In [82]:

```
import pandas as pd
import numpy as np
from numpy import nan, NaN,NAN
from matplotlib import pyplot as plt
import seaborn as sns
import warnings
import scipy
warnings.filterwarnings("ignore")
from scipy import stats
import statsmodels.api as sm
import datetime
import matplotlib.dates
```

In [2]:

```
delv=pd.read_csv("delhivery_data.txt")
```

In [3]:
```
df=delv.copy()
df.head(5)
```

Out[3]:

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

5 rows × 24 columns

In [4]:
```
df.shape
```

Out[4]: (144867, 24)

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
```

In [6]:
```
#Find number of missing values in each columns
df.isnull().sum()
```

Out[6]:
```
data                               0
trip_creation_time                 0
route_schedule_uuid                0
route_type                         0
trip_uuid                          0
source_center                      0
source_name                      293
destination_center                 0
destination_name                 261
od_start_time                      0
od_end_time                        0
start_scan_to_end_scan             0
is_cutoff                          0
cutoff_factor                      0
cutoff_timestamp                   0
actual_distance_to_destination     0
actual_time                        0
osrm_time                          0
osrm_distance                      0
factor                             0
segment_actual_time                0
segment_osrm_time                  0
segment_osrm_distance              0
segment_factor                     0
dtype: int64
```

There are missing values in Source_name and Destination_name.Marking them as Unknown

In [7]:
```
df["source_name"]=df["source_name"].fillna("Unknown")
df["destination_name"]=df["destination_name"].fillna("Unknown")
```

Drop the unknown fields like

is_cutoff,cutoff_factor,cutoff_timestamp,factor,segment_factor

In [8]:
```
df.drop(columns=["is_cutoff","cutoff_factor","cutoff_timestamp","factor","segment_factor"],inplace=True)
```

In [9]:
```
#convert to datetime datatype
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"])
```

In [10]:
```
#extract month and year from trip_creation_time .New feature added trip_creation_mon ,trip_creation_year and trip_creatio
df["trip_creation_mon"]=df["trip_creation_time"].dt.month_name()
df["trip_creation_year"]=df["trip_creation_time"].dt.year
df["trip_creation_day"]=df["trip_creation_time"].dt.day_name()
```

In [11]:
```
#Convert all time fields from mins to hrs
df["start_scan_to_end_scan"]=df["start_scan_to_end_scan"]/60
df["actual_time"]=df["actual_time"]/60
df["osrm_time"]=df["osrm_time"]/60
df["segment_actual_time"]=df["segment_actual_time"]/60
df["segment_osrm_time"]=df["segment_osrm_time"]/60
```

In [46]:
```
#categorical columns
cat_col=df.dtypes=='object'
cat_col=list(cat_col[cat_col].index)
cat_col.remove('trip_uuid')
cat_col.remove("source_center")
cat_col.remove("destination_center")
cat_col.remove("route_schedule_uuid")
cat_col
```

Out[46]:
```
['data',
 'route_type',
 'source_name',
 'destination_name',
 'trip_creation_mon',
 'trip_creation_day']
```

In [49]:
```
# %unique value counts
for c in cat_col:
    if c=='source_name' or c=='destination_name':
        continue
    else:
        print(round(df[c].value_counts(normalize=True)*100),2)
        print("*"*50)
```

```
training    72.0
test        28.0
Name: data, dtype: float64 2
**************************************************
FTL        69.0
Carting    31.0
Name: route_type, dtype: float64 2
**************************************************
September    88.0
October      12.0
Name: trip_creation_mon, dtype: float64 2
**************************************************
Wednesday    18.0
Thursday     14.0
Friday       14.0
Tuesday      14.0
Saturday     14.0
Monday       14.0
Sunday       12.0
Name: trip_creation_day, dtype: float64 2
**************************************************
```

The given dataset is for two months September(88%) and October(12%) for the year 2018

69% of data is FTL and 31% is Carting

18% trips happen on Wednesday and least on Sunday

In [14]:

```
"""Grouping the data based on Trip id,source and destination id.For each group the segmnent's osrm time and distances
are summed while for the actual time and distances the last row for the group is picked since in the original dataset
they are computed cumulatively.The result is stored in df_sd.This Dataframe has the dependent variables of time and dista
"""
df_sd=df.groupby(["trip_uuid","source_center","destination_center"])[["segment_actual_time","segment_osrm_time","segment_
df_sd.head(5)
```

Out[14]:

ource_center	destination_center	segment_actual_time	segment_osrm_time	segment_osrm_distance	actual_time	osrm_time	osrm_distance	actual_dis
ID209304AAA	IND000000ACB	12.133333	8.900000	670.6205	12.200000	5.816667	446.5496	
ID462022AAA	IND209304AAA	13.666667	7.900000	649.8528	13.833333	6.566667	544.8027	
ID561203AAB	IND562101AAA	0.766667	0.433333	28.1995	0.783333	0.433333	28.1994	
ID572101AAA	IND561203AAB	1.583333	0.650000	55.9899	1.600000	0.700000	56.9116	
ID000000ACB	IND160002AAC	10.133333	3.850000	317.7408	10.183333	3.533333	281.2109	

In [15]:
```
"""df1 is a dataframe created to merge df_sd.so that while merging most of the independent features are picked from df1"
df1=df.groupby(["trip_uuid","source_center","destination_center"])["data","trip_creation_time","trip_creation_mon","trip_

df1.head()
```

Out[15]:

	trip_uuid	source_center	destination_center	data	trip_creation_time	trip_creation_mon	trip_creation_year	trip_creation_day	route_
0	trip-153671041653548748	IND209304AAA	IND000000ACB	training	2018-09-12 00:00:16.535741	September	2018	Wednesday	
1	trip-153671041653548748	IND462022AAA	IND209304AAA	training	2018-09-12 00:00:16.535741	September	2018	Wednesday	
2	trip-153671042288605164	IND561203AAB	IND562101AAA	training	2018-09-12 00:00:22.886430	September	2018	Wednesday	Ca
3	trip-153671042288605164	IND572101AAA	IND561203AAB	training	2018-09-12 00:00:22.886430	September	2018	Wednesday	Ca
4	trip-153671043369099517	IND000000ACB	IND160002AAC	training	2018-09-12 00:00:33.691250	September	2018	Wednesday	

In [16]:
```
"""This is the final dataframe after merging the above two frames.Futhur EDA to be done on this dataframe"""
df_agg=pd.merge(df_sd,df1[["trip_uuid","source_center","destination_center","data","trip_creation_time","trip_creation_m
df_agg.head(5)
```

Out[16]:

	trip_uuid	source_center	destination_center	segment_actual_time	segment_osrm_time	segment_osrm_distance	actual_time	osrm_tim
0	trip-153671041653548748	IND209304AAA	IND000000ACB	12.133333	8.900000	670.6205	12.200000	5.81666
1	trip-153671041653548748	IND462022AAA	IND209304AAA	13.666667	7.900000	649.8528	13.833333	6.56666
2	trip-153671042288605164	IND561203AAB	IND562101AAA	0.766667	0.433333	28.1995	0.783333	0.43333
3	trip-153671042288605164	IND572101AAA	IND561203AAB	1.583333	0.650000	55.9899	1.600000	0.70000
4	trip-153671043369099517	IND000000ACB	IND160002AAC	10.133333	3.850000	317.7408	10.183333	3.53333

5 rows × 21 columns

In [17]:
```
df_agg.shape
```

Out[17]: (26368, 21)

In [18]:
```
"""New feature travel_time(in hrs) added .this is time taken between od_start_time and od_end_time"""
df_agg["travel_time"]=df_agg["od_end_time"]-df_agg["od_start_time"]
df_agg["travel_time"]=round(df_agg["travel_time"]/datetime.timedelta(hours=1),2)
```

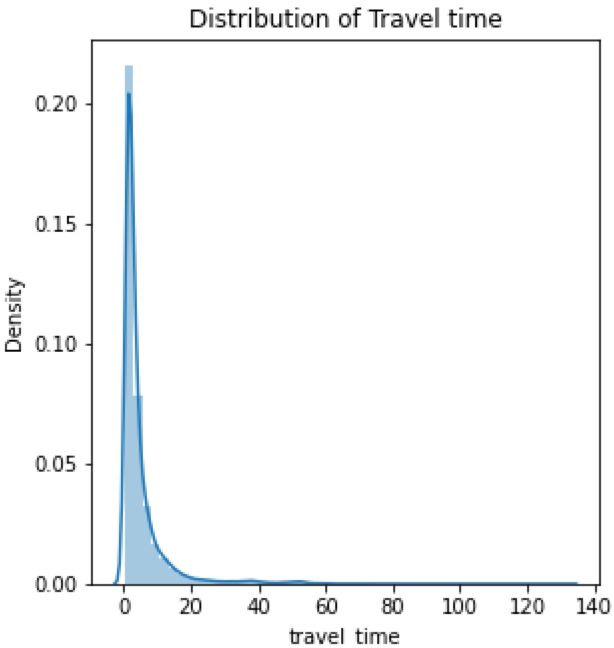
In [19]:
```
df_agg.describe().T
```

Out[19]:

	count	mean	std	min	25%	50%	75%	max
segment_actual_time	26368.0	3.314385	6.354720	0.150000	0.833333	1.383333	2.766667	75.066667
segment_osrm_time	26368.0	1.694689	3.594182	0.100000	0.416667	0.700000	1.316667	32.300000
segment_osrm_distance	26368.0	125.423680	285.932556	9.072900	28.471300	45.944400	91.351975	2640.924700
actual_time	26368.0	3.344837	6.414227	0.150000	0.850000	1.400000	2.800000	75.533333
osrm_time	26368.0	1.517881	3.096514	0.100000	0.416667	0.650000	1.216667	28.100000
osrm_distance	26368.0	115.252837	254.069218	9.072900	27.839750	43.760400	86.467200	2326.199100
actual_distance_to_destination	26368.0	92.540646	209.478657	9.001351	21.727218	35.244189	66.043534	1927.447705
trip_creation_year	26368.0	2018.000000	0.000000	2018.000000	2018.000000	2018.000000	2018.000000	2018.000000
start_scan_to_end_scan	26368.0	4.971311	7.342693	0.333333	1.516667	2.533333	5.116667	131.633333
travel_time	26368.0	4.979340	7.342634	0.350000	1.520000	2.540000	5.120000	131.640000

Looking at the mean,median and max values ,suggests there could be outliers lets check one of the feature(travel time) first and go on to the rest

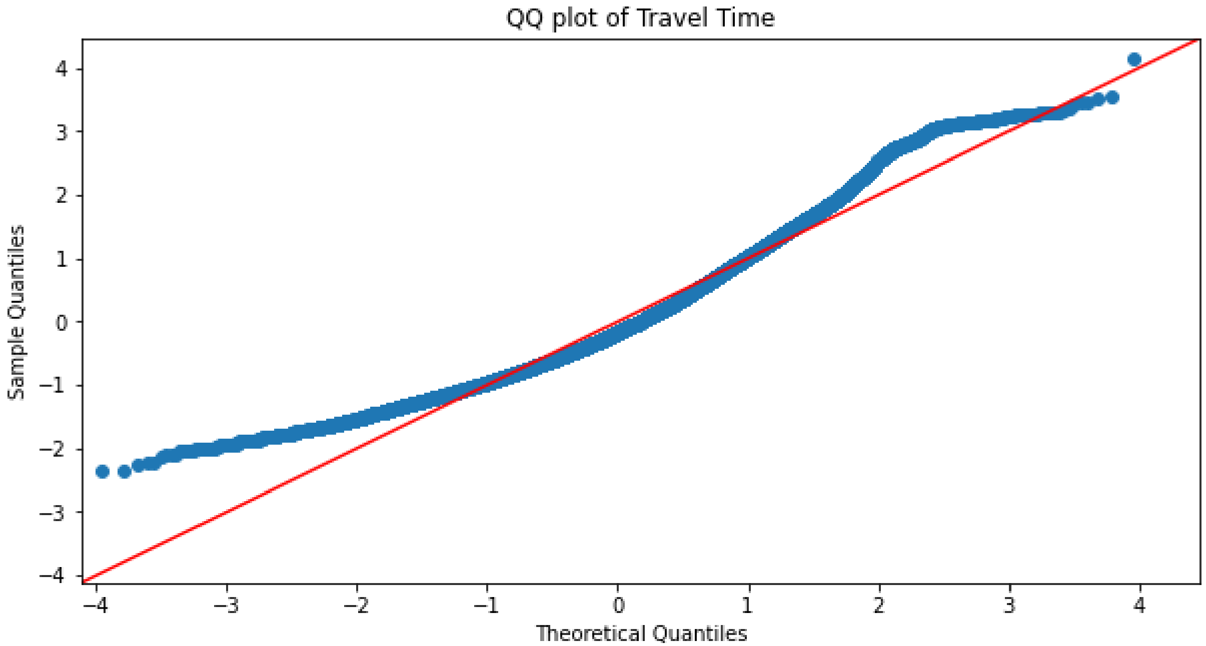
In [38]:
```
plt.rcParams["figure.figsize"] = (10,5)

plt.subplot(121)
plt.title("Distribution of Travel time")
sns.distplot(df_agg["travel_time"])
plt.subplot(122)
plt.title("Outlier Detection in Travel Time taken")
df_agg.boxplot("travel_time")
plt.show()
```



The distribution seems to be lognormal and the outliers in the boxplot can be due to the skewness in data.let's recheck wether the distribution is Log normal using a QQplot

In [39]:

```
fig=sm.qqplot(np.log(df_agg["travel_time"]),line='45',fit=True)
plt.title("QQ plot of Travel Time")
plt.show()
```



The QQplot suggests that travel time is not a Log normal Distribution.Thus the outliers to be treated

Introducing a custom function IQR_Detect to find outliers in other numerical columns.Input Parameters-Dataframe,column.Output-Distribution plot,Boxplot,QQplot and percentage outliers of the column

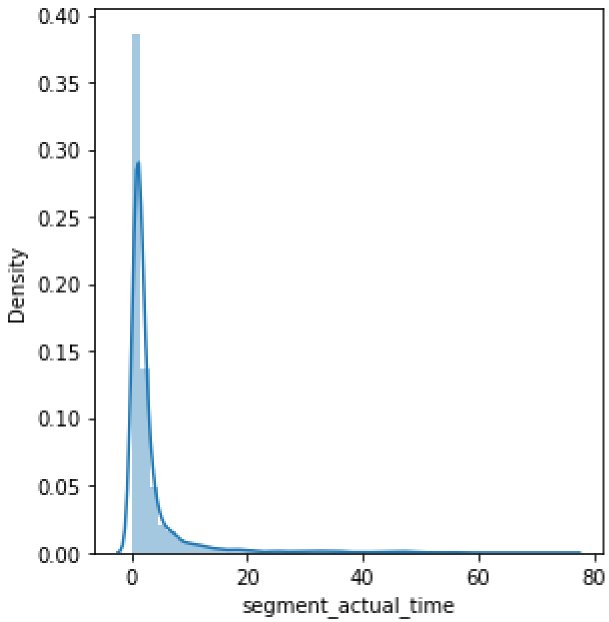
In [22]:
```
num_col=df_agg.dtypes=='float64'
num_col=list(num_col[num_col].index)
num_col
```

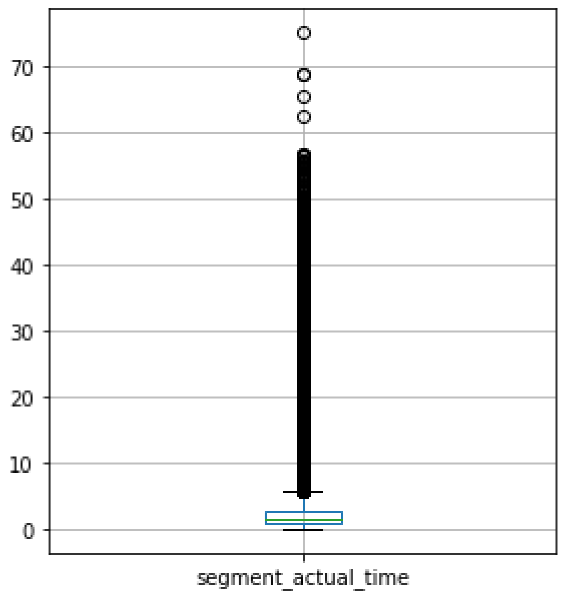
Out[22]:
```
['segment_actual_time',
 'segment_osrm_time',
 'segment_osrm_distance',
 'actual_time',
 'osrm_time',
 'osrm_distance',
 'actual_distance_to_destination',
 'start_scan_to_end_scan',
 'travel_time']
```

In [23]:
```
def IQR_Detect(dataframe,col):
    print("*"*50)
    plt.subplot(121)
    print("Plot1:Distribution of ",col)
    sns.distplot(dataframe[col])
    plt.subplot(122)
    print("Plot2:Outlier Detection in",col)
    dataframe.boxplot(col)
    plt.show()
    fig=sm.qqplot(np.log(dataframe[col]),line='45',fit=True)
    print("Plot3:QQ plot of ",col)
    plt.show()
    q1=dataframe[col].quantile(.25)
    q3=dataframe[col].quantile(.75)
    iqr=1.5*stats.iqr(dataframe[col])
    outlier_df=dataframe.loc[(dataframe[col]<q1-iqr)|(dataframe[col]>iqr+q3)]
    percent_out=round(len(outlier_df)*100/len(dataframe),2)
    print(percent_out,'% of data in column ',col,' is outlier data')
```

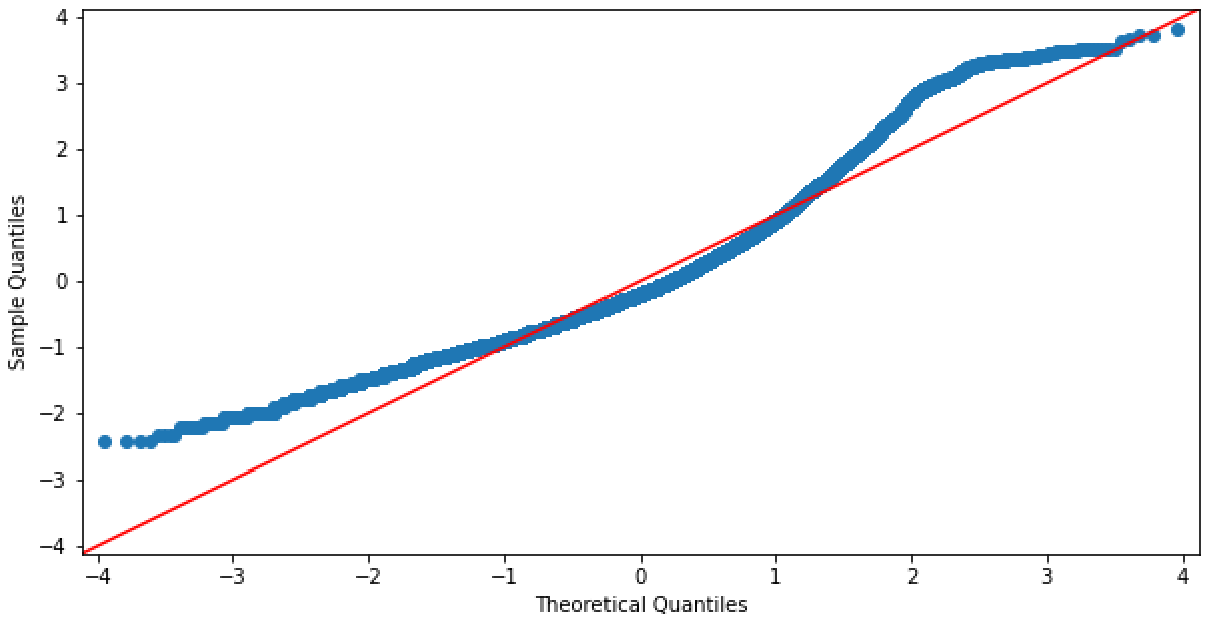
```
In [40]: for c in num_col:
             IQR_Detect(df_agg,c)
```

```
**************************************************
Plot1:Distribution of  segment_actual_time
Plot2:Outlier Detection in segment_actual_time
```

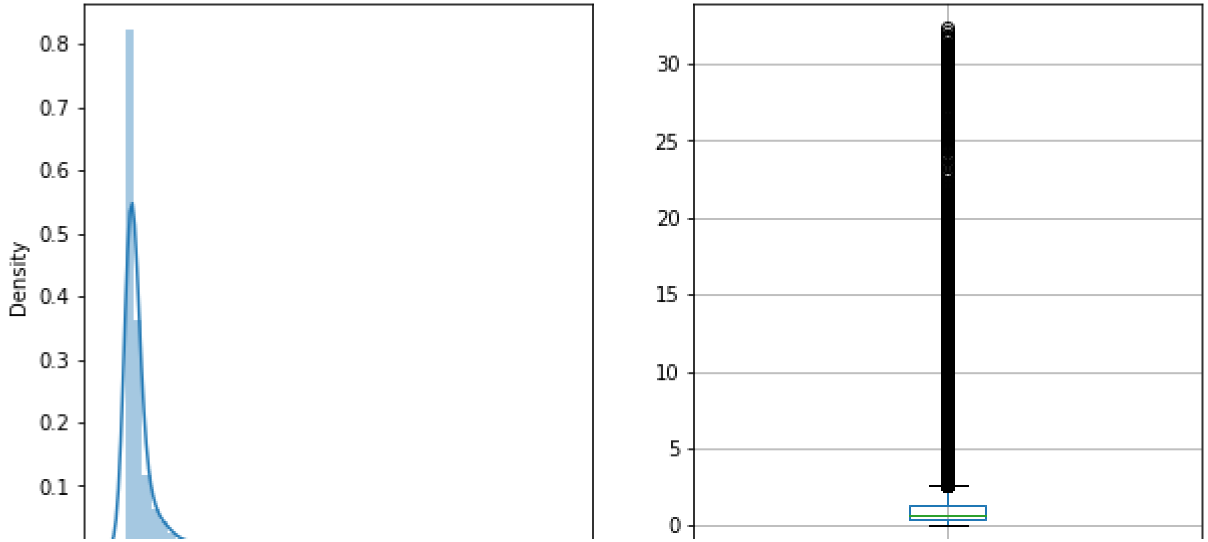




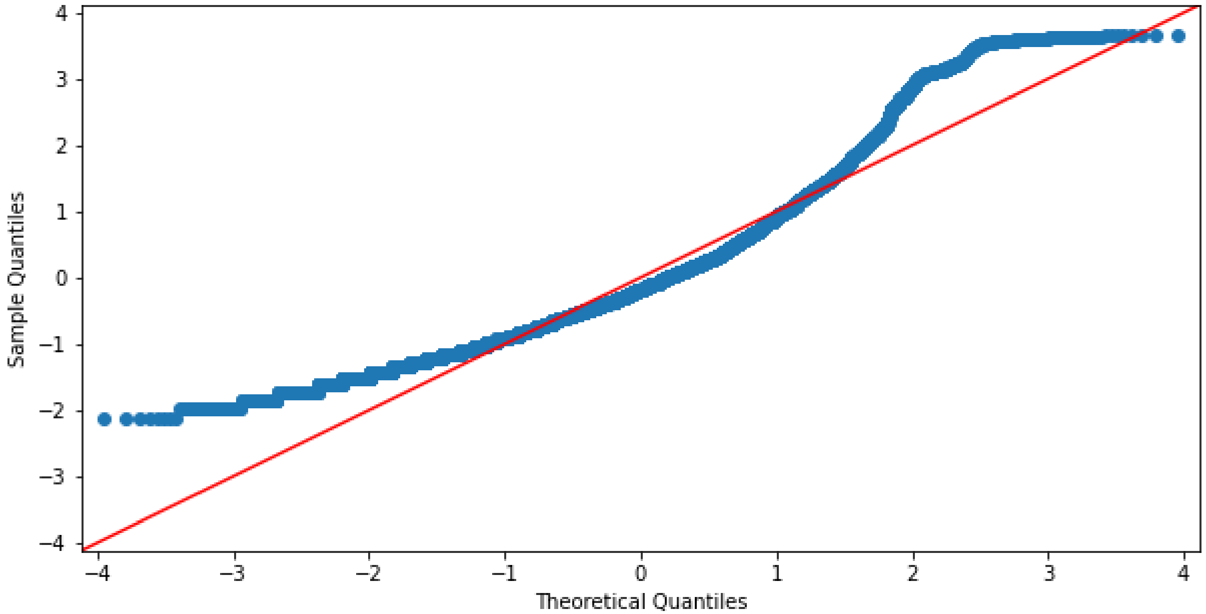

```
Plot3:QQ plot of  segment_actual_time
```



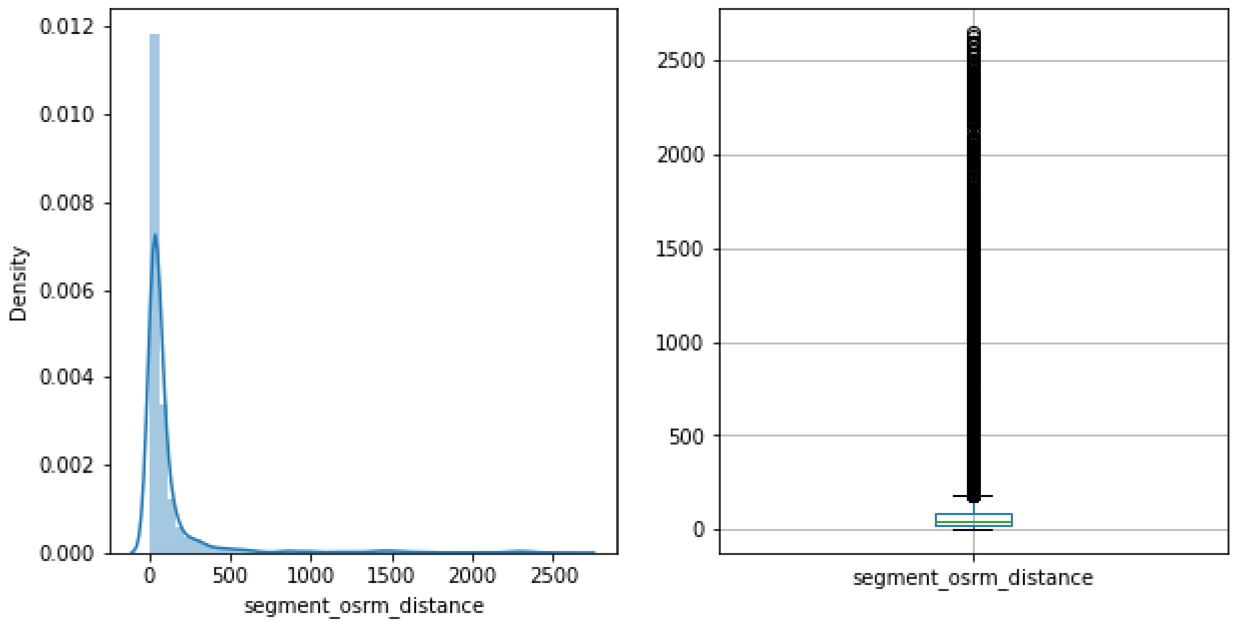

```
11.98 % of data in column  segment_actual_time  is outlier data
**************************************************
Plot1:Distribution of  segment_osrm_time
Plot2:Outlier Detection in segment_osrm_time
```



Plot3:QQ plot of segment_osrm_time

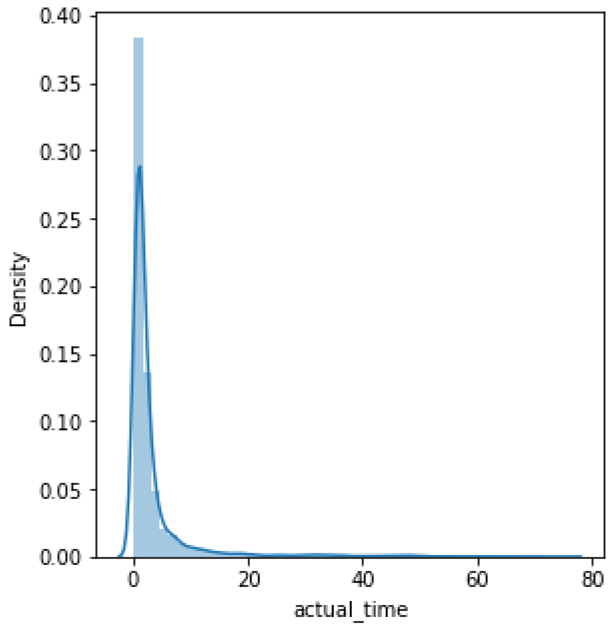


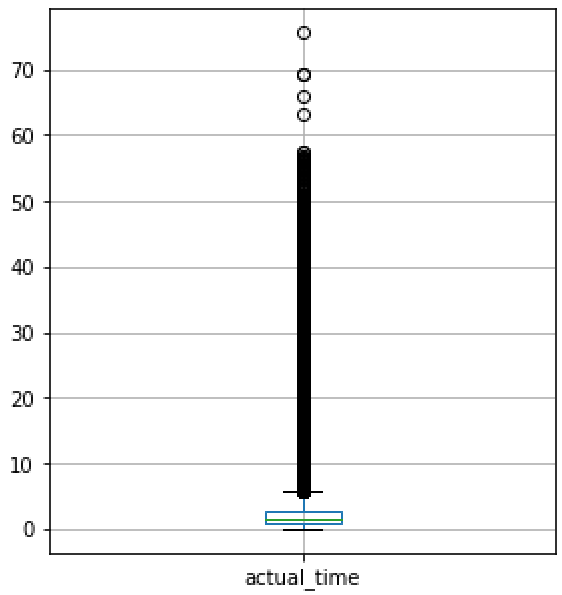

