Problem Statement

The company wants to understand and process the data coming out of data engineering pipelines:

1. Clean, sanitize and manipulate data to get useful features out of raw fields.
2. Make sense out of the raw data and help the data science team to build forecasting models on it.

Setting up environment

In [1]:
```
# importing important libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import datetime as dt
import warnings
from scipy import stats
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
warnings.filterwarnings('ignore')
from scipy.stats import ttest_ind,ttest_ind_from_stats,ttest_1samp,levene,shapiro,t,f_oneway,f,chi2_contingency,chi2,ttest_rel,k
```

!python -m wget https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/551/original/delhivery_data.csv (https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/551/original/delhivery_data.csv)

In [2]:
```
df = pd.read_csv('delhivery_data.csv')
```

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

Out[3]:

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_center	destination_
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_MotvdD (G
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_MotvdD (G
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_MotvdD (G
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_MotvdD (G
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_MotvdD (G

5 rows × 24 columns

EDA-1

In [4]:
```
# shape of data
print('Total number of rows:',df.shape[0])
print('Total number of columns:',df.shape[1])
```

```
Total number of rows: 144867
Total number of columns: 24
```

In [5]:
```
# data info
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]:
```
# data type correction for date time columns
df['trip_creation_time'] = pd.to_datetime(df['trip_creation_time'])
df['od_start_time'] = pd.to_datetime(df['od_start_time'])
df['od_end_time'] = pd.to_datetime(df['od_end_time'])
df['cutoff_timestamp'] = pd.to_datetime(df['cutoff_timestamp'])
```

In [7]:
```python
# data type conversion to category
df['data'] = df['data'].astype('category')
df['route_type'] = df['route_type'].astype('category')
```

In [8]:
```python
# statistical summary of numerical data
df.describe()
```

Out[8]:

	start_scan_to_end_scan	cutoff_factor	actual_distance_to_destination	actual_time	osrm_time	osrm_distance	factor	segment_actual_tim
count	144867.000000	144867.000000	144867.000000	144867.000000	144867.000000	144867.000000	144867.000000	144867.00000
mean	961.262986	232.926567	234.073372	416.927527	213.868272	284.771297	2.120107	36.1961
std	1037.012769	344.755577	344.990009	598.103621	308.011085	421.119294	1.715421	53.5711
min	20.000000	9.000000	9.000045	9.000000	6.000000	9.008200	0.144000	-244.0000
25%	161.000000	22.000000	23.355874	51.000000	27.000000	29.914700	1.604264	20.0000
50%	449.000000	66.000000	66.126571	132.000000	64.000000	78.525800	1.857143	29.0000
75%	1634.000000	286.000000	286.708875	513.000000	257.000000	343.193250	2.213483	40.0000
max	7898.000000	1927.000000	1927.447705	4532.000000	1686.000000	2326.199100	77.387097	3051.0000

In [9]:
```python
# statistical summary of categorical data
df.describe(include='category')
```

Out[9]:

	data	route_type
count	144867	144867
unique	2	2
top	training	FTL
freq	104858	99660

In [10]:
```python
# statistical summary of Time data
df.describe(include='datetime')
```

Out[10]:

	trip_creation_time	od_start_time	od_end_time	cutoff_timestamp
count	144867	144867	144867	144867
unique	14817	26369	26369	93180
top	2018-09-28 05:23:15.359220	2018-09-21 18:37:09.322207	2018-09-24 09:59:15.691618	2018-09-24 05:19:20
freq	101	81	81	40
first	2018-09-12 00:00:16.535741	2018-09-12 00:00:16.535741	2018-09-12 00:50:10.814399	2018-09-12 00:02:09.740725
last	2018-10-03 23:59:42.701692	2018-10-06 04:27:23.392375	2018-10-08 03:00:24.353479	2018-10-06 23:44:12

In [11]:
```python
# check for null values
df.isna().sum()
```

Out[11]:
```
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
```

In [12]:
```
# checking for duplicated values
df.duplicated().sum()
```

Out[12]:
```
0
```

Observations:

- Data has no duplicate values.
- data has 144867 rows and 24 columns.
- for same trip_uuid step wise rows are available which wil be aggregated to create the whole picture
- around 293 source and 261 destination info is missing.
- missing values can be treated better after aggregation
- there 2 category data types (data and route_type)

Data Cleaning

Merging of rows and aggregation of fields

In [13]:
```
# 1st aggregation
# grouping the data based on trip_uuid,destination and source
process1 = {
    'data' : 'first',
    'trip_creation_time' : 'first',
    'route_schedule_uuid' : 'first',
    'route_type' : 'first',
    'source_name' : 'first',
    'destination_name' : 'last',
    'od_start_time': 'first',
    'od_end_time': 'first',
    'start_scan_to_end_scan':'first',
    'actual_distance_to_destination' : 'last',
    'actual_time' : 'last',
    'osrm_time' : 'last',
    'osrm_distance' : 'last',
    'segment_actual_time' : 'sum',
    'segment_osrm_distance' : 'sum',
    'segment_osrm_time' : 'sum',
    }

df1 = df.groupby(['trip_uuid','source_center','destination_center']).agg(process1).reset_index()
```

In [14]:
```
# sorting the data based on time stamps to keep it in the order
df1.sort_values(by = ['trip_uuid','od_start_time'],inplace = True,ignore_index=True)
```

In [15]:
```
# 2nd aggregation
# aggregating to the level of unique trip_id
process2 = {
    'source_center':'first',
    'destination_center':'first',
    'data' : 'first',
    'trip_creation_time' : 'first',
    'route_schedule_uuid' : 'first',
    'route_type' : 'first',
    'source_name' : 'first',
    'destination_name' : 'last',
    'od_start_time': 'first',
    'od_end_time': 'last',
    'start_scan_to_end_scan':'sum',
    'actual_distance_to_destination' : 'sum',
    'actual_time' : 'sum',
    'osrm_time' : 'sum',
    'osrm_distance' : 'sum',
    'segment_actual_time' : 'sum',
    'segment_osrm_distance' : 'sum',
    'segment_osrm_time' : 'sum',
    }

df2 = df1.groupby(['trip_uuid']).agg(process2).reset_index()
df2
```

Out[15]:

	trip_uuid	source_center	destination_center	data	trip_creation_time	route_schedule_uuid	route_type	source_name	
0	trip-153671041653548748	IND462022AAA	IND209304AAA	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6...	FTL	Bhopal_Trnsport_H (Madhya Pradesh)	Gur
1	trip-153671042288605164	IND572101AAA	IND561203AAB	training	2018-09-12 00:00:22.886430	thanos::sroute:3a1b0ab2-bb0b-4c53-8c59-eb2a2c0...	Carting	Tumkur_Veersagr_I (Karnataka)	Chikl
2	trip-153671043369099517	IND562132AAA	IND000000ACB	training	2018-09-12 00:00:33.691250	thanos::sroute:de5e208e-7641-45e6-8100-4d9fb1e...	FTL	Bangalore_Nelmngla_H (Karnataka)	Chandig
3	trip-153671046011330457	IND400072AAB	IND401104AAA	training	2018-09-12 00:01:00.113710	thanos::sroute:f0176492-a679-4597-8332-bbd1c7f...	Carting	Mumbai Hub (Maharashtra)	M
4	trip-153671052974046625	IND583101AAA	IND583201AAA	training	2018-09-12 00:02:09.740725	thanos::sroute:d9f07b12-65e0-4f3b-bec8-df06134...	FTL	Bellary_Dc (Karnataka)	Bella
...	...	...	...	...	...	...	...	...	
14812	trip-153861095625827784	IND160002AAC	IND140603AAA	test	2018-10-03 23:55:56.258533	thanos::sroute:8a120994-f577-4491-9e4b-b7e4a14...	Carting	Chandigarh_Mehmdpur_H (Punjab)	Chandig
14813	trip-153861104386292051	IND121004AAB	IND121004AAA	test	2018-10-03 23:57:23.863155	thanos::sroute:b30e1ec3-3bfa-4bd2-a7fb-3b75769...	Carting	FBD_Balabhgarh_DPC (Haryana)	Farid
14814	trip-153861106442901555	IND209304AAA	IND208006AAA	test	2018-10-03 23:57:44.429324	thanos::sroute:5609c268-e436-4e0a-8180-3db4a74...	Carting	Kanpur_Central_H_6 (Uttar Pradesh)	Ka
14815	trip-153861115439069069	IND627005AAA	IND628801AAA	test	2018-10-03 23:59:14.390954	thanos::sroute:c5f2ba2c-8486-4940-8af6-d1d2a6a...	Carting	Tirunelveli_VdkkuSrt_I (Tamil Nadu)	Tiru
14816	trip-153861118270144424	IND583201AAA	IND583119AAA	test	2018-10-03 23:59:42.701692	thanos::sroute:412fea14-6d1f-4222-8a5f-a517042...	FTL	Hospet (Karnataka)	Bella

14817 rows × 19 columns

In [16]:
```
# checking for the null values in the final data
df2.isna().sum()
```

Out[16]:
```
trip_uuid                          0
source_center                      0
destination_center                 0
data                               0
trip_creation_time                 0
route_schedule_uuid                0
route_type                         0
source_name                       10
destination_name                   8
od_start_time                      0
od_end_time                        0
start_scan_to_end_scan             0
actual_distance_to_destination     0
actual_time                        0
osrm_time                          0
osrm_distance                      0
segment_actual_time                0
segment_osrm_distance              0
segment_osrm_time                  0
dtype: int64
```

observations:

- after aggregation we have only 10 null value in source and 8 in destination data.
- there are no duplicated values.
- after aggregation we are left with 14817 unique trip_uuids

Missing Value Treatment

In [17]:
```
# dropping the null values from the data set
df2.dropna(how='any',inplace = True)
```

In [18]:
```
# data information post merging the data and treating null values
# shape of data
print('Total number of rows:',df2.shape[0])
print('Total number of columns:',df2.shape[1])
```

```
Total number of rows: 14800
Total number of columns: 19
```

Feature Creation

creating feature from source and destination data

In [19]:
```
# creating function for feature extraction from the source and destination data
def place(x):
    return x.split('_')[0]
def state(x):
    return x.split('_')[-1]
def place1(x):
    return x.split('_')[1]
```

In [20]:
```
df2['source_name'] = df2['source_name'].str.replace('\s\(','_')
df2['source_name'] = df2['source_name'].str.replace('\)','')
df2['destination_name'] = df2['destination_name'].str.replace('\s\(','_')
df2['destination_name'] = df2['destination_name'].str.replace('\)','')
df2['source_city'] = df2['source_name'].apply(lambda x: place(x))
df2['source_state'] = df2['source_name'].apply(lambda x: state(x))
df2['source_place'] = df2['source_name'].apply(lambda x: place1(x))
df2['destination_city'] = df2['destination_name'].apply(lambda x: place(x))
df2['destination_state'] = df2['destination_name'].apply(lambda x: state(x))
df2['destination_place'] = df2['destination_name'].apply(lambda x: place1(x))
```

In [21]:
```
df2.iloc[:,-6:]
```

Out[21]:

	source_city	source_state	source_place	destination_city	destination_state	destination_place
0	Bhopal	Madhya Pradesh	Trnsport	Gurgaon	Haryana	Bilaspur
1	Tumkur	Karnataka	Veersagr	Chikblapur	Karnataka	ShntiSgr
2	Bangalore	Karnataka	Nelmngla	Chandigarh	Punjab	Mehmdpur
3	Mumbai Hub	Maharashtra	Maharashtra	Mumbai	Maharashtra	MiraRd
4	Bellary	Karnataka	Dc	Bellary	Karnataka	Dc
...	...	...	...	...	...	...
14812	Chandigarh	Punjab	Mehmdpur	Chandigarh	Punjab	Mehmdpur
14813	FBD	Haryana	Balabhgarh	Faridabad	Haryana	Blbgarh
14814	Kanpur	Uttar Pradesh	Central	Kanpur	Uttar Pradesh	Central
14815	Tirunelveli	Tamil Nadu	VdkkuSrt	Tirunelveli	Tamil Nadu	VdkkuSrt
14816	Hospet	Karnataka	Karnataka	Bellary	Karnataka	Dc

14800 rows × 6 columns

In [22]:
```
# calculating time difference between od_end_time and od_start_time
df2['time_diff'] = (df2['od_end_time']-df2['od_start_time'])/np.timedelta64(1,'m')
df2.iloc[:,-1:]
```

Out[22]:

	time_diff
0	2260.109800
1	181.611874
2	3934.362520
3	100.494935
4	718.349042
...	...
14812	405.485842
14813	60.590521
14814	422.119867
14815	348.512862
14816	354.407571

14800 rows × 1 columns

In [23]:
```
# extracting data from timestamps to
df2['day'] = df2['trip_creation_time'].dt.day
df2['month'] = df2['trip_creation_time'].dt.month
df2['year'] = df2['trip_creation_time'].dt.year
df2['time_of_day'] = df2['trip_creation_time'].dt.time
```

In [24]:
```
df2.iloc[:,-4:].head()
```

Out[24]:

	day	month	year	time_of_day
0	12	9	2018	00:00:16.535741
1	12	9	2018	00:00:22.886430
2	12	9	2018	00:00:33.691250
3	12	9	2018	00:01:00.113710
4	12	9	2018	00:02:09.740725

Observations:

- city, place and state are extracted from location data.
- day, month, year and time of day is extracted from timestamp when the trip was created.

Dropping columns which will not be used

In [25]:
```
df2.drop(columns=['route_schedule_uuid',
                  'source_center',
                  'destination_center',
                  'source_name',
                  'destination_name',
                  'od_start_time',
                  'od_end_time'],
         inplace = True)
```

In [26]:
```
# data information post deleting the unused columns
# shape of data
print('Total number of rows:',df2.shape[0])
print('Total number of columns:',df2.shape[1])
```

