Delhivery Case Study

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Github Link: https://github.com/gautamnaik1994/Delhivery-Data-Engineering-Case-Study

About Delhivery

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

Business Goal

The Data team at Delhivery is dedicated to leveraging data to enhance the company's quality, efficiency, and profitability, ultimately outperforming its competitors. By understanding and processing data from data engineering pipelines, the team ensures that data is cleaned and prepared for analysis. Aggregating data based on segments and trips empowers data scientists and analysts to make informed business decisions and forecast business performance.

Key Initiatives

- Investigating the busiest routes to optimize logistics and delivery networks.
- Comparing route types by time consumption to identify inefficiencies and potential improvements.
- Identifying the top cities in terms of order volume and delivery frequency.
- Conducting exploratory data analysis (EDA) on different features to uncover patterns and trends.
- Performing hypothesis testing between different features to identify correlations and relationships.

Dataset

Column Profiling:

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

In [ ]:
```
from sklearn.preprocessing import MinMaxScaler, StandardScaler, LabelEncoder
from scipy.stats import ttest_ind
import matplotlib.pyplot as plt
import seaborn as sns
import pickle
import pandas as pd
import numpy as np
import duckdb as db
pd.options.display.max_columns = None
sns.set_style("whitegrid")
```

In [ ]:
```
data = pd.read_csv("./delhivery_data.csv")
data.head()
```

Out[ ]:

	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_scar
0	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	2018-09-20 03:21:32.418600	2018-09-20 04:47:45.236797	
1	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	2018-09-20 03:21:32.418600	2018-09-20 04:47:45.236797	
2	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	2018-09-20 03:21:32.418600	2018-09-20 04:47:45.236797	
3	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	2018-09-20 03:21:32.418600	2018-09-20 04:47:45.236797	
4	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	2018-09-20 03:21:32.418600	2018-09-20 04:47:45.236797	

In [ ]:
```
data.info()
```

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

Observations

- We can see that there are missing values in the following columns: source_name and destination_name

Feature Engineering

In [ ]:
```
data = data.drop("data", axis=1)
```

In [ ]:
```
data["trip_uuid"] = data["trip_uuid"].str.split("-").str[1]
data["route_schedule_uuid"] = data["route_schedule_uuid"].str.split(":").str[3]
data["trip_creation_time"] = pd.to_datetime(data["trip_creation_time"])
data["od_start_time"] = pd.to_datetime(data["od_start_time"])
data["od_end_time"] = pd.to_datetime(data["od_end_time"])
# df["cutoff_timestamp"]=pd.to_datetime(df["cutoff_timestamp"])
```

Missing Values handling by merging the location data with the main data

In [ ]:
```
centers_df = db.sql("""
select distinct source_center as center, source_name as name from data where source_name is not null
union
select distinct destination_center as center, destination_name as name from data where destination_name is not null
""").to_df()
```

In [ ]:
```
centers_df["state"] = centers_df["name"].str.split("(").str[1].replace("\(?\)?", "", regex=True)
centers_df["temp"] = centers_df["name"].str.split(" ").str[0]
centers_df["city"] = centers_df["temp"].str.split("_").str[0]
centers_df["place"] = centers_df["temp"].str.split("_").str[1]
centers_df["code"] = centers_df["temp"].str.split("_").str[-1]
centers_df = centers_df.drop(["temp", "name"], axis=1)
```

In [ ]:
```
centers_df.sample(5)
```

Out[ ]:

	center	state	city	place	code
455	IND712602AAA	West Bengal	Arambag	BalibDPP	D
810	IND583121AAA	Karnataka	Siruguppa	Wrd12DPP	D
1206	IND464668AAA	Madhya Pradesh	Bareli	SourvDPP	D
1267	IND474003AAA	Madhya Pradesh	Gwalior	HrihrNgr	I
1089	IND388320AAA	Gujarat	Anand	Vaghasi	IP

In [ ]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144867 entries, 0 to 144866
Data columns (total 23 columns):
 #   Column                          Non-Null Count   Dtype         
---  ------                          --------------   -----         
 0   trip_creation_time              144867 non-null  datetime64[ns]
 1   route_schedule_uuid             144867 non-null  object        
 2   route_type                      144867 non-null  object        
 3   trip_uuid                       144867 non-null  object        
 4   source_center                   144867 non-null  object        
 5   source_name                     144574 non-null  object        
 6   destination_center              144867 non-null  object        
 7   destination_name                144606 non-null  object        
 8   od_start_time                   144867 non-null  datetime64[ns]
 9   od_end_time                     144867 non-null  datetime64[ns]
 10  start_scan_to_end_scan          144867 non-null  float64       
 11  is_cutoff                       144867 non-null  bool          
 12  cutoff_factor                   144867 non-null  int64         
 13  cutoff_timestamp                144867 non-null  object        
 14  actual_distance_to_destination  144867 non-null  float64       
 15  actual_time                     144867 non-null  float64       
 16  osrm_time                       144867 non-null  float64       
 17  osrm_distance                   144867 non-null  float64       
 18  factor                          144867 non-null  float64       
 19  segment_actual_time             144867 non-null  float64       
 20  segment_osrm_time               144867 non-null  float64       
 21  segment_osrm_distance           144867 non-null  float64       
 22  segment_factor                  144867 non-null  float64       
dtypes: bool(1), datetime64[ns](3), float64(10), int64(1), object(8)
memory usage: 24.5+ MB
```

In [ ]:
```
data["segment_key"] = data["trip_uuid"] + "_" + data["source_center"] + "_" + data["destination_center"]
```

In [ ]:
```
collapsed_inter_df = db.sql("""
select
        segment_key
        , first(trip_uuid) as trip_uuid
        , first(source_center) as source_center
        , first(destination_center) as destination_center
        , first(trip_creation_time) as trip_creation_time
        , first(route_type) as route_type
        , first(od_start_time) as od_start_time
        , last(od_end_time) as od_end_time
        , first(start_scan_to_end_scan) as start_scan_to_end_scan
        , last(actual_distance_to_destination) as actual_distance_to_destination
        , last(actual_time) as actual_time_to_destination
        , last(osrm_time) as osrm_time
        , sum(segment_actual_time) as segment_actual_time
        , sum(segment_osrm_time) as segment_osrm_time
        , last(osrm_distance) as osrm_distance
```

```
        , sum(segment_osrm_distance) as segment_osrm_distance
from data group by segment_key
""").to_df()
collapsed_inter_df.head()
```

Out[ ]:

	segment_key	trip_uuid	source_center	destination_center	trip_creation_time	route_type	od_start_time	od_end_time	start_scan_to_end_scan	actual_
0	153698045859626572_IND524101AAB_IND517501AAB	153698045859626572	IND524101AAB	IND517501AAB	2018-09-15 03:00:58.596515	FTL	2018-09-15 07:24:25.834574	2018-09-15 10:14:42.060695	170.0	
1	153833836174130977_IND673632AAA_IND673305AAA	153833836174130977	IND673632AAA	IND673305AAA	2018-09-30 20:12:41.741570	Carting	2018-09-30 20:12:41.741570	2018-10-01 01:04:41.744890	292.0	
2	153749921290385945_IND600056AAB_IND600044AAE	153749921290385945	IND600056AAB	IND600044AAE	2018-09-21 03:06:52.904238	Carting	2018-09-21 03:06:52.904238	2018-09-21 06:15:53.943104	189.0	
3	153838561974018796_IND473226AAA_IND473001AAA	153838561974018796	IND473226AAA	IND473001AAA	2018-10-01 09:20:19.740451	FTL	2018-10-01 09:20:19.740451	2018-10-01 11:15:57.418982	115.0	
4	153800528315390990_IND627811AAA_IND627401AAA	153800528315390990	IND627811AAA	IND627401AAA	2018-09-26 23:41:23.154160	FTL	2018-09-27 01:31:47.255547	2018-09-27 02:45:08.708179	73.0	

Missing values handling

In [ ]:
```
segment_df = db.sql("""
select collapsed_inter_df.*
       , scd.state as source_state
       , scd.city as source_city
       , dcd.state as destination_state
       , dcd.city as destination_city
   from collapsed_inter_df
      join centers_df scd on collapsed_inter_df.source_center=scd.center
      join centers_df dcd on collapsed_inter_df.destination_center=dcd.center
 """).to_df()
```

In [ ]:
```
segment_df = db.sql("""
select *, rank() over(partition by trip_uuid order by od_end_time ) rnk from segment_df
""").to_df()
```

In [ ]:
```
segment_df.head()
```

Out[ ]:

	segment_key	trip_uuid	source_center	destination_center	trip_creation_time	route_type	od_start_time	od_end_time	start_scan_to_end_scan	actual_dis
0	153671173668736946_IND110043AAA_IND110078AAA	153671173668736946	IND110043AAA	IND110078AAA	2018-09-12 00:22:16.687619	Carting	2018-09-12 00:22:16.687619	2018-09-12 01:29:19.277412	67.0	
1	153671277074687197_IND624001AAA_IND624619AAA	153671277074687197	IND624001AAA	IND624619AAA	2018-09-12 00:39:30.747127	FTL	2018-09-12 00:39:30.747127	2018-09-12 01:32:05.649177	52.0	
2	153671277074687197_IND624619AAA_IND624601AAA	153671277074687197	IND624619AAA	IND624601AAA	2018-09-12 00:39:30.747127	FTL	2018-09-12 01:32:05.649177	2018-09-12 02:52:44.647485	80.0	
3	153671277074687197_IND624601AAA_IND624101AAA	153671277074687197	IND624601AAA	IND624101AAA	2018-09-12 00:39:30.747127	FTL	2018-09-12 02:52:44.647485	2018-09-12 04:51:38.550800	118.0	
4	153671277074687197_IND624101AAA_IND624202AAA	153671277074687197	IND624101AAA	IND624202AAA	2018-09-12 00:39:30.747127	FTL	2018-09-12 04:51:38.550800	2018-09-12 06:45:07.329780	113.0	

In [ ]:
```
with open("segment_df.pkl", "wb") as f:
    pickle.dump(segment_df, f)
```

In [ ]:
```
trip_df = db.sql("""
select
    trip_uuid
    , first(source_center) as source_center
    , last(destination_center) as destination_center
    , count(*) as stops
    , first(trip_creation_time) as trip_creation_time
    , first(route_type) as route_type
    , first(od_start_time) as od_start_time
    , last(od_end_time) as od_end_time
    , sum(start_scan_to_end_scan) as start_scan_to_end_scan
    , sum(actual_distance_to_destination) as actual_distance_to_destination
    , sum(actual_time_to_destination) as actual_time_to_destination
    , sum(osrm_time) as osrm_time
    , sum(segment_actual_time) as segment_actual_time
    , sum(segment_osrm_time) as segment_osrm_time
    , sum(osrm_distance) as osrm_distance
    , sum(segment_osrm_distance) as segment_osrm_distance
    , first(source_state) as source_state
    , first(source_city) as source_city
    , first(destination_state) as destination_state
    , first(destination_city) as destination_city
from segment_df
    group by trip_uuid