```
11.97 % of data in column  segment_osrm_time  is outlier data
**************************************************
Plot1:Distribution of  segment_osrm_distance
Plot2:Outlier Detection in segment_osrm_distance
```



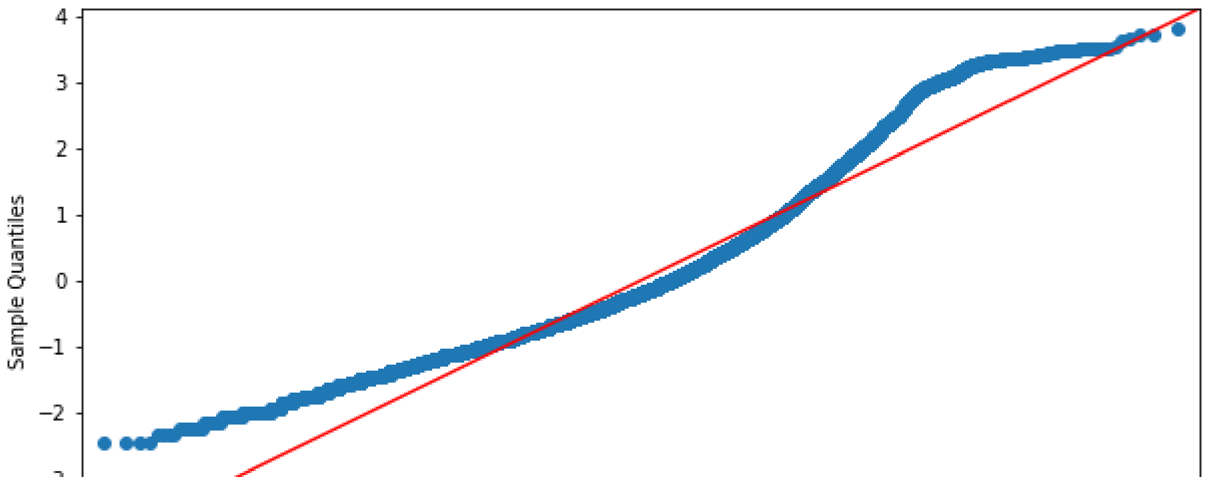
Plot3:QQ plot of segment_osrm_distance

11.78 % of data in column segment_osrm_distance is outlier data
****
Plot1:Distribution of actual_time
Plot2:Outlier Detection in actual_time



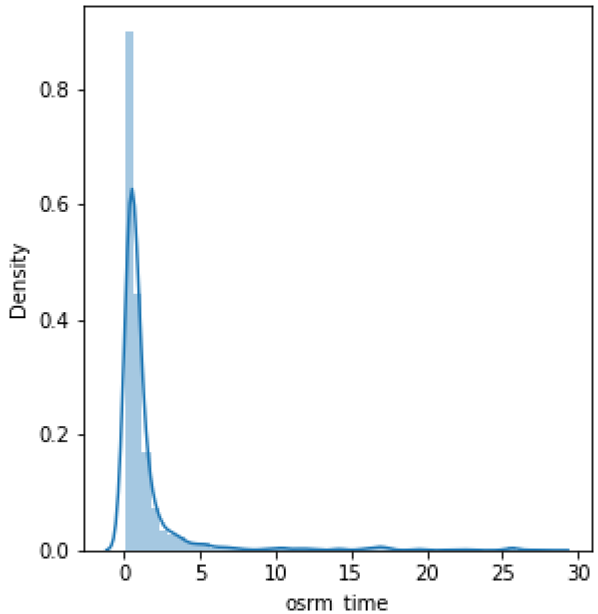


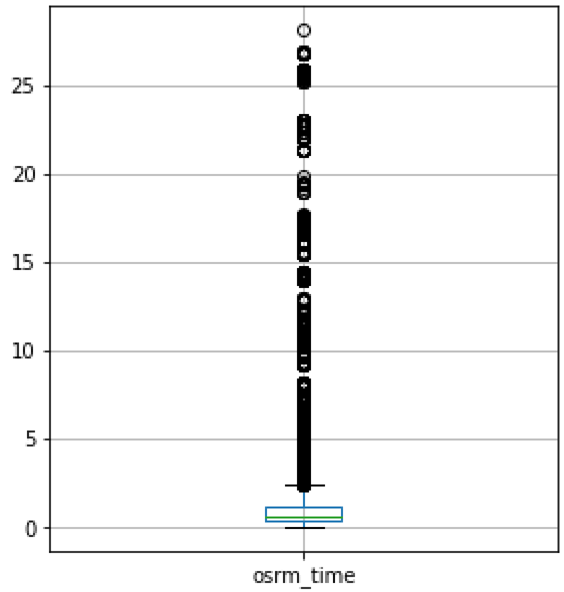
Plot3:QQ plot of actual_time



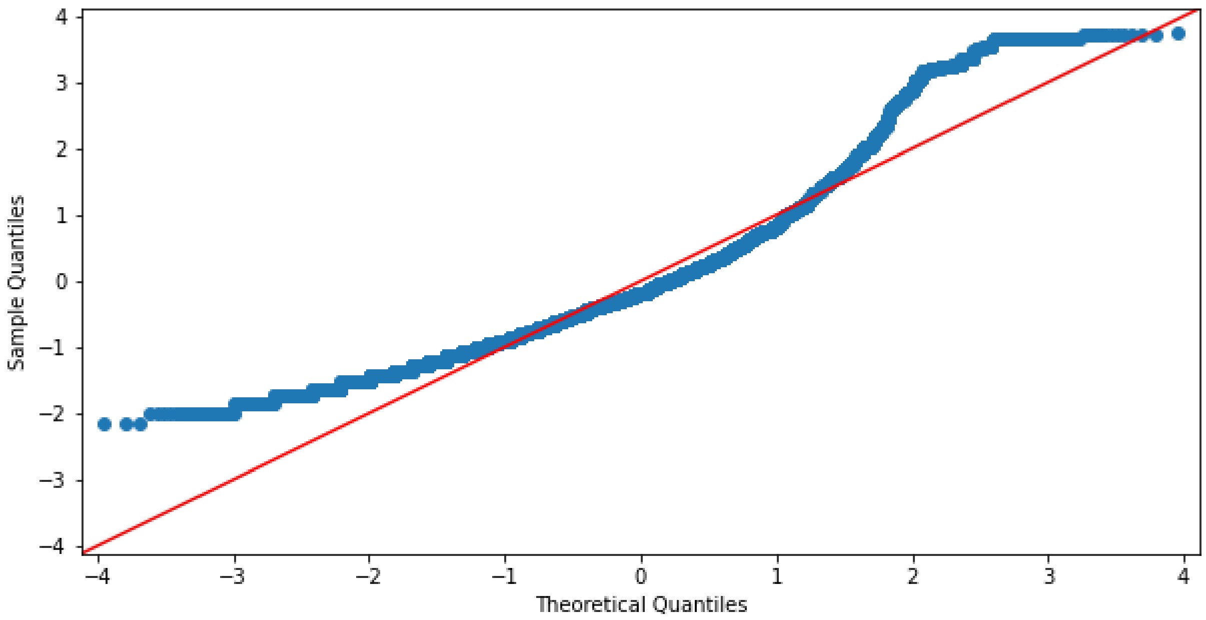
11.95 % of data in column actual_time is outlier data
****

Plot1:Distribution of osrm_time
Plot2:Outlier Detection in osrm_time

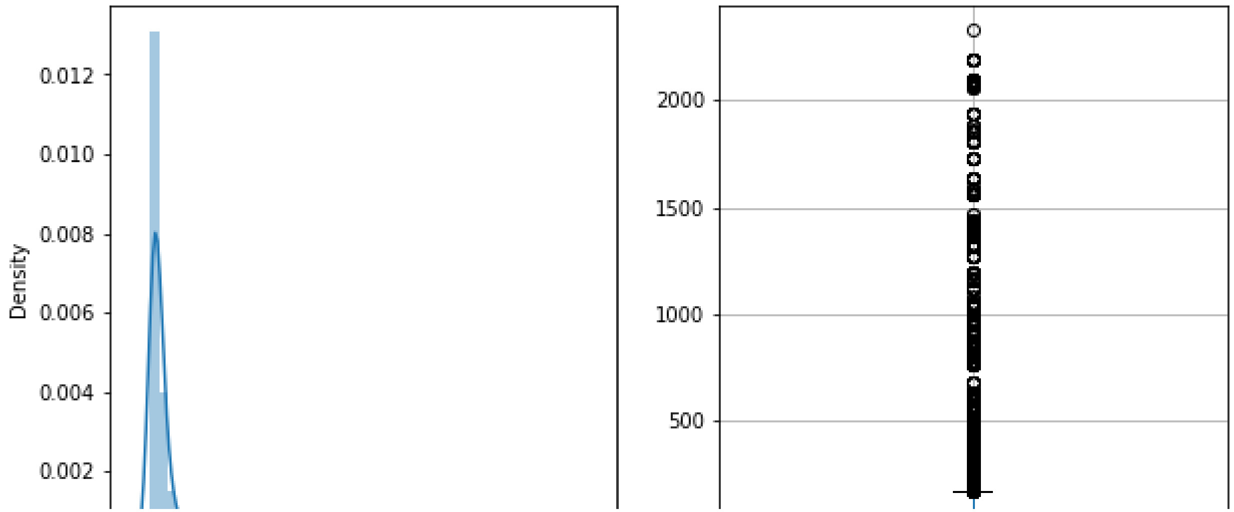




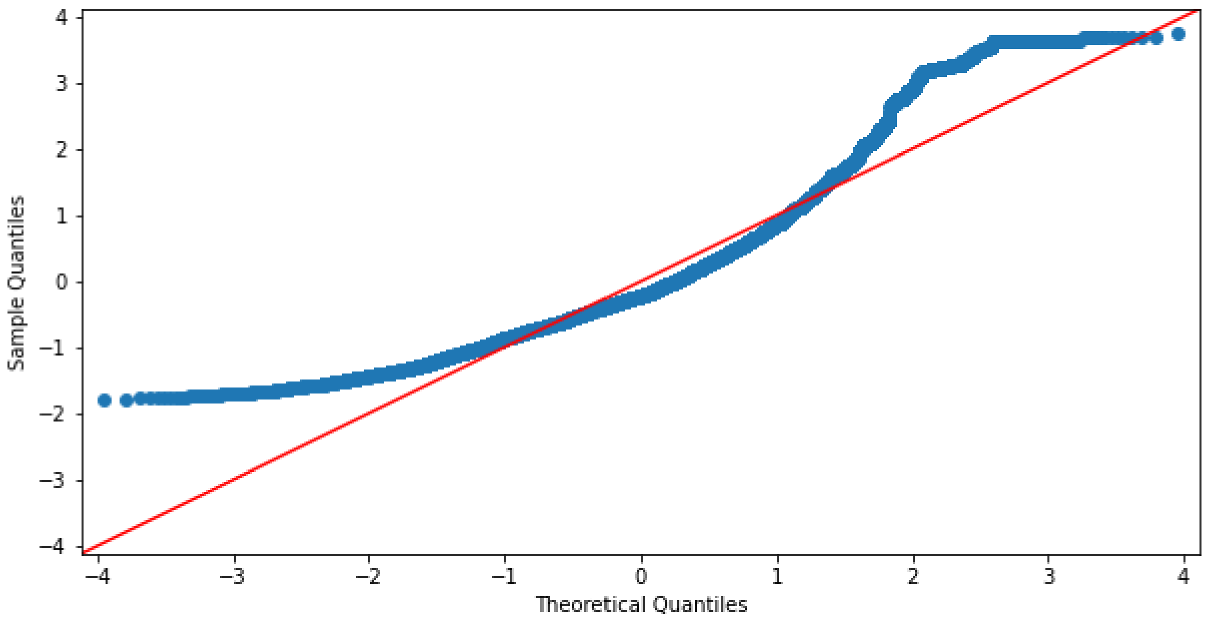
Plot3:QQ plot of osrm_time



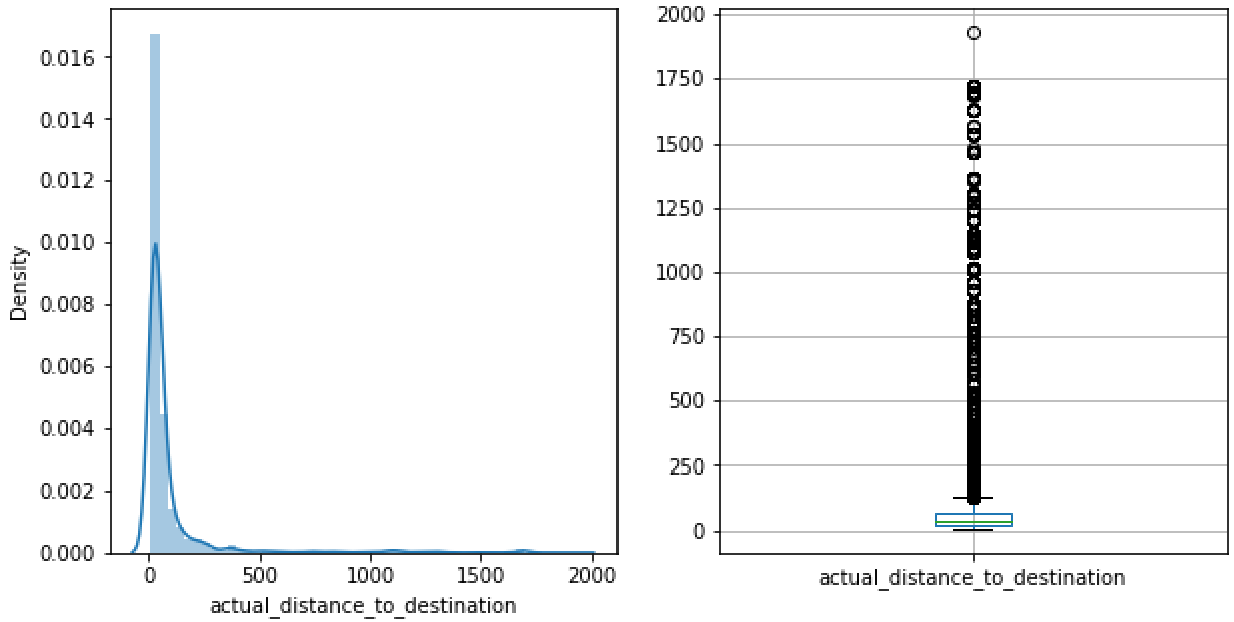