```
Total number of rows: 14800
Total number of columns: 23
```

In [27]:
```
df2.describe(include=["object"])
```

Out[27]:

	trip_uuid	source_city	source_state	source_place	destination_city	destination_state	destination_place	time_of_day
count	14800	14800	14800	14800	14800	14800	14800	14800
unique	14800	672	29	652	766	32	736	14800
top	trip-153671041653548748	Gurgaon	Maharashtra	Central	Bengaluru	Maharashtra	Central	00:00:16.535741
freq	1	1022	2682	1039	1056	2591	921	1

Unique data analysis

In [28]:
```python
df2.groupby('data')['trip_uuid'].nunique().to_frame().T
```

Out[28]:

data	test	training
trip_uuid	4153	10647

In [29]:
```python
df2.groupby('route_type')['trip_uuid'].nunique().to_frame().T
```

Out[29]:

route_type	Carting	FTL
trip_uuid	8906	5894

In [30]:
```python
df2.groupby('month')['trip_uuid'].nunique().to_frame().T
```

Out[30]:

month	9	10
trip_uuid	13020	1780

Observations:

1. 60% of the order delivered through carting and for rest of the Full truck load (FTL) is preferred.
2. Dataset is of two months only that is September and October.

Busy corridors (based on number of trip ids)

In [31]:
```
# top 10 states
display(df2.groupby('source_state')['trip_uuid'].nunique().sort_values(ascending=False).to_frame().head(10))
display(df2.groupby('destination_state')['trip_uuid'].nunique().sort_values(ascending=False).to_frame().head(10))
```

	trip_uuid
source_state	
Maharashtra	2682
Karnataka	2229
Haryana	1681
Tamil Nadu	1085
Delhi	791
Telangana	779
Gujarat	746
Uttar Pradesh	720
West Bengal	677
Punjab	630

	trip_uuid
destination_state	
Maharashtra	2591
Karnataka	2275
Haryana	1667
Tamil Nadu	1072
Telangana	838
Gujarat	746
Uttar Pradesh	732
West Bengal	708
Punjab	693
Delhi	675

In [32]:
```
# top 10 cities
display(df2.groupby('source_city')['trip_uuid'].nunique().sort_values(ascending=False).to_frame().head(10))
display(df2.groupby('destination_city')['trip_uuid'].nunique().sort_values(ascending=False).to_frame().head(10))
```

	trip_uuid
source_city	
Gurgaon	1022
Bengaluru	1015
Bhiwandi	811
Bangalore	755
Delhi	618
Mumbai	579
Hyderabad	562
Pune	445
Chandigarh	418
Kolkata	339

	trip_uuid
destination_city	
Bengaluru	1056
Mumbai	891
Gurgaon	869
Bangalore	646
Hyderabad	630
Bhiwandi	604
Delhi	576
Chandigarh	463
Chennai	388
Sonipat	375

In [33]:
```
2.groupby(['source_city','destination_city']).agg({'trip_uuid':'count'}).sort_values(by = ['trip_uuid'],ascending=False).head(10)
```

Out[33]:

source_city	destination_city	trip_uuid
Bengaluru	Bengaluru	549
Bangalore	Bengaluru	455
Hyderabad	Hyderabad	398
Bhiwandi	Mumbai	332
Bengaluru	Bangalore	326
Mumbai	Mumbai	264
Chandigarh	Chandigarh	250
Gurgaon	Delhi	240
Mumbai Hub	Mumbai	227
Mumbai	Bhiwandi	207

In [34]:
```
df2.groupby(['source_state','destination_state']).agg({'trip_uuid':'count'}).sort_values(by = ['trip_uuid'],ascending=False).hea
```

Out[34]:

source_state	destination_state	trip_uuid
Maharashtra	Maharashtra	2406
Karnataka	Karnataka	2015
Tamil Nadu	Tamil Nadu	1016
Haryana	Haryana	871
Telangana	Telangana	655
Gujarat	Gujarat	624
West Bengal	West Bengal	610
Uttar Pradesh	Uttar Pradesh	545
Punjab	Punjab	491
Rajasthan	Rajasthan	422

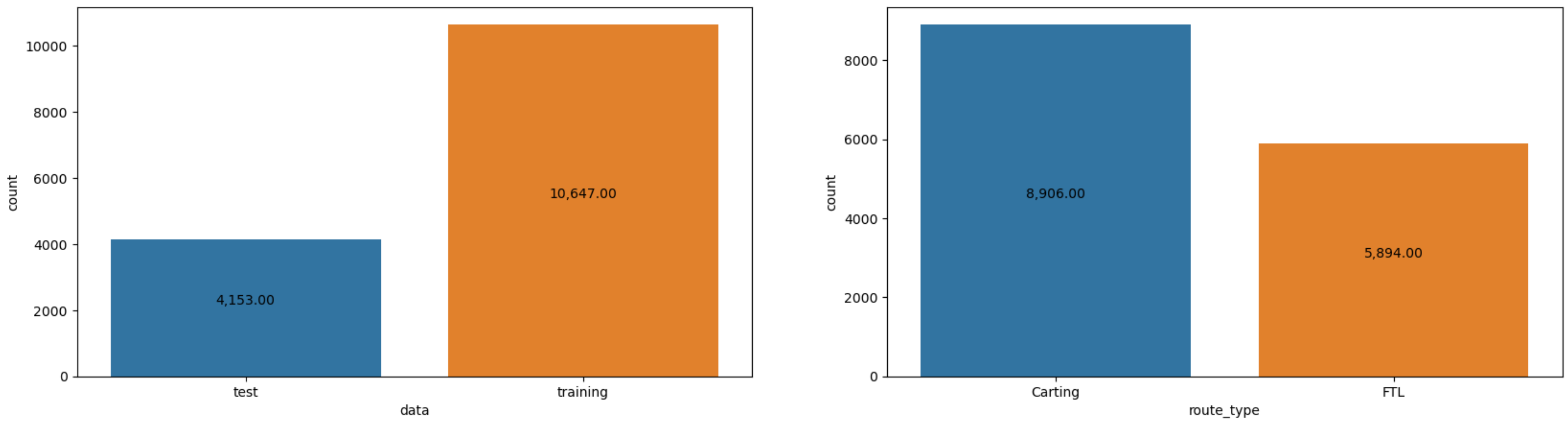
Observations:

- most number of orders are booked and recieved in Maharashtra.
- maharashtra, karnataka and haryana are the top 3 busy states.
- bengalore and Gurugram are the two most busiest cities.
- a lot of orders are moving in the same city.

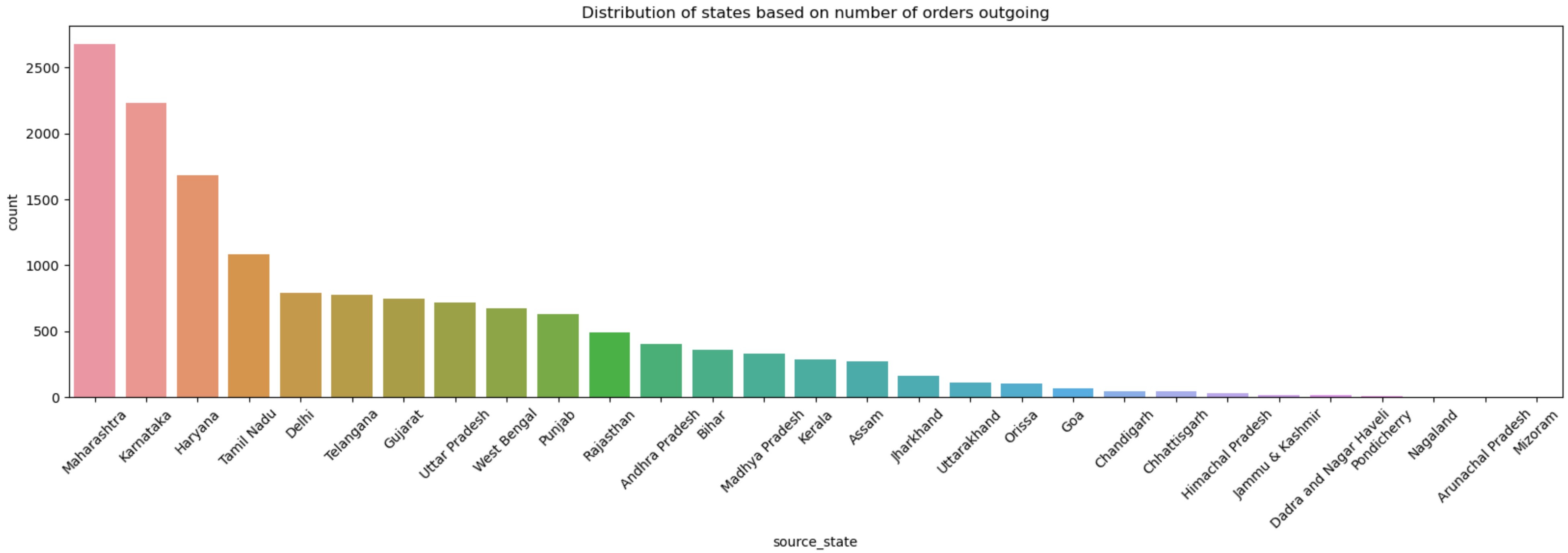
Visual Analysis

In [35]:

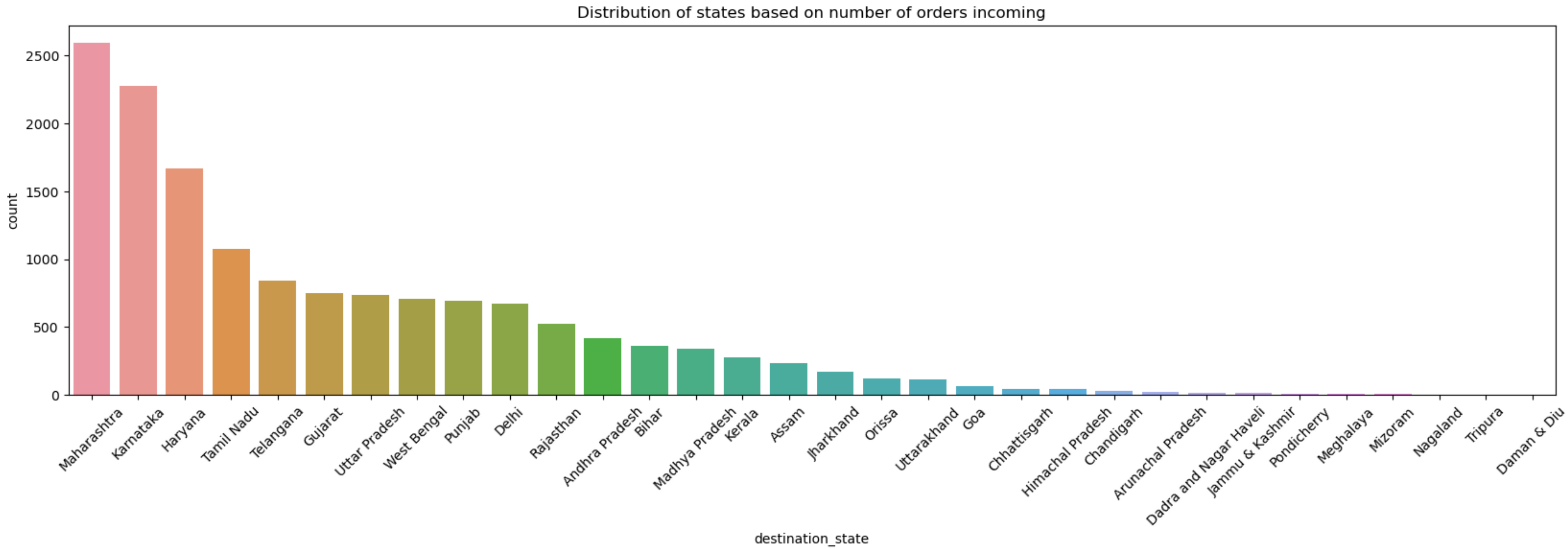
```
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
ax = sns.countplot(df2['data'])
for p in ax.patches:
  ax.annotate("{:,.2f}".format(p.get_height()),
 (p.get_x() + p.get_width()/2, p.get_height()/2),ha = 'center', va = 'bottom')
plt.subplot(1, 2, 2)
ax = sns.countplot(df2['route_type'])
for p in ax.patches:
  ax.annotate("{:,.2f}".format(p.get_height()),
 (p.get_x() + p.get_width()/2, p.get_height()/2),ha = 'center', va = 'bottom')
```



In [36]:
```
fig = plt.figure(figsize=(20,5))
sns.countplot(df2['source_state'], order = df2['source_state'].value_counts().index)
plt.xticks(rotation = 45)
plt.title('Distribution of states based on number of orders outgoing')
plt.show()
```



In [37]:
```
fig = plt.figure(figsize=(20,5))
sns.countplot(df2['destination_state'], order = df2['destination_state'].value_counts().index)
plt.xticks(rotation = 45)
plt.title('Distribution of states based on number of orders incoming')
plt.show()
```

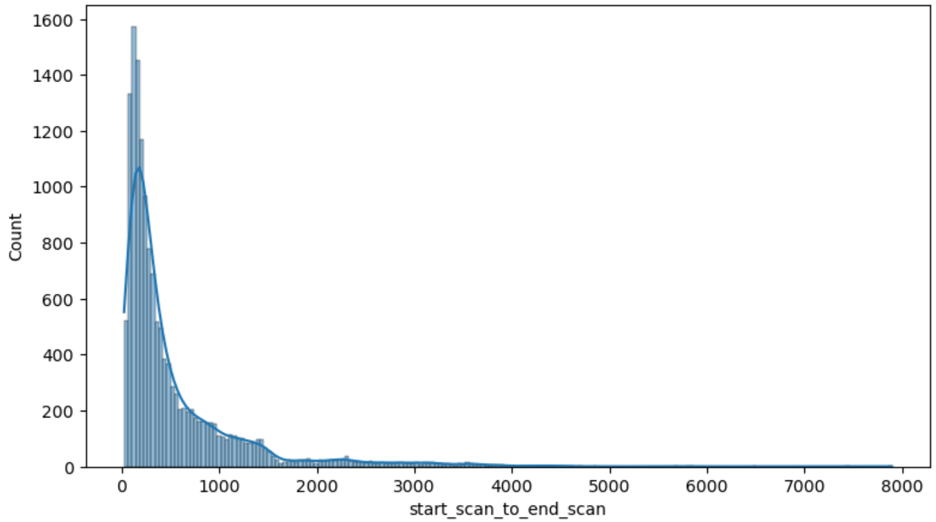


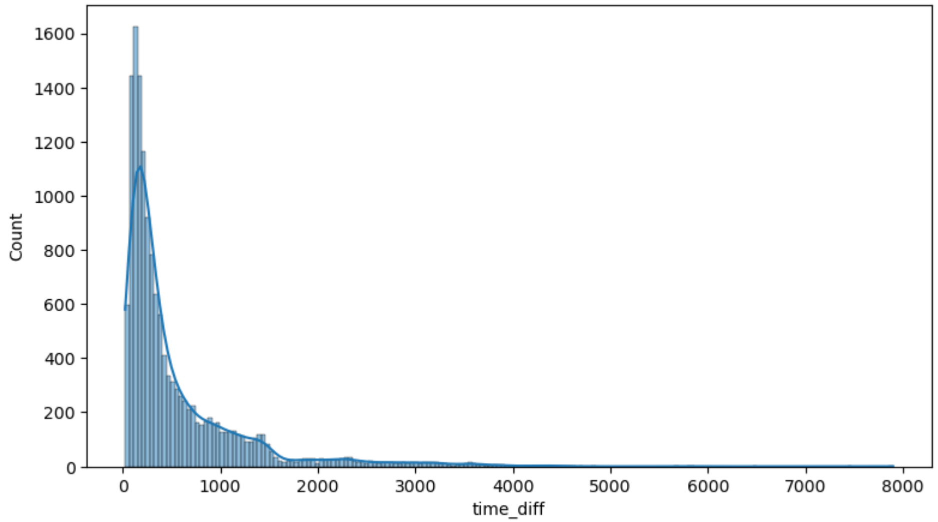
Observations

1. Top 5 source states are Maharashtra,Karnataka,Haryana TamilNadu and Delhi.
2. Source States with less than 10 orders are Nagaland, Mizoram, and Arunachal Pradesh.
3. Top 5 source cities are Gurgaon, Bengaluru ,Mumbai, Bhiwandi and Bangalore
4. Top 5 destination states are Maharashtra, Karnataka, Haryana, Tamil Nadu, and Telangana.
5. Destination states with less than 10 orders are Meghalaya, Mizoram Daman & Diu, Nagaland, and Tripura
6. Top 5 destination cities are Mumbai, Bengaluru, Gurgaon, Bangalore and Hyderabad.

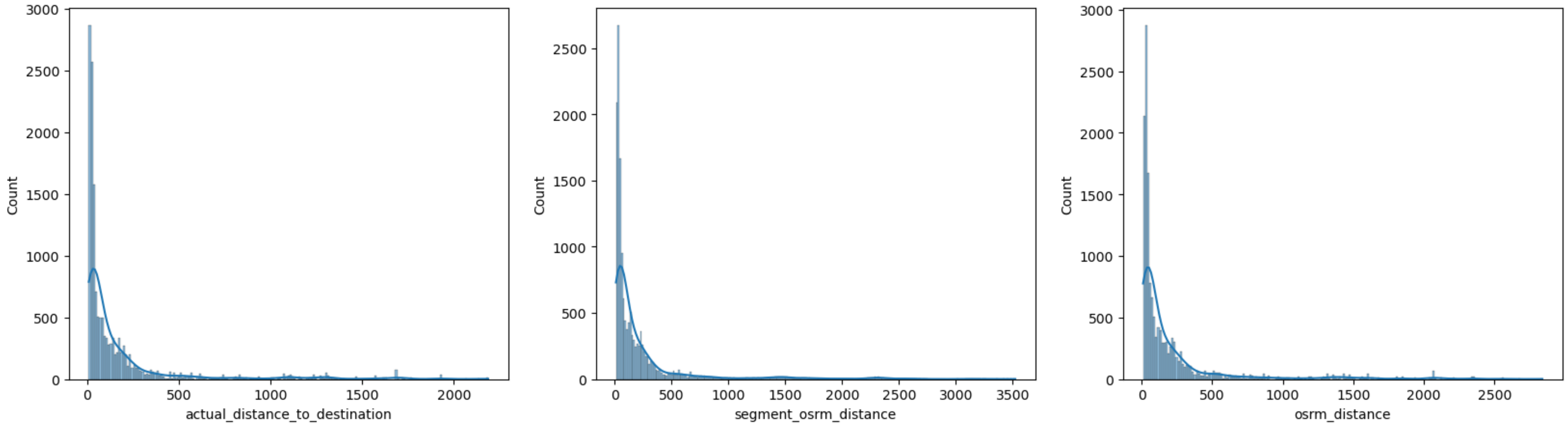
Histplot for continuous variables

In [38]:
```
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
sns.histplot(df2['start_scan_to_end_scan'],kde = True)
plt.subplot(1,2, 2)
sns.histplot(df2['time_diff'],kde = True)
plt.show()
```

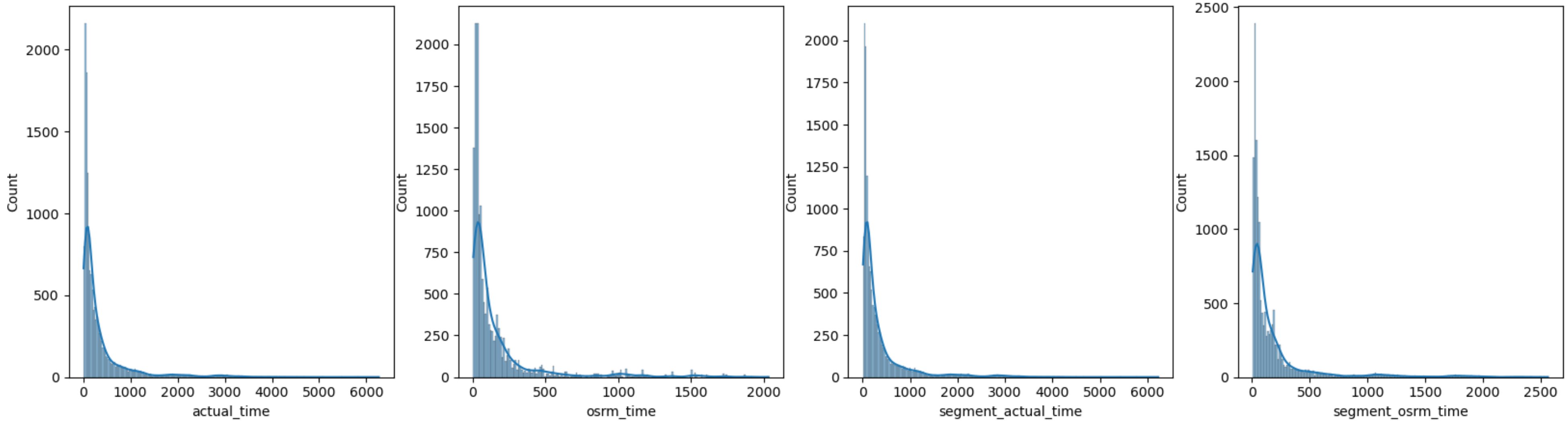




In [39]:
```
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 3, 1)
sns.histplot(df2['actual_distance_to_destination'],kde = True)
plt.subplot(1, 3, 2)
sns.histplot(df2['segment_osrm_distance'],kde = True)
plt.subplot(1, 3, 3)
sns.histplot(df2['osrm_distance'],kde = True)
plt.show()
```



In [40]:
```
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 4, 1)
sns.histplot(df2['actual_time'],kde = True)
plt.subplot(1, 4, 2)
sns.histplot(df2['osrm_time'],kde = True)
plt.subplot(1, 4, 3)
sns.histplot(df2['segment_actual_time'],kde = True)
plt.subplot(1, 4, 4)
sns.histplot(df2['segment_osrm_time'],kde = True)
plt.show()
```



Observations:

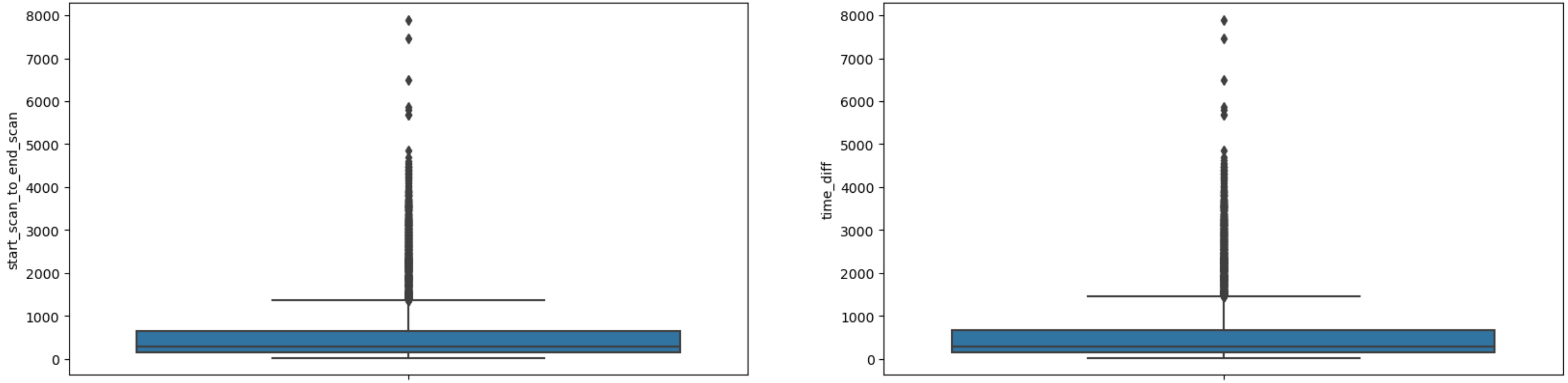
- all of the numerical data is right skewed.

Outlier Detection and treatment

In [41]:

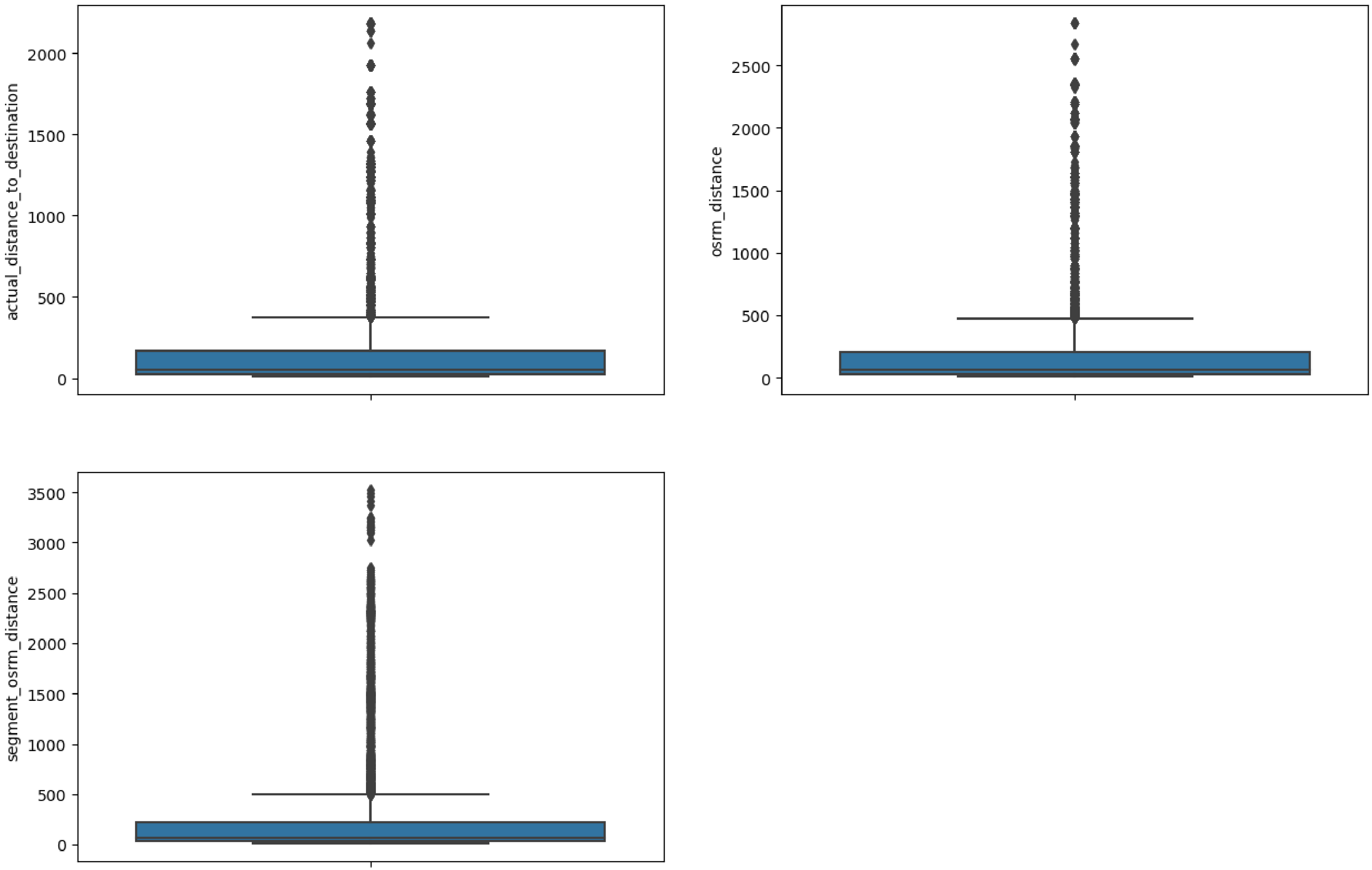
```
# outliers in time difference data
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
sns.boxplot(y = df2['start_scan_to_end_scan'])
plt.subplot(1,2, 2)
sns.boxplot(y = df2['time_diff'])
```

Out[41]: <AxesSubplot:ylabel='time_diff'>



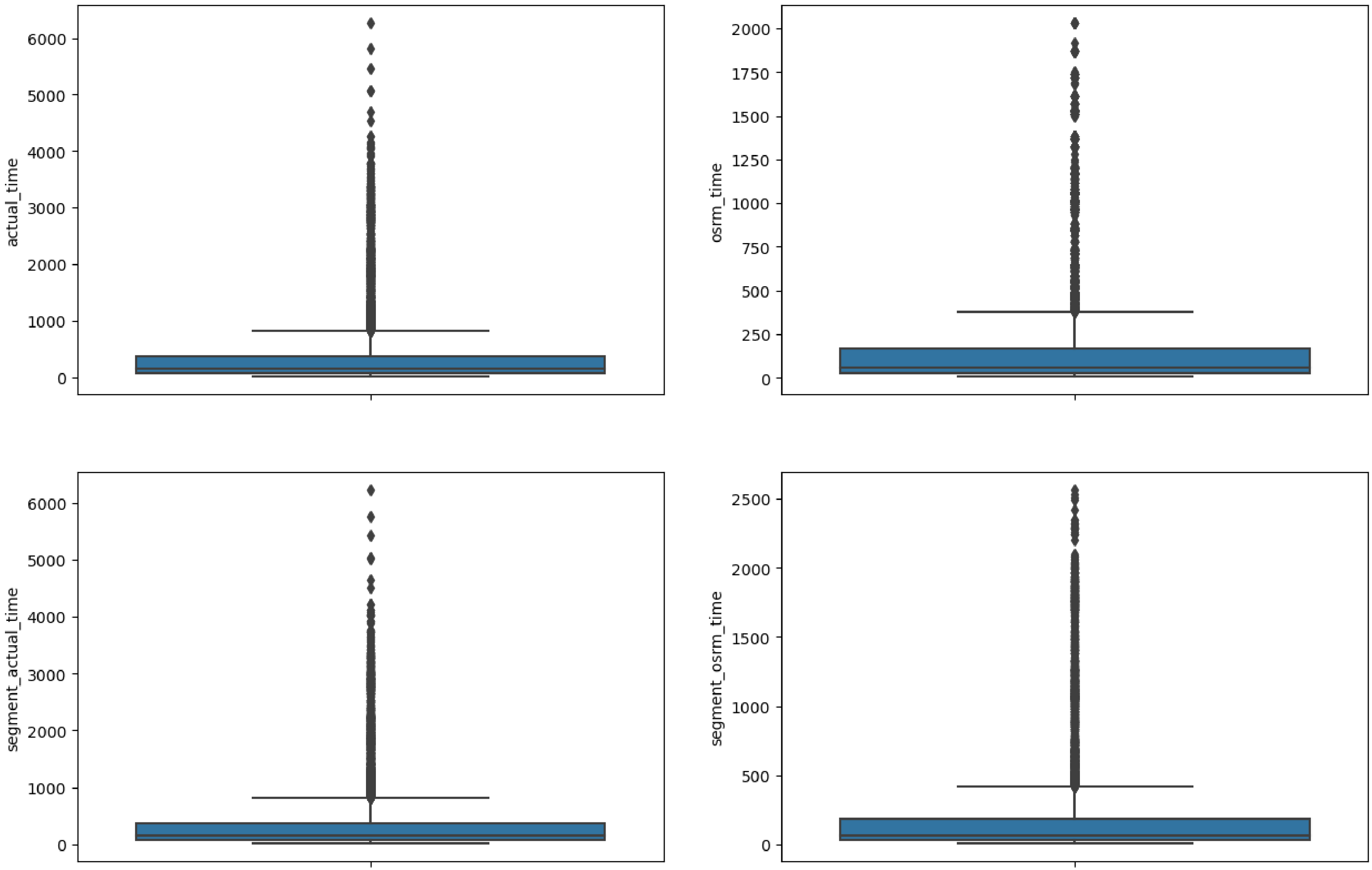
In [42]:
```python
# outliers in distance data
fig = plt.figure(figsize=(15,10))
plt.subplot(2,2, 1)
sns.boxplot(y = df2['actual_distance_to_destination'])
plt.subplot(2,2, 2)
sns.boxplot(y = df2['osrm_distance'])
plt.subplot(2,2, 3)
sns.boxplot(y = df2['segment_osrm_distance'])
```

Out[42]:
```
<AxesSubplot:ylabel='segment_osrm_distance'>
```


actual_distance_to_destination
0
500
1000
1500
2000
osrm_distance
0
500
1000
1500
2000
2500
segment_osrm_distance
0
500
1000
1500
2000
2500
3000
3500

In [43]:
```
# outliers in time data
fig = plt.figure(figsize=(15,10))
plt.subplot(2,2, 1)
sns.boxplot(y = df2['actual_time'])
plt.subplot(2,2, 2)
sns.boxplot(y = df2['osrm_time'])
plt.subplot(2,2, 3)
sns.boxplot(y = df2['segment_actual_time'])
plt.subplot(2,2, 4)
sns.boxplot(y = df2['segment_osrm_time'])
```

Out[43]:
```
<AxesSubplot:ylabel='segment_osrm_time'>
```



Observations

- all data of time and distance have high number of outliers, it was evident from right skewness of the data.

Outlier Treatment using IQR method

In [44]:
```
# copying the data to keep the original safe
df_out = df2.copy()
```

In [45]:
```
# removing outliers from the data
numerical_columns = ['start_scan_to_end_scan', 'actual_distance_to_destination',
       'actual_time', 'osrm_time', 'osrm_distance', 'segment_actual_time',
       'segment_osrm_distance', 'segment_osrm_time','time_diff']
for x in numerical_columns:
    Q25 = df_out[x].quantile(0.25)
    Q75 = df_out[x].quantile(0.75)
    IQR = Q75-Q25
    upper_limit = Q75 + 1.5*IQR
    lower_limit = Q25 - 1.5*IQR
    df_out = df_out[(df_out[x] > Q25 - 1.5*IQR) & (df_out[x] < Q75 + 1.5*IQR)]
```

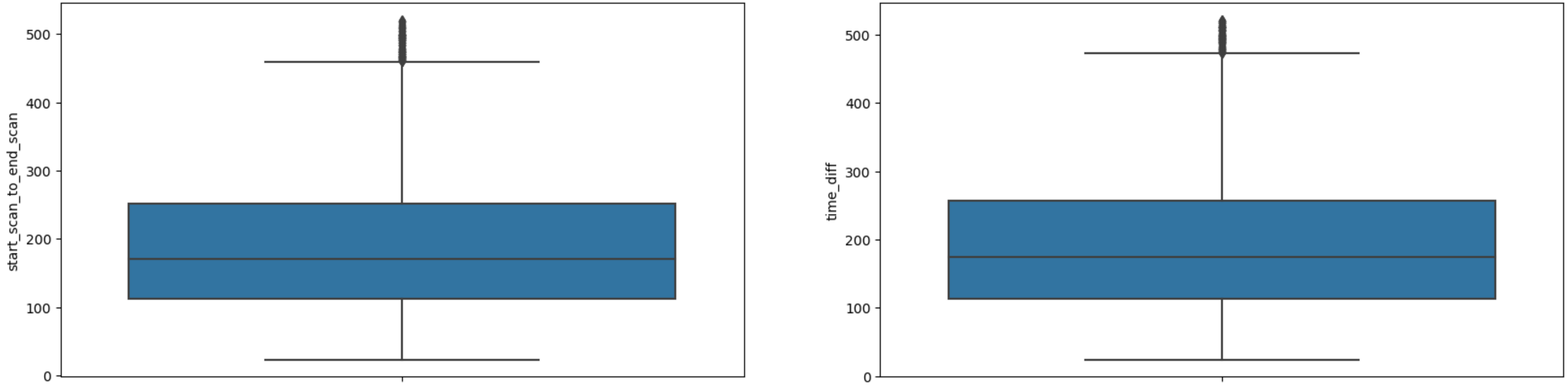
In [46]:
```
# data information post merging the data and treating null values
# shape of data
print('Total number of rows:',df_out.shape[0])
print('Total number of columns:',df_out.shape[1])
```

