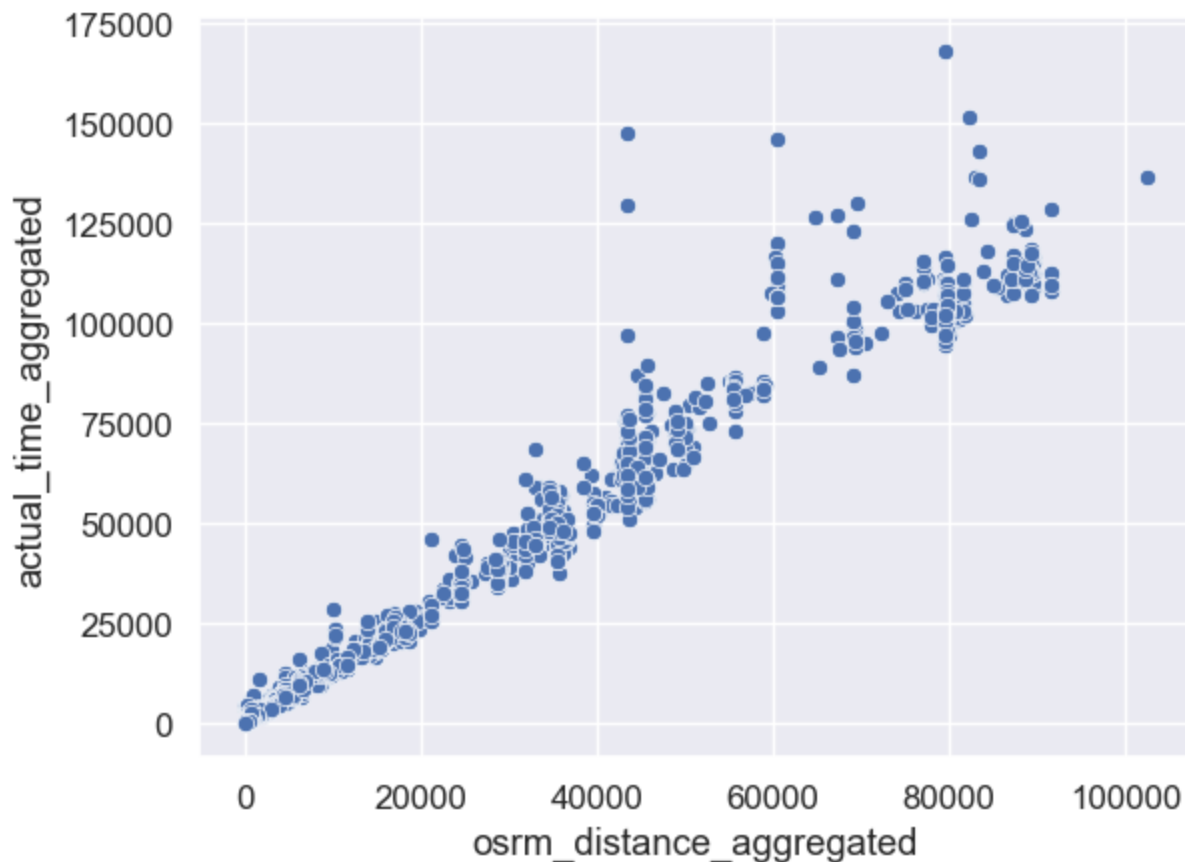
```
<AxesSubplot:xlabel='segment_osrm_distance_aggregated', ylabel='segment_osrm_time_aggregated'>
```



In [263]...

```
sns.scatterplot(x="osrm_distance_aggregated", y="actual_time_aggregated", data=df_agg)
```

Out[263]: <AxesSubplot: xlabel='osrm_distance_aggregated', ylabel='actual_time_aggregated'>



- **Conclusion**

- **Approximate Linear relationship observed** between following **aggregated features**
 - "osrm_distance_aggregated" vs "osrm_time_aggregated"
 - "segment_osrm_distance_aggregated" vs "segment_osrm_time_aggregated"
 - "osrm_distance_aggregated" vs "actual_time_aggregated"

Handling categorical values

- Categorical to Numerical encoding

```
In [264... df["route_type"].value_counts()
```

```
Out[264]: FTL          99660
Carting      45207
Name: route_type, dtype: int64
```

```
In [265... from sklearn.preprocessing import LabelEncoder
# Running level encoding for conversion from categorical to numerical data for feeding
label_encoder = LabelEncoder()
col='route_type'
df[col] = label_encoder.fit_transform(df[col])
```

```
In [266... df["route_type"].value_counts()
```

```
Out[266]: 1      99660
0       45207
Name: route_type, dtype: int64
```

Column Normalization /Column Standardization

- Normalize/ Standardize the numerical
 - MinMaxScaler
 - StandardScaler.