 """).to_df()
trip_df.head()
```

Out[ ]:

	trip_uuid	source_center	destination_center	stops	trip_creation_time	route_type	od_start_time	od_end_time	start_scan_to_end_scan	actual_distance_to_destination	actual_time_to_destin
0	153671174968648046	IND781005AAA	IND781018AAB	1	2018-09-12 00:22:29.686740	Carting	2018-09-12 03:53:13.532367	2018-09-12 06:11:57.563883	138.0	9.941525	
1	153671310683457427	IND700065AAA	IND712311AAA	1	2018-09-12 00:45:06.834828	Carting	2018-09-12 00:45:06.834828	2018-09-12 04:12:29.937384	207.0	15.738550	
2	153671321710455800	IND421302AAG	IND000000ACB	1	2018-09-12 00:46:57.104787	FTL	2018-09-12 00:46:57.104787	2018-09-13 15:45:19.916768	2338.0	1078.198022	2
3	153671402673350359	IND574211AAA	IND562132AAA	3	2018-09-12 01:00:26.733769	FTL	2018-09-12 02:03:04.041511	2018-09-12 14:28:00.360402	674.0	258.100383	
4	153671723500134877	IND110037AAM	IND211002AAB	2	2018-09-12 01:53:55.001720	FTL	2018-09-12 01:53:55.001720	2018-09-13 03:46:17.503775	1551.0	563.532023	1

In [ ]:
```
trip_df["trip_creation_hour"] = trip_df["trip_creation_time"].dt.hour
trip_df["trip_creation_day"] = trip_df["trip_creation_time"].dt.day
trip_df["trip_creation_month"] = trip_df["trip_creation_time"].dt.month
trip_df["trip_creation_weekday"] = trip_df["trip_creation_time"].dt.day_of_week

trip_df["od_start_time_month"] = trip_df["od_start_time"].dt.month
trip_df["od_end_time_month"] = trip_df["od_end_time"].dt.month
trip_df["od_end_time_day"] = trip_df["od_end_time"].dt.day
trip_df["od_start_time_day"] = trip_df["od_start_time"].dt.day
trip_df["od_start_time_hour"] = trip_df["od_start_time"].dt.hour
trip_df["od_end_time_hour"] = trip_df["od_end_time"].dt.hour
trip_df["od_start_time_minute"] = trip_df["od_start_time"].dt.minute
trip_df["od_end_time_minute"] = trip_df["od_end_time"].dt.minute
trip_df["od_diff_hours"] = (
    trip_df["od_end_time"]-trip_df["od_start_time"]).dt.total_seconds()/3600
trip_df = trip_df.drop(["od_start_time", "od_end_time","trip_creation_time"], axis=1)
```

In [ ]:
```
with open("trip_df.pkl", "wb") as f:
    pickle.dump(trip_df, f)
```

In [ ]:
```
with open("trip_df.pkl", "rb") as f:
    trip_df = pickle.load(f)
```

```
with open("segment_df.pkl", "rb") as f:
    segment_df = pickle.load(f)
```

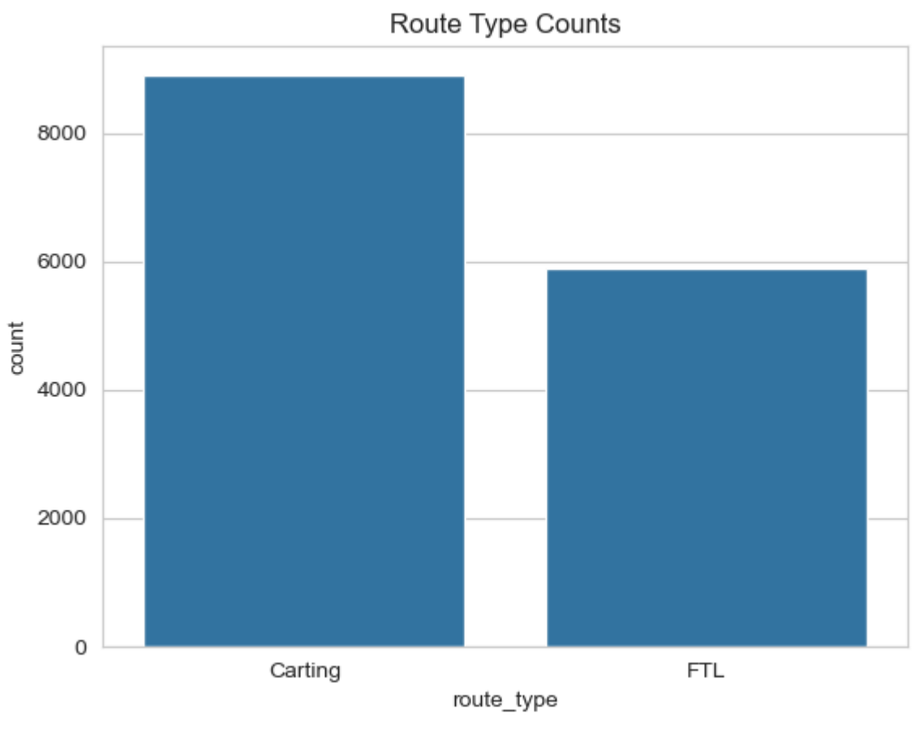
In [ ]:
```
trip_df.head()
```

Out[ ]:

	trip_uuid	source_center	destination_center	stops	route_type	start_scan_to_end_scan	actual_distance_to_destination	actual_time_to_destination	osrm_time	segment_actual_time	segment_osrr
0	153671174968648046	IND781005AAA	IND781018AAB	1	Carting	138.0	9.941525	110.0	18.0	109.0	
1	153671310683457427	IND700065AAA	IND712311AAA	1	Carting	207.0	15.738550	52.0	20.0	52.0	
2	153671321710455800	IND421302AAG	IND000000ACB	1	FTL	2338.0	1078.198022	2090.0	968.0	2073.0	
3	153671402673350359	IND574211AAA	IND562132AAA	3	FTL	674.0	258.100383	643.0	268.0	637.0	
4	153671723500134877	IND110037AAM	IND211002AAB	2	FTL	1551.0	563.532023	1025.0	473.0	1017.0	

EDA

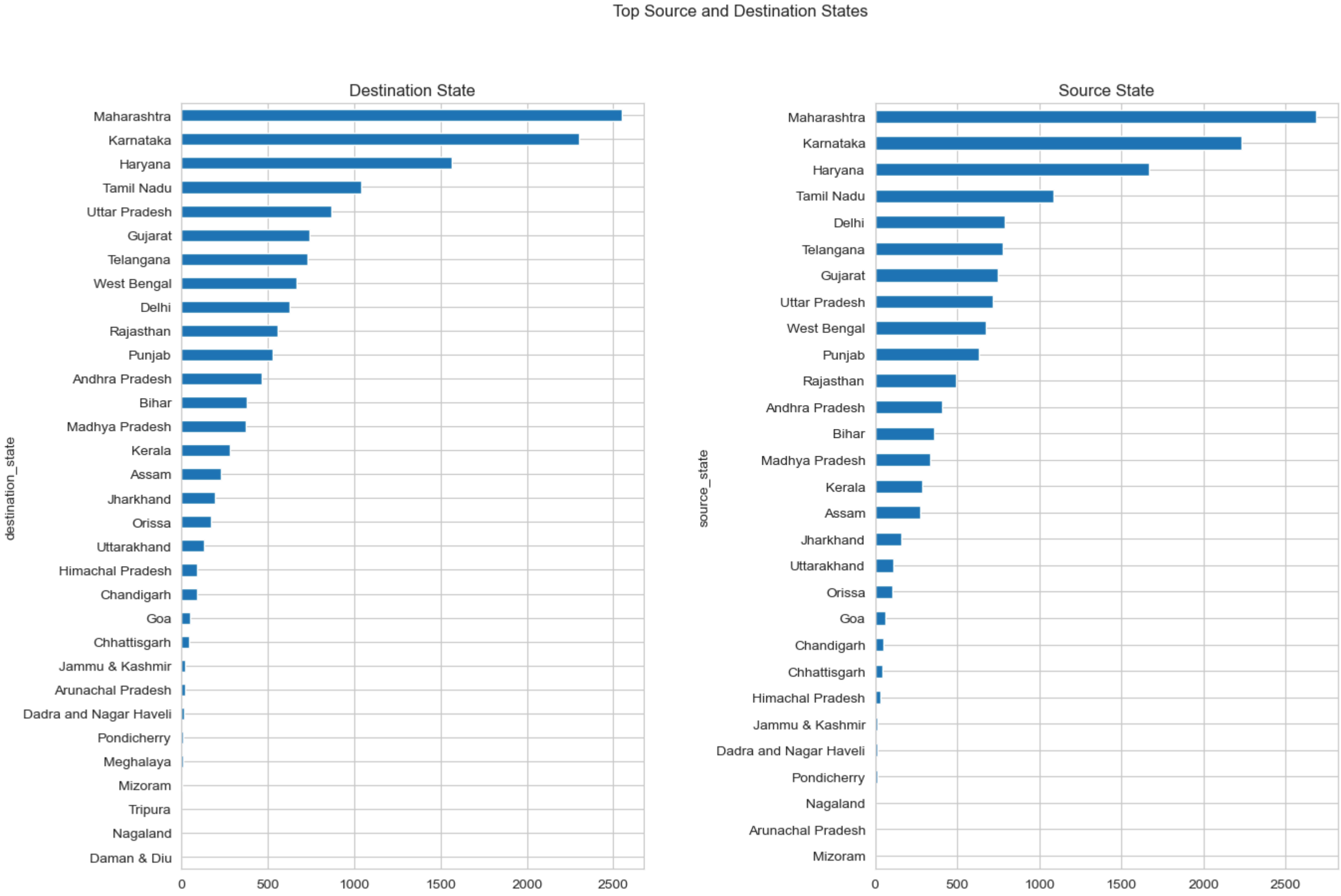
In [ ]:
```
sns.countplot(data=trip_df, x="route_type")
plt.title("Route Type Counts");
```



Observations

- We can see that Carting is the most popular route type

In [ ]:
```
fig, ax = plt.subplots(1, 2, figsize=(15, 10))