```
Total number of rows: 8968
Total number of columns: 23
```

Distribution of numerical data after removing outliers

In [47]:
```
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
sns.boxplot(y = df_out['start_scan_to_end_scan'])
plt.subplot(1,2, 2)
sns.boxplot(y = df_out['time_diff'])
```

Out[47]: <AxesSubplot:ylabel='time_diff'>

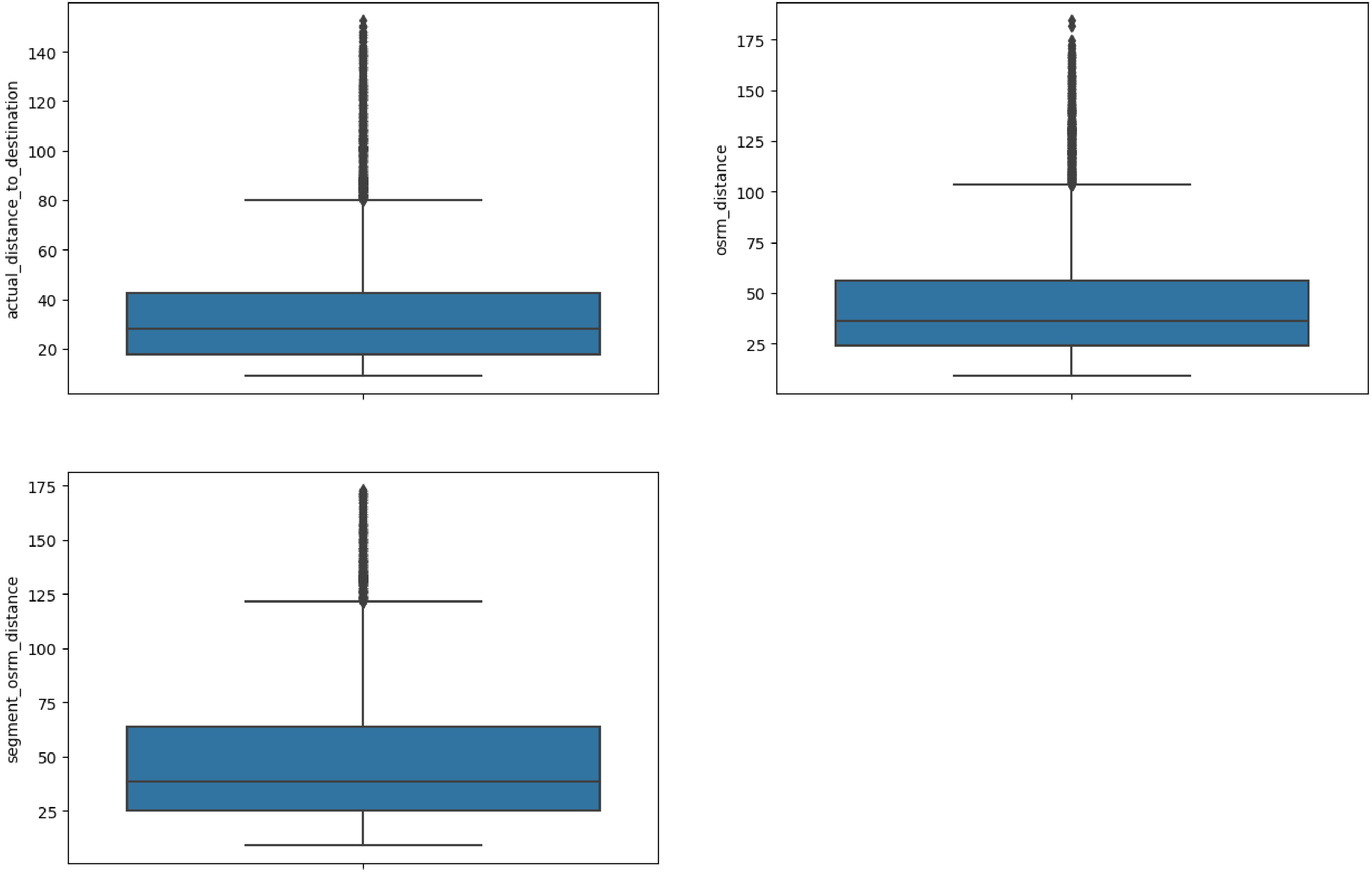


In [48]:

```
fig = plt.figure(figsize=(15,10))
plt.subplot(2,2, 1)
sns.boxplot(y = df_out['actual_distance_to_destination'])
plt.subplot(2,2, 2)
sns.boxplot(y = df_out['osrm_distance'])
plt.subplot(2,2, 3)
sns.boxplot(y = df_out['segment_osrm_distance'])
```

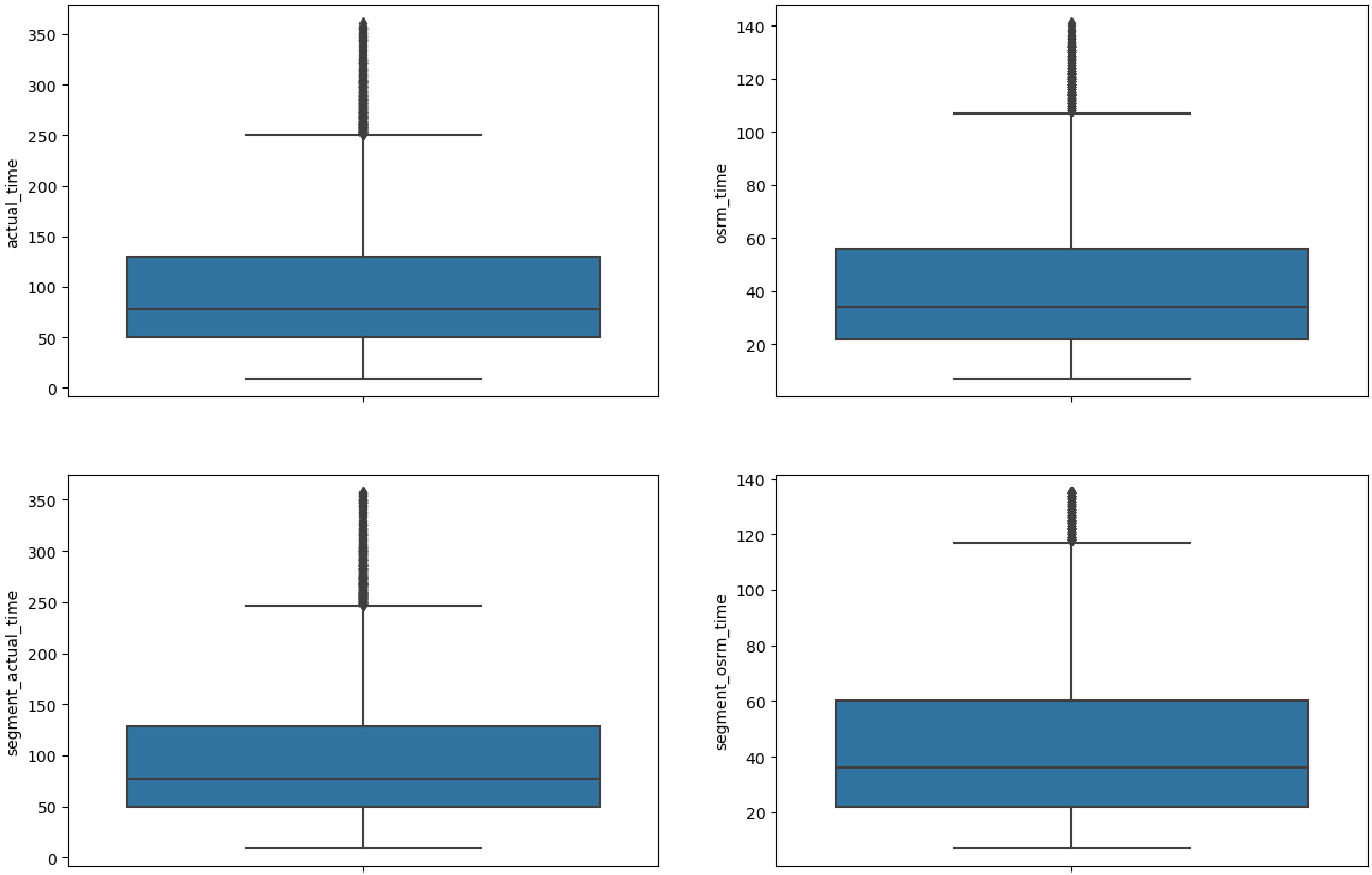
Out[48]:

```
<AxesSubplot:ylabel='segment_osrm_distance'>
```


actual_distance_to_destination
20
40
60
80
100
120
140
osrm_distance
25
50
75
100
125
150
175
segment_osrm_distance
25
50
75
100
125
150
175

In [49]:
```
fig = plt.figure(figsize=(15,10))
plt.subplot(2,2, 1)
sns.boxplot(y = df_out['actual_time'])
plt.subplot(2,2, 2)
sns.boxplot(y = df_out['osrm_time'])
plt.subplot(2,2, 3)
sns.boxplot(y = df_out['segment_actual_time'])
plt.subplot(2,2, 4)
sns.boxplot(y = df_out['segment_osrm_time'])
```

Out[49]:
```
<AxesSubplot:ylabel='segment_osrm_time'>
```

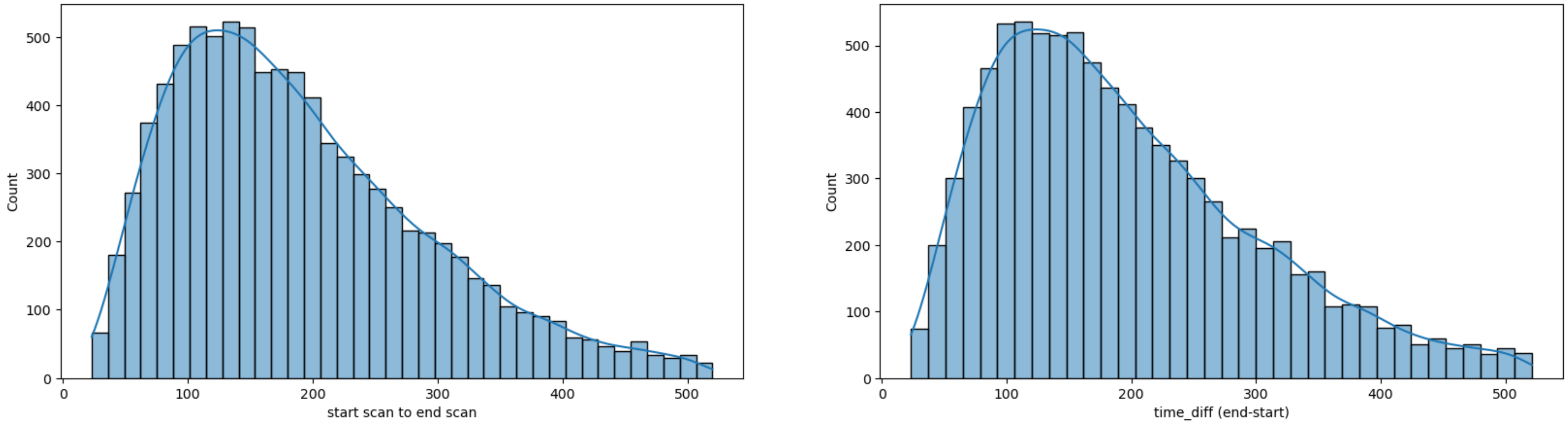


Hypothesis Testing

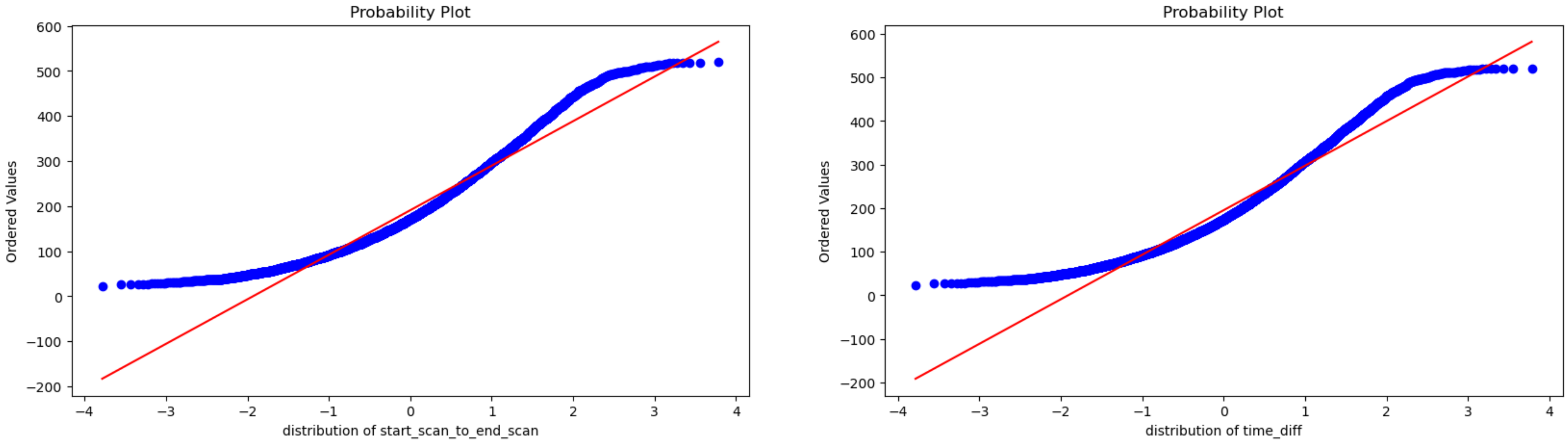
Test1: Compare the difference between time diff and start_scan_to_end_scan.

```
In [50]: # Data Extraction for the analysis
         start_scan_to_end_scan = df_out['start_scan_to_end_scan']
         diff = df_out['time_diff'] # data of timestamp difference
```

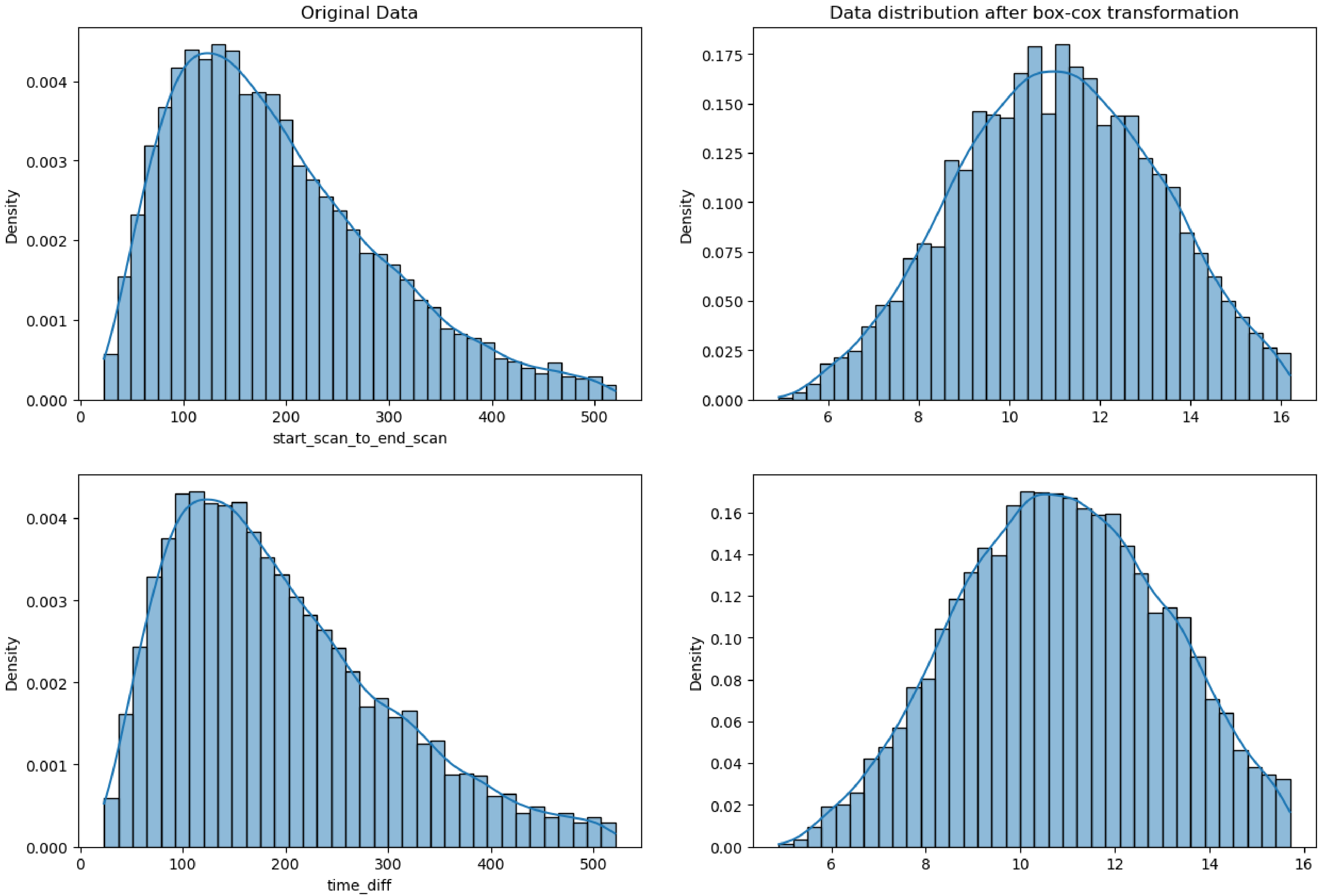
```
In [51]: # checking the data distribution using histograms
         fig = plt.figure(figsize=(20,5))
         plt.subplot(1, 2, 1)
         sns.histplot(start_scan_to_end_scan,kde = True)
         plt.xlabel('start scan to end scan',fontsize=10)
         plt.subplot(1, 2, 2)
         sns.histplot(diff,kde = True)
         plt.xlabel('time_diff (end-start)',fontsize=10)
         plt.show()
```



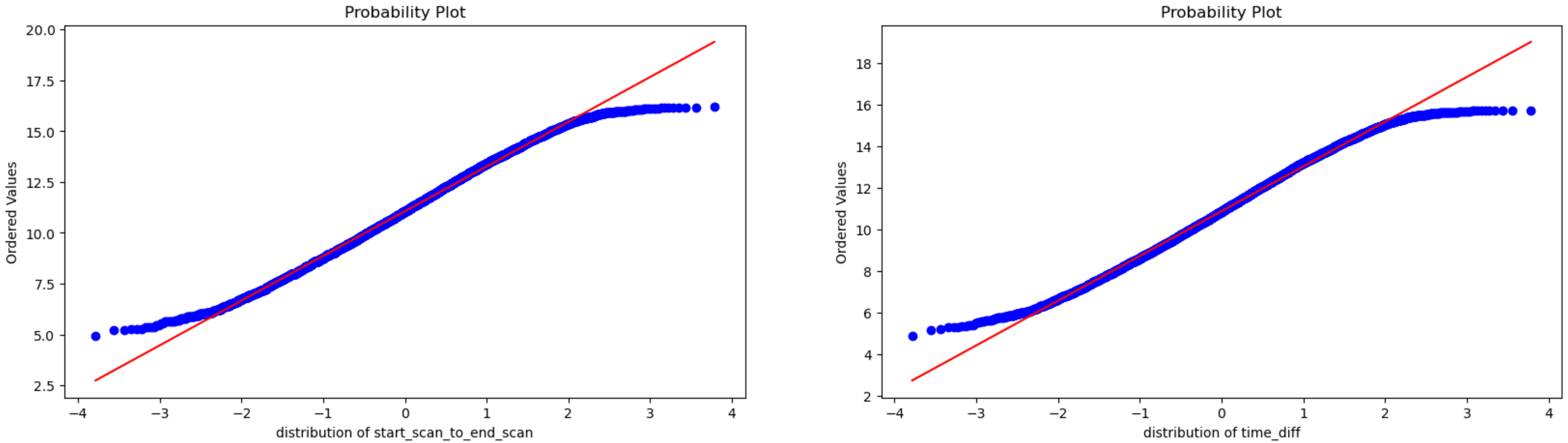
In [52]:
```
# Validation of Assumption 1 by performing Quantile-Quantile Plot Test:
# H0: The sample has a Gaussian distribution.
# H1: The sample does not have a Gaussian distribution.
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
stats.probplot(start_scan_to_end_scan,dist="norm",plot=plt)
plt.xlabel('distribution of start_scan_to_end_scan',fontsize=10)
plt.subplot(1, 2, 2)
stats.probplot(diff,dist="norm",plot=plt)
plt.xlabel('distribution of time_diff',fontsize=10)
plt.show()
```



In [53]:
```
# Transforming data by using boxcox transformation:
original_data1=start_scan_to_end_scan
original_data2=diff


fitted_data1, fitted_lambda1 = stats.boxcox(start_scan_to_end_scan)
fitted_data2, fitted_lambda2 = stats.boxcox(diff)


fig = plt.figure(figsize=(15,10))
plt.subplot(2, 2, 1)
sns.histplot(original_data1, kde=True, stat="density")
plt.title('Original Data')
plt.subplot(2, 2, 2)
sns.histplot(fitted_data1, kde=True, stat="density")
plt.title('Data distribution after box-cox transformation')

plt.subplot(2, 2, 3)
sns.histplot(original_data2, kde=True, stat="density")
plt.subplot(2, 2, 4)
sns.histplot(fitted_data2, kde=True, stat="density")
plt.show()
```


Original Data
Data distribution after box-cox transformation
Density
start_scan_to_end_scan
time_diff
0.000
0.001
0.002
0.003
0.004
0.025
0.050
0.075
0.100
0.125
0.150
0.175
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
0.16
0
100
200
300
400
500
6
8
10
12
14
16

In [54]:
```python
# Quantile-Quantile Plot post data transformation:
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
stats.probplot(fitted_data1,dist="norm",plot=plt)
plt.xlabel('distribution of start_scan_to_end_scan',fontsize=10)
plt.subplot(1, 2, 2)
stats.probplot(fitted_data2,dist="norm",plot=plt)
plt.xlabel('distribution of time_diff',fontsize=10)
plt.show()
```



In [55]:
```python
#  Validation of variance assumption:
# H0:variance of the sample is same.
# Ha:variances of the sample is not same.
alpha=0.05
levene_stat,p_value=levene(start_scan_to_end_scan, diff)
print("alpha:",0.05)
print("p_value:",p_value)
if p_value<alpha:
  print("Reject Null Hypothesis: Variance of the input datasets is not same")
else:
  print('Accept Null Hypothesis: Variance of the input datasets is Same/Close')
```