In [267...
continious_features

Out[267]: Index(['start_scan_to_end_scan', 'cutoff_factor',
'actual_distance_to_destination', 'actual_time', 'osrm_time',
'osrm_distance', 'factor', 'segment_actual_time', 'segment_osrm_time',
'segment_osrm_distance', 'segment_factor', 'trip_creation_time_year',
'trip_creation_time_weekday', 'trip_creation_time_day',
'od_start_time_year', 'od_start_time_weekday', 'od_start_time_day',
'od_end_time_year', 'od_end_time_weekday', 'od_end_time_day',
'time_taken_between_od_start_and_od_end_time',
'start_scan_to_end_scan_in_hrs'],
dtype='object')

In [268...
from sklearn.preprocessing import StandardScaler, MinMaxScaler

scaler = StandardScaler()
std_data = scaler.fit_transform(df[continious_features])
std_data = pd.DataFrame(std_data, columns=continious_features)
std_data.head()

Out[268]:

	start_scan_to_end_scan	cutoff_factor	actual_distance_to_destination	actual_time	osrm_time	osrm_distance	
0	-0.844026	-0.649525	-0.648246	-0.673677	-0.658642	-0.647814	-0.4
1	-0.844026	-0.623419	-0.623604	-0.656958	-0.629422	-0.624640	-0.5
2	-0.844026	-0.597314	-0.598385	-0.630207	-0.603449	-0.598958	-0.4
3	-0.844026	-0.571208	-0.573802	-0.593424	-0.564489	-0.568034	-0.3
4	-0.844026	-0.562506	-0.564329	-0.583392	-0.551502	-0.547479	-0.3

5 rows × 22 columns

In [269...
scaler = MinMaxScaler()
max_scaler_data = scaler.fit_transform(df[continious_features])
max_scaler_data = pd.DataFrame(max_scaler_data, columns=continious_features)
max_scaler_data.head()

Out[269]:

	start_scan_to_end_scan	cutoff_factor	actual_distance_to_destination	actual_time	osrm_time	osrm_distance	
0	0.008378	0.000000	0.000748	0.001105	0.002976	0.001276	0.0
1	0.008378	0.004692	0.005180	0.003316	0.008333	0.005488	0.0
2	0.008378	0.009385	0.009715	0.006854	0.013095	0.010155	0.0
3	0.008378	0.014077	0.014135	0.011718	0.020238	0.015775	0.0
4	0.008378	0.015641	0.015839	0.013044	0.022619	0.019511	0.0

5 rows × 22 columns

Business Insights - Should include patterns observed in the data along

with what you can infer from it.

- Relatively **less full truck loads** trips **starting on 5th or 6th day of the month**
- Relatively **large full truck loads** trips **ending on 5th or 6th day of the month**
- Relatively **less full truck loads** trips **ending on 7th or 8th day of the month**
- **Most Time taken route** (i.e. for route type full truck load) to deliver from source to destination are
 - **Haryana**
 - **Karnataka**
 - **Maharashtra**
 - **Delhi**
 - **Telangana**
- Actual **time taken to complete the delivery** are ****high** for source/destination
 - **Haryana**
 - **Karnataka**
 - **Maharashtra**
 - **Delhi**
 - **Telangana**
- Most **distanced cities** for full truck deliveries are **Gurgaon , Bengaluru , Bhiwandi**
- **Most trips** are being **booked on 12,13,15,17,18,20,21,22,25,26 days of the month**
- **osrm_time** (i.e. An open-source routing engine calculated time) is **not close to actual time** of delivery
 - **Estimation of delivery time needs more accurate prediction**
 - **Once delivery time is accurately predicted** then **more pre-booking** can be taken up
- Approximate **Linear relationship observed** between **following distance and time features**
 - "actual_distance_to_destination" vs "osrm_time"
 - "osrm_distance" vs "osrm_time"
 - "start_scan_to_end_scan" vs "actual_time"
 - "osrm_distance" vs "osrm_time"