```
11.0 % of data in column  osrm_time  is outlier data
**************************************************
Plot1:Distribution of  osrm_distance
Plot2:Outlier Detection in osrm_distance
```



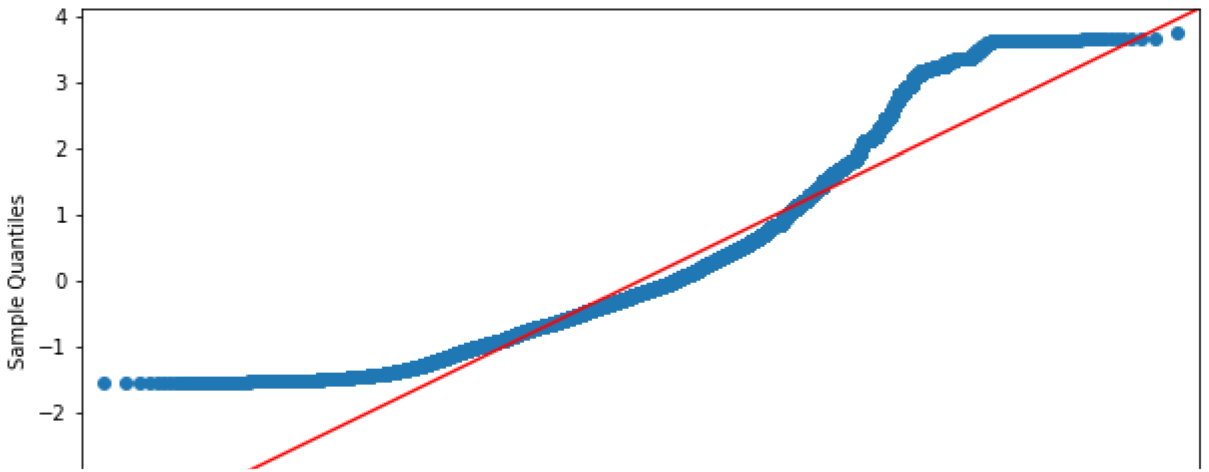
Plot3:QQ plot of osrm_distance



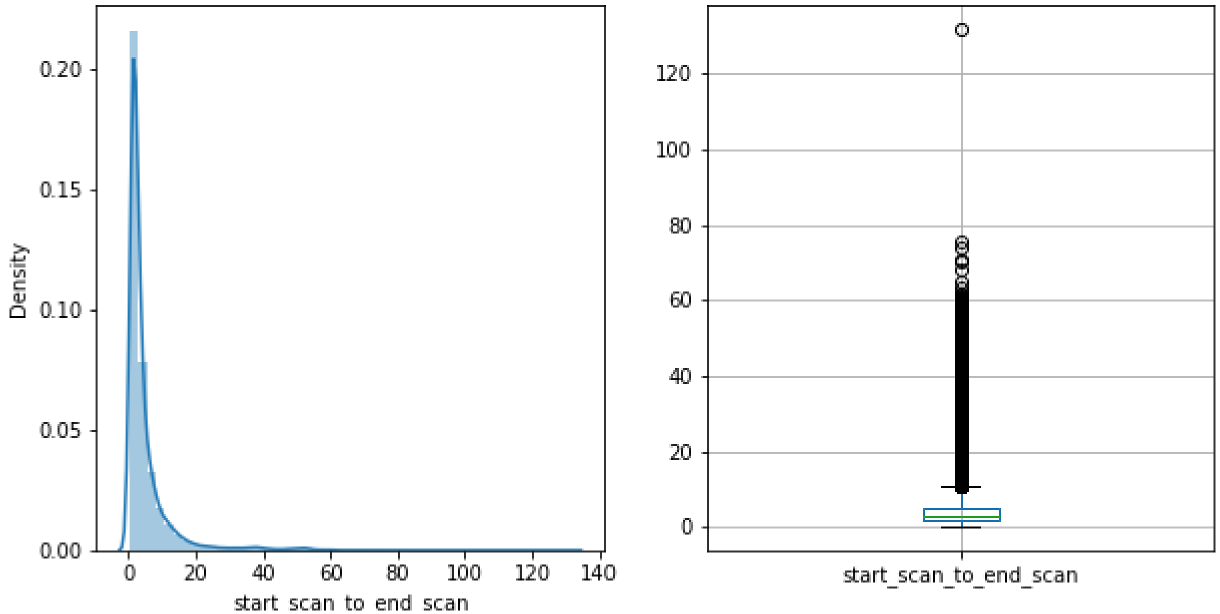
11.65 % of data in column osrm_distance is outlier data
****
Plot1:Distribution of actual_distance_to_destination
Plot2:Outlier Detection in actual_distance_to_destination



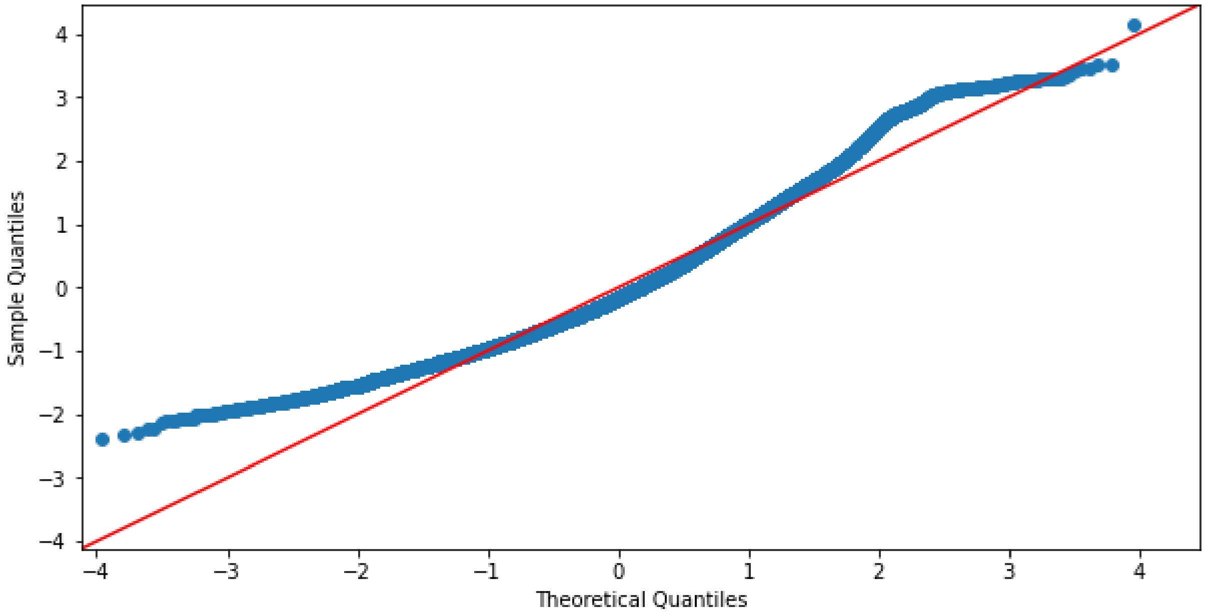
Plot3:QQ plot of actual_distance_to_destination



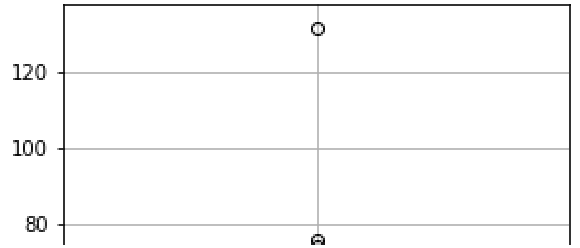
12.45 % of data in column actual_distance_to_destination is outlier data
****
Plot1:Distribution of start_scan_to_end_scan
Plot2:Outlier Detection in start_scan_to_end_scan



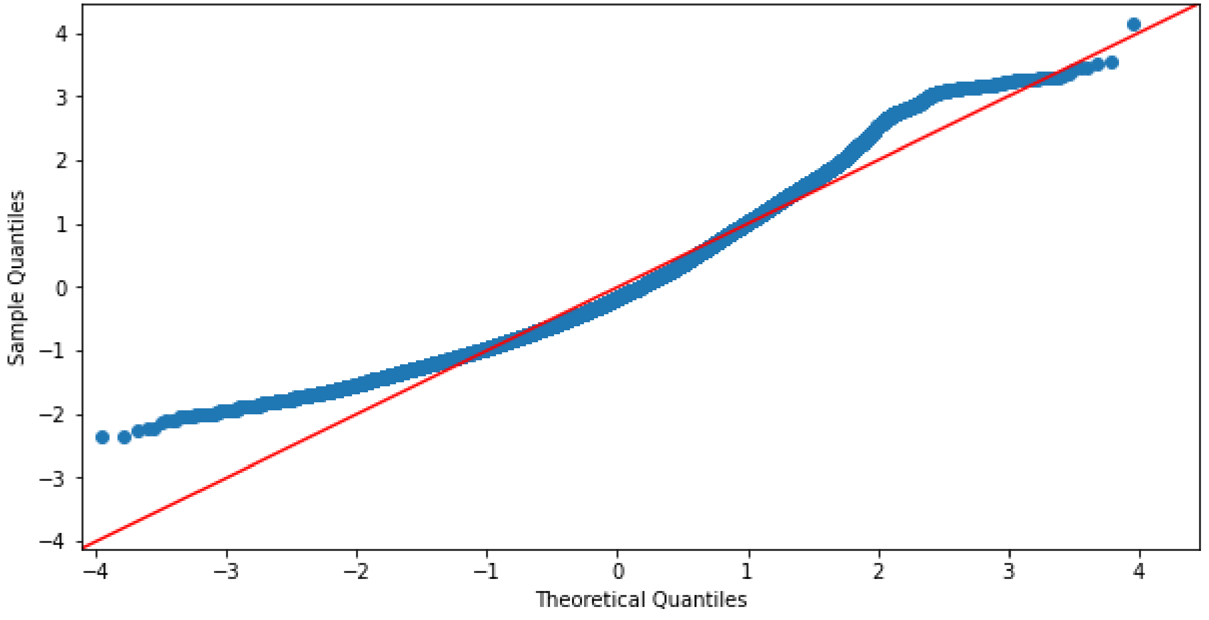
Plot3:QQ plot of start scan to end scan



10.35 % of data in column start_scan_to_end_scan is outlier data
****
Plot1:Distribution of travel_time
Plot2:Outlier Detection in travel_time



Plot3:QQ plot of travel_time



10.33 % of data in column travel_time is outlier data

All the numerical features has almost same amount of outliers ,the distribution also looks similar.Hence removing outliers from one column can bring about a same change to other numercal columns.Lets remove the outliers from column Travel time

In [25]:
```
#Outlier Removal
q1=df_agg["travel_time"].quantile(.25)
q3=df_agg["travel_time"].quantile(.75)
iqr=1.5*stats.iqr(df_agg["travel_time"])
df_agg_clean=df_agg.loc[(df_agg["travel_time"]>q1-iqr)&(df_agg["travel_time"]<=iqr+q3)]
```

In [26]:
```
df_agg_clean.shape
```

Out[26]:
```
(23643, 22)
```

In [289]:
```
#Before Outlier removal
df_agg.describe().T
```

Out[289]:

	count	mean	std	min	25%	50%	75%	max
segment_actual_time	26368.0	3.314385	6.354720	0.150000	0.833333	1.383333	2.766667	75.066667
segment_osrm_time	26368.0	1.694689	3.594182	0.100000	0.416667	0.700000	1.316667	32.300000
segment_osrm_distance	26368.0	125.423680	285.932556	9.072900	28.471300	45.944400	91.351975	2640.924700
actual_time	26368.0	3.344837	6.414227	0.150000	0.850000	1.400000	2.800000	75.533333
osrm_time	26368.0	1.517881	3.096514	0.100000	0.416667	0.650000	1.216667	28.100000
osrm_distance	26368.0	115.252837	254.069218	9.072900	27.839750	43.760400	86.467200	2326.199100
actual_distance_to_destination	26368.0	92.540646	209.478657	9.001351	21.727218	35.244189	66.043534	1927.447705
trip_creation_year	26368.0	2018.000000	0.000000	2018.000000	2018.000000	2018.000000	2018.000000	2018.000000
start_scan_to_end_scan	26368.0	4.971311	7.342693	0.333333	1.516667	2.533333	5.116667	131.633333
travel_time	26368.0	4.979340	7.342634	0.350000	1.520000	2.540000	5.120000	131.640000

In [27]:
```
#After outlier removal
df_agg_clean.describe().T
```

Out[27]:

	count	mean	std	min	25%	50%	75%	max
segment_actual_time	23643.0	1.777697	1.517312	0.150000	0.800000	1.266667	2.183333	10.416667
segment_osrm_time	23643.0	0.918934	0.859238	0.100000	0.400000	0.633333	1.066667	9.983333
segment_osrm_distance	23643.0	63.424882	62.273331	9.072900	27.382000	42.266700	72.692100	725.377200
actual_time	23643.0	1.794571	1.528832	0.150000	0.800000	1.266667	2.200000	10.433333
osrm_time	23643.0	0.838284	0.713474	0.100000	0.400000	0.600000	1.000000	6.166667
osrm_distance	23643.0	59.431465	55.325413	9.072900	26.740850	40.822600	70.228450	497.581000
actual_distance_to_destination	23643.0	46.774533	44.875432	9.001351	20.935029	32.192760	54.374739	403.226215
trip_creation_year	23643.0	2018.000000	0.000000	2018.000000	2018.000000	2018.000000	2018.000000	2018.000000
start_scan_to_end_scan	23643.0	3.031281	2.202487	0.333333	1.433333	2.266667	3.916667	10.683333
travel_time	23643.0	3.039284	2.201925	0.350000	1.440000	2.270000	3.920000	10.520000

The above is the statistical info before and after outlier removal.The mean ,median looks closer than before

In [28]:
```
df_agg_clean.describe(include='object')
```

Out[28]:

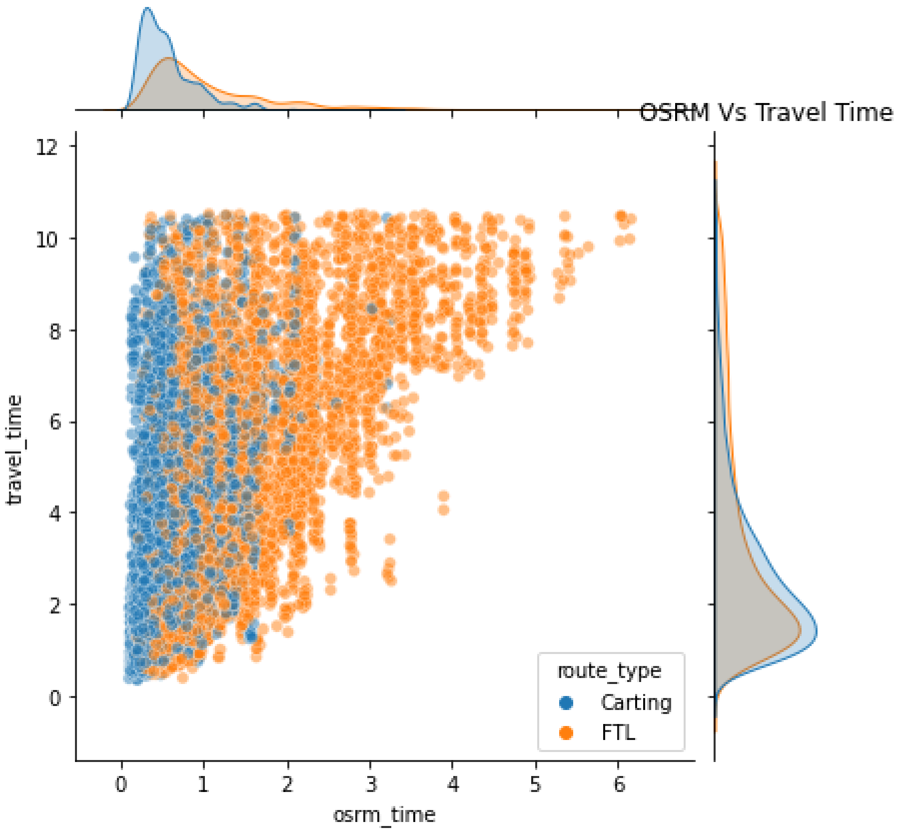
	trip_uuid	source_center	destination_center	data	trip_creation_mon	trip_creation_day	route_type	source_name	destina
unt	23643	23643	23643	23643	23643	23643	23643	23643	
que	13574	1463	1460	2	2	7	2	1454	
top	trip-153710494321650505	IND000000ACB	IND000000ACB	training	September	Wednesday	Carting	Gurgaon_Bilaspur_HB (Haryana)	Gurgaon_B
req	8	636	617	16942	20755	4353	12141	636	

Gurgaon is the busiest spot.Most trips are created on Wednesdays

Hypothesis Test between Travel time and Osrm time

In [37]:

```
sns.jointplot(x="osrm_time",y='travel_time',data=df_agg_clean,hue="route_type",alpha=.5)
plt.title("OSRM Vs Travel Time")
plt.show()
```



The plot suggests they seem to be correlated.Lets recheck this using spearman rank correlation coefficient Test

In [30]:
```
#df1-dataframe for FTL route type,df2-dataframe for Carting route type.Conduct Spearman rank correlation test for osrm ar
df1=df_agg_clean.loc[df_agg_clean["route_type"]=='FTL']
df2=df_agg_clean.loc[df_agg_clean["route_type"]=="Carting"]
print("Null Hypothesis-OSRM and Travel time are uncorrelated")
print("Alternate Hypothesis-the correlation is positive")
print("Spearman rank correlation for FTL route type",stats.spearmanr(df1["osrm_time"],df1["travel_time"],alternative='gr
print("Spearman rank correlation for Carting route type",stats.spearmanr(df2["osrm_time"],df2["travel_time"],alternative
print("OSRM and Travel time are positively correalted.The corelation is more for FTL route type .Rejecting Null hypothes
```