trip_df["destination_state"].value_counts().sort_values().plot(kind="barh", ax=ax[0])
trip_df["source_state"].value_counts().sort_values().plot(kind="barh", ax=ax[1])
plt.subplots_adjust(wspace=0.5)
# plt.subplots_adjust(top=-1.85)
ax[0].set_title("Destination State")
ax[1].set_title("Source State")
plt.suptitle("Top Source and Destination States");
```

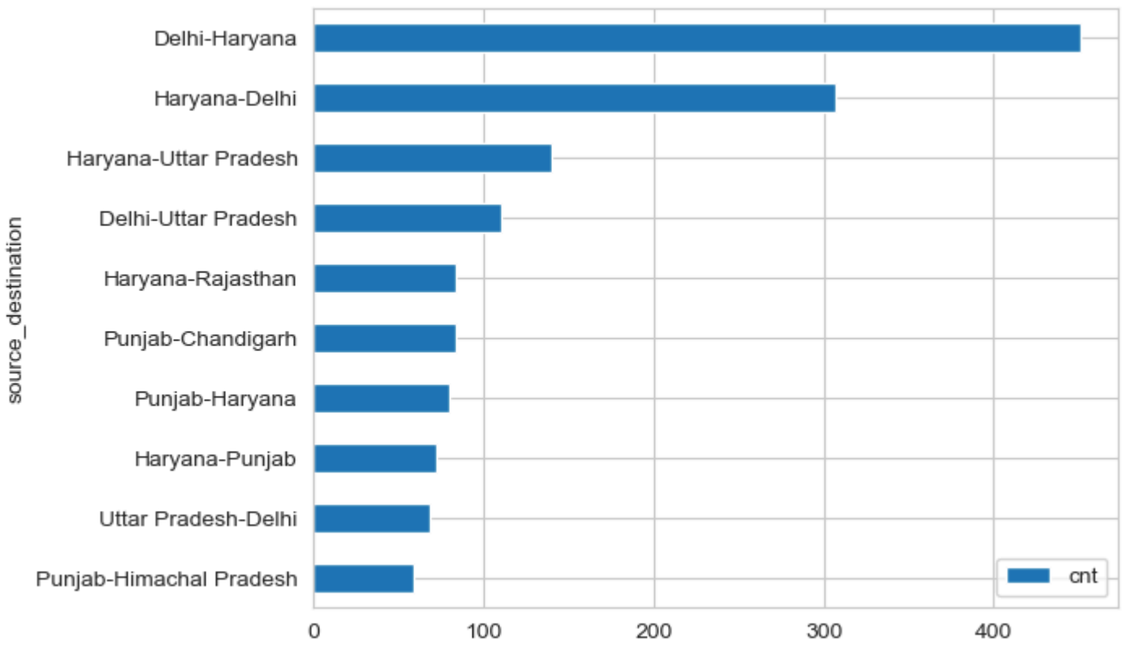


Observations

- From above plot we can see that most of the trips are from Maharashtra

In [ ]:
```
db.sql("""
select
    concat(source_state,'-',destination_state) as source_destination
    , count(*) cnt
    from trip_df
       where source_state != destination_state
       group by source_state, destination_state
```

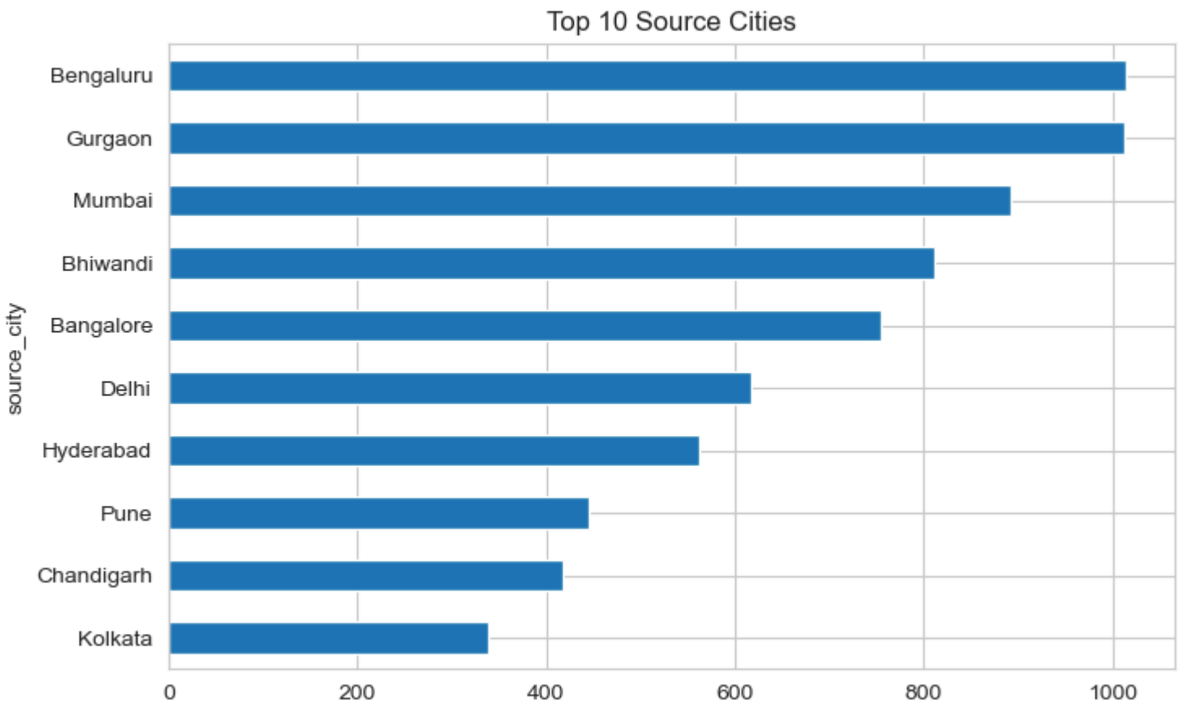
```
        order by cnt desc
""").to_df().head(10).sort_values(by="cnt").plot(kind="barh", x="source_destination", y="cnt");
```



Observations

- From above plot we can see that most of trips have been made between Delhi and Haryana

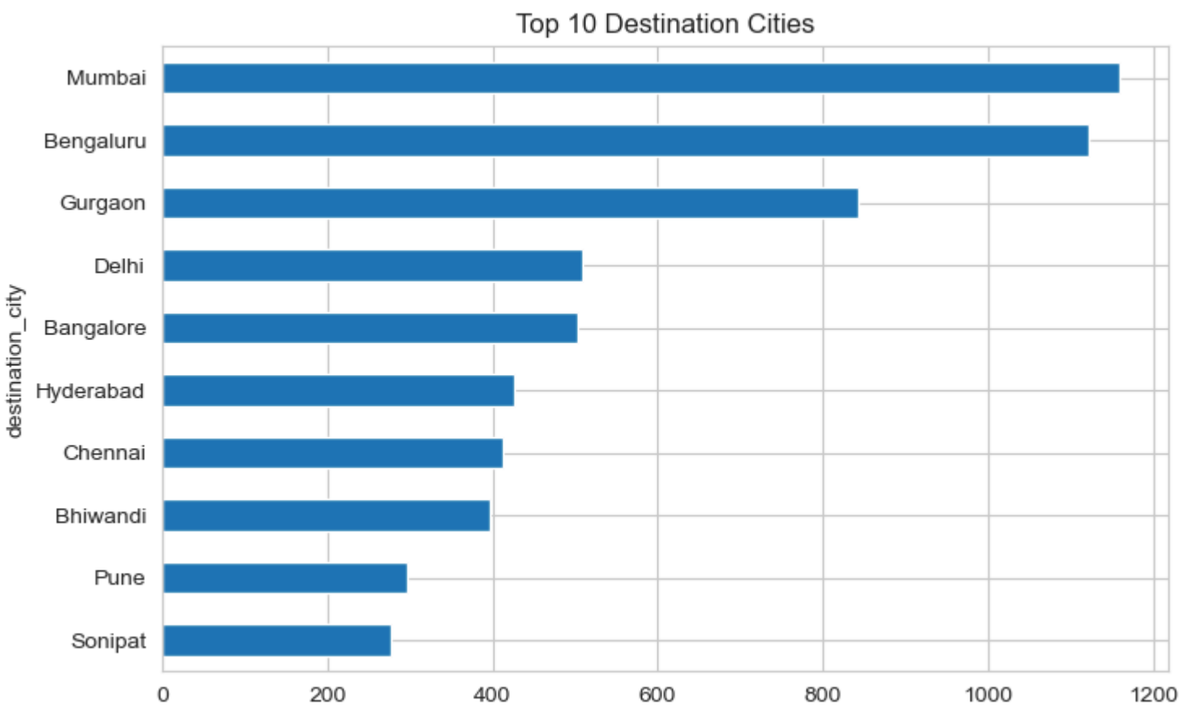
In [ ]:
```
trip_df["source_city"].value_counts().sort_values()[-10:].plot(kind="barh", figsize=(8, 5))
plt.title("Top 10 Source Cities");
```



Observations

- Bengaluru is the most popular source city

In [ ]:
```
trip_df["destination_city"].value_counts().sort_values()[-10:].plot(kind="barh", figsize=(8, 5))
plt.title("Top 10 Destination Cities");
```

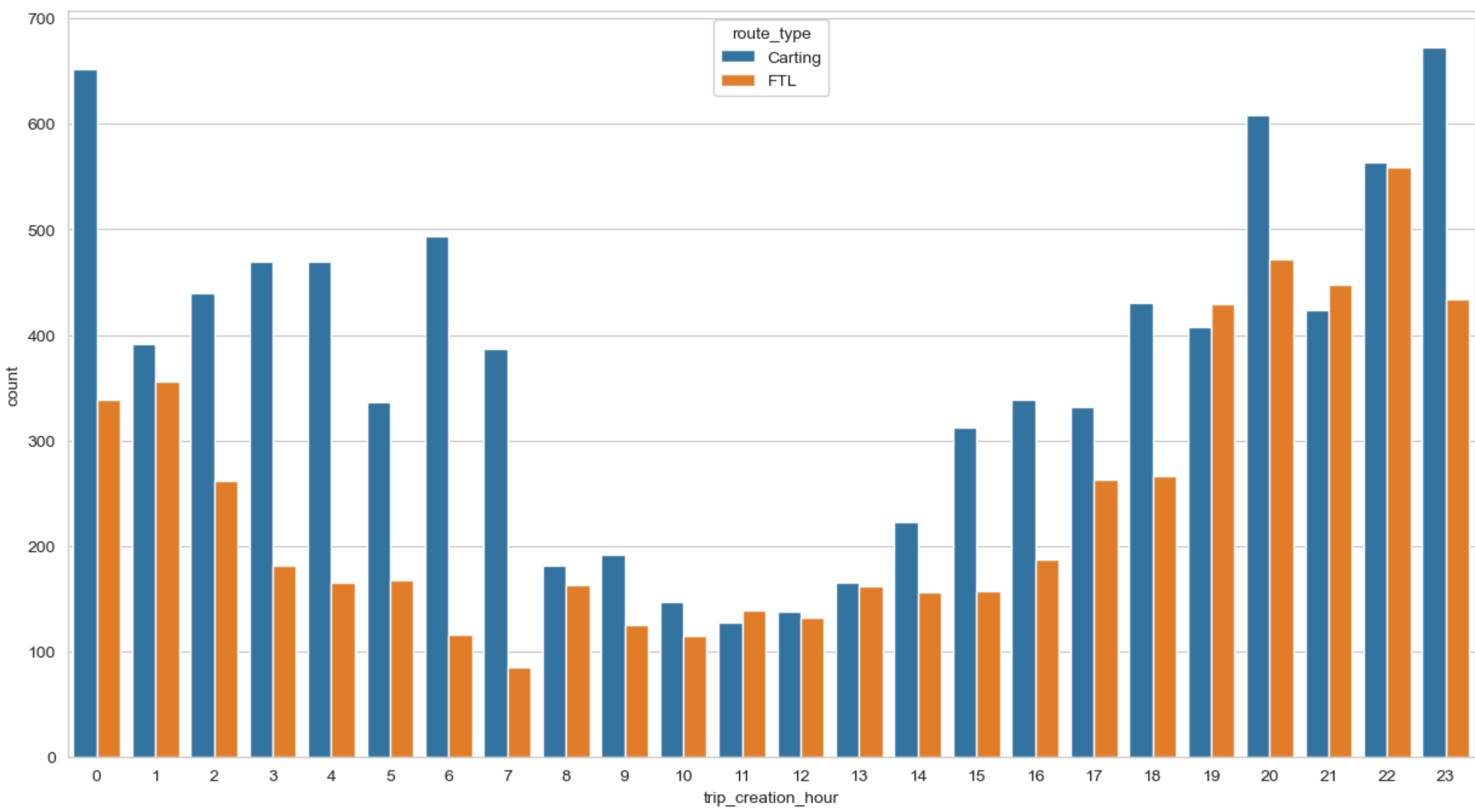


Observations

- Mumbai is the most popular destination city

In [ ]:
```
plt.figure(figsize=(15, 8))
sns.countplot(data=trip_df, x="trip_creation_hour", hue="route_type");
```

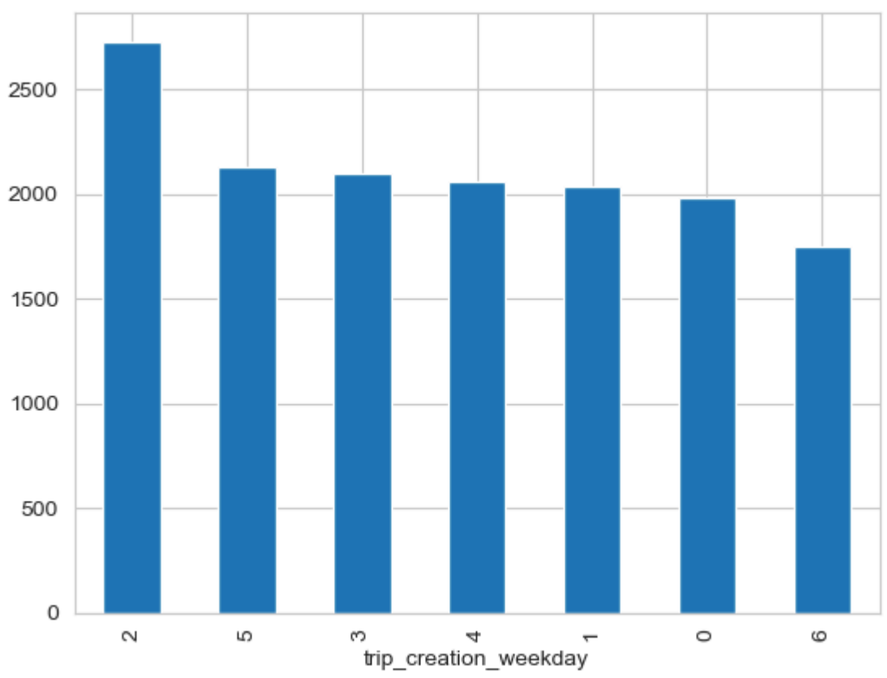
Out[ ]:
```