Check from where most orders are coming from (State, Corridor etc)

```
In [270... df["source_name_city"].value_counts()
```

```
Out[270]: Gurgaon          23639
Bengaluru        14206
Bhiwandi         9088
Delhi            4318
Pune             4160
...
Kayamkulam       1
Chikhli          1
Kothanalloor    1
Thirthahalli     1
Soro             1
Name: source_name_city, Length: 560, dtype: int64
```

```
In [271... selected_features = ['route_type', 'source_center', 'source_name', 'destination_center',
df_selected = df[selected_features]
```

```
In [272... # Show percentage values on the top of the bar
def show_values_on_bars(axes, h_v="v", space=1):
    total = float(len(df_selected))
    def _show_on_single_plot(ax):
```

```

if h_v == "v":
    for p in ax.patches:
        _x = p.get_x() + p.get_width() / 2
        _y = p.get_y() + p.get_height()
        value='{:.1f}%'.format(100 * p.get_height()/total)
        ax.text(_x, _y, value, ha="center")
elif h_v == "h":
    for p in ax.patches:
        _x = p.get_x() + p.get_width() + float(space)
        _y = p.get_y() + p.get_height()
        value='{:.1f}%'.format(100 * p.get_width()/total)
        ax.text(_x, _y, value, ha="left")
if isinstance(axs, np.ndarray):
    for idx, ax in np.ndenumerate(axs):
        _show_on_single_plot(ax)
else:
    _show_on_single_plot(axs)

```

In [273...

```

# plot top orders by feature name using count plot with percentage displayed on the top
# Top 5 orders are being plotted
def plot_orders_by_feature(feature_list):
    for feature_name in feature_list:
        sns.set(style="whitegrid")
        sns.set(font_scale = 1.1)
        plt.figure(figsize=(15,5))
        ax = sns.countplot(x=feature_name,data=df_selected,hue="route_type",order=df_selected)
        plt.xlabel(feature_name, fontsize=17)
        plt.ylabel("Number of Orders",fontsize=17)
        plt.title("Most Orders (TOP 5) by "+feature_name,fontdict={"fontsize": 17})
        show_values_on_bars(ax,h_v="v",space=1)

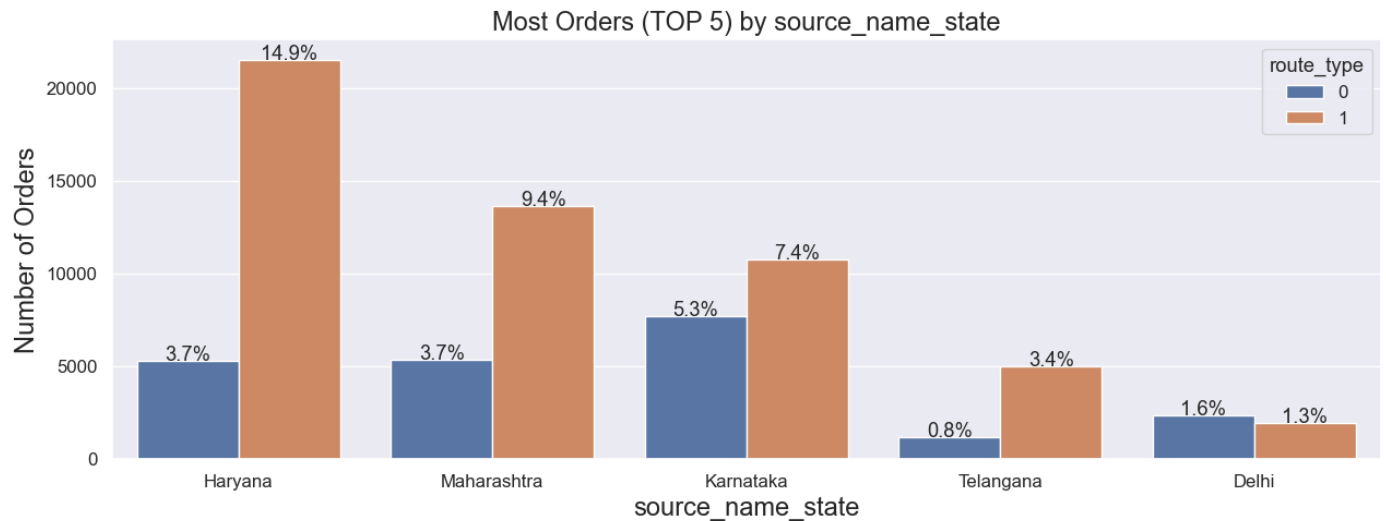
```