```
Null Hypothesis-OSRM and Travel time are uncorrelated
Alternate Hypothesis-the correlation is positive
Spearman rank correlation for FTL route type SpearmanrResult(correlation=0.7667033981481818, pvalue=0.0)
Spearman rank correlation for Carting route type SpearmanrResult(correlation=0.5112181520058369, pvalue=0.0)
OSRM and Travel time are positively correalted.The corelation is more for FTL route type .Rejecting Null hypothesis
```

From the distribution plot of travel time and OSRM time it is evident that some packages took very long time to reach their destinations eventhough their OSRM time estimated was less.Lets dig a bit deeper to this and see wether we can draw some insights.As a threshold lets find out the trips which took 10 times more than estimated OSRM time

In [43]:
```
#df3-datframe which contains trips that took 10 times more than the estimated OSRM time
df3=df_agg_clean.loc[df_agg_clean["travel_time"]>(df_agg_clean["osrm_time"]*10)]
df3.shape
```

Out[43]:
```
(1467, 22)
```

In [66]:
```
for c in cat_col[1:]:
    print(df3[c].value_counts().head(10))
    print("*"*50)
```

```
Carting    1200
FTL         267
Name: route_type, dtype: int64
**************************************************
Bhiwandi_Mankoli_HB (Maharashtra)     155
Bangalore_Nelmngla_H (Karnataka)       49
Mumbai Hub (Maharashtra)               47
Ahmedabad_East_H_1 (Gujarat)           44
Mumbai_Chndivli_PC (Maharashtra)       38
Aluva_Peedika_H (Kerala)               33
Kanpur_Central_H_6 (Uttar Pradesh)     32
Noida_Sector02_C (Uttar Pradesh)       31
Pune_Tathawde_H (Maharashtra)          24
Vellore_GndhiNgr_IP (Tamil Nadu)       21
Name: source_name, dtype: int64
**************************************************
Bhiwandi_Mankoli_HB (Maharashtra)    123
Hyderabad_Shamshbd_H (Telangana)      45
Mumbai Hub (Maharashtra)              44
Bengaluru_Peenya_L (Karnataka)        42
Mumbai_Sanpada_I (Maharashtra)        33
Mumbai_East_I_21 (Maharashtra)        33
Surat_Central_I_4 (Gujarat)           31
Del_Okhla_PC (Delhi)                  31
Gurgaon_Bilaspur_HB (Haryana)         30
Kolkata_Dankuni_HB (West Bengal)      25
Name: destination_name, dtype: int64
**************************************************
September    1273
October       194
Name: trip_creation_mon, dtype: int64
**************************************************
Wednesday    288
Saturday     233
Tuesday      216
Friday       210
Thursday     202
```

```
Monday        167
Sunday        151
Name: trip_creation_day, dtype: int64
**************************************************
```

The above non-graphical representation depicts some of the places which took longer transit time than expected the highest number of times .For instance whenever Bhiwandi_Mankoli_HB (MH) has been the source or destination the transit time has gone way longer than expected.Similar is tha case for places like Bangalore_Nelmngla,Hyderabad_Shamshbd etc

In [115]:

```
#create time bins
bins = [0, 6, 12, 18, 24]

# add custom labels
labels = ['00:00-05:59', '06:00-11:59', '12:00-17:59', '18:00-23:59']

# add the bins to the dataframe
df3['start_time_bin'] = pd.cut(df3["od_start_time"].dt.hour, bins, labels=labels, right=False)
df3['end_time_bin'] = pd.cut(df3["od_end_time"].dt.hour, bins, labels=labels, right=False)
```

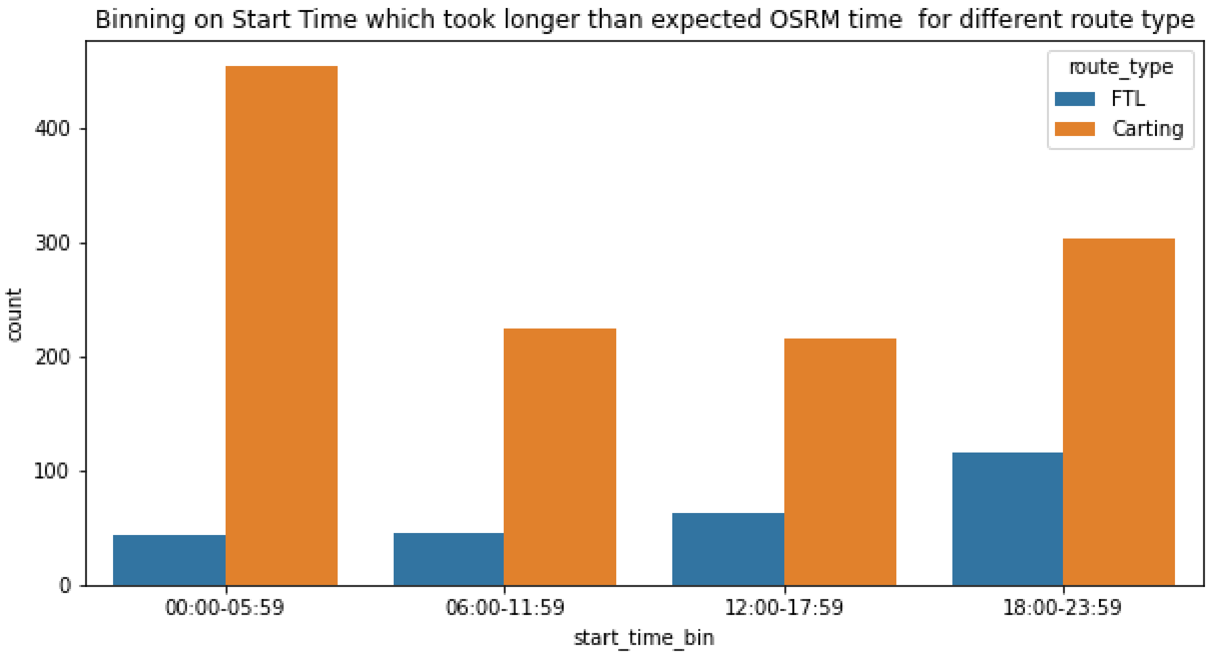
In [119]: df3

```
df3
```

Out[119]:

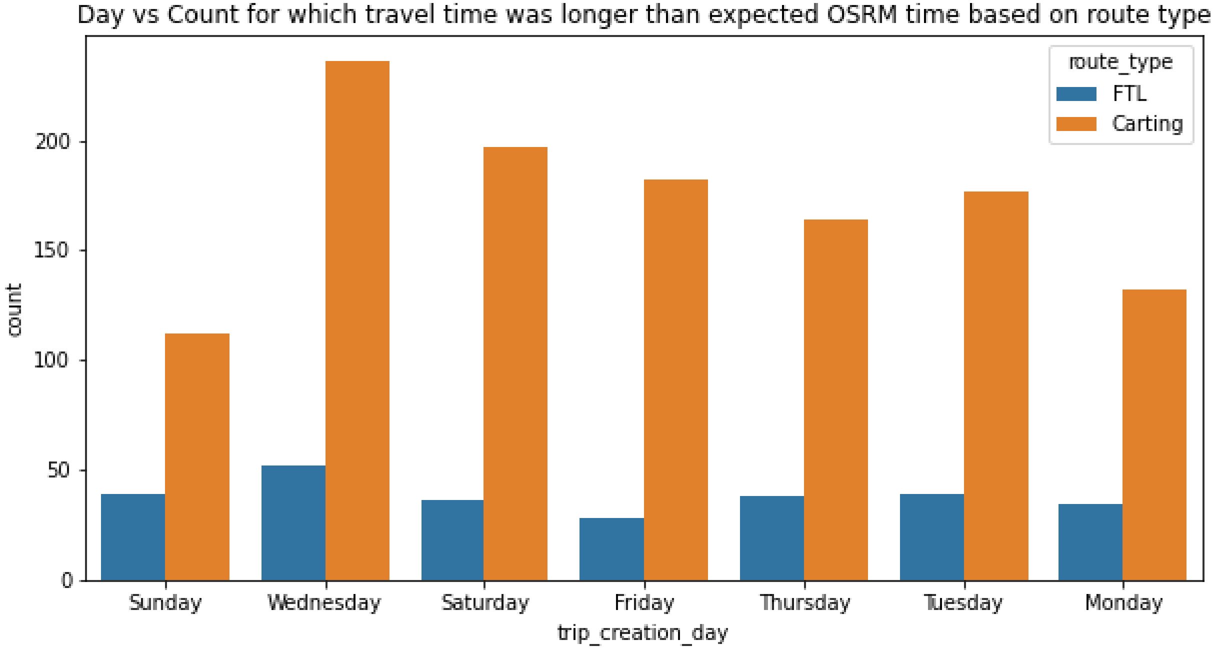
ype	source_name	destination_name	od_start_time	od_end_time	start_scan_to_end_scan	travel_time	start_time_bin	end_time_bin
TL	Giddarbaha_DC (Punjab)	Muktsar_DPC (Punjab)	2018-09-30 04:21:02.259090	2018-09-30 14:49:45.271635	10.466667	10.48	00:00-05:59	12:00-17:59
TL	Silchar_Sirikona_H (Assam)	Hailakandi_kalibari_D (Assam)	2018-09-12 20:01:23.957887	2018-09-13 06:28:29.618054	10.450000	10.45	18:00-23:59	06:00-11:59
ing	Chintamani_Central_D_2 (Karnataka)	Bangalore_East_I_20 (Karnataka)	2018-09-23 04:23:57.337731	2018-09-23 14:48:13.686803	10.400000	10.40	00:00-05:59	12:00-17:59
ing	Delhi_PunjabiB_L (Delhi)	Gurgaon_Bilaspur_HB (Haryana)	2018-09-12 10:04:48.201546	2018-09-12 20:27:56.448795	10.383333	10.39	06:00-11:59	18:00-23:59
ing	Gurgaon_Bilaspur_HB (Haryana)	Delhi_PunjabiB_L (Delhi)	2018-09-21 20:27:38.480244	2018-09-22 06:50:57.915384	10.383333	10.39	18:00-23:59	06:00-11:59
...	...	...	...	...	...	...	...	...
ing	Allahabad_Central_H_1 (Uttar Pradesh)	Allahabad_Central_D_5 (Uttar Pradesh)	2018-09-29 03:04:32.126499	2018-09-29 04:27:56.631050	1.383333	1.39	00:00-05:59	00:00-05:59
ing	Bhubaneshwar_Nayapalli (Orissa)	Bhubaneshwar_Hub (Orissa)	2018-09-14 08:56:33.852830	2018-09-14 10:17:55.990780	1.350000	1.36	06:00-11:59	06:00-11:59
ing	Allahabad_Central_H_1 (Uttar Pradesh)	Allahabad_Central_D_5 (Uttar Pradesh)	2018-09-26 03:23:35.264359	2018-09-26 04:43:28.933503	1.316667	1.33	00:00-05:59	00:00-05:59
ing	Allahabad_Central_H_1 (Uttar Pradesh)	Allahabad_Central_D_5 (Uttar Pradesh)	2018-09-23 02:59:52.470616	2018-09-23 04:15:08.246489	1.250000	1.25	00:00-05:59	00:00-05:59
ing	Sonipat_AmzonDev_V (Haryana)	Sonipat_Kundli_P (Haryana)	2018-09-27 09:01:26.493020	2018-09-27 10:11:34.472014	1.166667	1.17	06:00-11:59	06:00-11:59

In [125]:
```
sns.countplot(df3["start_time_bin"],hue=df3["route_type"])
plt.title("Binning on Start Time which took longer than expected OSRM time  for different route type")
plt.show()
```



Recommendation-For Carting route type ,travel time took longer than expected OSRM time when their trip's start time was in between 12:00am and 6:00am.Hence for such type trip need to start on some other point of a day rather than this time.Similary for FTL this happened when start time was in between 6pm and 12am

In [126]:
```
sns.countplot(df3["trip_creation_day"],hue=df3["route_type"])
plt.title("Day vs Count for which travel time was longer than expected OSRM time based on route type" )
plt.show()
```



Recommendation-For Carting route type the trips which occurred on Wednesdays took longer than expected.Hence for such route type its better to do the deliveries on Sundays.For FTL route type it's not much dependent on the days

Next lets try to draw some insights from features related to source_name an destination_name

In [128]:
```
#df4 copy of the aggregated dataframe
df4=df_agg_clean.copy()
```

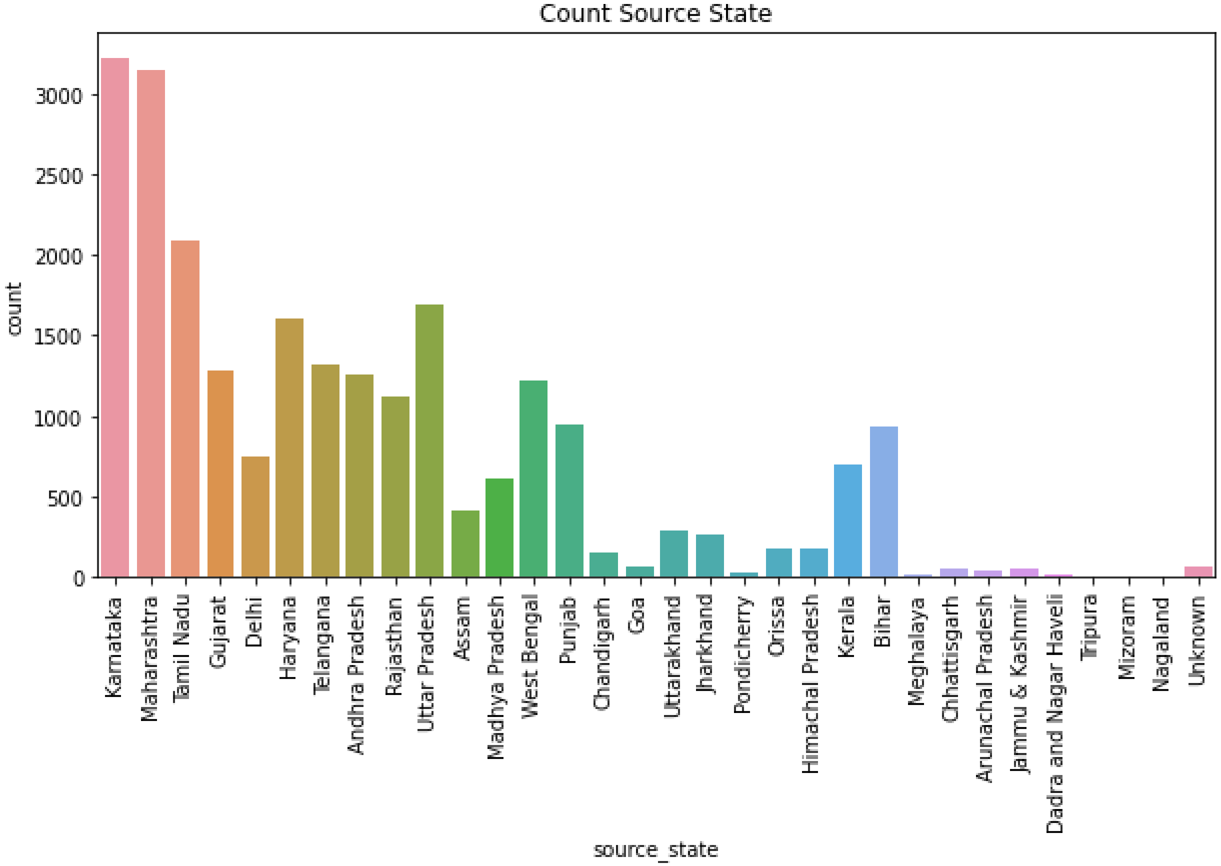
In [151]:
```
#Extract state from source name and creating a new feature source_state
sn_list=df4["source_name"].to_list()
state_list=list()
for x in sn_list:

    if x!='Unknown':