<Axes: xlabel='trip_creation_hour', ylabel='count'>
```



Observations

- From above plot we can see that most of the FTL trips at night time whereas Carting trips are made throughout the day excluding morining hours

In [ ]:
```
trip_df["trip_creation_weekday"].value_counts().plot(kind="bar");
```



Observations

- From above plot we can see that most of the trips are made on Tuesdays

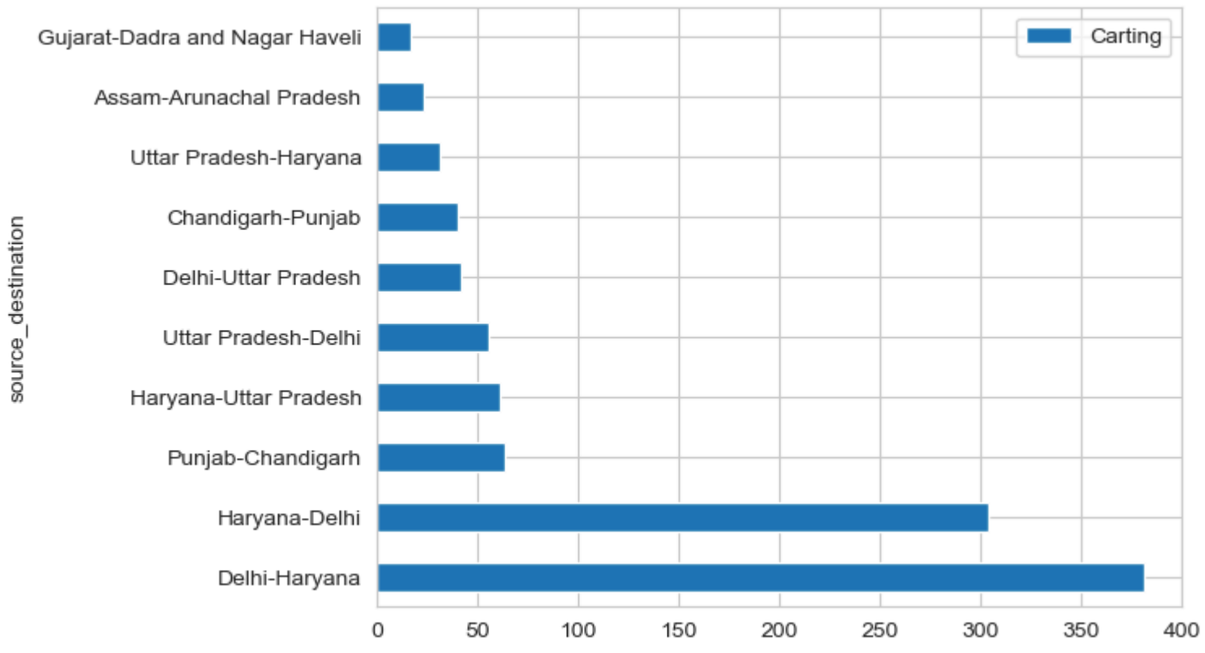
In [ ]:
```
route_based_cnt = db.sql("""
select
    concat(source_state,'-',destination_state) as source_destination
    , route_type
    , count(*) cnt
    from trip_df
       where source_state != destination_state
       group by source_state, destination_state , route_type
       order by cnt desc
""").to_df().pivot(index="source_destination", columns="route_type", values="cnt")
route_based_cnt = route_based_cnt.reset_index()
route_based_cnt
```

Out[ ]:

route_type	source_destination	Carting	FTL
0	Andhra Pradesh-Karnataka	2.0	14.0
1	Andhra Pradesh-Orissa	4.0	2.0
2	Andhra Pradesh-Telangana	NaN	16.0
3	Arunachal Pradesh-Assam	4.0	NaN
4	Assam-Arunachal Pradesh	23.0	1.0
...	...	...	...
107	West Bengal-Assam	NaN	8.0
108	West Bengal-Bihar	NaN	1.0
109	West Bengal-Haryana	NaN	11.0
110	West Bengal-Jharkhand	NaN	20.0
111	West Bengal-Orissa	NaN	27.0

112 rows × 3 columns

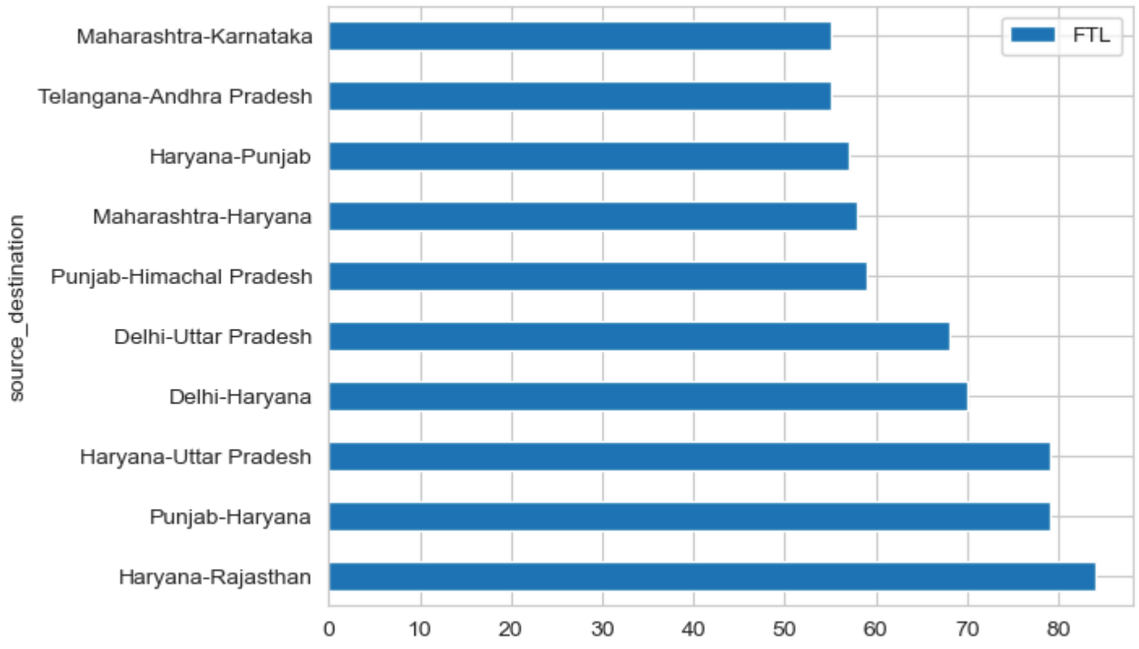
In [ ]:
```
route_based_cnt[["source_destination", "Carting"]].sort_values(
by="Carting", ascending=False).head(10).plot(kind="barh", x="source_destination", y="Carting");
```



Observations

- From above plot we can see that most of the trips have been made between Delhi and Haryana are of Carting route type

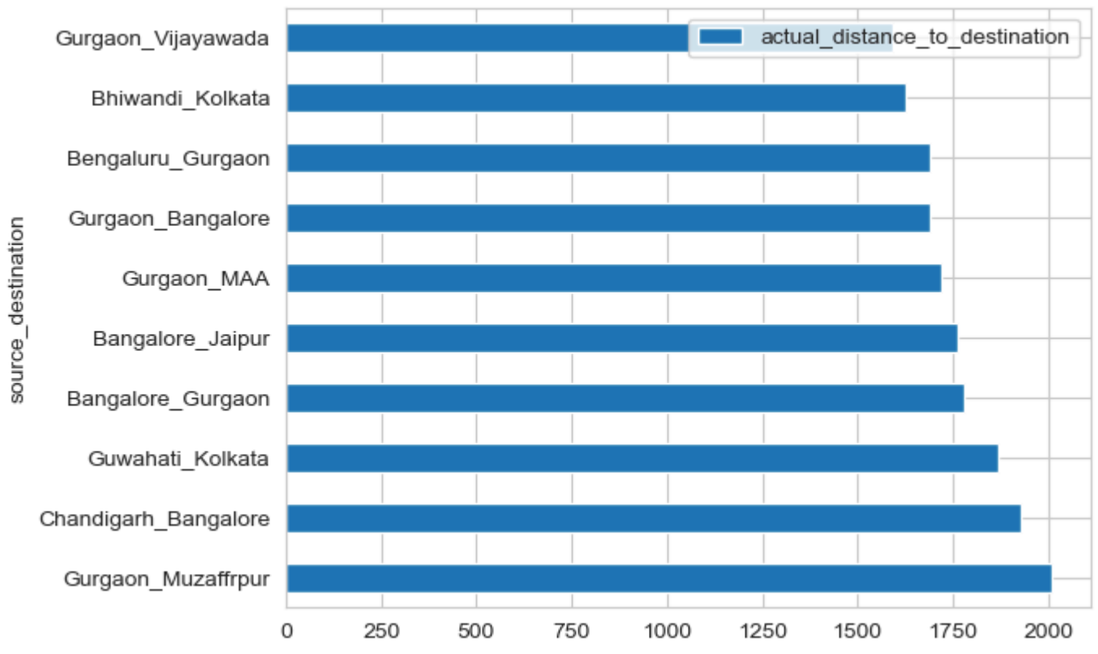
In [ ]:
```
route_based_cnt[["source_destination", "FTL"]].sort_values(
    by="FTL", ascending=False).head(10).plot(kind="barh", x="source_destination", y="FTL");
```



Observations

- From above plot we can see that most of the trips have been made between Haryana and Rajasthan are of FTL route type

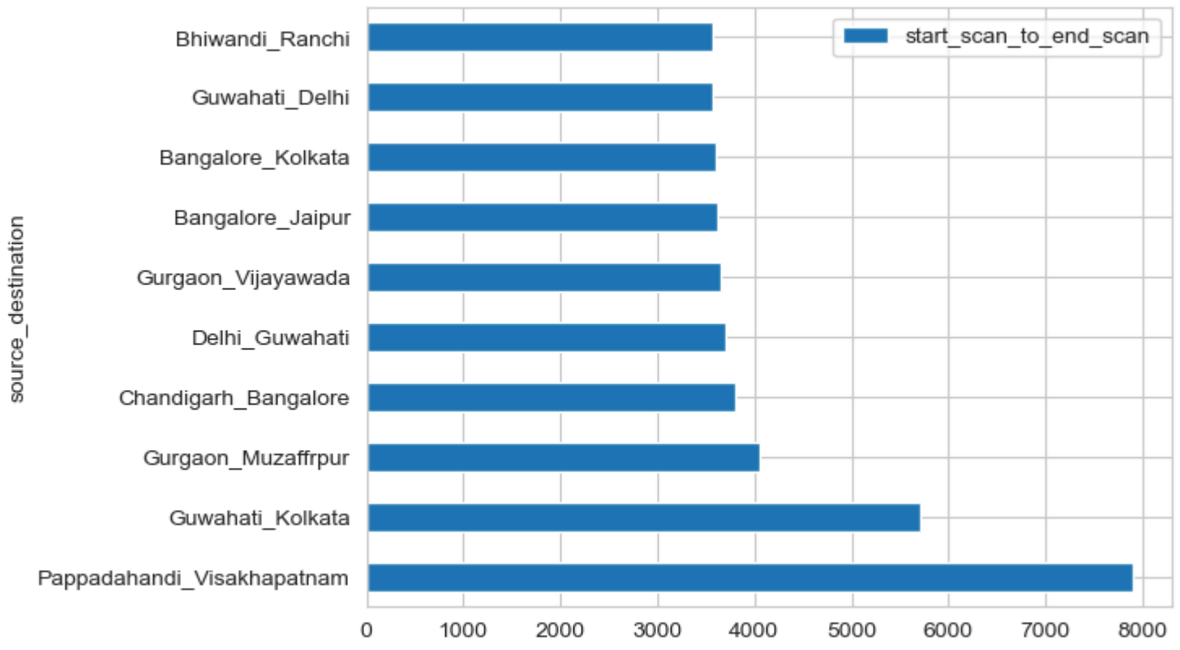
In [ ]:
```
db.sql("""
select
       concat(source_city,'_', destination_city) source_destination
       , round(avg(actual_distance_to_destination),2) actual_distance_to_destination
       from trip_df
       group by source_city, destination_city
       order by actual_distance_to_destination desc
       limit 10
""").to_df().plot(kind="barh", x="source_destination", y="actual_distance_to_destination");
```



Observations

- Above plot shows longest delivery distance between two cities

In [ ]:
```
db.sql("""
select
       concat(source_city,'_', destination_city) source_destination
       , round(avg(start_scan_to_end_scan),2) start_scan_to_end_scan
       from trip_df
       group by source_city, destination_city
       order by start_scan_to_end_scan desc
       limit 10
""").to_df().plot(kind="barh", x="source_destination", y="start_scan_to_end_scan");
```



Observations

- Above plot shows highest average time taken to reach destination from source

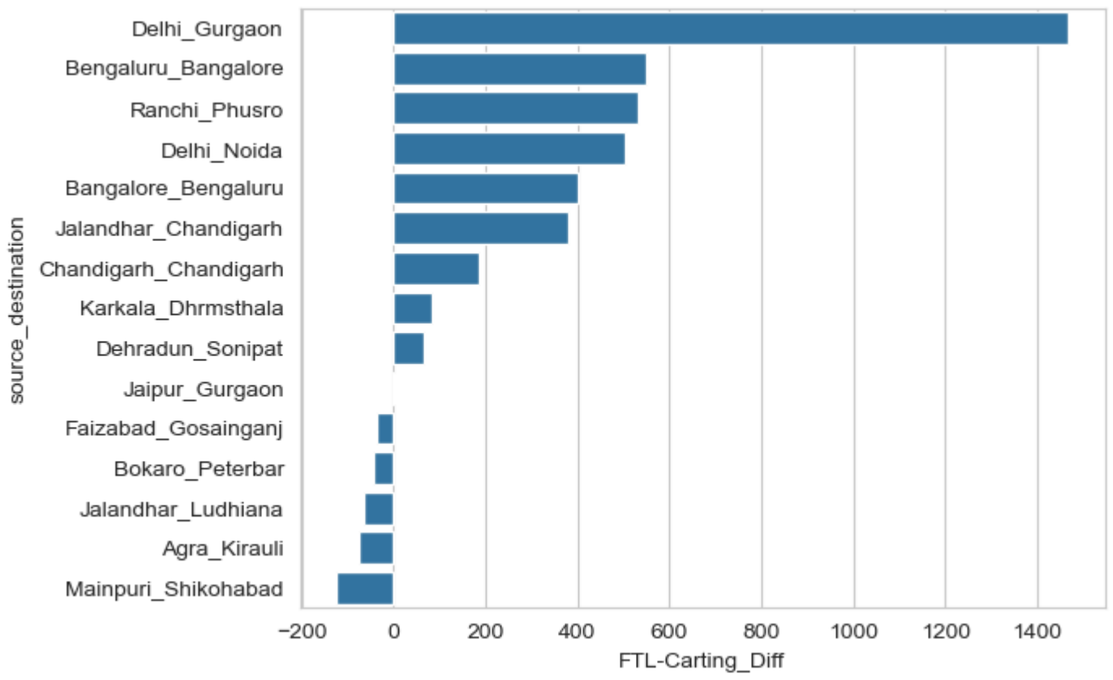
In [ ]:
```
carting_ftl=db.sql("""
select
       concat(source_city,'_', destination_city) source_destination
       , route_type
       , round(avg(actual_time_to_destination),2) actual_time_to_destination
       from trip_df
       group by source_city, destination_city , route_type
       order by source_destination

""").to_df().pivot(index="source_destination", columns="route_type", values="actual_time_to_destination").dropna()
```

In [ ]:
```
carting_ftl["FTL-Carting_Diff"] = carting_ftl["FTL"] - carting_ftl["Carting"]
carting_ftl=carting_ftl.sort_values(by="FTL-Carting_Diff", ascending=False)
carting_ftl
```

Out[ ]:

route_type	Carting	FTL	Carting_Diff	FTL-Carting_Diff
source_destination				
Delhi_Gurgaon	177.49	1644.20	1466.71	1466.71
Bengaluru_Bangalore	92.35	642.00	549.65	549.65
Ranchi_Phusro	295.00	826.00	531.00	531.00
Delhi_Noida	83.60	586.27	502.67	502.67
Bangalore_Bengaluru	78.44	478.95	400.51	400.51
Jalandhar_Chandigarh	292.40	674.00	381.60	381.60
Chandigarh_Chandigarh	118.09	302.62	184.53	184.53
Karkala_Dhrmsthala	95.00	180.00	85.00	85.00
Dehradun_Sonipat	464.00	530.00	66.00	66.00
Jaipur_Gurgaon	313.00	315.17	2.17	2.17
Faizabad_Gosainganj	142.91	107.50	-35.41	-35.41
Bokaro_Peterbar	555.00	512.00	-43.00	-43.00
Jalandhar_Ludhiana	224.00	160.17	-63.83	-63.83
Agra_Kirauli	187.00	110.86	-76.14	-76.14
Mainpuri_Shikohabad	559.00	435.50	-123.50	-123.50

In [ ]:
```
sns.barplot(data=carting_ftl, y="source_destination", x="FTL-Carting_Diff");
```



Observations

- From above plot we can see that average time taken to reach destination from source for some route pairs is more for FTL.

In [ ]:
```
trip_df.head()
```

Out[ ]:

	trip_uuid	source_center	destination_center	stops	route_type	start_scan_to_end_scan	actual_distance_to_destination	actual_time_to_destination	osrm_time	segment_actual_time	segment_osrr
0	153671174968648046	IND781005AAA	IND781018AAB	1	Carting	138.0	9.941525	110.0	18.0	109.0	
1	153671310683457427	IND700065AAA	IND712311AAA	1	Carting	207.0	15.738550	52.0	20.0	52.0	
2	153671321710455800	IND421302AAG	IND000000ACB	1	FTL	2338.0	1078.198022	2090.0	968.0	2073.0	
3	153671402673350359	IND574211AAA	IND562132AAA	3	FTL	674.0	258.100383	643.0	268.0	637.0	
4	153671723500134877	IND110037AAM	IND211002AAB	2	FTL	1551.0	563.532023	1025.0	473.0	1017.0	

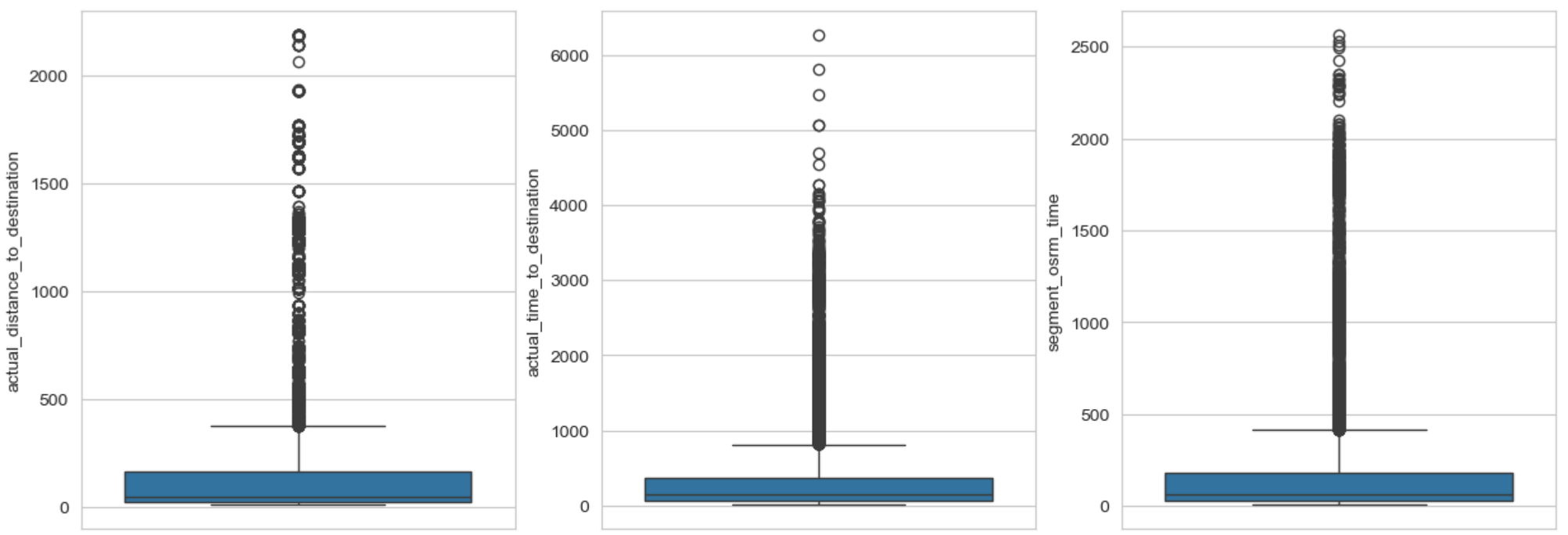
In [ ]:
```
columns = ['start_scan_to_end_scan', 'actual_distance_to_destination',
           'actual_time_to_destination', 'segment_osrm_time', 'osrm_distance','segment_actual_time', 'osrm_time',
           'segment_osrm_distance', 'od_diff_hours']
```

In [ ]:
```
plt.figure(figsize=(10, 8))
sns.heatmap(trip_df[columns].corr(), annot=True);
```

Observations

- From above plot we can see the correlation between different features.
- We can use this plot to remove highly correlated features from the dataset

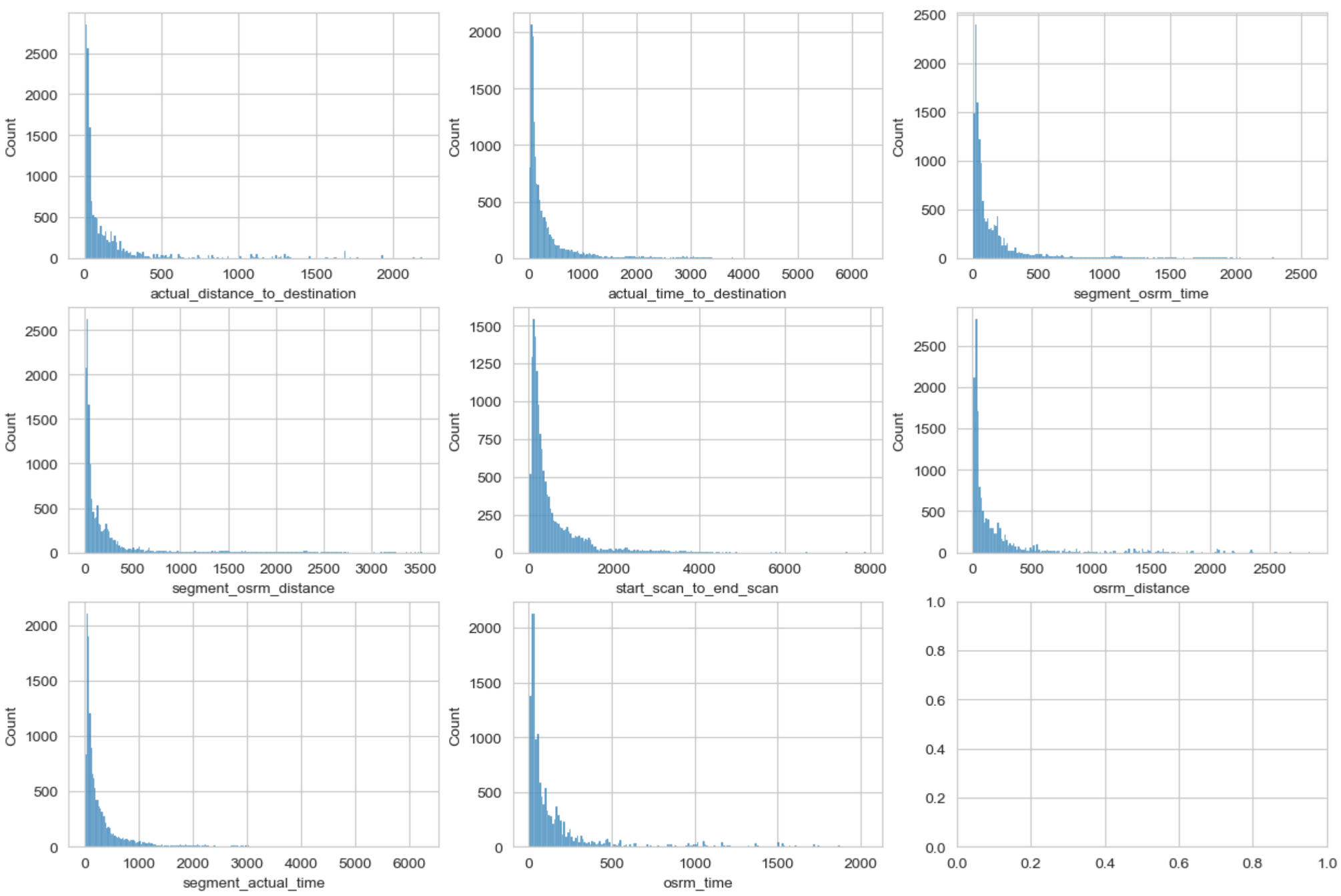
In [ ]:
```
fig, ax = plt.subplots(3, 3, figsize=(15, 18))
sns.boxplot(data=trip_df, y="actual_distance_to_destination", ax=ax[0, 0])
sns.boxplot(data=trip_df, y="actual_time_to_destination", ax=ax[0, 1])
sns.boxplot(data=trip_df, y="segment_osrm_time", ax=ax[0, 2])
sns.boxplot(data=trip_df, y="segment_osrm_distance", ax=ax[1, 0])
sns.boxplot(data=trip_df, y="start_scan_to_end_scan", ax=ax[1, 1])
sns.boxplot(data=trip_df, y="osrm_distance", ax=ax[1, 2])
sns.boxplot(data=trip_df, y="segment_actual_time", ax=ax[2, 0]);
sns.boxplot(data=trip_df, y="osrm_time", ax=ax[2, 1]);
```



Observations

- Lot of outliers as per box plot.

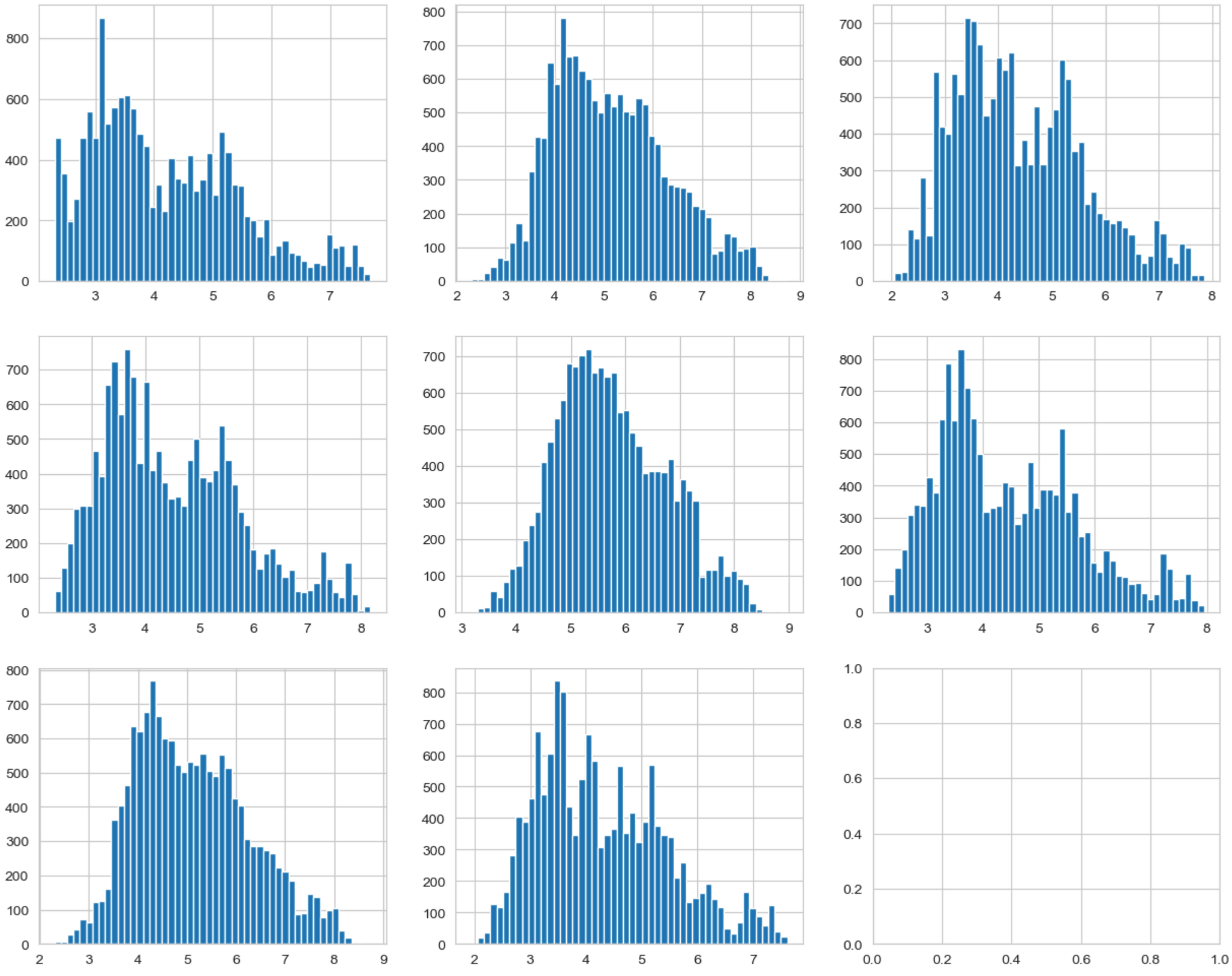
In [ ]:
```
fig, ax = plt.subplots(3 , 3, figsize=(15, 10))
sns.histplot(data=trip_df, x="actual_distance_to_destination", ax=ax[0, 0])
sns.histplot(data=trip_df, x="actual_time_to_destination", ax=ax[0, 1])
sns.histplot(data=trip_df, x="segment_osrm_time", ax=ax[0, 2])
sns.histplot(data=trip_df, x="segment_osrm_distance", ax=ax[1, 0])
sns.histplot(data=trip_df, x="start_scan_to_end_scan", ax=ax[1, 1])
sns.histplot(data=trip_df, x="osrm_distance", ax=ax[1, 2])
sns.histplot(data=trip_df, x="segment_actual_time", ax=ax[2, 0]);
sns.histplot(data=trip_df, x="osrm_time", ax=ax[2, 1]);
```



Observations

- From above plots we can see that most of the features are not normally distributed.
- We need to apply log transformation to features to convert non normal data to normal distribution.

In [ ]:
```
fig, ax = plt.subplots(3, 3, figsize=(15, 12))

np.log1p(trip_df["actual_distance_to_destination"]).hist(bins=50, ax=ax[0, 0])
np.log1p(trip_df["actual_time_to_destination"]).hist(bins=50, ax=ax[0, 1])
np.log1p(trip_df["segment_osrm_time"]).hist(bins=50, ax=ax[0, 2])
np.log1p(trip_df["segment_osrm_distance"]).hist(bins=50, ax=ax[1, 0])
np.log1p(trip_df["start_scan_to_end_scan"]).hist(bins=50, ax=ax[1, 1])
np.log1p(trip_df["osrm_distance"]).hist(bins=50, ax=ax[1, 2])
np.log1p(trip_df["segment_actual_time"]).hist(bins=50, ax=ax[2, 0]);
np.log1p(trip_df["osrm_time"]).hist(bins=50, ax=ax[2, 1]);
```



- From above plots we can see that most of the features are normally distributed after applying log transformation.

Data Preprocessing

In [ ]:
```
processed_df = trip_df.copy()
```

Applying log transformation to convert non normal data to normal distribution

In [ ]:
```
processed_df["actual_distance_to_destination"] = np.log1p(processed_df["actual_distance_to_destination"])
processed_df["actual_time_to_destination"] = np.log1p(processed_df["actual_time_to_destination"])
processed_df["segment_osrm_time"] = np.log1p(processed_df["segment_osrm_time"])
processed_df["segment_osrm_distance"] = np.log1p(processed_df["segment_osrm_distance"])
processed_df["start_scan_to_end_scan"] = np.log1p(processed_df["start_scan_to_end_scan"])
processed_df["osrm_distance"] = np.log1p(processed_df["osrm_distance"])
processed_df["segment_actual_time"] = np.log1p(processed_df["segment_actual_time"])
processed_df["osrm_time"] = np.log1p(processed_df["osrm_time"])
```

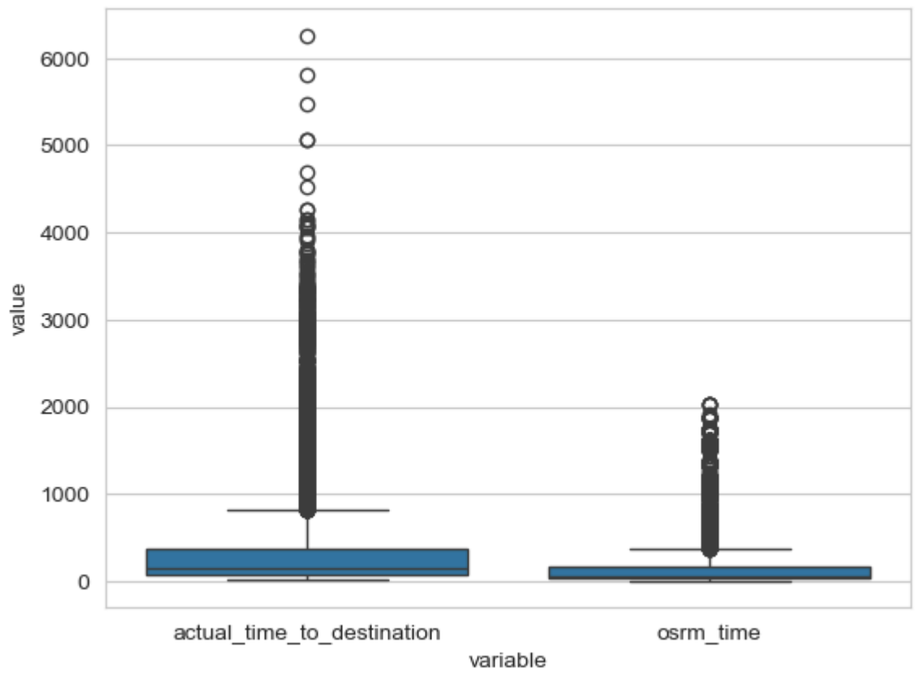
Hypothesis testing

Actual time to destination vs osrm time

H0 = "The actual time to destination equal to osrm time"

H1 = "The actual time to destination is different from osrm time"

In [ ]:
```
sns.boxplot(data=pd.melt(trip_df[["actual_time_to_destination","osrm_time"]]), x="variable", y="value");
```



In [ ]:
```
ttest_ind(trip_df["actual_time_to_destination"],trip_df["osrm_time"])
```

Out[ ]:
```
TtestResult(statistic=38.08071567723596, pvalue=8.2146191343466e-310, df=29572.0)
```

Insights

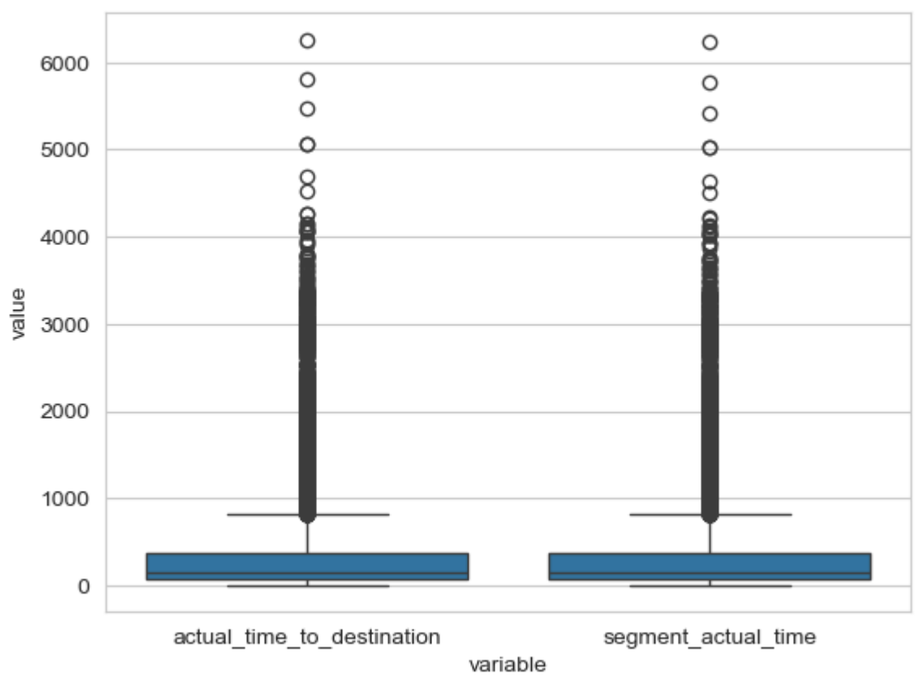
- Since p-value is less than 0.05, we reject the null hypothesis. ie the actual_time_to_destination is different from osrm_time

Actual time to destination vs segment actual time

H0 = "The Actual time to destination equal to segment actual time"

H1 = "The Actual time to destination is different from segment actual time"

In [ ]:
```
sns.boxplot(data=pd.melt(trip_df[["actual_time_to_destination","segment_actual_time"]]), x="variable", y="value");
```



In [ ]:
```
ttest_ind(trip_df["actual_time_to_destination"], trip_df["segment_actual_time"])
```

Out[ ]:
```
TtestResult(statistic=0.499475764573994, pvalue=0.6174479719707524, df=29572.0)
```

Insights

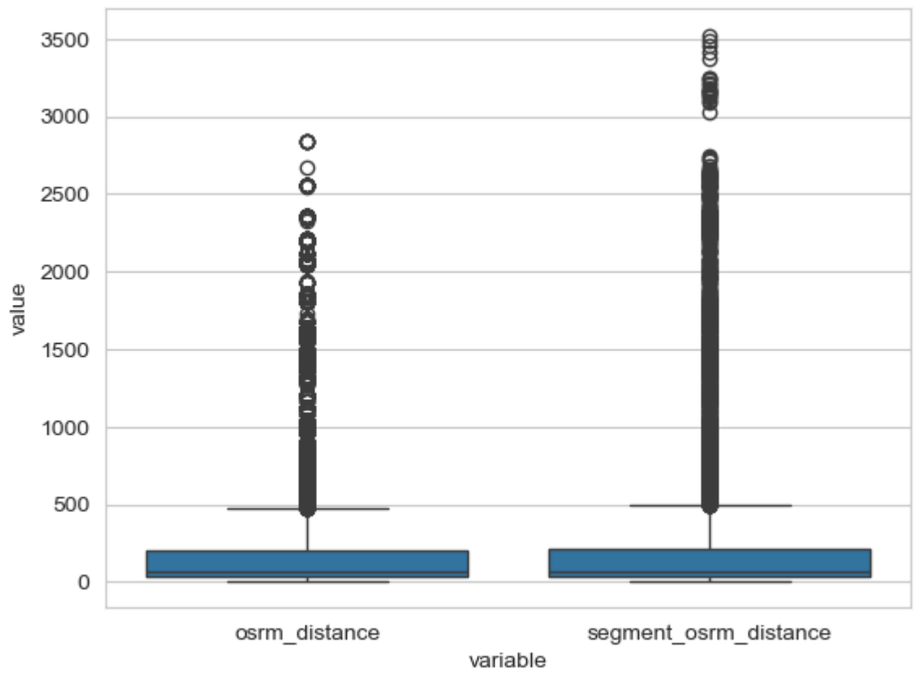
- Since p-value is grater than 0.05, we accept the null hypothesis. ie the The Actual time to destination equal to segment actual time.

Osrm distance vs segment osrm distance

H0 = "The osrm distance equal to segment osrm distance"

H1 = "The osrm distance is different from segment osrm distance"

In [ ]:
```
sns.boxplot(data=pd.melt(trip_df[["osrm_distance","segment_osrm_distance"]]), x="variable", y="value");
```



In [ ]:
```
ttest_ind(trip_df["osrm_distance"], trip_df["segment_osrm_distance"])
```

Out[ ]:
```
TtestResult(statistic=-4.102786976805525, pvalue=4.09295781912011e-05, df=29572.0)
```

Insights

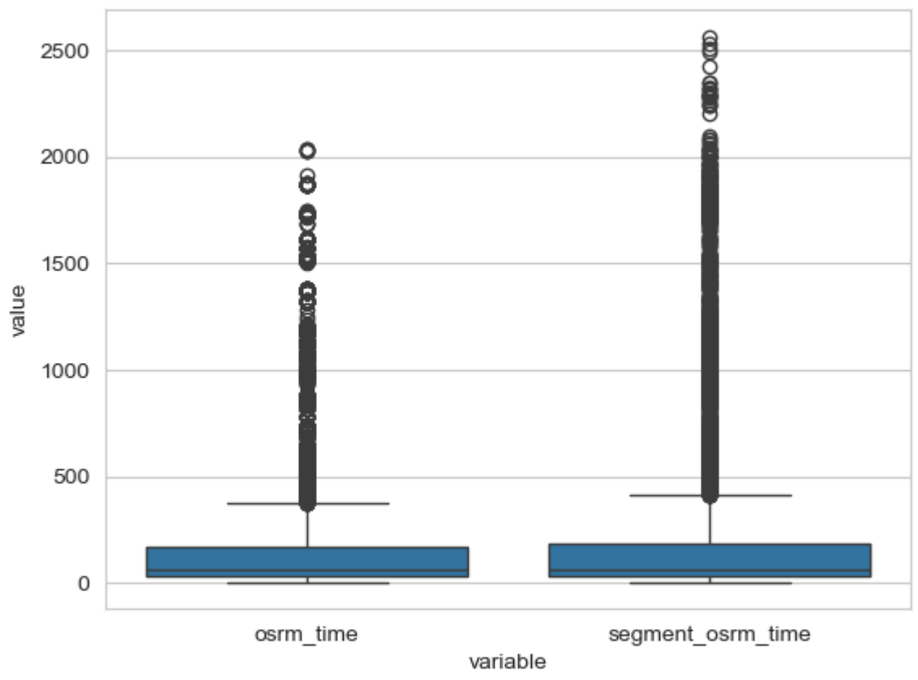
- Since p-value is less than 0.05, we reject the null hypothesis. ie The osrm distance is different from segment osrm distance

Osrm time vs segment osrm time

H0 = "The osrm time equal to segment osrm time"

H1 = "The osrm time is different from segment osrm time"

In [ ]:
```
sns.boxplot(data=pd.melt(trip_df[["osrm_time","segment_osrm_time"]]), x="variable", y="value");
```



In [ ]:
```
ttest_ind(trip_df["osrm_time"], trip_df["segment_osrm_time"])
```

Out[ ]:
```
TtestResult(statistic=-5.711782161676085, pvalue=1.128703468644937e-08, df=29572.0)
```

Insights

- Since p-value is less than 0.05, we reject the null hypothesis.ie The osrm time is different from segment osrm time