In [274...

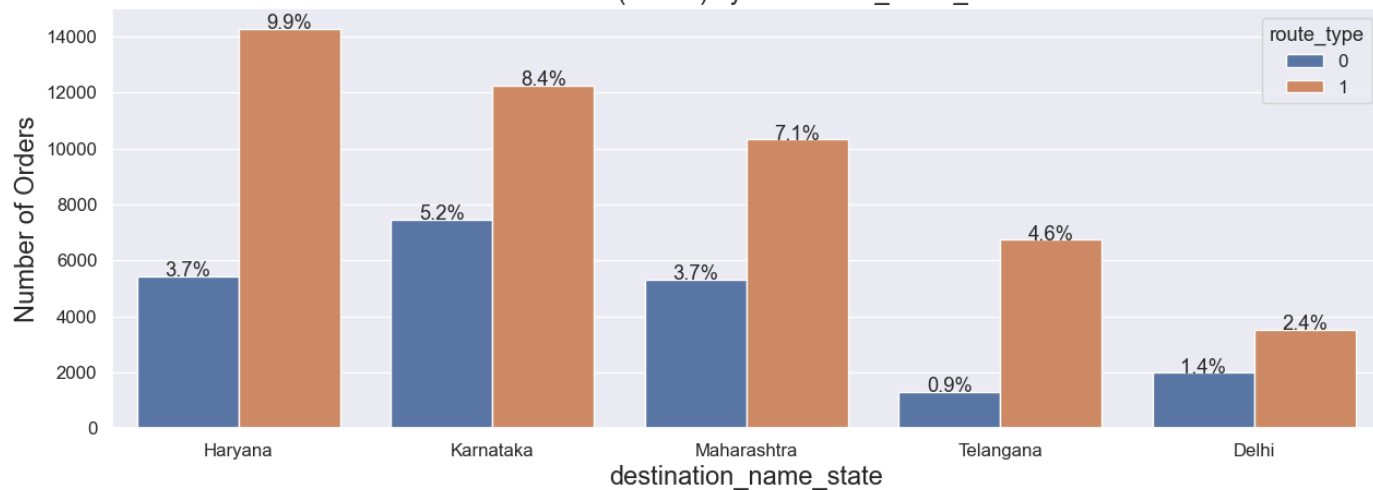
```

plot_orders_by_feature(['source_name_state','destination_name_state','source_name_city',

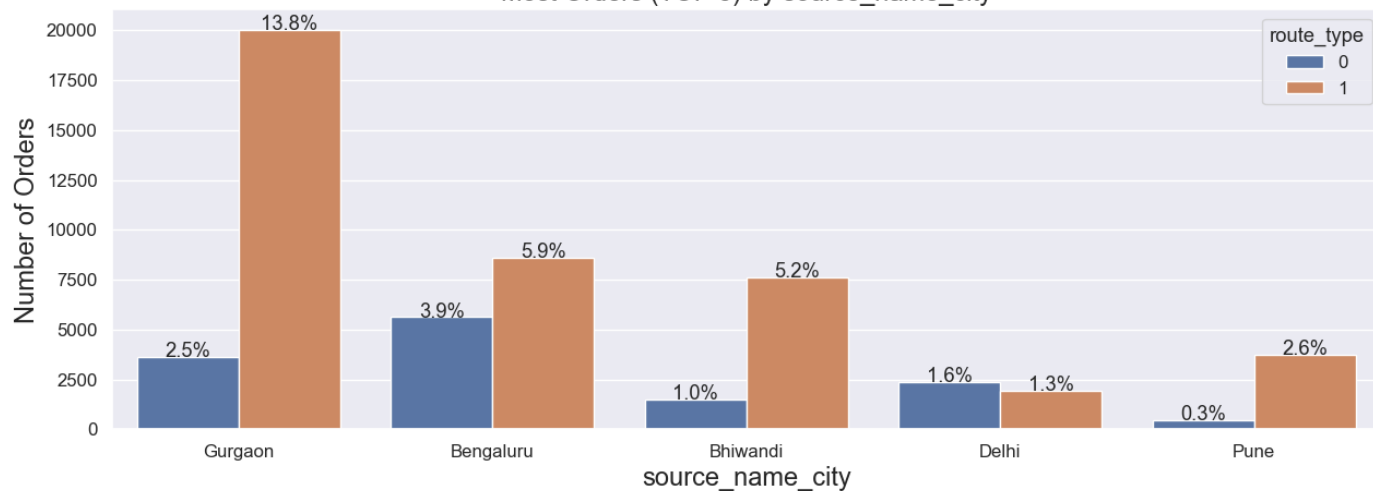
```