```
alpha: 0.05
p_value: 0.0025573994985197534
Reject Null Hypothesis: Variance of the input datasets is not same
```

Observations on the assumption:

1. with confidence level 0.05 both data sets have statistically different variance.
2. after outlier removal the data is slightly right skewed which is converted to normal using box_cox transformation.

Hypothesis setup for ttest:

1. **Null Hypothesis:** mean of both samples are equal.
2. **Alternate:** mean of both samples is different.

In [56]:
```
print('start_scan_to_end_scan Mean:', start_scan_to_end_scan.mean())
print('diff Mean:', diff.mean())
```

```
start_scan_to_end_scan Mean: 190.7164362176628
diff Mean: 194.9273568628434
```

In [57]:
```
# Paired Student's t-test
t_stat,p_value=ttest_ind(start_scan_to_end_scan,diff)
alpha = 0.05
print("Alpha:",alpha)
print("p value:",p_value)
print("t statistics:",t_stat)
if p_value<alpha:
    print("Reject Null Hypothesis: The means of the samples are different")
else:
    print('Accept Null Hypothesis: The means of the samples are equal')
```

```
Alpha: 0.05
p value: 0.006411717541824584
t statistics: -2.726268007838676
Reject Null Hypothesis: The means of the samples are different
```

In [58]:
```
# correlation tets
print('pearson correlation coefficient:', stats.pearsonr(start_scan_to_end_scan,diff)[0])
```

```
pearson correlation coefficient: 0.9824981004420749
```

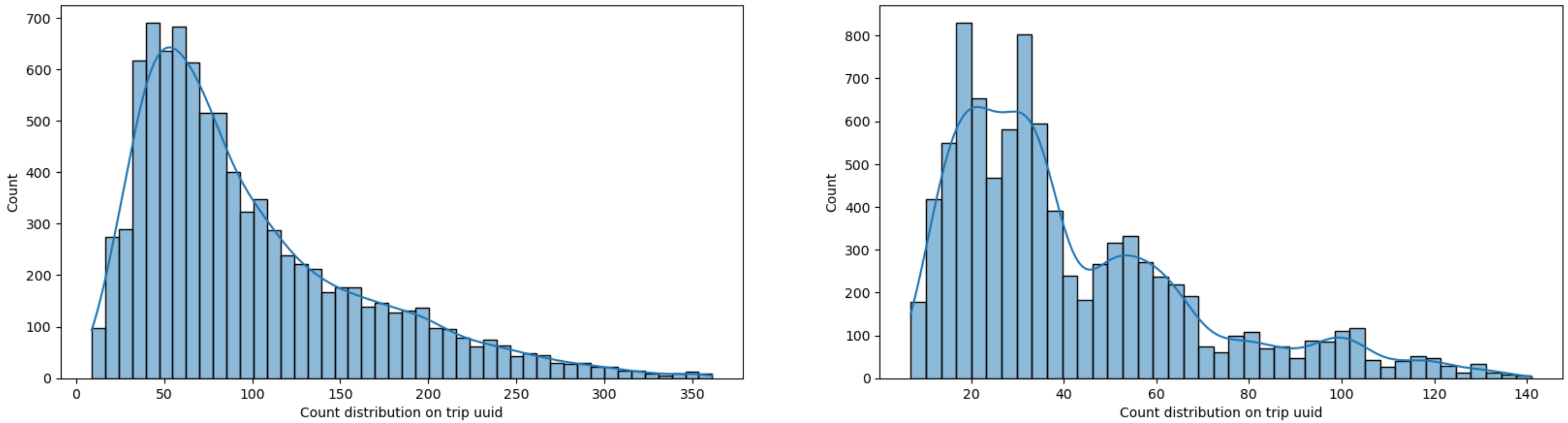
Observations:

1. both data have statistically different mean value (p_val = 0.006)
2. but both the data are very highly correlated (cc = 0.98)

Test-2: Do hypothesis testing/ visual analysis between actual_time aggregated value and OSRM time aggregated value

In [59]:
```
actual_agg = df_out['actual_time']
osrm_agg = df_out['osrm_time']
```

In [60]:
```
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
sns.histplot(actual_agg,kde = True)
plt.xlabel('Count distribution on trip uuid',fontsize=10)
plt.subplot(1, 2, 2)
sns.histplot(osrm_agg,kde = True)
plt.xlabel('Count distribution on trip uuid',fontsize=10)
plt.show()
```

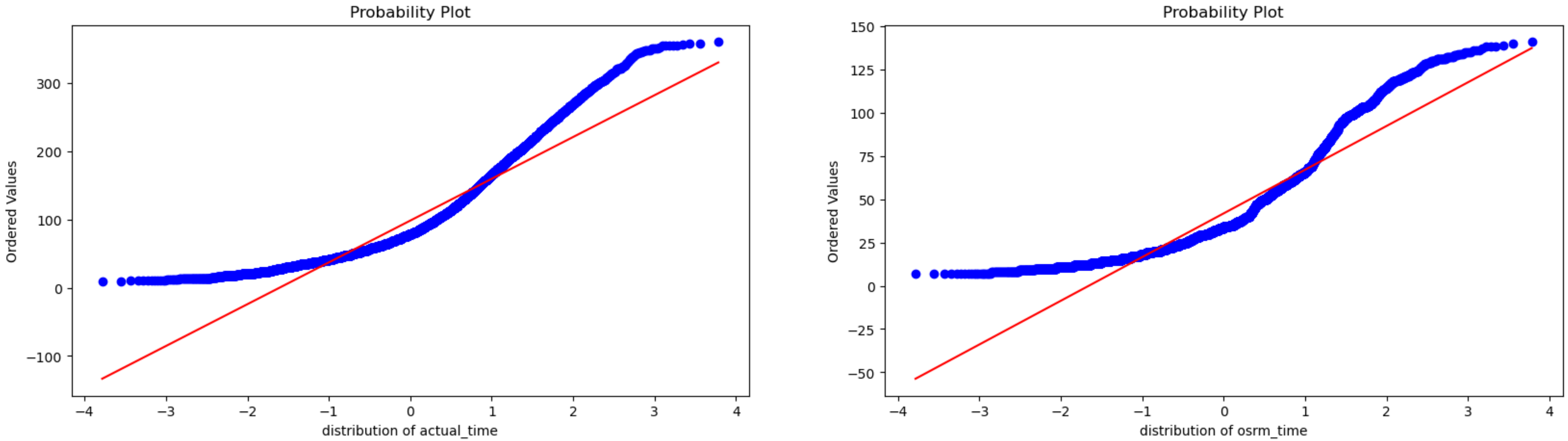


Assumptions under t-test:

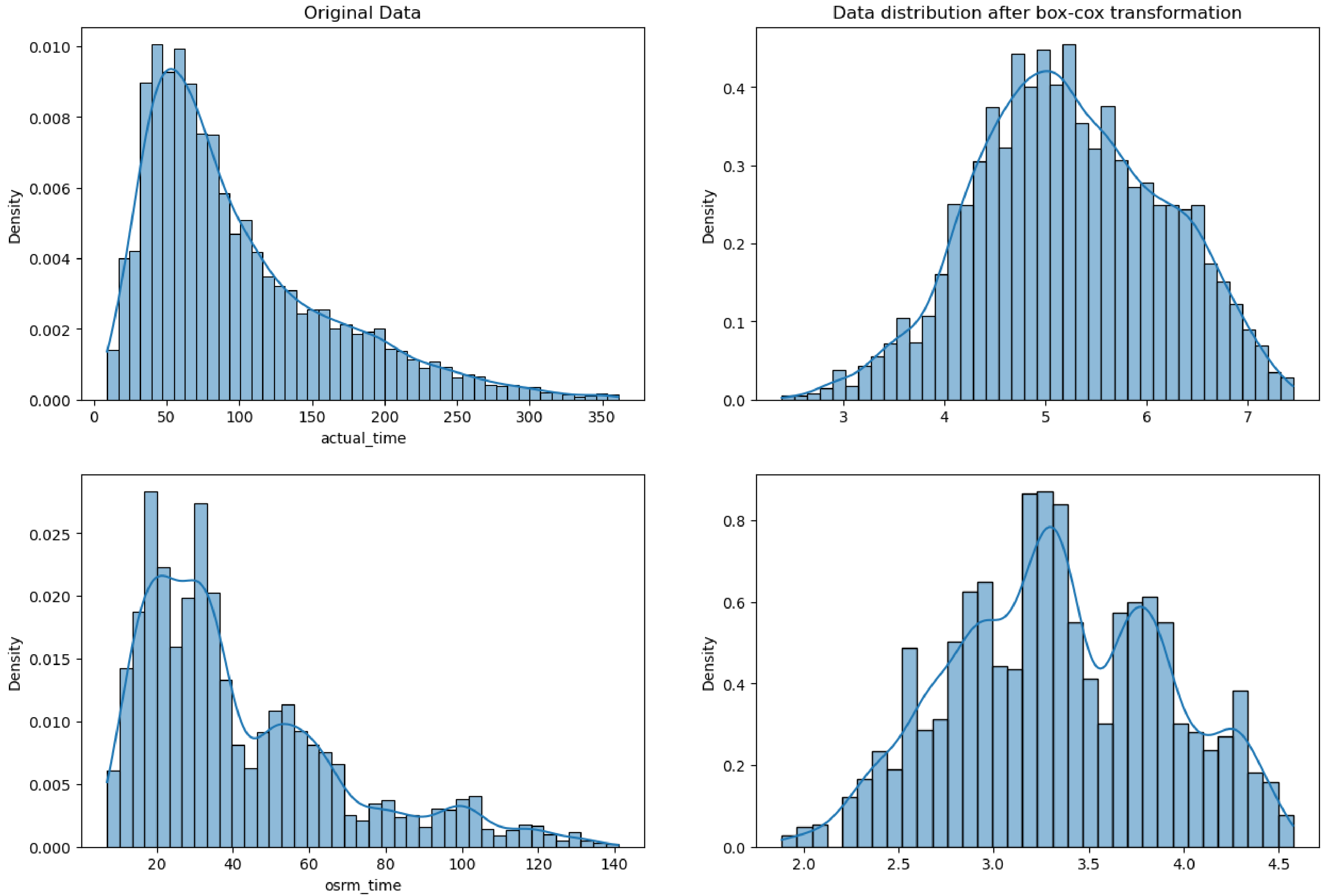
- Observations in each sample are normally distributed.
- Observations in each sample have close to same variance.

In [61]:

```
# Validation of Assumption 2 by performing Quantile-Quantile Plot Test:
# H0: The sample has a Gaussian distribution.
# H1: The sample does not have a Gaussian distribution.
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
probplot(actual_agg,dist="norm",plot=plt)
plt.xlabel('distribution of actual_time',fontsize=10)
plt.subplot(1, 2, 2)
probplot(osrm_agg,dist="norm",plot=plt)
plt.xlabel('distribution of osrm_time',fontsize=10)
plt.show()
```

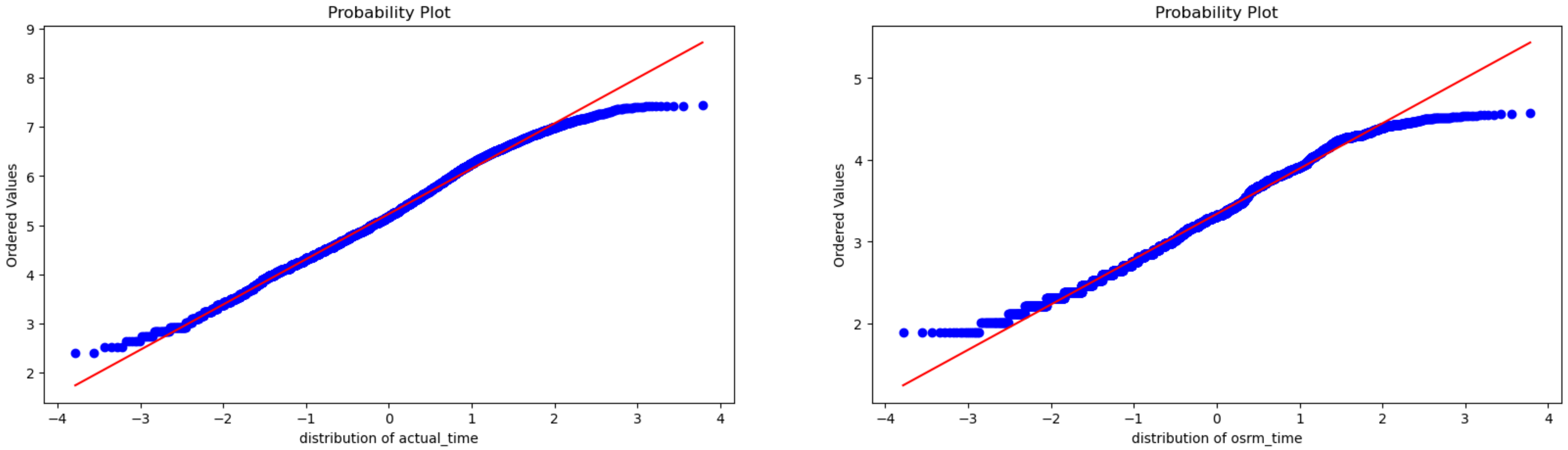


In [62]:
```
# Transforming data by using boxcox transformation:
original_data1=actual_agg
original_data2=osrm_agg

fitted_data1, fitted_lambda1 = boxcox(actual_agg)
fitted_data2, fitted_lambda2 = boxcox(osrm_agg)

fig = plt.figure(figsize=(15,10))
plt.subplot(2,2, 1)
sns.histplot(original_data1, kde=True, stat="density")
plt.title('Original Data')
plt.subplot(2,2, 2)
sns.histplot(fitted_data1, kde=True, stat="density")
plt.title('Data distribution after box-cox transformation')
plt.subplot(2,2, 3)
sns.histplot(original_data2, kde=True, stat="density")
plt.subplot(2,2, 4)
sns.histplot(fitted_data2, kde=True, stat="density")
plt.show()
```



Original Data
Data distribution after box-cox transformation
Density
actual_time
osrm_time

In [63]:
```
# Quantile-Quantile Plot after data transformation:
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
probplot(fitted_data1,dist="norm",plot=plt)
plt.xlabel('distribution of actual_time',fontsize=10)
plt.subplot(1, 2, 2)
probplot(fitted_data2,dist="norm",plot=plt)
plt.xlabel('distribution of osrm_time',fontsize=10)
plt.show()
```



In [64]:
```
#  Validation of Assumption 3:
# H0:variance of the sample is same.
# Ha:variances of the sample is not same.
alpha=0.05
levene_stat,p_value=levene(osrm_agg, actual_agg)
print("alpha:",0.05)
print("p_value:",p_value)
if p_value<alpha:
  print("Reject Null Hypothesis: Variance of the input datasets is not same")
else:
  print('Accept Null Hypothesis: Variance of the input datasets is Same/Close')
```

```
alpha: 0.05
p_value: 0.0
Reject Null Hypothesis: Variance of the input datasets is not same
```

Observations on the assumption:

1. with confidence level 0.05 both data sets have statistically different variance.
2. after outlier removal the data is slightly right skewed which is converted to normal using box_cox transformation.

Hypothesis setup for ttest:

1. **Null Hypothesis:** mean of both samples are equal.
2. **Alternate:** mean of both samples is different.

In [65]:
```
print('actual time mean:', actual_agg.mean())
print('osrm time mean:', osrm_agg.mean())
```

```
actual time mean: 98.47546833184657
osrm time mean: 41.80619982158787
```

In [66]:
```
alpha = 0.05
t_stat,p_value=ttest_ind(actual_agg,osrm_agg)
print("p value:",p_value)
print("t statistics:",t_stat)
if p_value<alpha:
    print("Reject Null Hypothesis: The means of the samples are unequal")
else:
    print('Accept Null Hypothesis: The means of the samples are equal')
```

```
p value: 0.0
t statistics: 76.26012622156738
Reject Null Hypothesis: The means of the samples are unequal
```

In [67]:
```
# correlation tets
print('pearson correlation coefficient:', stats.pearsonr(osrm_agg, actual_agg)[0])
```