        sidx=x.index('(')
        eidx=x.index(')')
        state=x[sidx+1:eidx]
    #print(state)
        state_list.append(state)
    else:
        state_list.append('Unknown')
```

In [148]:
```
df4["source_state"]=np.array(state_list)
```

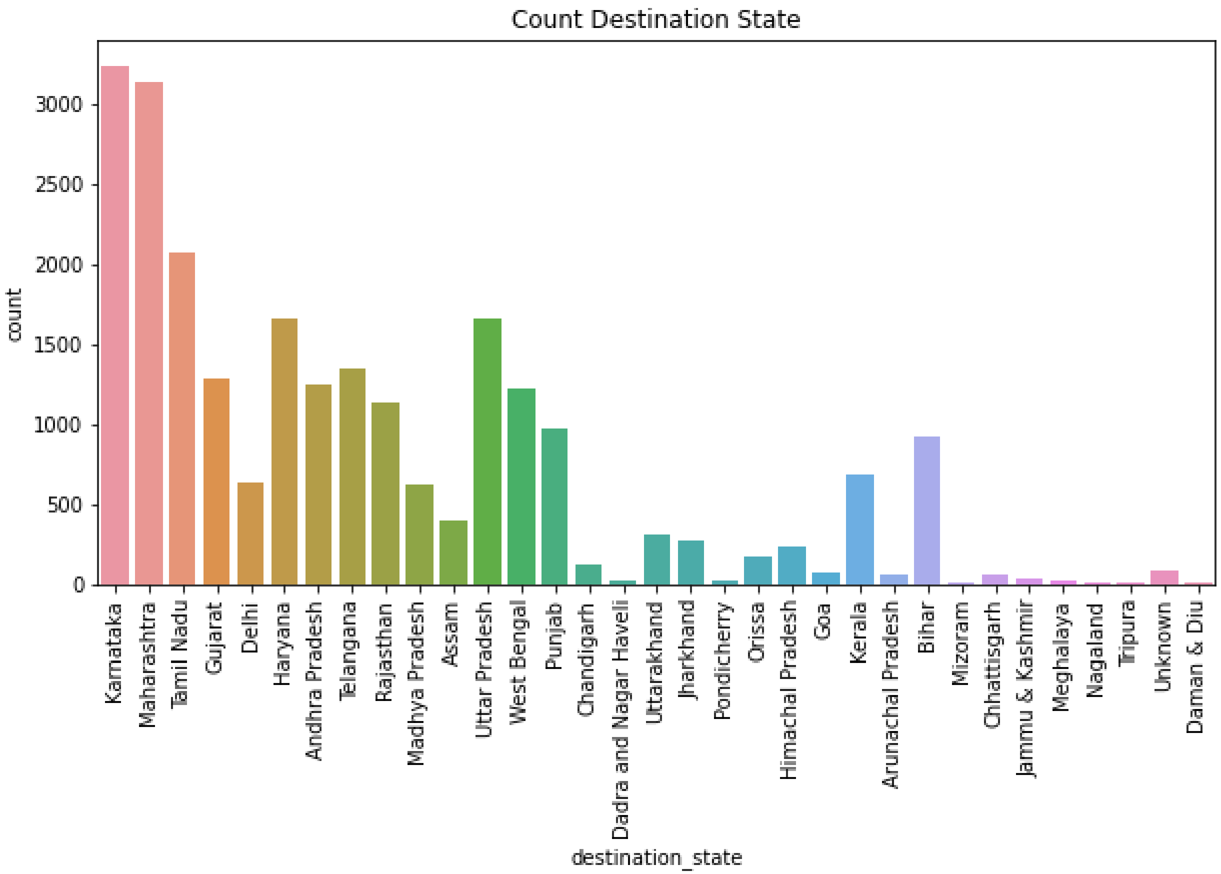
In [152]:
```
#Extract state from destination_name and create a new feature destination_state
sn_list=df4["destination_name"].to_list()
state_list=list()
for x in sn_list:

    if x!='Unknown':

        sidx=x.index('(')
        eidx=x.index(')')
        state=x[sidx+1:eidx]
    #print(state)
        state_list.append(state)
    else:
        state_list.append('Unknown')
df4["destination_state"]=np.array(state_list)
```

In [161]:

```
sns.countplot(df4["source_state"])
plt.xticks(rotation=90)
plt.title("Count Source State")
plt.show()
```



In [162]:
```
sns.countplot(df4["destination_state"])
plt.xticks(rotation=90)
plt.title("Count Destination State")
plt.show()
```



The largest number of shipments have taken place in Karnataka and Maharashtra.

Recommendation-Strategies need to be taken to improve business in most of the North-Eastern States and the Union territories like more vehicles to be deployed in these areas for delivery

In [163]:

```
#New feature source_destination which is concatenation of source_name and destination_name
df4["source_destination"]=df4["source_name"]+df4["destination_name"]
```

In [167]:

```
#No:of shipments made between a source-destination combo.Top 20
df4["source_destination"].value_counts().head(20)
```

Out[167]:

```
Bangalore_Nelmngla_H (Karnataka)Bengaluru_KGAirprt_HB (Karnataka)     151
Bangalore_Nelmngla_H (Karnataka)Bengaluru_Bomsndra_HB (Karnataka)     126
Bengaluru_Bomsndra_HB (Karnataka)Bengaluru_KGAirprt_HB (Karnataka)    121
Bengaluru_KGAirprt_HB (Karnataka)Bangalore_Nelmngla_H (Karnataka)     108
Pune_Tathawde_H (Maharashtra)Bhiwandi_Mankoli_HB (Maharashtra)        107
Bhiwandi_Mankoli_HB (Maharashtra)Mumbai Hub (Maharashtra)             105
Bengaluru_Bomsndra_HB (Karnataka)Bangalore_Nelmngla_H (Karnataka)     102
Delhi_Gateway_HB (Delhi)Gurgaon_Bilaspur_HB (Haryana)                  99
Mumbai_Chndivli_PC (Maharashtra)Bhiwandi_Mankoli_HB (Maharashtra)      99
Gurgaon_Bilaspur_HB (Haryana)Sonipat_Kundli_H (Haryana)                91
Bengaluru_KGAirprt_HB (Karnataka)Bengaluru_Bomsndra_HB (Karnataka)     86
Sonipat_Kundli_H (Haryana)Gurgaon_Bilaspur_HB (Haryana)                85
Bhiwandi_Mankoli_HB (Maharashtra)Mumbai_MiraRd_IP (Maharashtra)        78
Del_Okhla_PC (Delhi)Gurgaon_Bilaspur_HB (Haryana)                      76
Mumbai Hub (Maharashtra)Mumbai_MiraRd_IP (Maharashtra)                 72
Ludhiana_MilrGanj_HB (Punjab)Chandigarh_Mehmdpur_H (Punjab)            71
Bhiwandi_Mankoli_HB (Maharashtra)Pune_Tathawde_H (Maharashtra)         70
Mumbai Hub (Maharashtra)Mumbai_Sanpada_I (Maharashtra)                 67
Chennai_Hub (Tamil Nadu)MAA_Poonamallee_HB (Tamil Nadu)                64
Mumbai Hub (Maharashtra)Bhiwandi_Mankoli_HB (Maharashtra)              63
Name: source_destination, dtype: int64
```

The above non graphical representation shows the top 20 corridors. The busiest corridor is that between Bangalore_Nelmngla_H and Bengaluru_KGAirprt_HB wherein a total of 151 shipments were made

In [292]:
```
#No:of shipments made between a source-destination combo.least 20
df4["source_destination"].value_counts().tail(20)
```

Out[292]:
```
Patran_MheshNGR_D (Punjab)Samana_PODPP_D (Punjab)                      1
Banka_Wardno6_D (Bihar)Kahalgaon_NdiaTola_D (Bihar)                    1
Tezpur_Mhbhirab_D (Assam)Bhalukpong_Khenewa_D (Arunachal Pradesh)      1
Hisar_AgrohDPP_D (Haryana)Fatehabad_SirsaDPP_D (Haryana)               1
Kottayam_Central_H_1 (Kerala)Kothanalloor_Majoor_D (Kerala)            1
Amd_Chandkheda_Dc (Gujarat)Ahmedabad_East_H_1 (Gujarat)                1
Berhampur_Khajuria_I (Orissa)Tangi_SriDPP_D (Orissa)                   1
Shillong (Meghalaya)Guwahati_Hub (Assam)                               1
Uchila_Busstand_D (Karnataka)Kundapura_DC (Karnataka)                  1
Neemrana_Rcocmplx_D (Rajasthan)Narnaul_DC (Haryana)                    1
Barbil_PunjbiPd_D (Orissa)Kendujhar_Sirjudin_D (Orissa)                1
Kozhikode_Feroke_H (Kerala)Vadakara_Mandodi_D (Kerala)                 1
Wanaparthy_VallaDPP_D (Telangana)Unknown                               1
SultnBthry_Kollgpra_D (Kerala)Mananthavady_Central_D_1 (Kerala)        1
Moga_DPC (Punjab)Bhatinda_DPC (Punjab)                                 1
Ghazipur_Kaithwal_D (Uttar Pradesh)Ghosi_Jamalpur_D (Uttar Pradesh)    1
Sultana_Central_DPP_1 (Rajasthan)Buhana_CourtDPP_D (Rajasthan)         1
Chikhli_KKndrDPP_D (Maharashtra)Buldhana_Thsil3PL_D (Maharashtra)      1
Kanti_Central_DPP_2 (Bihar)Muzaffrpur_Bbganj_I (Bihar)                 1
Jaipur_NgrNigam_DC (Rajasthan)Jaipur_Central_D_1 (Rajasthan)           1
Name: source_destination, dtype: int64
```

Recommendation-The above shows some of the least busiest routes.Strategies to be adopted to improve business in these regions

Next let's compute the average distance and travel time for the Top 20 corridors

In [220]:
```
#Create a new dataframe df5 which contains the top 20 corridors
df5=df4["source_destination"].value_counts().head(20).to_frame().reset_index()
df5.rename(columns={"source_destination":"count_trips","index":"source_destination"},inplace=True)
df5
```

Out[220]:

	source_destination	count_trips
0	Bangalore_Nelmngla_H (Karnataka)Bengaluru_KGAi...	151
1	Bangalore_Nelmngla_H (Karnataka)Bengaluru_Boms...	126
2	Bengaluru_Bomsndra_HB (Karnataka)Bengaluru_KGA...	121
3	Bengaluru_KGAirprt_HB (Karnataka)Bangalore_Nel...	108
4	Pune_Tathawde_H (Maharashtra)Bhiwandi_Mankoli_...	107
5	Bhiwandi_Mankoli_HB (Maharashtra)Mumbai Hub (M...	105
6	Bengaluru_Bomsndra_HB (Karnataka)Bangalore_Nel...	102
7	Delhi_Gateway_HB (Delhi)Gurgaon_Bilaspur_HB (H...	99
8	Mumbai_Chndivli_PC (Maharashtra)Bhiwandi_Manko...	99
9	Gurgaon_Bilaspur_HB (Haryana)Sonipat_Kundli_H ...	91
10	Bengaluru_KGAirprt_HB (Karnataka)Bengaluru_Bom...	86
11	Sonipat_Kundli_H (Haryana)Gurgaon_Bilaspur_HB ...	85
12	Bhiwandi_Mankoli_HB (Maharashtra)Mumbai_MiraRd...	78
13	Del_Okhla_PC (Delhi)Gurgaon_Bilaspur_HB (Haryana)	76
14	Mumbai Hub (Maharashtra)Mumbai_MiraRd_IP (Maha...	72
15	Ludhiana_MilrGanj_HB (Punjab)Chandigarh_Mehmdp...	71
16	Bhiwandi_Mankoli_HB (Maharashtra)Pune_Tathawde...	70
17	Mumbai Hub (Maharashtra)Mumbai_Sanpada_I (Maha...	67
18	Chennai_Hub (Tamil Nadu)MAA_Poonamallee_HB (Ta...	64
19	Mumbai Hub (Maharashtra)Bhiwandi_Mankoli_HB (M...	63

In [221]:
```
#New features avg_distance and avg_time to be computed for the top 20 corridors
df5.insert(2,"avg_distance","")
df5.insert(3,"avg_time","")
```

In [222]:
```
df5
```
Out[222]:

	source_destination	count_trips	avg_distance	avg_time
0	Bangalore_Nelmngla_H (Karnataka)Bengaluru_KGAi...	151		
1	Bangalore_Nelmngla_H (Karnataka)Bengaluru_Boms...	126		
2	Bengaluru_Bomsndra_HB (Karnataka)Bengaluru_KGA...	121		
3	Bengaluru_KGAirprt_HB (Karnataka)Bangalore_Nel...	108		
4	Pune_Tathawde_H (Maharashtra)Bhiwandi_Mankoli_...	107		
5	Bhiwandi_Mankoli_HB (Maharashtra)Mumbai Hub (M...	105		
6	Bengaluru_Bomsndra_HB (Karnataka)Bangalore_Nel...	102		
7	Delhi_Gateway_HB (Delhi)Gurgaon_Bilaspur_HB (H...	99		
8	Mumbai_Chndivli_PC (Maharashtra)Bhiwandi_Manko...	99		
9	Gurgaon_Bilaspur_HB (Haryana)Sonipat_Kundli_H ...	91		
10	Bengaluru_KGAirprt_HB (Karnataka)Bengaluru_Bom...	86		
11	Sonipat_Kundli_H (Haryana)Gurgaon_Bilaspur_HB ...	85		
12	Bhiwandi_Mankoli_HB (Maharashtra)Mumbai_MiraRd...	78		
13	Del_Okhla_PC (Delhi)Gurgaon_Bilaspur_HB (Haryana)	76		
14	Mumbai Hub (Maharashtra)Mumbai_MiraRd_IP (Maha...	72		
15	Ludhiana_MilrGanj_HB (Punjab)Chandigarh_Mehmdp...	71		
16	Bhiwandi_Mankoli_HB (Maharashtra)Pune_Tathawde...	70		
17	Mumbai Hub (Maharashtra)Mumbai_Sanpada_I (Maha...	67		
18	Chennai_Hub (Tamil Nadu)MAA_Poonamallee_HB (Ta...	64		
19	Mumbai Hub (Maharashtra)Bhiwandi_Mankoli_HB (M...	63		

In [223]:
```python
#Store their name as a list to be used in the for loop below
Y=df5["source_destination"].to_list()
Y
```

Out[223]:
```
['Bangalore_Nelmngla_H (Karnataka)Bengaluru_KGAirprt_HB (Karnataka)',
 'Bangalore_Nelmngla_H (Karnataka)Bengaluru_Bomsndra_HB (Karnataka)',
 'Bengaluru_Bomsndra_HB (Karnataka)Bengaluru_KGAirprt_HB (Karnataka)',
 'Bengaluru_KGAirprt_HB (Karnataka)Bangalore_Nelmngla_H (Karnataka)',
 'Pune_Tathawde_H (Maharashtra)Bhiwandi_Mankoli_HB (Maharashtra)',
 'Bhiwandi_Mankoli_HB (Maharashtra)Mumbai Hub (Maharashtra)',
 'Bengaluru_Bomsndra_HB (Karnataka)Bangalore_Nelmngla_H (Karnataka)',
 'Delhi_Gateway_HB (Delhi)Gurgaon_Bilaspur_HB (Haryana)',
 'Mumbai_Chndivli_PC (Maharashtra)Bhiwandi_Mankoli_HB (Maharashtra)',
 'Gurgaon_Bilaspur_HB (Haryana)Sonipat_Kundli_H (Haryana)',
 'Bengaluru_KGAirprt_HB (Karnataka)Bengaluru_Bomsndra_HB (Karnataka)',
 'Sonipat_Kundli_H (Haryana)Gurgaon_Bilaspur_HB (Haryana)',
 'Bhiwandi_Mankoli_HB (Maharashtra)Mumbai_MiraRd_IP (Maharashtra)',
 'Del_Okhla_PC (Delhi)Gurgaon_Bilaspur_HB (Haryana)',
 'Mumbai Hub (Maharashtra)Mumbai_MiraRd_IP (Maharashtra)',
 'Ludhiana_MilrGanj_HB (Punjab)Chandigarh_Mehmdpur_H (Punjab)',
 'Bhiwandi_Mankoli_HB (Maharashtra)Pune_Tathawde_H (Maharashtra)',
 'Mumbai Hub (Maharashtra)Mumbai_Sanpada_I (Maharashtra)',
 'Chennai_Hub (Tamil Nadu)MAA_Poonamallee_HB (Tamil Nadu)',
 'Mumbai Hub (Maharashtra)Bhiwandi_Mankoli_HB (Maharashtra)']
```

In [224]:
```
#For loop to compute the avg distance and avg travel time between the top 20 busiest corridors
for y in Y:
    travel_time_list=[]
    act_dist_list=[]


    travel_time=df4.loc[df4["source_destination"]==y]["travel_time"]
    travel_time_list.append(travel_time)

    act_dist=df4.loc[df4["source_destination"]==y]["actual_distance_to_destination"]
    act_dist_list.append(act_dist)



    avg_dist=np.mean(np.array(act_dist))
    avg_time=np.mean(np.array(travel_time))


    idx=df5.loc[df5["source_destination"]==y].index
    df5.loc[idx,["avg_distance"]]=avg_dist
    df5.loc[idx,["avg_time"]]=avg_time
```

In [225]:
```
df5
```
Out[225]:

	source_destination	count_trips	avg_distance	avg_time
0	Bangalore_Nelmngla_H (Karnataka)Bengaluru_KGAi...	151	28.031635	3.059272
1	Bangalore_Nelmngla_H (Karnataka)Bengaluru_Boms...	126	39.495588	4.576905
2	Bengaluru_Bomsndra_HB (Karnataka)Bengaluru_KGA...	121	41.72738	3.312479
3	Bengaluru_KGAirprt_HB (Karnataka)Bangalore_Nel...	108	28.087494	3.191759
4	Pune_Tathawde_H (Maharashtra)Bhiwandi_Mankoli_...	107	100.882221	5.381402
5	Bhiwandi_Mankoli_HB (Maharashtra)Mumbai Hub (M...	105	21.425833	2.815238
6	Bengaluru_Bomsndra_HB (Karnataka)Bangalore_Nel...	102	39.626143	4.45598
7	Delhi_Gateway_HB (Delhi)Gurgaon_Bilaspur_HB (H...	99	36.912185	4.278182
8	Mumbai_Chndivli_PC (Maharashtra)Bhiwandi_Manko...	99	20.117543	3.361212
9	Gurgaon_Bilaspur_HB (Haryana)Sonipat_Kundli_H ...	91	70.423939	6.51033
10	Bengaluru_KGAirprt_HB (Karnataka)Bengaluru_Bom...	86	42.000833	3.646047
11	Sonipat_Kundli_H (Haryana)Gurgaon_Bilaspur_HB ...	85	72.305566	5.748235
12	Bhiwandi_Mankoli_HB (Maharashtra)Mumbai_MiraRd...	78	16.472094	3.126282
13	Del_Okhla_PC (Delhi)Gurgaon_Bilaspur_HB (Haryana)	76	48.755288	3.368816
14	Mumbai Hub (Maharashtra)Mumbai_MiraRd_IP (Maha...	72	17.371716	1.658333
15	Ludhiana_MilrGanj_HB (Punjab)Chandigarh_Mehmdp...	71	87.712683	4.146901
16	Bhiwandi_Mankoli_HB (Maharashtra)Pune_Tathawde...	70	101.171219	6.328286
17	Mumbai Hub (Maharashtra)Mumbai_Sanpada_I (Maha...	67	13.993514	1.845224
18	Chennai_Hub (Tamil Nadu)MAA_Poonamallee_HB (Ta...	64	31.400778	2.048594
19	Mumbai Hub (Maharashtra)Bhiwandi_Mankoli_HB (M...	63	21.476129	3.914762

The above frame give the avg distance and avg travel time taken for the top 20 busiest corridors in the given dataset

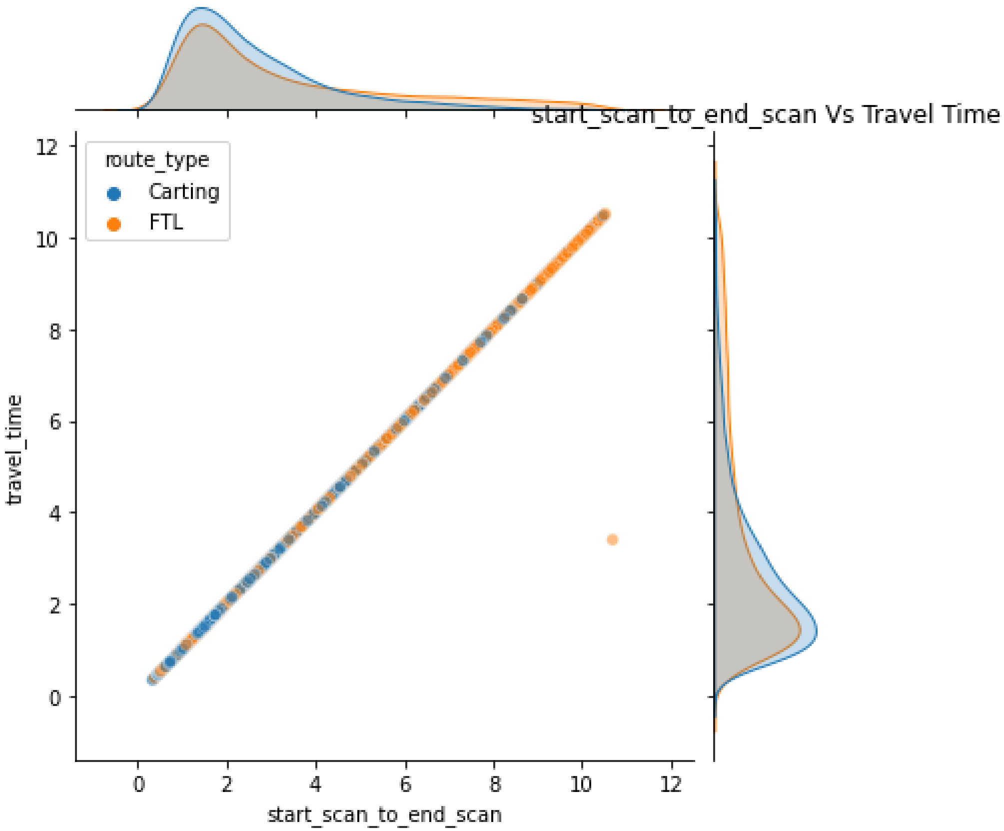
Hypothesis test between start_scan_to_end_scan Vs Travel Time

Ho:start_scan_to_end_scan and Travel Time are uncorrelated

Ha:start_scan_to_end_scan and Travel Time are positively correlated

Significance level 5%

In [33]:
```
sns.jointplot(x="start_scan_to_end_scan",y='travel_time',data=df_agg_clean,hue="route_type",alpha=.5)
plt.title("start_scan_to_end_scan Vs Travel Time")
plt.show()
```



In [34]:
```
#FTL
stats.spearmanr(df1["start_scan_to_end_scan"],df1["travel_time"],alternative='greater')
```

Out[34]:
```
SpearmanrResult(correlation=0.9999165735729818, pvalue=0.0)
```

In [35]:
```python
#Carting
stats.spearmanr(df2["start_scan_to_end_scan"],df2["travel_time"],alternative='greater')
```

Out[35]:
```
SpearmanrResult(correlation=0.9999864645861619, pvalue=0.0)
```

The spearman rank test suggests that the start_scan_to_end_scan and travel_time are almost perfectly linearly correlated for both FTL and Carting with the coefficient=0.999 with p_val < alpha.Hence Reject Ho.Their distribution plots also coveys the same

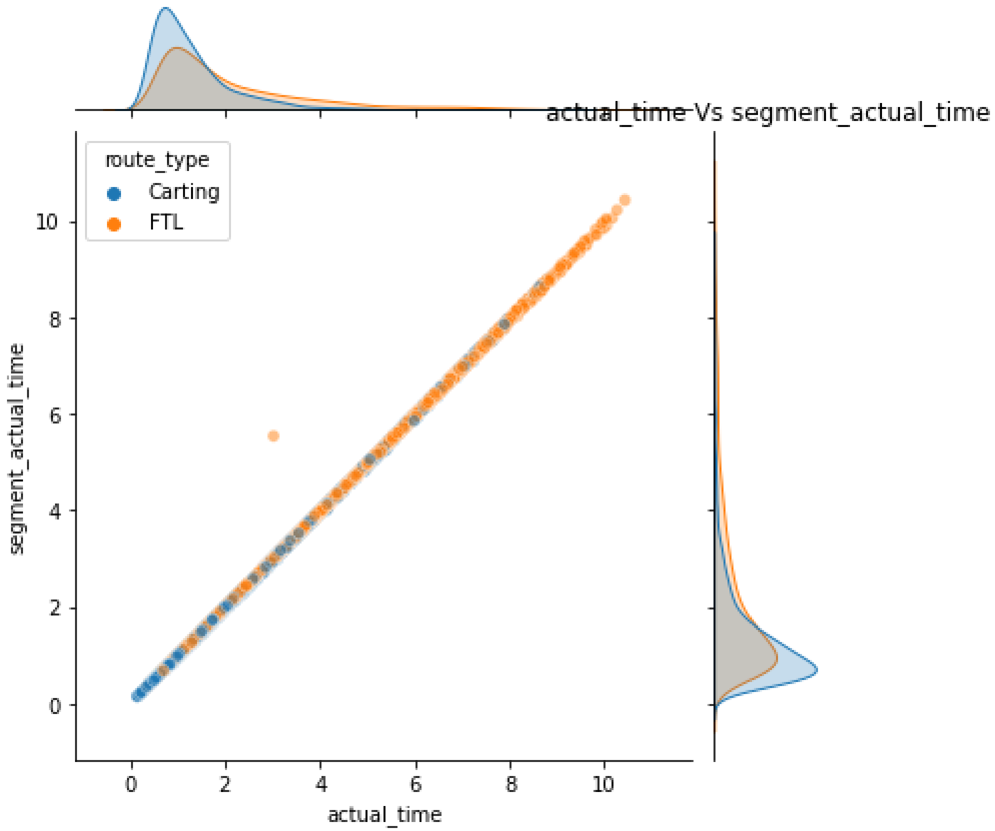
Hypothesis test between actual_time and segment actual time

Ho:actual_time and segment actual time are uncorrelated

Ha:actual_time and segment actual time are positively correlated

Significance level 5%

In [227]:
```
sns.jointplot(x="actual_time",y='segment_actual_time',data=df_agg_clean,hue="route_type",alpha=.5)
plt.title("actual_time Vs segment_actual_time")
plt.show()
```



In [230]:
```
#FTL
stats.spearmanr(df1["actual_time"],df1["segment_actual_time"],alternative='greater')
```

Out[230]:
```
SpearmanrResult(correlation=0.9999250885803729, pvalue=0.0)
```

In [231]:
```
#Carting
stats.spearmanr(df2["actual_time"],df2["segment_actual_time"],alternative='greater')
```

Out[231]:
```
SpearmanrResult(correlation=0.9997665662307961, pvalue=0.0)
```

The spearman rank test suggests that the actual_time and segment_actual_time are almost perfectly linearly correlated for both FTL and Carting with the coefficient=0.999 with p value < alpha.Hence Reject Ho.Their distribution plots also coveys the same

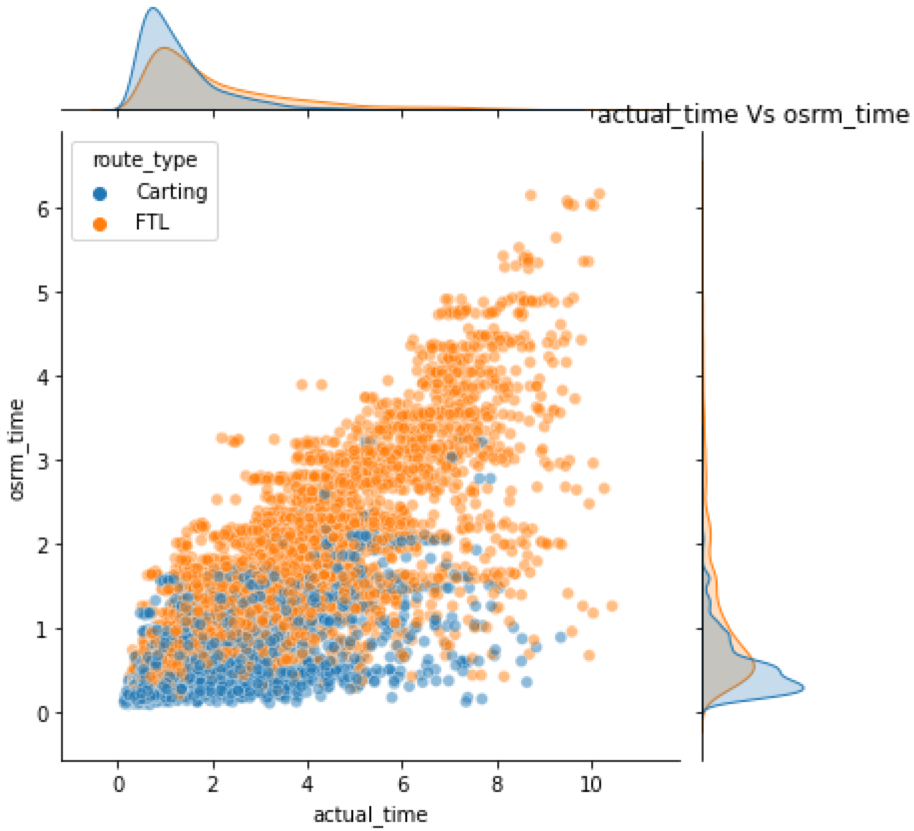
Hypothesis test between actual_time and osrm_time

Ho:actual_time and osrm_time are uncorrelated

Ha:actual_time and osrm_time are positively correlated

Significance level 5%

In [232]:
```
sns.jointplot(x="actual_time",y='osrm_time',data=df_agg_clean,hue="route_type",alpha=.5)
plt.title("actual_time Vs osrm_time")
plt.show()
```



In [235]:
```
#FTL
stats.spearmanr(df1["actual_time"],df1["osrm_time"],alternative='greater')
```

Out[235]: SpearmanrResult(correlation=0.8676137654977552, pvalue=0.0)

In [236]:
```
#Carting
stats.spearmanr(df2["actual_time"],df2["osrm_time"],alternative='greater')
```

Out[236]:
```
SpearmanrResult(correlation=0.6895278606679303, pvalue=0.0)
```

Since p_val is less than significance level .Reject Ho.Actual time and Osrm Time are positivey correlated but a stronger positive correlation exists for FTL than carting route type.The Plot also suggests the same

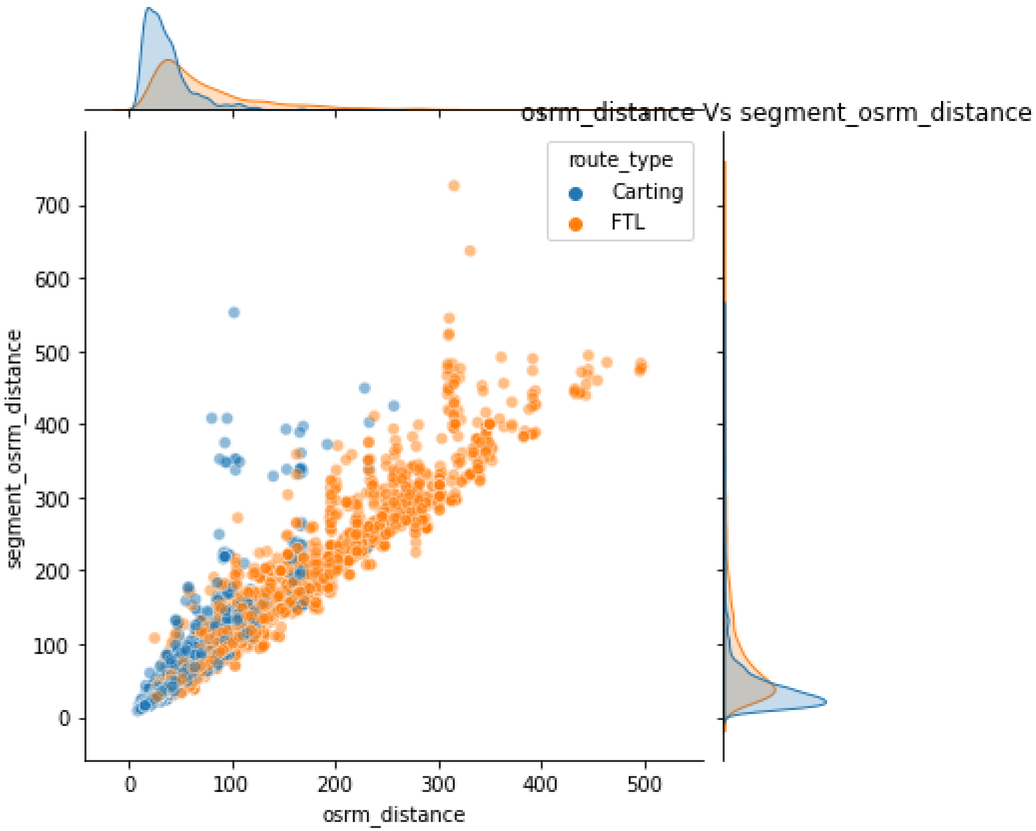
Hypothesis test between osrm distance and segment osrm distance

Ho:osrm distance and segment osrm distance are uncorrelated

Ha:osrm distance and segment osrm distance are positively correlated

Significance level 5%

In [237]:
```