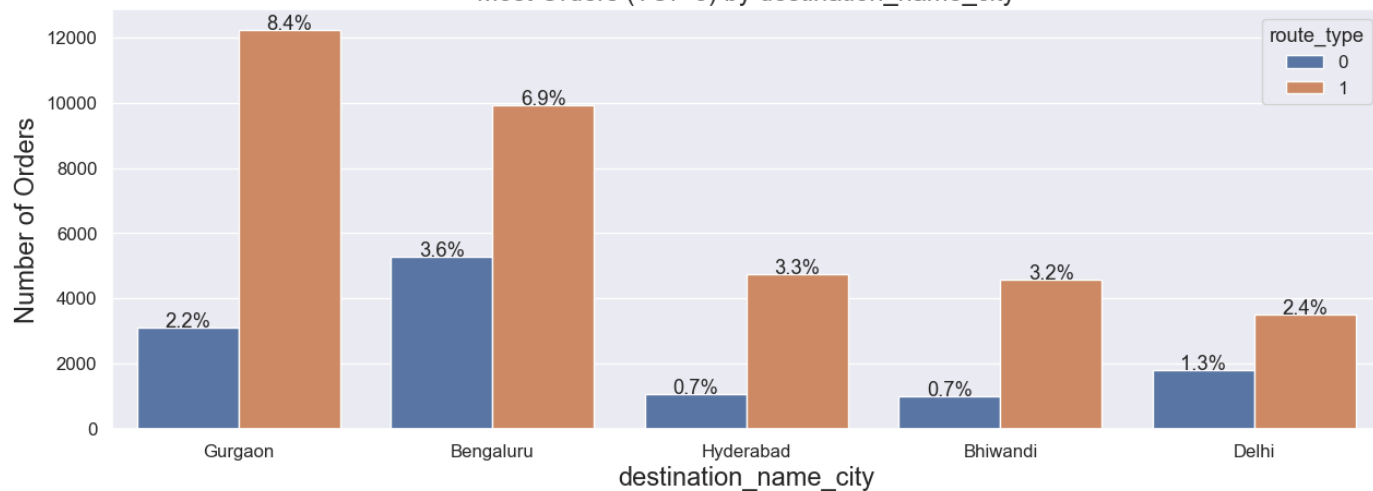
Most Orders (TOP 5) by destination_name_state