```
pearson correlation coefficient: 0.7228021360966055
```

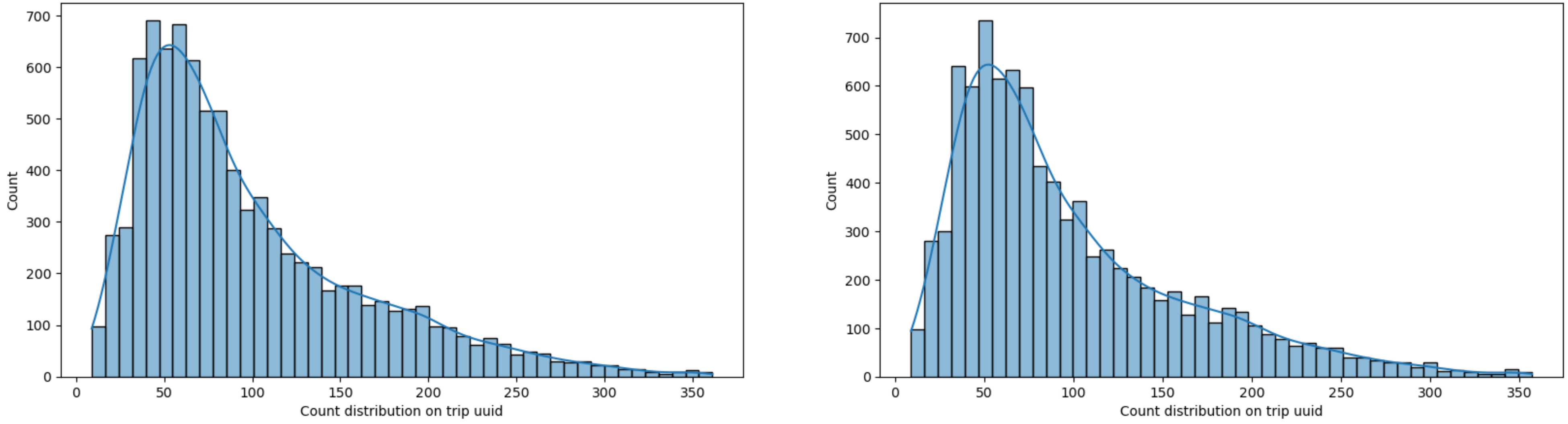
Observations:

1. both data have statistically different mean value (p_val = 0)
2. Null hypothesis Rejected
3. but both the data are very highly correlated (cc = 0.722)

Test3: Do hypothesis testing/ visual analysis between actual_time aggregated value and segment actual time aggregated value

In [68]:
```
actual_agg = df_out['actual_time']
seg_agg = df_out['segment_actual_time']
```

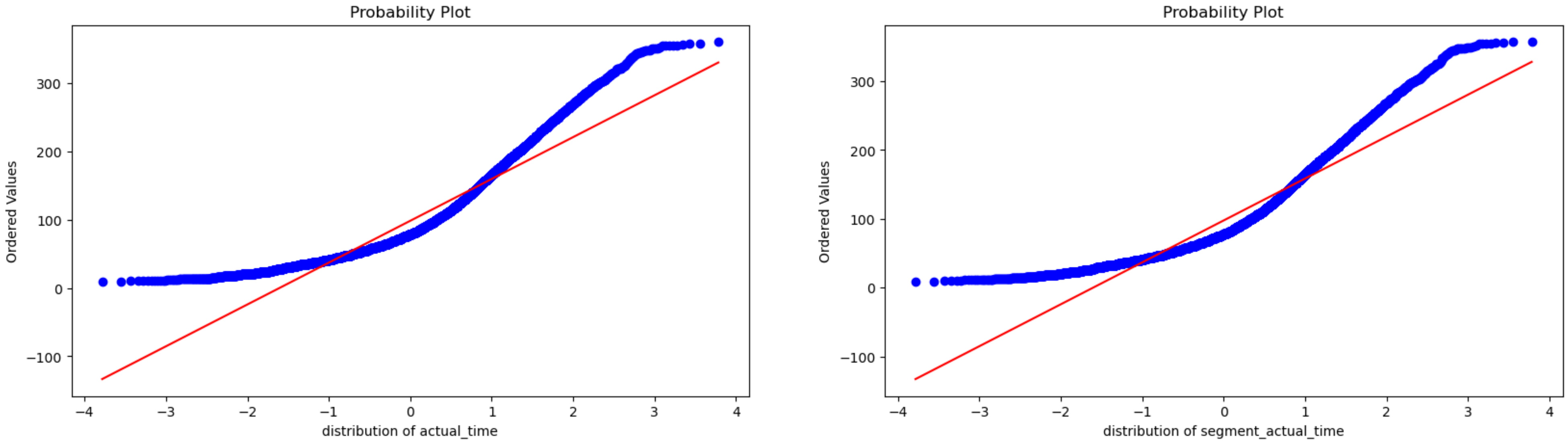
In [69]:
```
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
sns.histplot(actual_agg,kde = True)
plt.xlabel('Count distribution on trip uuid',fontsize=10)
plt.subplot(1, 2, 2)
sns.histplot(seg_agg,kde = True)
plt.xlabel('Count distribution on trip uuid',fontsize=10)
plt.show()
```



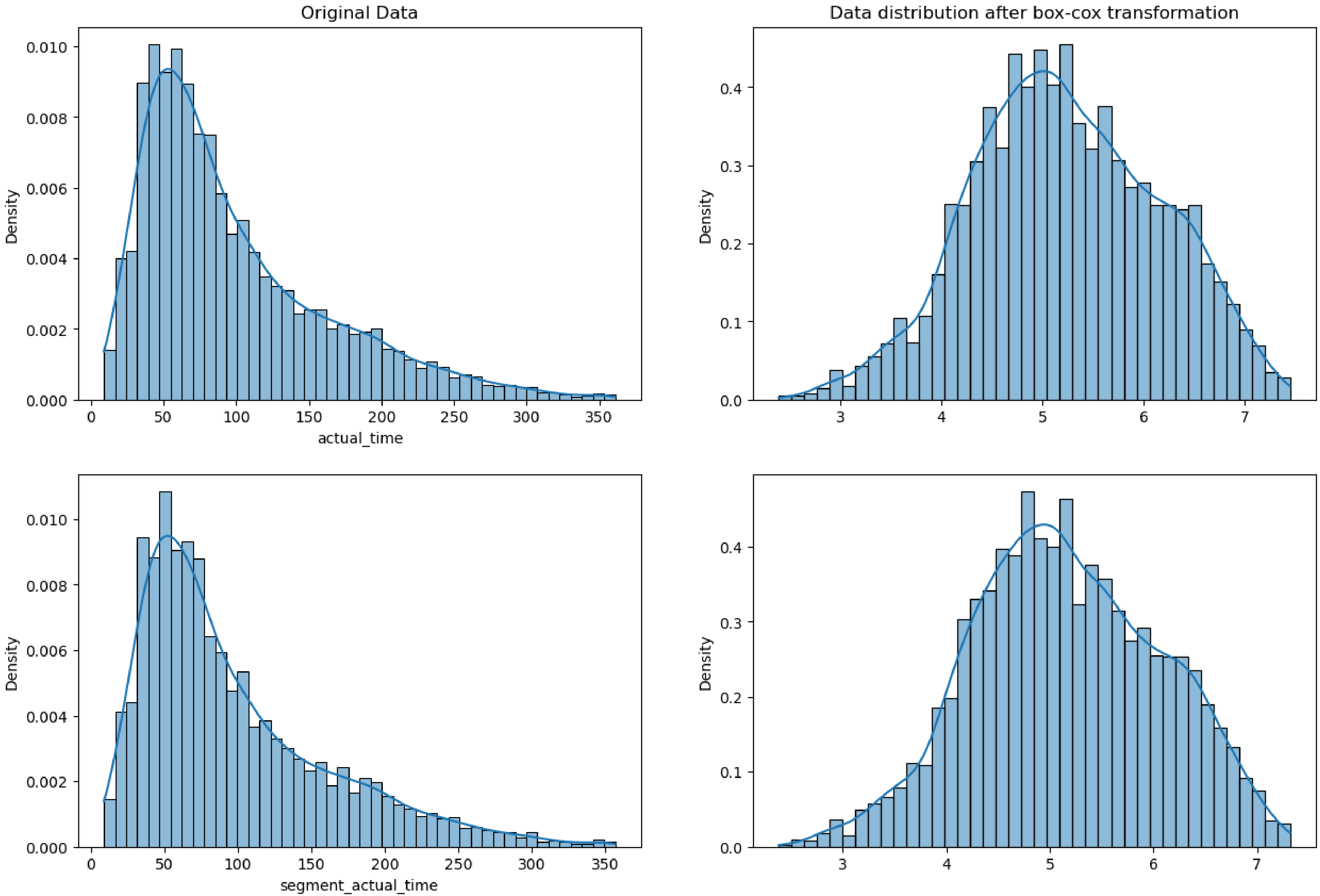
Assumptions under t-test:

- Observations in each sample are normally distributed.
- Observations in each sample have close to same variance

In [70]:
```
# H0: The sample has a Gaussian distribution.
# H1: The sample does not have a Gaussian distribution.
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
probplot(actual_agg,dist="norm",plot=plt)
plt.xlabel('distribution of actual_time',fontsize=10)
plt.subplot(1, 2, 2)
probplot(seg_agg,dist="norm",plot=plt)
plt.xlabel('distribution of segment_actual_time',fontsize=10)
plt.show()
```

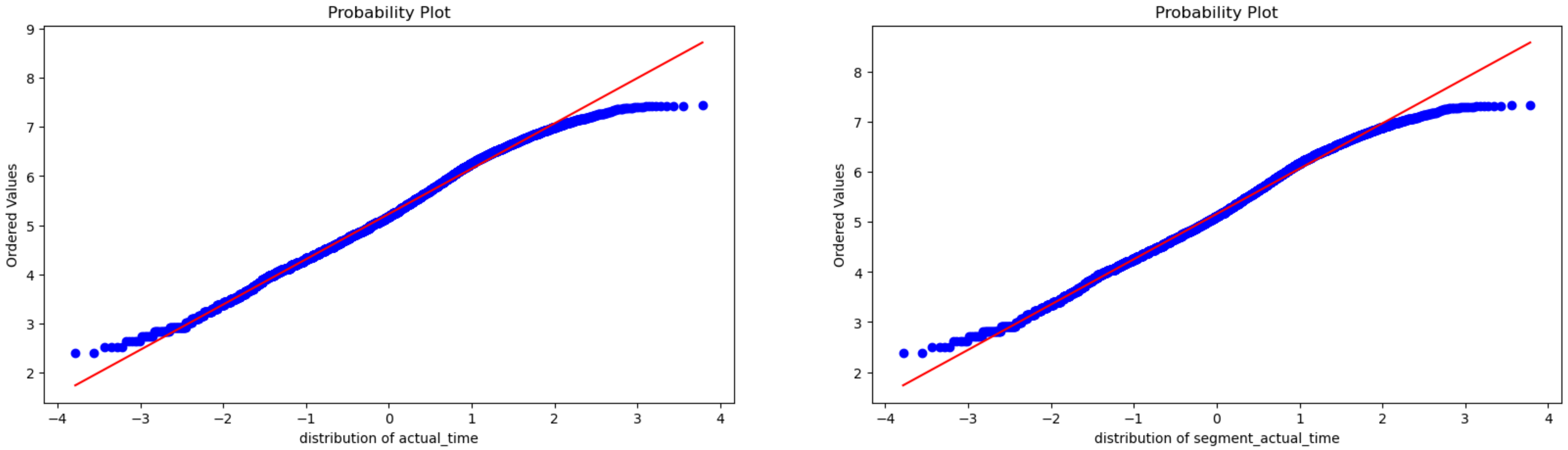


In [71]:
```
# Transforming data by using boxcox transformation:
original_data1=actual_agg
original_data2=seg_agg

fitted_data1, fitted_lambda1 = boxcox(actual_agg)
fitted_data2, fitted_lambda2 = boxcox(seg_agg)

fig = plt.figure(figsize=(15,10))
plt.subplot(2,2, 1)
sns.histplot(original_data1, kde=True, stat="density")
plt.title('Original Data')
plt.subplot(2,2, 2)
sns.histplot(fitted_data1, kde=True, stat="density")
plt.title('Data distribution after box-cox transformation')

plt.subplot(2,2, 3)
sns.histplot(original_data2, kde=True, stat="density")
plt.subplot(2,2, 4)
sns.histplot(fitted_data2, kde=True, stat="density")

plt.show()
```



Original Data
Data distribution after box-cox transformation
Density
actual_time
segment_actual_time
0.000
0.002
0.004
0.006
0.008
0.010
0
50
100
150
200
250
300
350
0.0
0.1
0.2
0.3
0.4
3
4
5
6
7

In [72]:
```
# Quantile-Quantile Plot after data transformation:
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
probplot(fitted_data1,dist="norm",plot=plt)
plt.xlabel('distribution of actual_time',fontsize=10)
plt.subplot(1, 2, 2)
probplot(fitted_data2,dist="norm",plot=plt)
plt.xlabel('distribution of segment_actual_time',fontsize=10)
plt.show()
```



In [73]:
```
# H0:variance of the sample is same.
# Ha:variances of the sample is not same.
alpha=0.05
levene_stat,p_value=levene(actual_agg, seg_agg)
print("alpha:",0.05)
print("p_value:",p_value)
if p_value<alpha:
  print("Reject Null Hypothesis: Variance of the input datasets is not same")
else:
  print('Accept Null Hypothesis: Variance of the input datasets is Same/Close')
```

```
alpha: 0.05
p_value: 0.5791411251061716
Accept Null Hypothesis: Variance of the input datasets is Same/Close
```

Hypothesis setup for ttest:

1. **Null Hypothesis:** mean of both samples are equal.
2. **Alternate:** mean of both samples is different.

In [74]:
```
print('Actual time mean:', actual_agg.mean())
print('segment time mean:', seg_agg.mean())
```

```
Actual time mean: 98.47546833184657
segment time mean: 97.4528322925959
```

In [75]:
```
alpha = 0.05
t_stat,p_value=ttest_ind(actual_agg,seg_agg)
print("p value:",p_value)
print("t statistics:",t_stat)
if p_value<alpha:
    print("Reject Null Hypothesis: The means of the samples are unequal")
else:
    print('Accept Null Hypothesis: The means of the samples are equal')
```

```
p value: 0.29068292756540426
t statistics: 1.0566558214779944
Accept Null Hypothesis: The means of the samples are equal
```

In [76]:
```
print('pearson correlation coefficient:', stats.pearsonr(actual_agg,seg_agg)[0])
```

```
pearson correlation coefficient: 0.9998966577410145
```

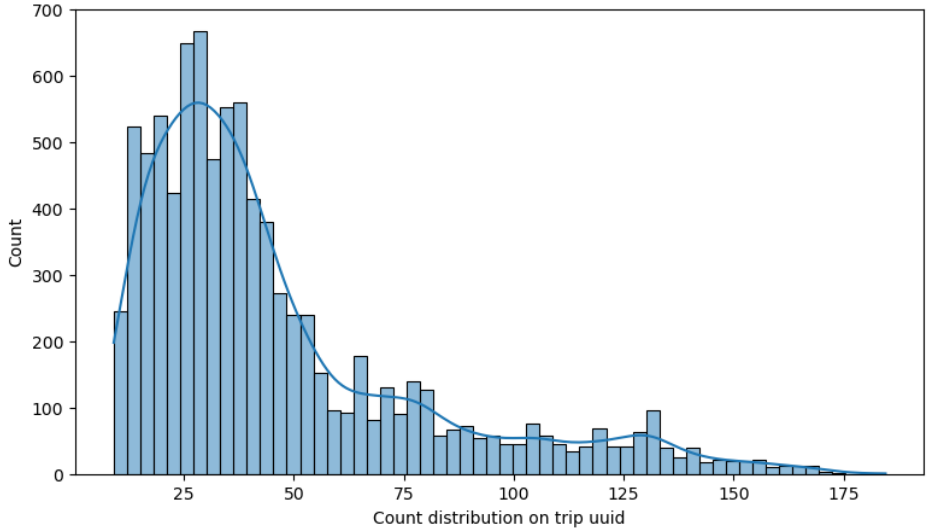
Observations:

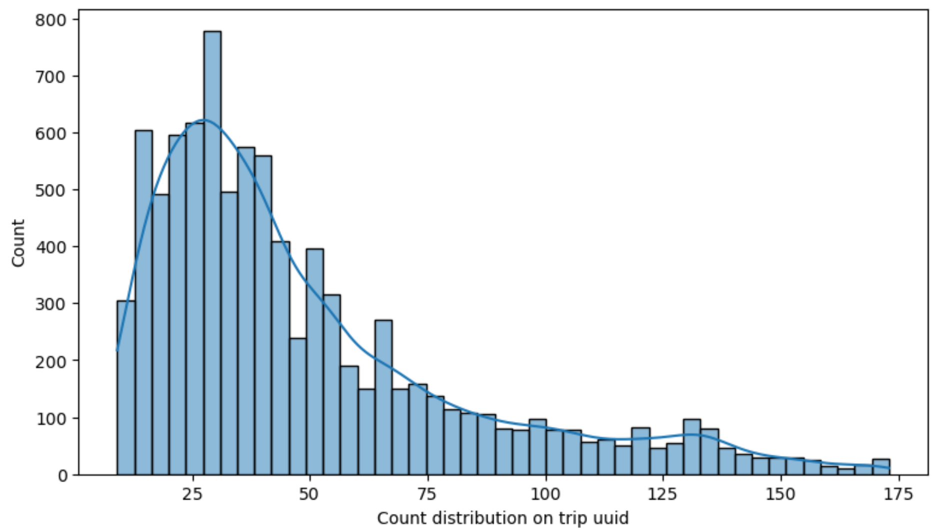
1. The calculated p-value : 0.29, which is greater than the significance level.
2. Null Hypothesis is accepted.
3. The means of the actual time and segment actual times are equal

Test4 : Do hypothesis testing/ visual analysis between osrm distance aggregated value and segment osrm distance aggregated value

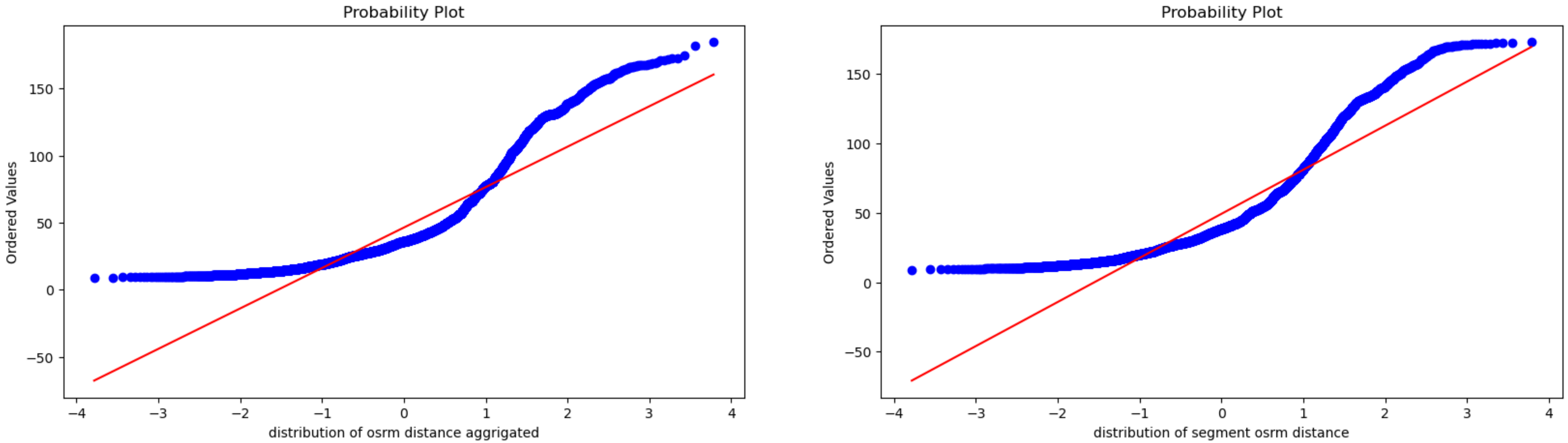
In [77]:
```
osrm_dist_agg = df_out['osrm_distance']
seg_osrm_dist_agg = df_out['segment_osrm_distance']
```

In [78]:
```
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
sns.histplot(osrm_dist_agg,kde = True)
plt.xlabel('Count distribution on trip uuid',fontsize=10)
plt.subplot(1, 2, 2)
sns.histplot(seg_osrm_dist_agg,kde = True)
plt.xlabel('Count distribution on trip uuid',fontsize=10)
plt.show()
```



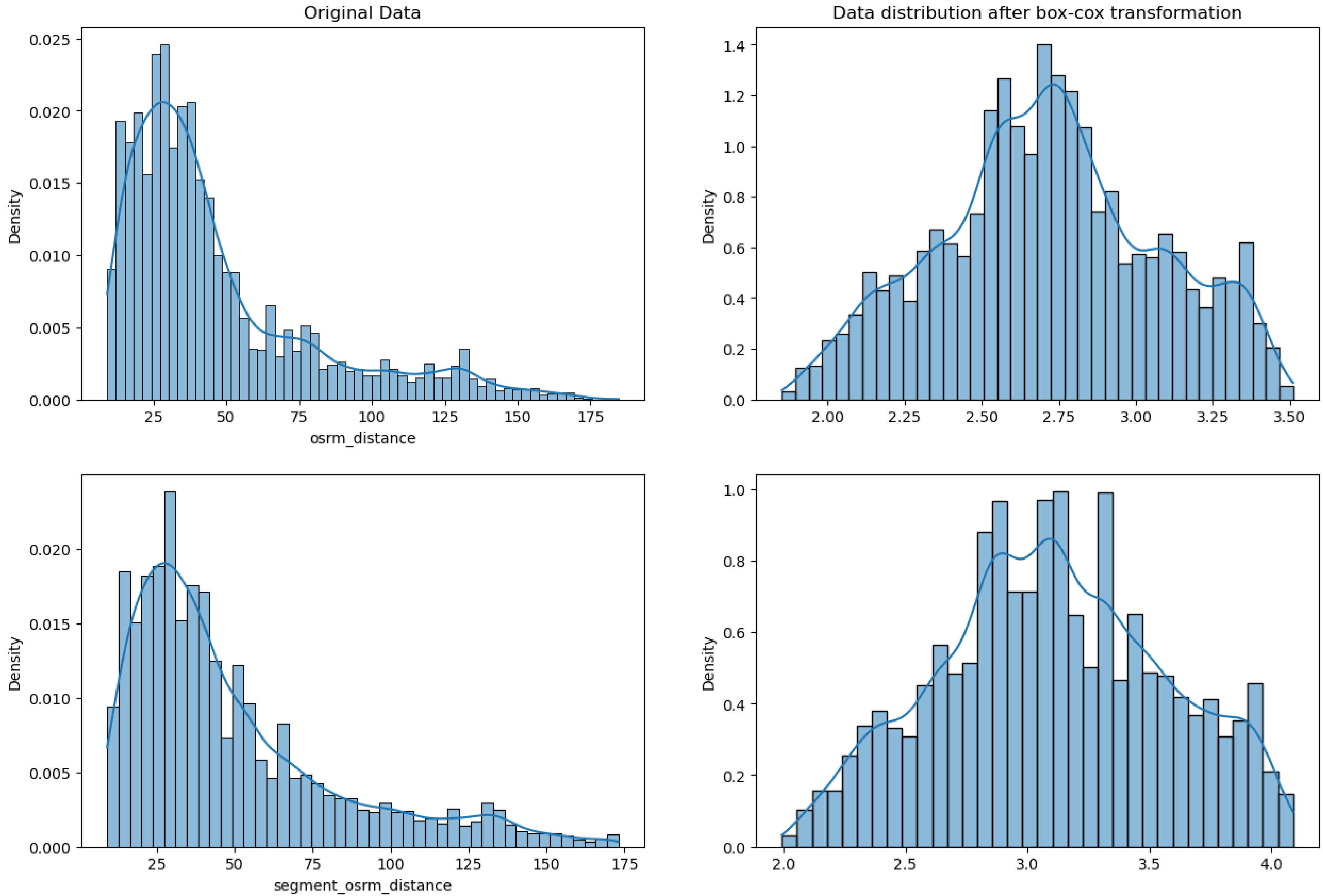


In [79]:
```
# Validation of Assumption 2 by performing Quantile-Quantile Plot Test:
# H0: The sample has a Gaussian distribution.
# H1: The sample does not have a Gaussian distribution.
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
probplot(osrm_dist_agg,dist="norm",plot=plt)
plt.xlabel('distribution of osrm distance aggrigated',fontsize=10)
plt.subplot(1, 2, 2)
probplot(seg_osrm_dist_agg,dist="norm",plot=plt)
plt.xlabel('distribution of segment osrm distance',fontsize=10)
plt.show()
```

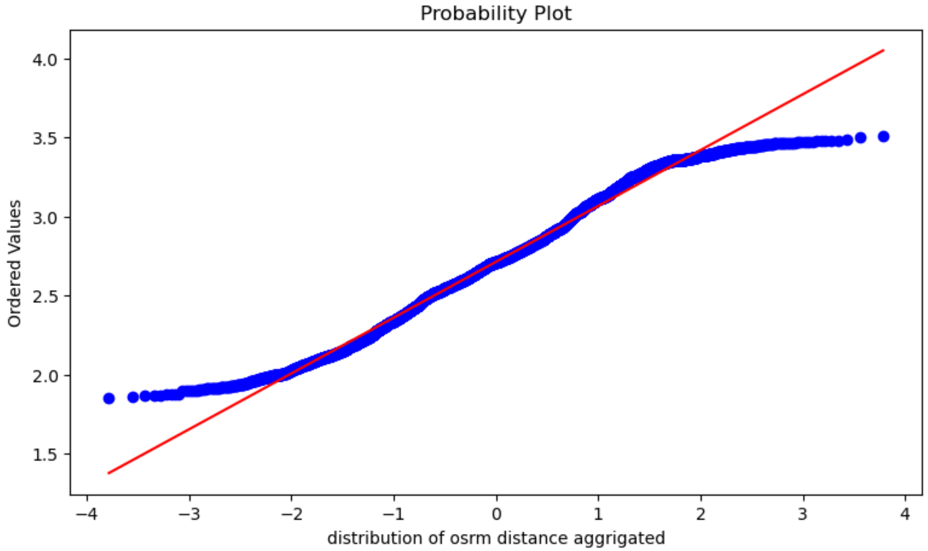


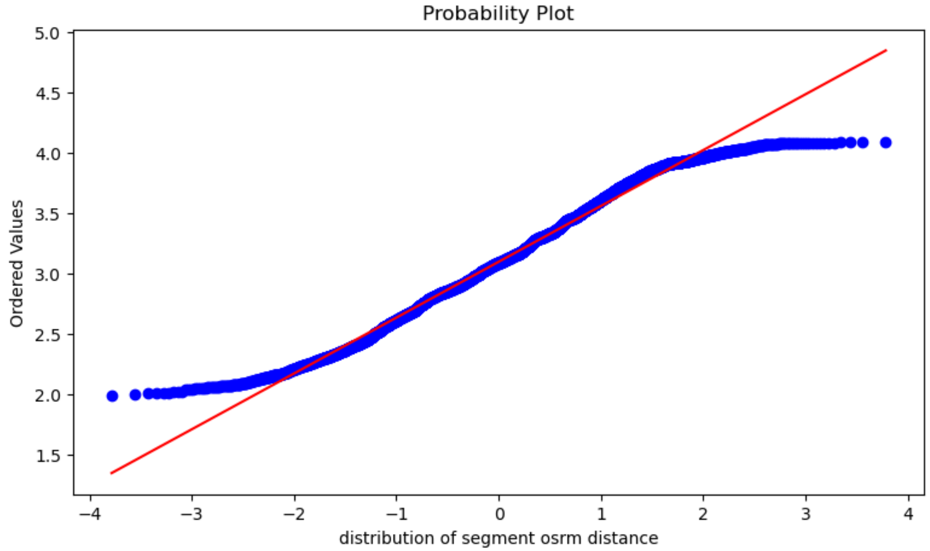
In [80]:

```python
# Transforming data by using boxcox transformation:
original_data1=osrm_dist_agg
original_data2=seg_osrm_dist_agg

fitted_data1, fitted_lambda1 = boxcox(osrm_dist_agg)
fitted_data2, fitted_lambda2 = boxcox(seg_osrm_dist_agg)

fig = plt.figure(figsize=(15,10))
plt.subplot(2,2, 1)
sns.histplot(original_data1, kde=True, stat="density")
plt.title('Original Data')
plt.subplot(2,2, 2)
sns.histplot(fitted_data1, kde=True, stat="density")
plt.title('Data distribution after box-cox transformation')
plt.subplot(2,2, 3)
sns.histplot(original_data2, kde=True, stat="density")
plt.subplot(2,2, 4)
sns.histplot(fitted_data2, kde=True, stat="density")

plt.show()
```


Original Data
Data distribution after box-cox transformation
Density
osrm_distance
segment_osrm_distance
0.000
0.005
0.010
0.015
0.020
0.025
25
50
75
100
125
150
175
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
2.00
2.25
2.50
2.75
3.00
3.25
3.50
2.0
2.5
3.0
3.5
4.0

In [81]:
```
# Quantile-Quantile Plot after data transformation:
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
probplot(fitted_data1,dist="norm",plot=plt)
plt.xlabel('distribution of osrm distance aggrigated',fontsize=10)
plt.subplot(1, 2, 2)
probplot(fitted_data2,dist="norm",plot=plt)
plt.xlabel('distribution of segment osrm distance',fontsize=10)
plt.show()
```





In [82]:
```
# H0:variance of the sample is same.
# Ha:variances of the sample is not same.
alpha=0.05
levene_stat,p_value=levene(osrm_dist_agg, seg_osrm_dist_agg)
print("alpha:",0.05)
print("p_value:",p_value)
if p_value<alpha:
  print("Reject Null Hypothesis: Variance of the input datasets is not same")
else:
  print('Accept Null Hypothesis: Variance of the input datasets is Same/Close')
```

```
alpha: 0.05
p_value: 2.484328091817772e-06
Reject Null Hypothesis: Variance of the input datasets is not same
```

In [83]:
```
print('osrm_dist_agg Mean:', osrm_dist_agg.mean())
print('seg_osrm_dist_agg Mean:', seg_osrm_dist_agg.mean())
```

```
osrm_dist_agg Mean: 46.35217801070486
seg_osrm_dist_agg Mean: 49.291729136931274
```

In [84]:
```
alpha = 0.05
t_stat,p_value=ttest_ind(osrm_dist_agg, seg_osrm_dist_agg)
print("p value:",p_value)
print("t statistics:",t_stat)
if p_value<alpha:
    print("Reject Null Hypothesis: The means of the samples are unequal")
else:
    print('Accept Null Hypothesis: The means of the samples are equal')
```

```
p value: 5.165879005140737e-09
t statistics: -5.844600346414713
Reject Null Hypothesis: The means of the samples are unequal
```

In [85]:
```
print('pearson correlation coefficient:', stats.pearsonr(osrm_dist_agg, seg_osrm_dist_agg)[0])
```

```
pearson correlation coefficient: 0.9740636014552427
```

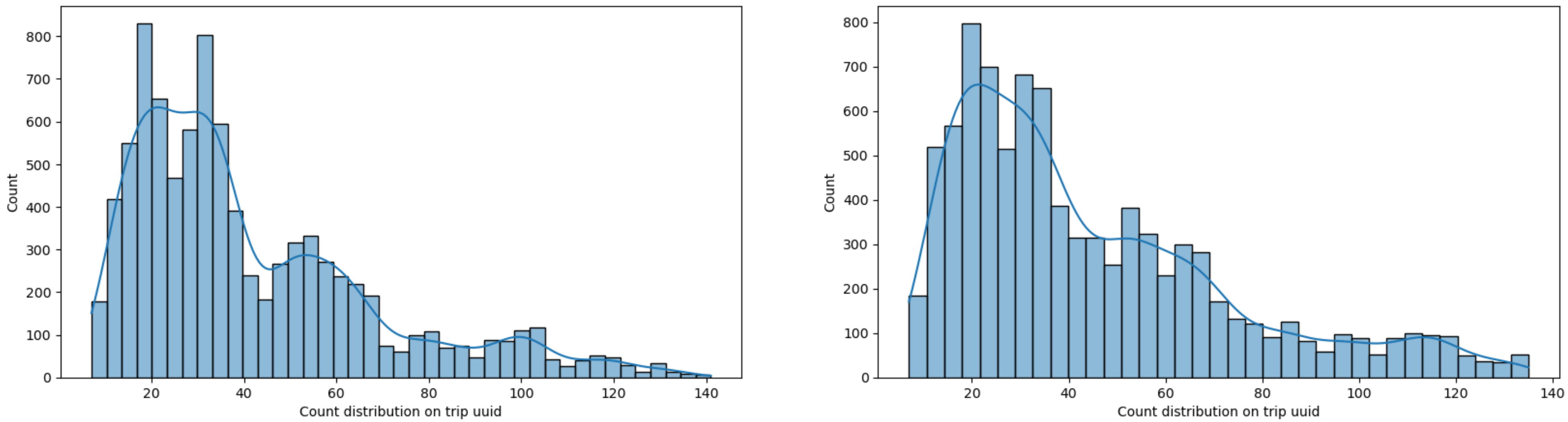
Observations:

1. both data have statistically different mean value (p_val = 5.165879005140737e-09)
2. but both the data are very highly correlated (cc = 0.97)

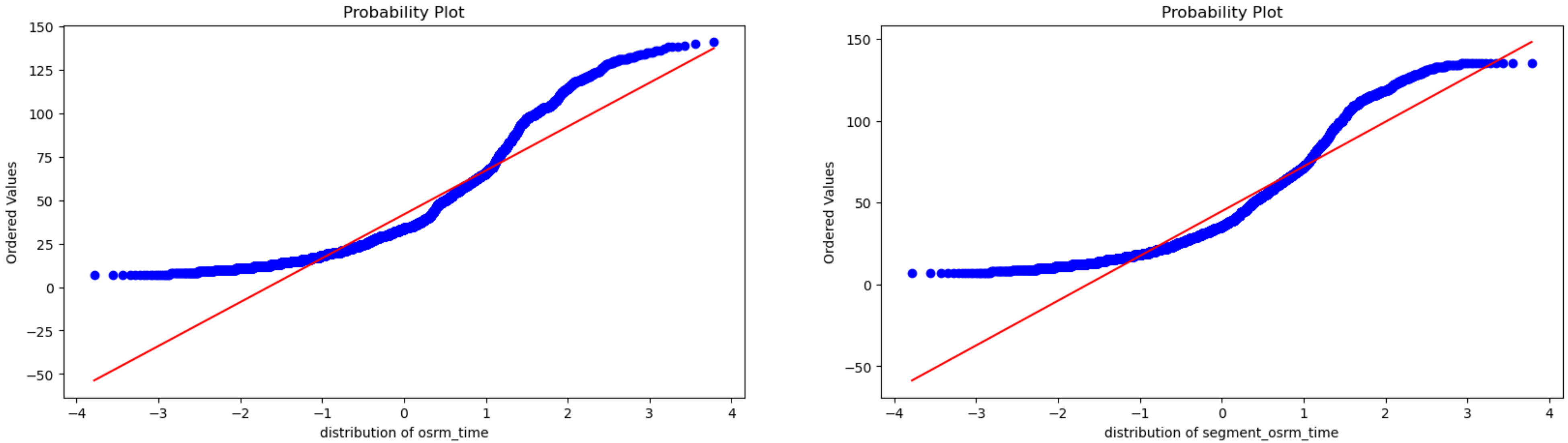
Test5: Do hypothesis testing/ visual analysis between osrm time aggregated value and segment osrm time aggregated value

In [86]:
```
osrm_time = df_out['osrm_time']
seg_osrm_time = df_out['segment_osrm_time']
```

In [87]:
```
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
sns.histplot(osrm_time,kde = True)
plt.xlabel('Count distribution on trip uuid',fontsize=10)
plt.subplot(1, 2, 2)
sns.histplot(seg_osrm_time,kde = True)
plt.xlabel('Count distribution on trip uuid',fontsize=10)
plt.show()
```

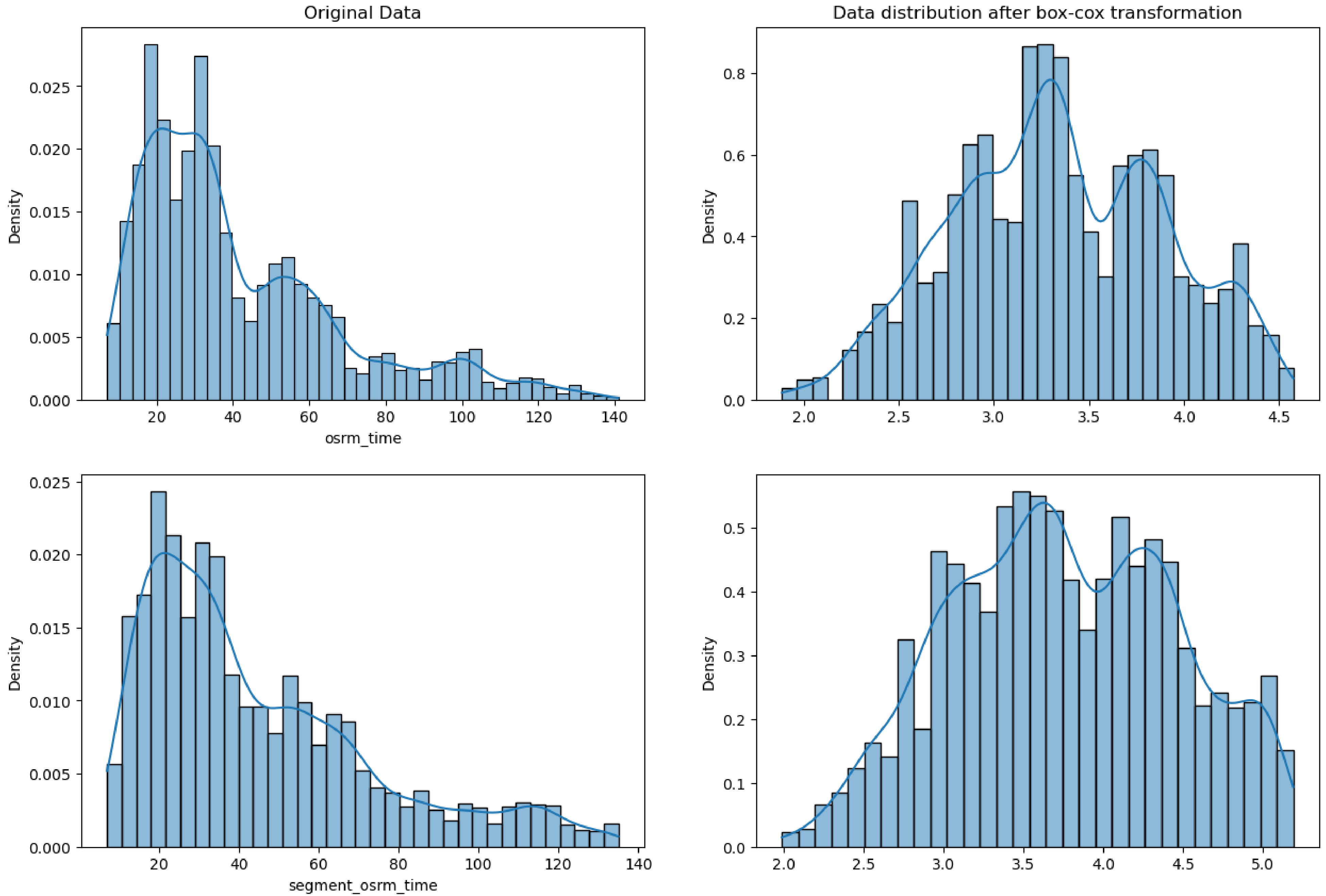


In [88]:
```
# H0: The sample has a Gaussian distribution.
# H1: The sample does not have a Gaussian distribution.
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
probplot(osrm_time,dist="norm",plot=plt)
plt.xlabel('distribution of osrm_time',fontsize=10)
plt.subplot(1, 2, 2)
probplot(seg_osrm_time,dist="norm",plot=plt)
plt.xlabel('distribution of segment_osrm_time',fontsize=10)
plt.show()
```



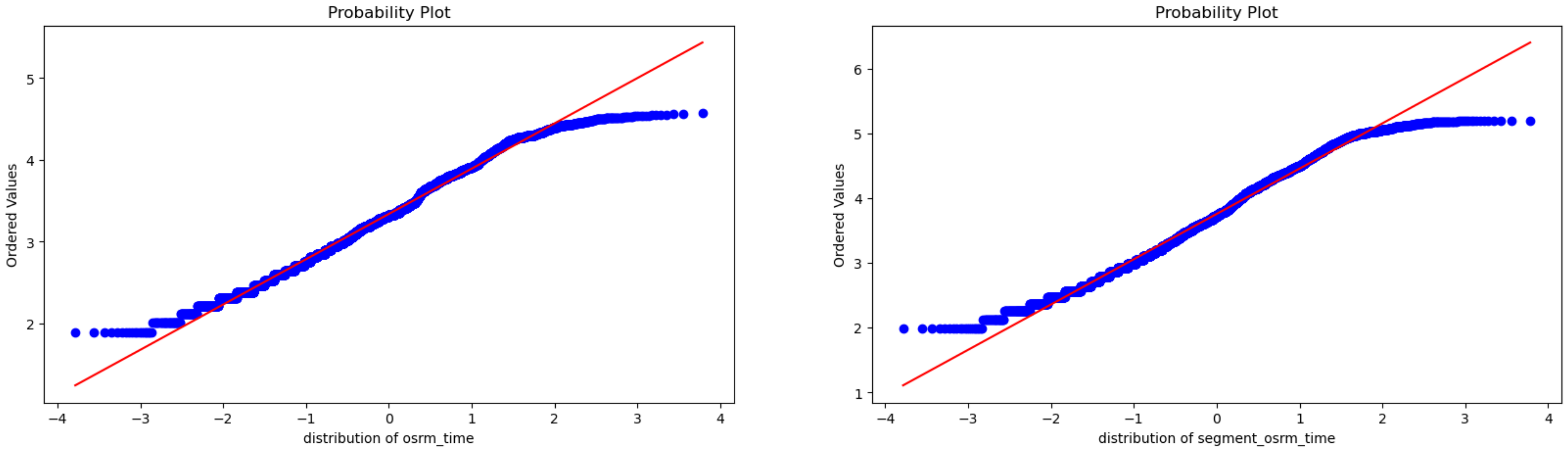
In [89]:

```
# Transforming data by using boxcox transformation:
original_data1=osrm_time
original_data2=seg_osrm_time

fitted_data1, fitted_lambda1 = boxcox(osrm_time)
fitted_data2, fitted_lambda2 = boxcox(seg_osrm_time)

fig = plt.figure(figsize=(15,10))
plt.subplot(2,2, 1)
sns.histplot(original_data1, kde=True, stat="density")
plt.title('Original Data')
plt.subplot(2,2, 2)
sns.histplot(fitted_data1, kde=True, stat="density")
plt.title('Data distribution after box-cox transformation')

plt.subplot(2,2, 3)
sns.histplot(original_data2, kde=True, stat="density")
plt.subplot(2,2, 4)
sns.histplot(fitted_data2, kde=True, stat="density")

plt.show()
```



Original Data
Data distribution after box-cox transformation
Density
osrm_time
segment_osrm_time

In [90]:
```
# Quantile-Quantile Plot after data transformation:
fig = plt.figure(figsize=(20,5))
plt.subplot(1, 2, 1)
probplot(fitted_data1,dist="norm",plot=plt)
plt.xlabel('distribution of osrm_time',fontsize=10)
plt.subplot(1, 2, 2)
probplot(fitted_data2,dist="norm",plot=plt)
plt.xlabel('distribution of segment_osrm_time',fontsize=10)
plt.show()
```



In [91]:
```
#  Validation of Assumption 3:
# H0:variance of the sample is same.
# Ha:variances of the sample is not same.
alpha=0.05
levene_stat,p_value=levene(osrm_time, seg_osrm_time)
print("alpha:",0.05)
print("p_value:",p_value)
if p_value<alpha:
  print("Reject Null Hypothesis: Variance of the input datasets is not same")
else:
  print('Accept Null Hypothesis: Variance of the input datasets is Same/Close')
```

```
alpha: 0.05
p_value: 2.888882960532929e-13
Reject Null Hypothesis: Variance of the input datasets is not same
```

In [92]:
```
alpha = 0.05
t_stat,p_value=ttest_ind(osrm_time, seg_osrm_time)
print("p value:",p_value)
print("t statistics:",t_stat)
if p_value<alpha:
    print("Reject Null Hypothesis: The means of the samples are unequal")
else:
    print('Accept Null Hypothesis: The means of the samples are equal')
```

```
p value: 2.1479512843092573e-12
t statistics: -7.029458109386468
Reject Null Hypothesis: The means of the samples are unequal
```

In [93]:
```
print('pearson correlation coefficient:', stats.pearsonr(osrm_time, seg_osrm_time)[0])
```

```
pearson correlation coefficient: 0.9696933987545999
```

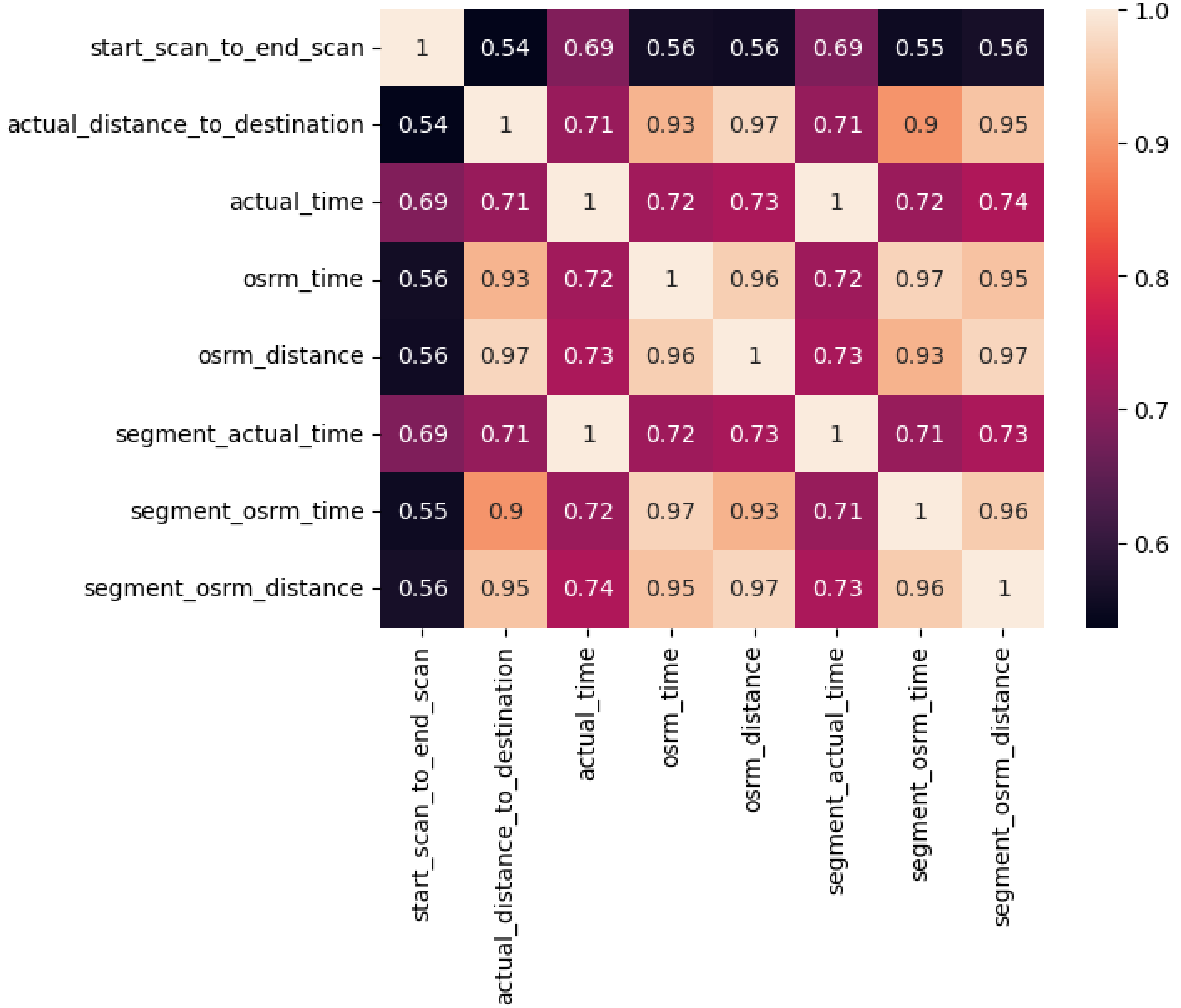
Observations:

1. both data have statistically different mean value, null hypothesis rejected
2. but both the data are very highly correlated (cc = 0.96)

Correlation b/w different data points

In [94]:
```
sns.heatmap(df_out[['start_scan_to_end_scan',
                 'actual_distance_to_destination',
                 'actual_time',
                 'osrm_time',
                 'osrm_distance',
                 'segment_actual_time',
                 'segment_osrm_time',
                 'segment_osrm_distance']].corr(), annot=True)
```

Out[94]:
```
<AxesSubplot:>
```



observations:

- mostly numerical data is highly correlated.
- min value of correlation coefficient is around 0.56.
- all the values are positively correlated.

Handling categorical values

one-hot encoding of categorical variables

In [95]:
```
# applying one hot encoding on categorical variables
one_hot_encoded_data = pd.get_dummies(df2, columns = ['data', 'route_type'])
one_hot_encoded_data.iloc[:,-4:]  # last 4 columns showing encoded data
```

Out[95]:

	data_test	data_training	route_type_Carting	route_type_FTL
0	0	1	0	1
1	0	1	1	0
2	0	1	0	1
3	0	1	1	0
4	0	1	0	1
...	...	...	...	...
14812	1	0	1	0
14813	1	0	1	0
14814	1	0	1	0
14815	1	0	1	0
14816	1	0	0	1

14800 rows × 4 columns

Column Normalization /Column Standardization

using StandardScaler

In [96]:
```
# extracting columns with numerical data to be Standardized
numerical_columns = ['start_scan_to_end_scan', 'actual_distance_to_destination',
       'actual_time', 'osrm_time', 'osrm_distance', 'segment_actual_time',
       'segment_osrm_distance', 'segment_osrm_time']
std_df = df_out.copy()
std_df1 = df_out.copy()
```

In [97]:
```
# standardising using standared scaler
scaler = StandardScaler()
scaler.fit(std_df[numerical_columns])
std_df[numerical_columns] = scaler.transform(std_df[numerical_columns])
```

In [98]:
```
std_df[numerical_columns]
```

Out[98]:

	start_scan_to_end_scan	actual_distance_to_destination	actual_time	osrm_time	osrm_distance	segment_actual_time	segment_osrm_distance	segment_
1	-0.105422	1.357511	0.684701	0.974144	1.173938	0.674336	1.016672	
3	-0.892416	-0.706752	-0.607056	-0.996919	-0.807854	-0.595449	-0.856949	
5	-0.016885	-0.433228	-0.576300	-0.699400	-0.553896	-0.579964	-0.618406	
6	-0.912091	-1.004340	-1.145289	-1.071298	-1.039911	-1.137431	-1.085881	
7	-0.439895	-0.513306	-0.530166	-0.290311	-0.527982	-0.518023	-0.593480	
...	...	...	...	...	...	...	...	
14811	-1.010465	-0.685193	-0.929996	-0.959729	-0.782821	-0.936123	-0.838598	
14812	0.652060	0.789051	-0.237983	0.751005	0.821140	-0.239290	0.453407	
14813	-1.285913	-0.767984	-1.191423	-1.108488	-0.916644	-1.183886	-0.967313	
14814	2.265398	0.085965	2.822252	0.230347	0.380164	2.842262	1.619642	
14816	1.596453	1.095648	2.714606	0.974144	1.036662	2.733866	0.911481	

8968 rows × 8 columns

Observations:

Using MinMaxScaler

In [99]:
```
scaler = MinMaxScaler()
scaler.fit(std_df1[numerical_columns])
std_df1[numerical_columns] = scaler.transform(std_df1[numerical_columns])
```

In [100]:
```
std_df1[numerical_columns]
```

Out[100]:

	start_scan_to_end_scan	actual_distance_to_destination	actual_time	osrm_time	osrm_distance	segment_actual_time	segment_osrm_distance	segment_
1	0.315895	0.446612	0.380682	0.455224	0.433398	0.379310	0.458126	
3	0.154930	0.056869	0.142045	0.059701	0.060458	0.143678	0.065890	
5	0.334004	0.108511	0.147727	0.119403	0.108248	0.146552	0.115829	
6	0.150905	0.000682	0.042614	0.044776	0.016789	0.043103	0.017964	
7	0.247485	0.093392	0.156250	0.201493	0.113125	0.158046	0.121047	
...	...	...	...	...	...	...	...	
14811	0.130785	0.060939	0.082386	0.067164	0.065169	0.080460	0.069732	
14812	0.470825	0.339284	0.210227	0.410448	0.367007	0.209770	0.340209	
14813	0.074447	0.045307	0.034091	0.037313	0.039985	0.034483	0.042786	
14814	0.800805	0.206538	0.775568	0.305970	0.284023	0.781609	0.584356	
14816	0.663984	0.397171	0.755682	0.455224	0.407565	0.761494	0.436105	

8968 rows × 8 columns

Observations:

- After Normalization of numerical dataset, all values are converted within the new range of 0 and 1.
- It is done by the help of this expression y = (x – min) / (max – min)

Insights

1. Delhivery provided data of 2 months with 144867 rows and 24 columns.

2. aggregating the data set helped us to look at the data on macro level.
3. overall it has 14817 unique trip ids out of which 17 are dropped because of null values.
4. Highest order received by Bengalore city.
5. Highest order received by state-wise is Maharashtra.
6. Top 5 source states are Maharashtra, Karnataka, Haryana, Tamil Nadu, and Delhi.
7. Top 5 source cities are Bangalore, Gurgaon ,Mumbai and Bhiwandi. (**To be noted Bengalore have 2 different names in dataset)
8. Longest Corridor between cities is Guwahati to Bhiwandi having distance of 2140 Km and taking average time around 5457 minutes to delivered order.
9. Based on two sample t-test, there is NO difference between mean of Actual time and segment actual time.
10. The difference of mean between (order start time - order end time) and start scan to end scan is high.
11. There is significant difference between mean of Actual time and osrm time.
12. There is significant difference between mean of osrm distance and segment osrm distance. And mean of segment osrm distance is higher than the osrm distance.
13. Based on two sample t-test, the mean of the osrm time is lesser than segment osrm time.

Recommendation

1. As the actual time is more than the osrm time, the estimated should be done on the basis of actual time.
2. As the segment osrm distance is more than osrm distance, the segments are considered of higher length.
3. the osrm data is collected from the 3rd party maps or servers, that is why we have higher number of variation in actual and osrm data.
4. optimized selections of the distribution centre can reduce average travel time to the customers.
5. All products picked up at the same source city and destined to the same destination city must be shipped with FTL (full truck load).
6. all same citi orders can be shipped using carting method.
7. Distribution centers and check points must be linked with advanced information systems to ensure that all pickups and deliveries are made within the schedule time.

Type *Markdown* and LaTeX: α^2