sns.jointplot(x="osrm_distance",y='segment_osrm_distance',data=df_agg_clean,hue="route_type",alpha=.5)
plt.title("osrm_distance Vs segment_osrm_distance")
plt.show()
```



In [239]:
```
#FTL
stats.spearmanr(df1["osrm_distance"],df1["segment_osrm_distance"],alternative='greater')
```

Out[239]:
```
SpearmanrResult(correlation=0.9881720499879001, pvalue=0.0)
```

In [238]:
```
#Carting
stats.spearmanr(df2["osrm_distance"],df2["segment_osrm_distance"],alternative='greater')
```

Out[238]:
```
SpearmanrResult(correlation=0.9786114589444174, pvalue=0.0)
```

Since p_val is less than significance level .Reject Ho.osrm distance and segment osrm distance are positively correlated with correlation coefficient as shown above

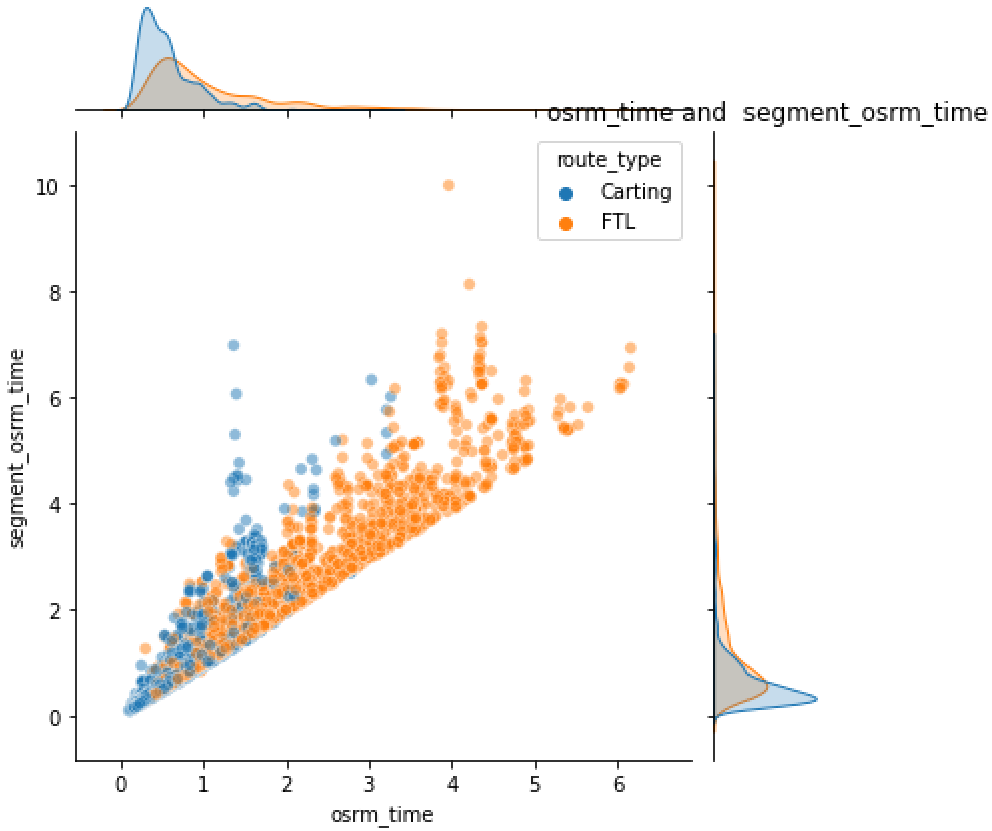
Hypothesis test between osrm_time and segment_osrm_time

Ho:osrm_time and segment_osrm_time are uncorrelated

Ha:osrm_time and segment_osrm_timedistance are positively correlated

Significance level 5%

In [240]:
```
sns.jointplot(x="osrm_time",y='segment_osrm_time',data=df_agg_clean,hue="route_type",alpha=.5)
plt.title("osrm_time and  segment_osrm_time")
plt.show()
```



In [242]:
```
#FTL
stats.spearmanr(df1["osrm_time"],df1["segment_osrm_time"],alternative='greater')
```

Out[242]: SpearmanrResult(correlation=0.9867243745601064, pvalue=0.0)

In [241]:
```
#Carting
stats.spearmanr(df2["osrm_time"],df2["segment_osrm_time"],alternative='greater')
```

Out[241]: SpearmanrResult(correlation=0.9752162843185177, pvalue=0.0)

Since p_val is less than significance level .Reject Ho.osrm time and segment osrm time are positively correlated with correlation coefficient as shown above

One Hot encoding of column Route type

In [246]:
```
#use get_dummies method
one_hot_encoded_data = pd.get_dummies(df_agg_clean, columns = ['route_type'])
one_hot_encoded_data.iloc[:,21:23]
```

Out[246]:

	route_type_Carting	route_type_FTL
2	1	0
3	1	0
6	1	0
7	0	1
8	0	1
...	...	...
26363	1	0
26364	1	0
26365	1	0
26366	0	1
26367	0	1

23643 rows × 2 columns

Find Correlation coefficients between different columns

Convert all categorical to numerical features

In [281]:
```
#Copy of the aggregated dataframe
df_corr=df_agg_clean.copy()
df_to_check=df_agg_clean.copy()
```

In [282]:
```
#New feature source_destination concat of source_center and destination_center
df_corr["source_destination"]=df_corr["source_center"]+df_corr["destination_center"]
df_to_check["source_destination"]=df_to_check["source_center"]+df_to_check["destination_center"]
```

In [283]:
```
#drop unwanted columns
df_corr.drop(["trip_uuid","source_center","source_name","destination_name","destination_center","trip_creation_time","od_
```

In [284]:
```
#Label encoding categorical features
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
for col in ("data","trip_creation_mon","trip_creation_day","route_type","source_destination"):
    df_corr[col]=le.fit_transform(df_corr[col])
```

In [285]:

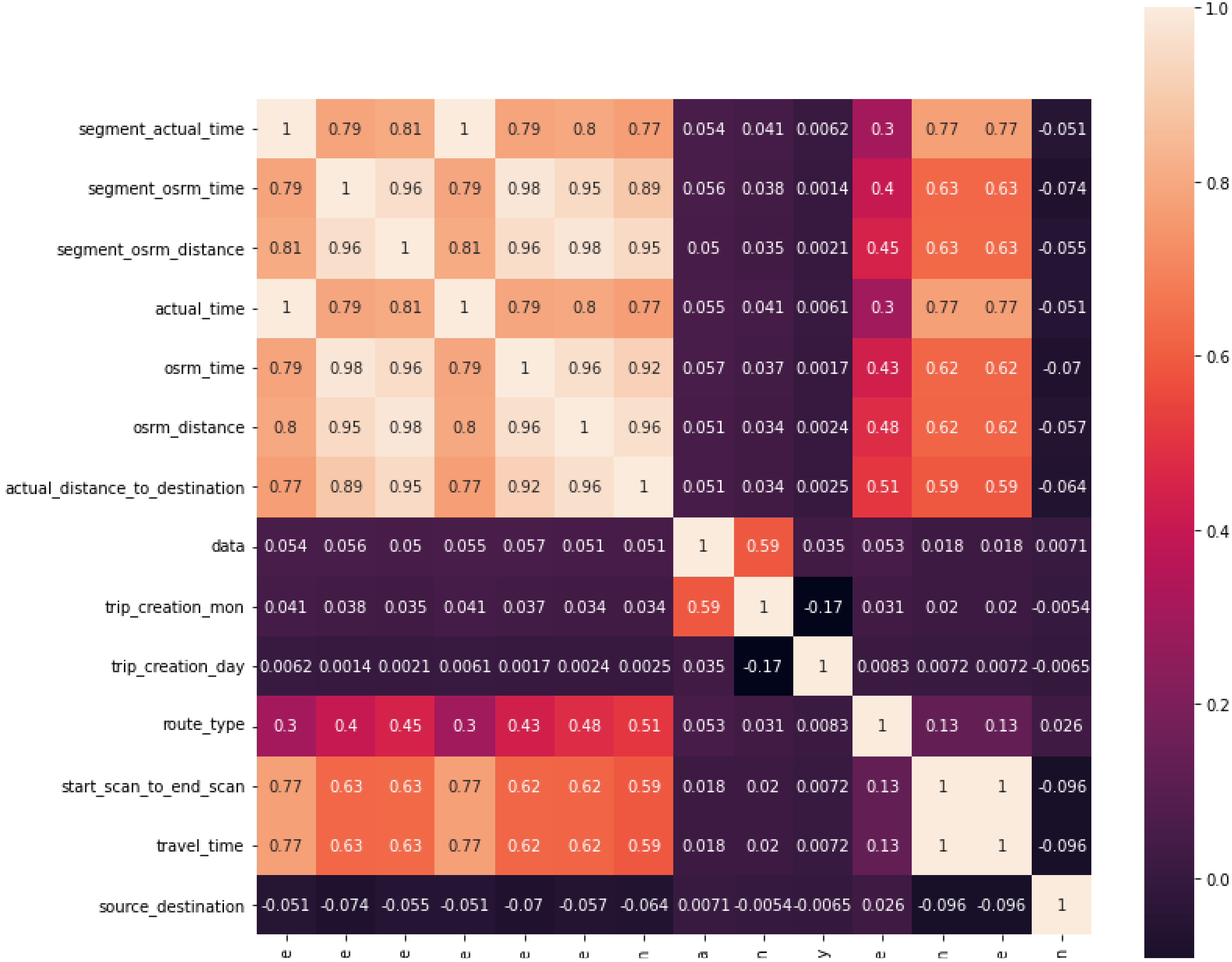
```python
#Check the counts with original frame before and after label encoding
for col in ("data","trip_creation_mon","trip_creation_day","route_type","source_destination"):
    print(df_to_check[col].value_counts())
    print(df_corr[col].value_counts())
    print("*"*50)
```

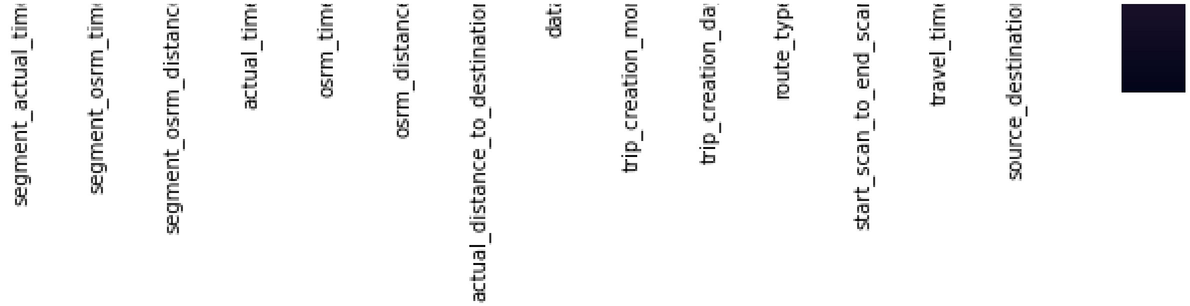
```
training    16942
test         6701
Name: data, dtype: int64
1    16942
0     6701
Name: data, dtype: int64
**************************************************
September    20755
October       2888
Name: trip_creation_mon, dtype: int64
1    20755
0     2888
Name: trip_creation_mon, dtype: int64
**************************************************
Wednesday    4353
Thursday     3432
Tuesday      3374
Friday       3366
Saturday     3233
Monday       3131
Sunday       2754
Name: trip_creation_day, dtype: int64
6    4353
4    3432
5    3374
0    3366
2    3233
1    3131
3    2754
Name: trip_creation_day, dtype: int64
**************************************************
Carting    12141
FTL        11502
Name: route_type, dtype: int64
0    12141
```

```
1    11502
Name: route_type, dtype: int64
**************************************************
IND562132AAAIND560300AAA    151
IND562132AAAIND560099AAB    126
IND560099AABIND560300AAA    121
IND560300AAAIND562132AAA    108
IND411033AAAIND421302AAG    107
                           ...
IND144514AAAIND000000ACA      1
IND560300AABIND563116AAA      1
IND273303AAAIND273304AAA      1
IND695572AABIND000000AFJ      1
IND302004AAAIND302033AAB      1
Name: source_destination, Length: 2567, dtype: int64
1621    151
1620    126
1576    121
1590    108
994     107
       ...
254       1
1595      1
569       1
2077      1
618       1
Name: source_destination, Length: 2567, dtype: int64
**************************************************
```

In [286]:

```python
#Heat map of Spearman Rank Correlation Coefficients
plt.figure(figsize=(12, 12))
sns.heatmap(df_corr.corr(method='spearman'),square=True,annot=True)
plt.show()
```





Inferences from Heat Map

The source and destination of the shipments are not correlated with trip dates ie,there is no such criteria on selecting a day on which a trip should be made for a particular source_destination.(SCC~-0.001)

The computed time between a source and destination(travel_time)and start_scan_to_end_scan have a perfect linear relationship

Segment actual time and actual time also have a perfect linear relationship

The day on which a trip is made is mostly independent of all the time and distance features(SCC~0.001)

Almost all the time and distance fields are positively correlated