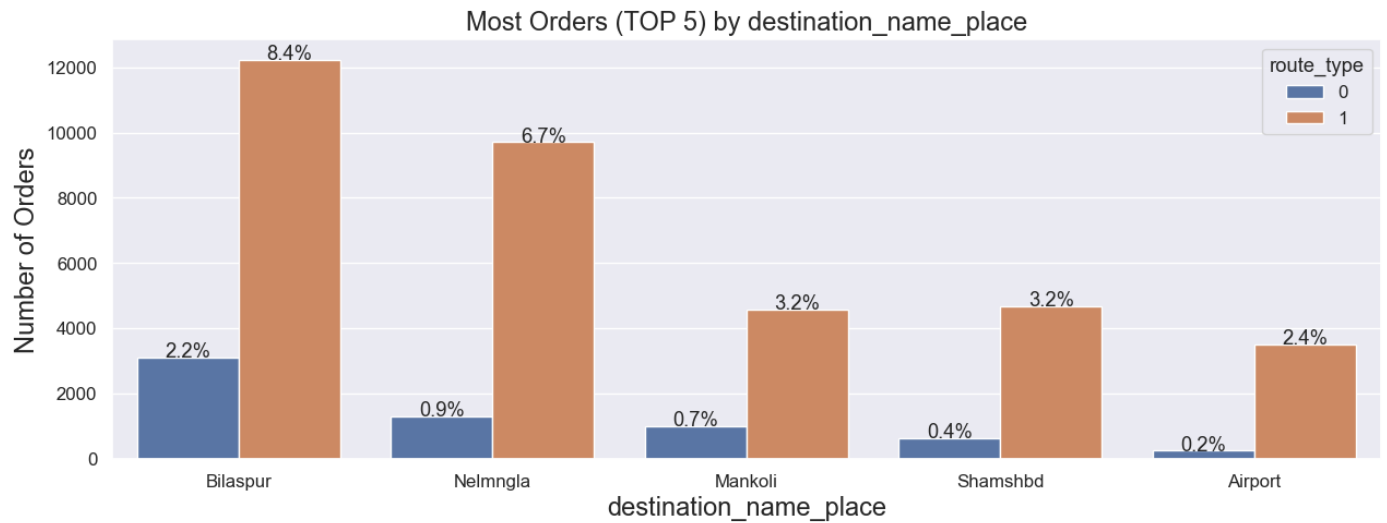
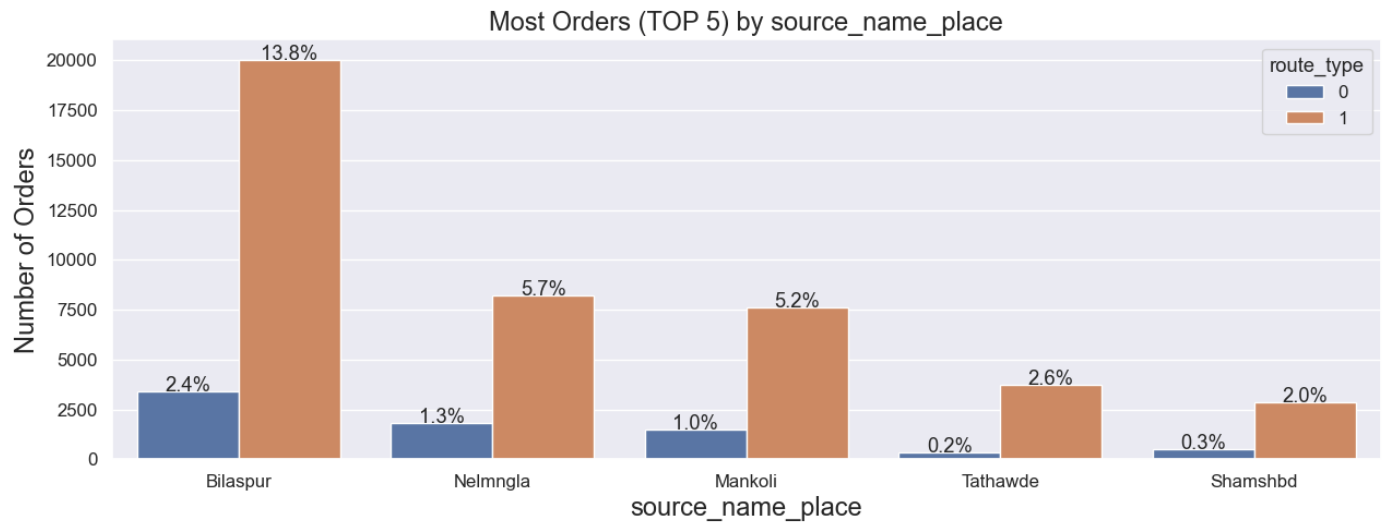


Most Orders (TOP 5) by source_name_city



Most Orders (TOP 5) by destination_name_city





- **Insights** on Busiest State/Corridor

- **Busiest source states** are:

- **Haryana**(14.9% Full truck load , 3.7% Carting)
 - **Maharashtra** (9.4% Full truck load , 3.7% Carting)
 - **Karnataka** (7.4% Full truck load , 5.3% Carting)