Categorical Feature Encoding

In [ ]:
```
processed_df["route_type"] = processed_df["route_type"].apply(
    lambda x: 1 if x == "FTL" else 0)
```

In [ ]:
```
label_encoder_source_destination = LabelEncoder()
unique_source_destination_list = list(set([*processed_df["source_center"].unique(), *processed_df["destination_center"].unique()]))
label_encoder_source_destination.fit(unique_source_destination_list)
processed_df["source_center"] = label_encoder_source_destination.transform(processed_df["source_center"])
processed_df["destination_center"] = label_encoder_source_destination.transform(processed_df["destination_center"])
```

In [ ]:
```
labe_encoder_state = LabelEncoder()
unique_state_list = list(set([*processed_df["source_state"].unique(), *processed_df["destination_state"].unique()]))
labe_encoder_state.fit(unique_state_list)
processed_df["source_state"] = labe_encoder_state.transform(processed_df["source_state"])
processed_df["destination_state"] = labe_encoder_state.transform(processed_df["destination_state"])
```

In [ ]:
```
labe_encoder_city = LabelEncoder()
unique_city_list = list(set([*processed_df["source_city"].unique(), *processed_df["destination_city"].unique()]))
labe_encoder_city.fit(unique_city_list)
processed_df["source_city"] = labe_encoder_city.transform(processed_df["source_city"])
processed_df["destination_city"] = labe_encoder_city.transform(processed_df["destination_city"])
```

In [ ]:
```
with open("processed_df.pkl", "wb") as f:
    pickle.dump(processed_df, f)
```

Numerical Feature Scaling

In [ ]:
```
standard_scaling_columns = ["start_scan_to_end_scan", "actual_distance_to_destination",
                            "actual_time_to_destination", "segment_osrm_time", "segment_osrm_distance", "od_diff_hours", "osrm_distance",
                            "segment_actual_time", "osrm_time"]
```

In [ ]:
```
sc = StandardScaler()
processed_df[standard_scaling_columns] = sc.fit_transform(
    processed_df[standard_scaling_columns])
```

In [ ]:
```
min_max_scaling_columns = ["trip_creation_hour", "trip_creation_day", "trip_creation_month", "trip_creation_weekday", "od_start_time_month",
                           "od_end_time_month", "od_end_time_day", "od_start_time_day", "od_start_time_hour", "od_end_time_hour",
                           "od_start_time_minute", "od_end_time_minute"]
```

In [ ]:
```
min_max_sc = MinMaxScaler()
processed_df[min_max_scaling_columns] = min_max_sc.fit_transform(
    processed_df[min_max_scaling_columns])
```

In [ ]:
```
processed_df.sample(5)
```

Out[ ]:

	trip_uuid	source_center	destination_center	stops	route_type	start_scan_to_end_scan	actual_distance_to_destination	actual_time_to_destination	osrm_time	segment_actual_time	segment
2999	153729863029649858	552	598	1	1	1.256140	1.526449	1.416606	1.431403	1.416163	
10138	153682425683336487	33	7	1	0	-0.176805	-0.232870	0.077484	-0.157303	0.077061	
11113	153697923296988490	422	431	3	1	0.699675	1.068885	0.973853	1.234510	0.970278	
735	153821467414628127	518	518	3	0	0.004215	-0.318035	0.054157	-0.260086	0.053504	
13342	153766486594351691	29	201	2	1	1.540887	1.712381	1.484161	1.587825	1.479736	

Recommendations and Business Insights

- Carting route type is the most popular route type. This can be further improved by increasing the delivery hubs in different states.
- Delhi-Haryana is the busiest state pair.
- Increasing the delivery capacity on all Delhi-Haryana routes will be beneficial.
- Delhi-Gurugram route needs to have more Carting type route as having FTL increases the time by a huge ammount.
- Most of the trips are made on Tuesdays
- Most of the FTL trips are at night time whereas Carting trips are made throughout the day excluding morning hours
- Bengaluru and Mumbai are the most popular source and destination cities.
- The OSRM system should be tweaked to improve the accuracy as it overestimates the distance between two points but underestimates the time taken to travel between two points.
- Pappadahandi-Visakhapatnam is the highest time taking trip whereas Gurgaon-Muzaffrpur is the longest distance trip.