- **Busiest Destination states** are:

- **Haryana**(9.9% Full truck load , 3.7% Carting)
 - **Karnataka** (8.4% Full truck load , 5.2% Carting)
 - **Maharashtra** (7.1% Full truck load , 3.7% Carting)

- **Busiest source city** are:

- **Gurgaon**(13.8% Full truck load , 2.5% Carting)
 - **Bengaluru** (5.9% Full truck load , 3.9% Carting)
 - **Bhiwandi** (5.2% Full truck load , 1% Carting)

- **Busiest Destination city** are:

- **Gurgaon**(8.4% Full truck load , 2.2% Carting)
 - **Bengaluru** (6.9% Full truck load , 3.6% Carting)
 - **Hyderabad** (3.3% Full truck load , 0.7% Carting)

- **Busiest source Place** are:

- **Bilaspur**(13.8% Full truck load , 2.4% Carting)
 - **Nelmnnga** (5.7% Full truck load , 1.3% Carting)
 - **Mankoli** (5.2% Full truck load , 1% Carting)

- **Busiest Destination Place** are:

- **Bilaspur**(8.4% Full truck load , 2.2% Carting)
- **Nelmngla** (6.7% Full truck load , 0.9% Carting)
- **Mankoli** (3.2% Full truck load , 0.7% Carting)

Busiest corridor | avg distance , avg time taken

```
In [275... stats.ttest_ind(df["start_scan_to_end_scan"],df["actual_time"])
```

```
Out[275]: Ttest_indResult(statistic=173.06512569398697, pvalue=0.0)
```

```
In [276... df_busiest_corridor = df[(df["destination_name_city"] == 'Gurgaon') | (df["destination_name_city"] == 'Bengaluru') | (df["destination_name_city"] == 'Bhiwandi') | (df["destination_name_city"] == 'Hyderabad')]
df_busiest_corridor = df_busiest_corridor[["actual_distance_to_destination","actual_time"]]
```

Calculate "avg time" of destination busiest corridor - Gurgaon , Bangaluru , Hyderabad

```
In [277... avg_time_taken = df_busiest_corridor.groupby(['destination_name_city'])['actual_time'].mean()
avg_time_taken.reset_index().sort_values(['mean','destination_name_city'],ascending=False)
```

```
Out[277]:
```

	destination_name_city	mean
2	Gurgaon	739.855776
0	Bengaluru	677.203274
1	Bhiwandi	667.344970
3	Hyderabad	512.264766

Calculate "avg distance" of destination busiest corridor - Gurgaon , Bangaluru , Hyderabad

```
In [278... avg_distance_taken = df_busiest_corridor.groupby(['destination_name_city'])['actual_distance_to_destination'].mean()
avg_distance_taken.reset_index().sort_values(['mean','destination_name_city'],ascending=False)
```

```
Out[278]:
```

	destination_name_city	mean
2	Gurgaon	437.276411
0	Bengaluru	412.491168
1	Bhiwandi	367.409988
3	Hyderabad	295.929211

Recommendations - Actionable items for business. No technical jargon. No complications. Simple action items that everyone can understand.

- **Key considerations:**
 - Below recommendation will be more effective when more appropriate measures taken care wrt. outliers and more granular feature engineering are taken care as well
- **Actionable items for business**
 - **State/Place/City based marketing** would be **more effective:**
 - More **discounts on reverse routes** to **raise volume of orders**
 - **Long term Reserved booking discounts** between **top source and destinations**

- **Days based promotions when** there are **less truck loads bookings**
- **Volume based marketing** on **popular source and destinations** would be more effective
- **Delivery time estimation to be predicted accurately**
 - **More pre-booking order** can be taken up **based on estimated delivery time**
 - **More promotions on pre-booking and discounting offers**
 - **Orders on 5th, 6th and 7th day of the month** should **maximized based on delivery time estimates** as their minimal operations on those days
- **Route based promotions** can be more **effective**
 - **Full truck load promotions in states such as Haryana, Maharashtra, Karnataka, Delhi, Telangana**
 - **Carting promotions in states such as "Uttarakhand", "Rajasthan", "Jharkhand"**

In []: