Delhivery_CaseStudy

August 11, 2024

Business Problem:

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

The team has to build intelligence and capabilities using this data that helps them to widen the gap between the quality, efficiency, and profitability of their business versus their competitors.

[1921]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import statsmodels.api as sm
import sklearn.preprocessing as sl
import warnings
warnings.filterwarnings('ignore')
```

0.0.1 Importing Delhivery data

[1922]:
```
raw_data = pd.read_csv('https://d2beiqkhq929f0.cloudfront.net/public_assets/
↪assets/000/001/551/original/delhivery_data.csv?1642751181')
```

[1923]:
```
raw_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144867 entries, 0 to 144866
Data columns (total 24 columns):
 #   Column                          Non-Null Count   Dtype
---  ------                          --------------   -----
 0   data                            144867 non-null  object
 1   trip_creation_time              144867 non-null  object
 2   route_schedule_uuid             144867 non-null  object
 3   route_type                      144867 non-null  object
 4   trip_uuid                       144867 non-null  object
 5   source_center                   144867 non-null  object
 6   source_name                     144574 non-null  object
```

```
 7   destination_center              144867 non-null  object
 8   destination_name                144606 non-null  object
 9   od_start_time                   144867 non-null  object
 10  od_end_time                     144867 non-null  object
 11  start_scan_to_end_scan          144867 non-null  float64
 12  is_cutoff                       144867 non-null  bool
 13  cutoff_factor                   144867 non-null  int64
 14  cutoff_timestamp                144867 non-null  object
 15  actual_distance_to_destination  144867 non-null  float64
 16  actual_time                     144867 non-null  float64
 17  osrm_time                       144867 non-null  float64
 18  osrm_distance                   144867 non-null  float64
 19  factor                          144867 non-null  float64
 20  segment_actual_time             144867 non-null  float64
 21  segment_osrm_time               144867 non-null  float64
 22  segment_osrm_distance           144867 non-null  float64
 23  segment_factor                  144867 non-null  float64
dtypes: bool(1), float64(10), int64(1), object(12)
memory usage: 25.6+ MB
```

Null values treament

[1924]:
```python
pd.DataFrame((np.round(100*raw_data.isna().sum(axis = 0)/len(raw_data),3)).
 ↪sort_values(ascending = False),columns = ['% Missing']).head(10)
```

[1924]:

	% Missing
source_name	0.202
destination_name	0.180
data	0.000
cutoff_factor	0.000
segment_osrm_distance	0.000
segment_osrm_time	0.000
segment_actual_time	0.000
factor	0.000
osrm_distance	0.000
osrm_time	0.000

Source Name and Destination name has minor missing or null values (less than 1%)

For Null values in Destination name column,

1. We can check and get the value by matching the destination center values in source center and extracting the source name column from matched source center.

[1925]:
```python
destination_name_nulls = raw_data.loc[raw_data['destination_name'].
 ↪isnull(),'destination_center'].unique()
_source_name = raw_data.loc[raw_data['source_center'].
 ↪isin(destination_name_nulls),['source_center','source_name']]
print('column length: ',len(_source_name))
```

```
_source_name.isna().sum(axis = 0)
```

```
column length:  290
```

[1925]:
```
source_center      0
source_name      290
dtype: int64
```

There is no data available in source name as well for missing destination_center code.

[1926]:
```
source_name_nulls = raw_data.loc[raw_data['source_name'].
 ↪isnull(),'source_center'].unique()
_destination_name = raw_data.loc[raw_data['destination_center'].
 ↪isin(source_name_nulls),['destination_center','destination_name']]
print('column length: ',len(_destination_name))
_destination_name.isna().sum(axis = 0)
```

```
column length:  240
```

[1926]:
```
destination_center      0
destination_name      240
dtype: int64
```

There is no data available in destination name as well for missing source_center code.

Remove the null value rows from dataframe

[1927]:
```
raw_data = raw_data.dropna(subset=['source_name','destination_name'],axis = 0)
```

Converting the trip_creation_time, od_start_time, od_end_time datatypes to datetime format.

[1928]:
```
raw_data[['trip_creation_time','od_start_time','od_end_time']] =␣
 ↪raw_data[['trip_creation_time','od_start_time','od_end_time']].apply(pd.
 ↪to_datetime)
raw_data[['trip_creation_time','od_start_time','od_end_time']].dtypes
```

[1928]:
```
trip_creation_time    datetime64[ns]
od_start_time         datetime64[ns]
od_end_time           datetime64[ns]
dtype: object
```

reduce the data shape by grouping the rows.

[1929]:
```
data = raw_data.copy(deep = True)

#Sorting the delhivery data data based on trip unique id, order start and end␣
 ↪time in ascending

cols = ['trip_uuid','od_start_time','od_end_time']
```

```
data = data.sort_values(by = cols ,ascending = [True,True,True]).
 ↪reset_index(drop=True)
```

[1930]:
```
dict_agg = {'segment_actual_time':np.cumsum,'segment_osrm_time':np.
 ↪cumsum,'segment_osrm_distance':np.cumsum}
data[['segment_actual_time_sum','segment_osrm_time_sum','segment_osrm_distance_sum']]␣
 ↪= data.groupby(cols).agg(dict_agg)
```

[1931]:
```
create_segment_dict = {
    'data':'first', 'trip_creation_time':'first', 'route_schedule_uuid':
 ↪'first', 'route_type':'first',
      'source_name':'first','destination_name':'last', 'od_start_time':'min',␣
 ↪'od_end_time':'max',
       'start_scan_to_end_scan':'first', 'actual_distance_to_destination':
 ↪'last', 'actual_time':'last',
       'osrm_time':'last', 'osrm_distance':'last',
       'segment_actual_time_sum':'last', 'segment_osrm_time_sum':'last',
       'segment_osrm_distance_sum':'last'}

data = data.groupby(['trip_uuid','source_center','destination_center']).
 ↪aggregate(create_segment_dict).reset_index()
data = data.
 ↪sort_values(by=['trip_uuid','od_start_time','od_end_time'],ascending =␣
 ↪[True,True,True]).reset_index(drop=True)
```

[1932]:
```
data['od_time_diff_hours'] = np.round((data['od_end_time'] -␣
 ↪data['od_start_time']).dt.total_seconds()/3600,2)
```

[1933]:
```
cols_dict = {
    'source_center':'first', 'destination_center':'last', 'data':'first',
       'trip_creation_time':'max', 'route_schedule_uuid':'first', 'route_type':
 ↪'first',
       'source_name':'first', 'destination_name':'last', 'od_start_time':'min',␣
 ↪'od_end_time':'max',
       'start_scan_to_end_scan':'sum', 'actual_distance_to_destination':'sum',
       'actual_time':'sum', 'osrm_time':'sum', 'osrm_distance':'sum',␣
 ↪'segment_actual_time_sum':'sum',
       'segment_osrm_time_sum':'sum', 'segment_osrm_distance_sum':'sum',
       'od_time_diff_hours':'sum'}

data = data.groupby('trip_uuid').aggregate(cols_dict).reset_index()
```

Feature Engineering

[1934]:
```
#City-place-code (State) -> source_name, destination_name
data.source_name = data.source_name.str.lower()
```

```
data.destination_name = data.destination_name.str.lower()
data[['s1','source_state']] = data.source_name.str.extract(r'^([a-zA-Z0-9 &-_␣
↪]+)\s\(([a-zA-Z0-9& ]+)\)$')
data[['d1','destination_state']] = data.destination_name.str.
↪extract(r'^([a-zA-Z0-9 &-_ ]+)\s\(([a-zA-Z0-9& ]+)\)$')
```

[1935]:
```
#City-place-code -> s1 and d1
#Checking the string format for edgecases detection.
data['s1'].str.split('_').str.len().value_counts()
```

[1935]:
```
s1
3    11432
4     1545
2     1170
1      640
Name: count, dtype: int64
```

[1936]:
```
data.loc[data['s1'].str.split('_').str.len() == 1,'s1'].value_counts().head(7)
```

[1936]:
```
s1
mumbai hub              300
hbr layout pc            79
pnq pashan dpc           32
pnq vadgaon sheri dpc    28
faridabad                26
tiruchi                  25
haridwar                 18
Name: count, dtype: int64
```

we can correct these like below

- pnq rahatani dpc - pune_Rahatani_dpc
- mumbai antop hill - Mumbai_Antop Hill
- bhopal mp nagar - Bhopal_MP Nagar
- mumbai mahim - Mumbai_mahim
- pnq pashan dpc - Pune_pashan_dpc
- pnq vadgaon sheri dpc - Pune_vadgaon sheri_dpc
- hbr layout pc - Bangalore_hbr layout_pc

[1937]:
```
def set_address_values(df):
  df = df.str.replace('pnq rahatani dpc','pune_rahatani_dpc')
  df = df.str.replace('mumbai antop hill','mumbai_antop hill')
  df = df.str.replace('bhopal mp nagar','bhopal_mp nagar')
  df = df.str.replace('mumbai mahim','mumbai_mahim')
  df = df.str.replace('pnq pashan dpc','pune_pashan_dpc')
  df = df.str.replace('pnq vadgaon sheri dpc','pune_vadgaon sheri_dpc')
  df = df.str.replace('hbr layout pc','bangalore_hbr layout_pc')
  return df
```

```
data['s1'] = set_address_values(data['s1'])
data['d1'] = set_address_values(data['d1'])
```

[1938]:
```
#converting all the city_hub values to 'city hub'
data.loc[data['s1'].str.contains('^.*hub$'),'s1'] = data.loc[data['s1'].str.
 ↪contains('^.*hub$'),'s1'].str.replace('_',' ')
```

[1939]:
```
def get_city(val):
  if len(val.split('_'))>1:
    return val.split('_')[0]

  return val.split(' ')[0]

def adjust_city_names(val):
  if val == 'bengaluru':
    return 'bangalore'
  elif val == 'maa':
    return 'chennai'
  elif val == 'del':
    return 'delhi'
  elif val == 'ccu':
    return 'kolkata'
  return val

data['source_city'] = data['s1'].apply(get_city)
data['source_city'] = data['source_city'].apply(adjust_city_names)

data['destination_city'] = data['d1'].apply(get_city)
data['destination_city'] = data['destination_city'].apply(adjust_city_names)



def get_place(val):
  if len(val.split('_')) >= 3:
    return val.split('_')[1]

  if len(val.split('_')) == 2:
    return val.split('_')[0]
  return val.split(' ')[0]

data['source_place'] = data['s1'].apply(get_place)
data['destination_place'] = data['d1'].apply(get_place)
```

```
def get_code(val):
  if len(val.split('_')) >= 3:
    return val.split('_')[-1]
  return 'none'

data['source_code'] = data['s1'].apply(get_code)
data['destination_code'] = data['d1'].apply(get_code)
```

[1940]:

```
data.head(2)
```

[1940]:

```
                  trip_uuid source_center destination_center      data  \
0  trip-153671041653548748  IND462022AAA      IND000000ACB  training
1  trip-153671042288605164  IND572101AAA      IND562101AAA  training

          trip_creation_time  \
0 2018-09-12 00:00:16.535741
1 2018-09-12 00:00:22.886430

                                 route_schedule_uuid route_type  \
0  thanos::sroute:d7c989ba-a29b-4a0b-b2f4-288cdc6…        FTL
1  thanos::sroute:3a1b0ab2-bb0b-4c53-8c59-eb2a2c0…    Carting

                       source_name                   destination_name  \
0  bhopal_trnsport_h (madhya pradesh)      gurgaon_bilaspur_hb (haryana)
1       tumkur_veersagr_i (karnataka)  chikblapur_shntisgr_d (karnataka)

               od_start_time  …                  s1    source_state  \
0 2018-09-12 00:00:16.535741  …  bhopal_trnsport_h  madhya pradesh
1 2018-09-12 00:00:22.886430  …  tumkur_veersagr_i       karnataka

                      d1  destination_state  source_city  destination_city  \
0    gurgaon_bilaspur_hb            haryana       bhopal           gurgaon
1  chikblapur_shntisgr_d          karnataka       tumkur        chikblapur

   source_place  destination_place  source_code  destination_code
0      trnsport           bilaspur            h                hb
1      veersagr           shntisgr            i                 d

[2 rows x 30 columns]
```

[1941]:

```
data['trip_creation_month'] = data['trip_creation_time'].dt.month
data['trip_creation_day'] = data['trip_creation_time'].dt.day
data['trip_creation_dayname'] = data['trip_creation_time'].dt.day_name()
data['order_start_time'] = data['od_start_time'].dt.hour
```

[1942]:

```
data["order_timeslot"] = data["order_start_time"].apply(lambda x: "Dawn␣
↪(12am-4am)" if x<=4 else ("Early Morning (5am-9am)" if x<=9 else
```

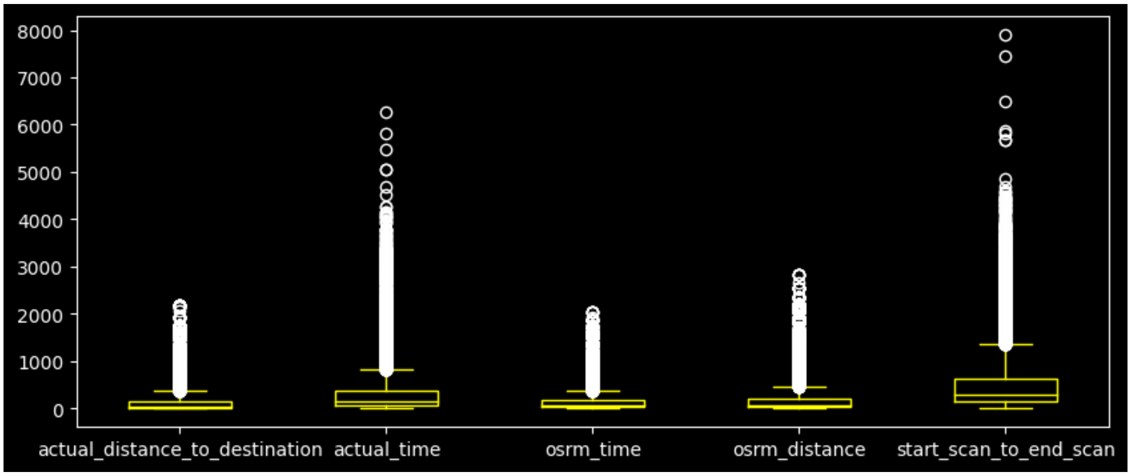
```
    ("Noon (10am-16pm)" if x<=16 else
     ("Late Evening (17pm-21pm)" if x<=21 else
      "Night (22pm-12am)"))))
```

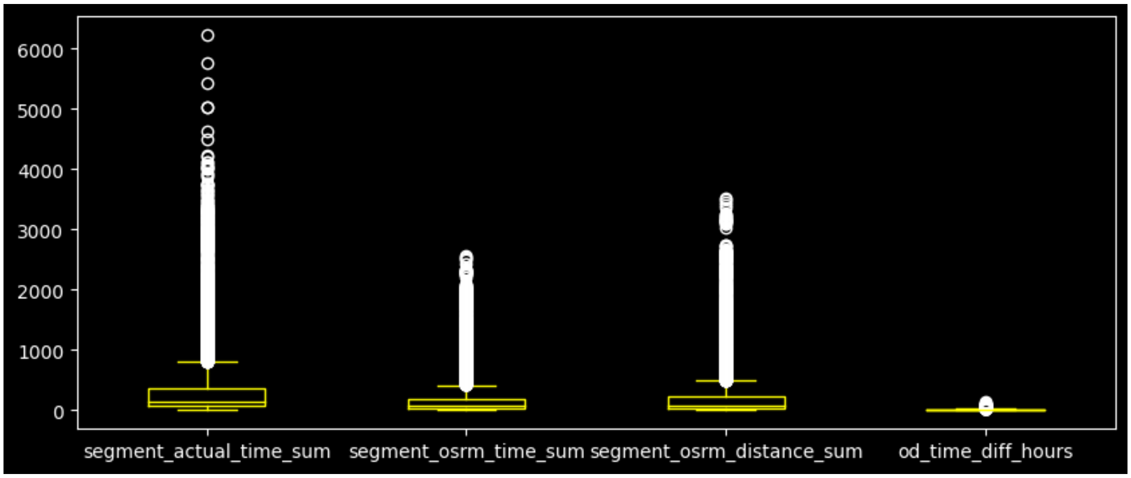
[1943]:
```
#creating a column based on the weekend or not"""

data['is_weekend'] = data['trip_creation_dayname'].apply(lambda x: 1 if x in␣
↪['Saturday','Sunday'] else 0)
```

[1944]:
```
#remove intermediate/unwanted columns from dataframe

data.drop(columns = ['s1','d1'],inplace = True)
```

Outliers Treatment

[1945]:
```
#checking outliers from data for below columns

numerical_cols = ['actual_distance_to_destination','actual_time',
                  'osrm_time','osrm_distance','start_scan_to_end_scan',
                  'segment_actual_time_sum','segment_osrm_time_sum',
                  'segment_osrm_distance_sum','od_time_diff_hours']

plt.style.use('dark_background')

col1 = ['actual_distance_to_destination','actual_time','osrm_time',
        'osrm_distance','start_scan_to_end_scan']
data[col1].plot(kind = 'box',figsize = (10,4),color='yellow')

col2 = ['segment_actual_time_sum','segment_osrm_time_sum',
        'segment_osrm_distance_sum','od_time_diff_hours']
data[col2].plot(kind = 'box',figsize = (10,4),color='yellow')
plt.show()
```





[1946]:
```
q1 = data[numerical_cols].quantile(0.25)
q3 = data[numerical_cols].quantile(0.75)
IQR = q3-q1
```

[1947]:
```
data = data.loc[(~((data[numerical_cols] > (q3+IQR*1.5)) |␣
↪(data[numerical_cols] < (q1-IQR*1.5))).any(axis = 1))].reset_index(drop=True)
```

[1948]:
```
#Normalize the numerical data to avoid the differences in feature units.
df = data.copy(deep = True)
df[numerical_cols] = pd.DataFrame(sl.StandardScaler().
↪fit_transform(data[numerical_cols]),columns= numerical_cols)
```

[1949]:
```
df[numerical_cols].describe()
```

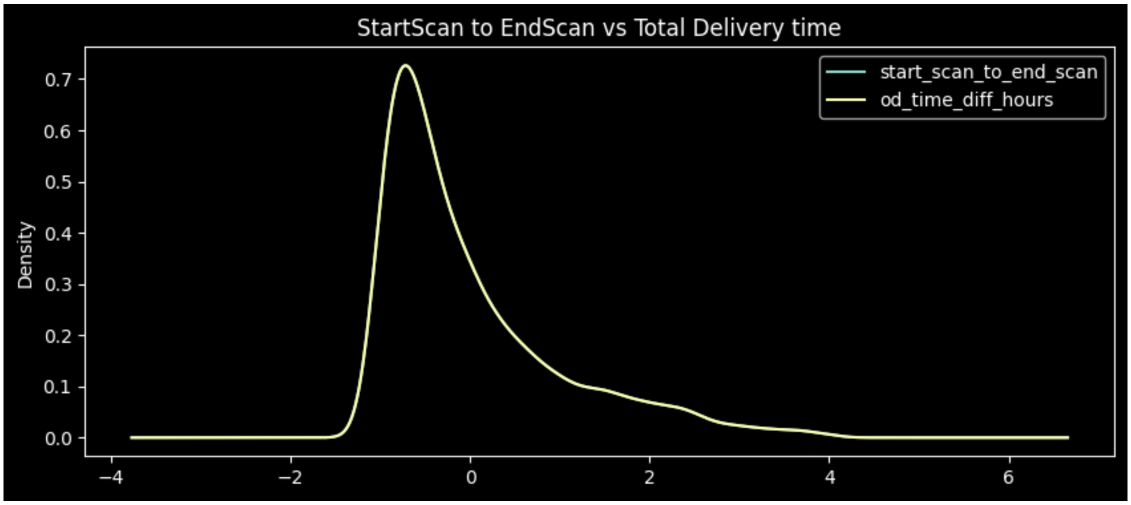
[1949]:
```
       actual_distance_to_destination   actual_time     osrm_time  \
count                    1.272300e+04  1.272300e+04  1.272300e+04
mean                    -7.595206e-17 -8.041983e-17  4.467769e-17
std                      1.000039e+00  1.000039e+00  1.000039e+00
min                     -8.785574e-01 -1.065181e+00 -1.001514e+00
25%                     -7.065920e-01 -7.363685e-01 -7.111809e-01
50%                     -4.689012e-01 -4.012322e-01 -3.931975e-01
75%                      4.073375e-01  4.650634e-01  4.224989e-01
max                      4.178358e+00  4.031419e+00  4.113871e+00

       osrm_distance  start_scan_to_end_scan  segment_actual_time_sum  \
count   1.272300e+04            1.272300e+04             1.272300e+04
mean    3.797603e-17           -1.619566e-17            -3.127438e-17
std     1.000039e+00            1.000039e+00             1.000039e+00
min    -9.229378e-01           -1.162918e+00            -1.061764e+00
```

```
25%    -7.077649e-01           -7.207269e-01             -7.371165e-01
50%    -4.836339e-01           -3.411472e-01             -3.997380e-01
75%     4.419548e-01            4.023595e-01              4.596223e-01
max     4.150641e+00            4.049455e+00              4.037107e+00

       segment_osrm_time_sum  segment_osrm_distance_sum  od_time_diff_hours
count           1.272300e+04               1.272300e+04        1.272300e+04
mean            6.031487e-17              -8.488760e-17       -6.729576e-17
std             1.000039e+00               1.000039e+00        1.000039e+00
min            -1.003850e+00              -9.375981e-01       -1.163168e+00
25%            -7.274750e-01              -7.228116e-01       -7.199772e-01
50%            -4.134119e-01              -4.628077e-01       -3.424443e-01
75%             4.910897e-01               4.488499e-01        4.020692e-01
max             4.046283e+00               4.130135e+00        4.051944e+00
```

0.0.2 Comparision of 'start_scan_to_end_scan' and 'od_time_diff_hours'

[1950]:

```
df[['start_scan_to_end_scan','od_time_diff_hours']].plot(kind='density',figsize␣
↪= (10,4),title='StartScan to EndScan vs Total Delivery time')
plt.show()

#Their distribution are similar to each other
```



[1951]:

```
df[['start_scan_to_end_scan','od_time_diff_hours']].corr()
```

[1951]:

	start_scan_to_end_scan	od_time_diff_hours
start_scan_to_end_scan	1.000000	0.999997
od_time_diff_hours	0.999997	1.000000

[1952]:
```
#Hypothesis testing
#H0 : 'start_scan_to_end_scan','od_time_diff_hours' are similar.
#H1 : 'start_scan_to_end_scan','od_time_diff_hours' are different.
_,p_value = stats.
↪ttest_ind(df['start_scan_to_end_scan'],df['od_time_diff_hours'])
if p_value > 0.05:
  print("Accept the null hypothesis")
  print("There is no significance difference between 'start_scan_to_end_scan'␣
↪and 'od_time_diff_hours'")
else:
  print("Reject the null hypothesis")
  print("There is a significant difference between 'start_scan_to_end_scan' and␣
↪'od_time_diff_hours'")
```

```
Accept the null hypothesis
There is no significance difference between 'start_scan_to_end_scan' and
'od_time_diff_hours'
```

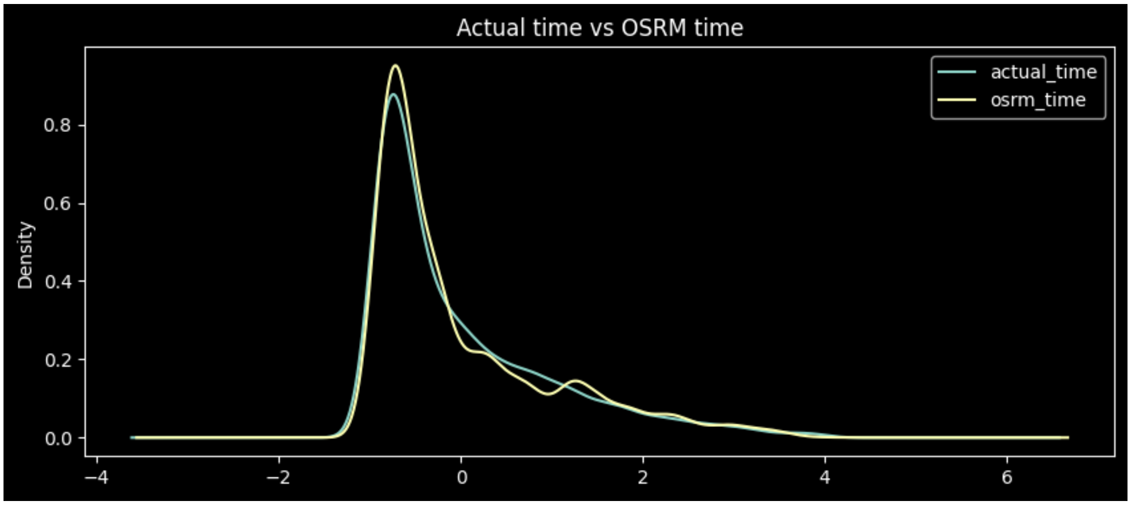
0.0.3 actual_time aggregated value and OSRM time aggregated value.

[1953]:
```
#actual_time aggregated value and OSRM time aggregated value.
#actualtime is time taken to reach destination.
#OSRM is predicted time to reach destination

df[['actual_time','osrm_time']].sample(5)
```

[1953]:

	actual_time	osrm_time
12147	0.680056	0.408674
1661	0.401830	1.611480
12356	-0.957685	-0.863260
6339	-0.375939	-0.185817
6992	2.077511	2.634557

[1954]:
```
df[['actual_time','osrm_time']].plot(kind='density',figsize =␣
↪(10,4),title='Actual time vs OSRM time')
plt.show()
```



Distributions looks close to each other. Actual time and predicted time looks similar.

Lets check through statistical test.

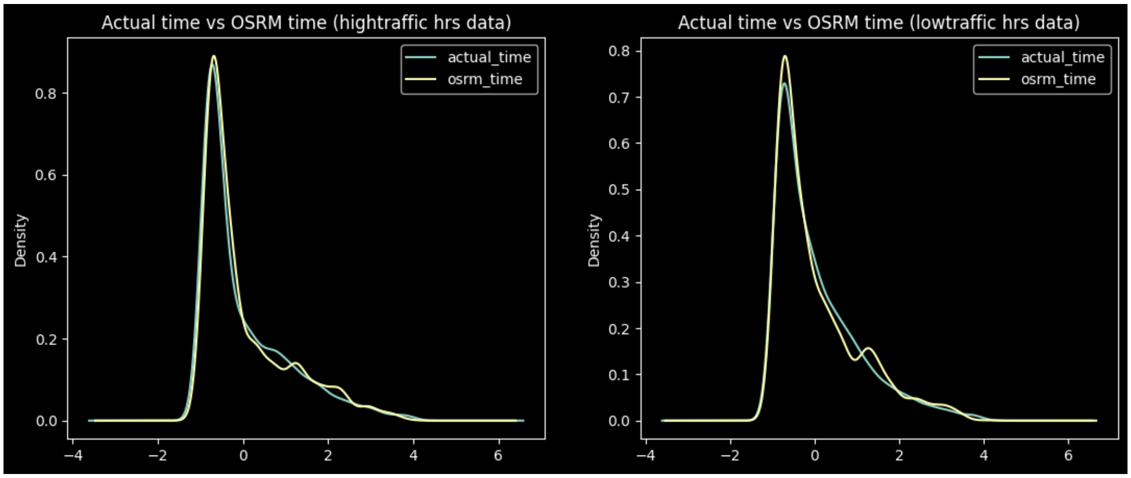
[1955]:
```
#Hypothesis testing
#H0 : 'actual_time' and 'osrm_time' are similar.
#H1 : 'actual_time' and 'osrm_time' are different.

_,p_value = stats.ttest_rel(df['actual_time'],df['osrm_time'])
if p_value > 0.05:
  print("Accept the null hypothesis")
  print("There is no significance difference between 'actual_time' and␣
 ↪'osrm_time'")
else:
  print("Reject the null hypothesis")
  print("There is a significant difference between 'actual_time' and␣
 ↪'osrm_time'")

statisticvalue,_=stats.spearmanr(df['actual_time'],df['osrm_time'])
print()
print(np.round(statisticvalue,2), "'actual_time' and 'osrm_time' are strongly␣
 ↪correlated to each other")
```

```
Accept the null hypothesis
There is no significance difference between 'actual_time' and 'osrm_time'

0.87 'actual_time' and 'osrm_time' are strongly correlated to each other
```

hightraffic hrs and low traffic hrs segmented data

[1956]:
```
#checking based on the shipment Time.
#Most of the orders are within cities.
#By changing data based on the usual traffic may help to find the ORSM time␣
↪prediction effectiveness.
#Segmenting data into hightraffic hrs and low traffic hrs data.

hts_data = df.loc[df['order_timeslot'].isin(['Noon (10am-16pm)','Late Evening␣
↪(17pm-21pm)'])]
lts_data = df.loc[df['order_timeslot'].isin(['Dawn (12am-4am)','Night␣
↪(22pm-12am)'])]
```

[1957]:
```
_,ax=plt.subplots(1,2,figsize=(13,5))

cols = ['actual_time','osrm_time']
hts_data[cols].plot(kind = 'density',title = 'Actual time vs OSRM time␣
↪(hightraffic hrs data)',ax=ax[0])
lts_data[cols].plot(kind = 'density',title = 'Actual time vs OSRM time␣
↪(lowtraffic hrs data)',ax=ax[1])
plt.show()
```



- Distributions looks similar for both hightraffichrs data and low traffichrs data

[1958]:
```
#checking though statistical method

#Hypothesis testing
#H0 : 'actual_time' and 'osrm_time' are similar.
#H1 : 'actual_time' and 'osrm_time' are different.

print('Hypothesis during High Trafic Hours','\n')
_,p_value = stats.ttest_rel(hts_data['actual_time'],hts_data['osrm_time'])
if p_value > 0.05:
```

```
  print("Accept the null hypothesis")
  print("There is no significance difference between 'actual_time' and␣
↪'osrm_time'")
else:
  print("Reject the null hypothesis")
  print("There is a significant difference between 'actual_time' and␣
↪'osrm_time'")

print('Hypothesis during Low Trafic Hours','\n')

_,p_value = stats.ttest_rel(lts_data['actual_time'],lts_data['osrm_time'])
if p_value > 0.05:
  print("Accept the null hypothesis")
  print("There is no significance difference between 'actual_time' and␣
↪'osrm_time'")
else:
  print("Reject the null hypothesis")
  print("There is a significant difference between 'actual_time' and␣
↪'osrm_time'")
```

```
Hypothesis during High Trafic Hours

Reject the null hypothesis
There is a significant difference between 'actual_time' and 'osrm_time'
Hypothesis during Low Trafic Hours

Accept the null hypothesis
There is no significance difference between 'actual_time' and 'osrm_time'
```

route type segmented data.

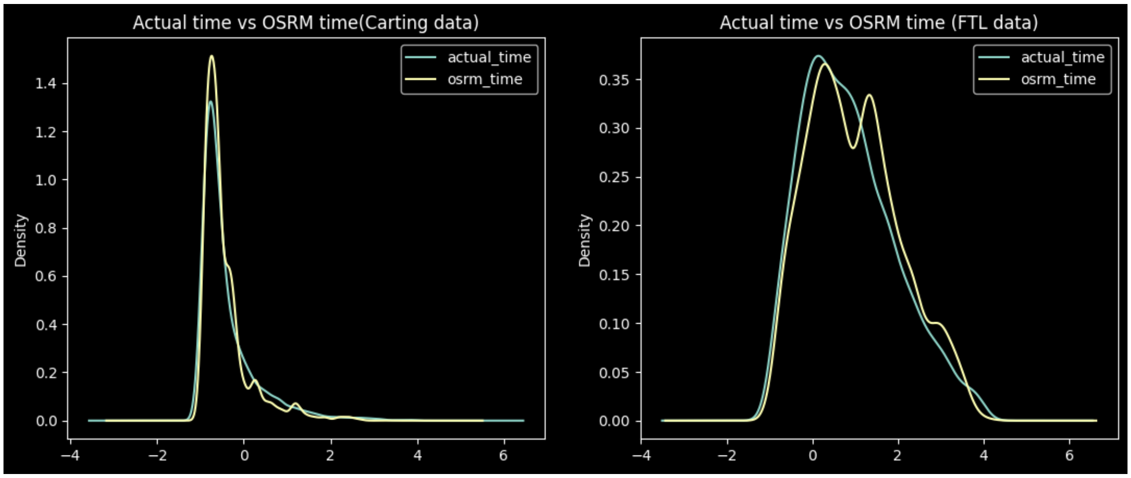
[1959]:
```
#checking on the basis of route type(FTL vs Carting)
100*df['route_type'].value_counts(normalize = True)
```

[1959]:
```
route_type
Carting    69.260395
FTL        30.739605
Name: proportion, dtype: float64
```

[1960]:
```
carting_data = df.loc[(df['route_type'] == 'Carting')]
ftl_data = df.loc[(df['route_type'] == 'FTL')]
```

[1961]:
```
_,ax=plt.subplots(1,2,figsize=(13,5))
cols = ['actual_time','osrm_time']
carting_data[cols].plot(kind = 'density',ax=ax[0],title = 'Actual time vs OSRM␣
↪time(Carting data)')
```

```
ftl_data[cols].plot(kind = 'density',ax=ax[1],title = 'Actual time vs OSRM time␣
↪(FTL data)')
plt.show()
```



- FTL data distribution seams slight deviated actual_time and osrm_data.
- Carting data distribution between actual_time and osrm_data looks similar.

[1962]:
```
#Lets conclude thorugh statistical test

def test(data):
  #Hypothesis testing
  #HO : 'actual_time' and 'osrm_time' are similar.
  #H1 : 'actual_time' and 'osrm_time' are different.
  _,p_value = stats.ttest_rel(data['actual_time'],data['osrm_time'])
  if p_value > 0.05:
    print("Accept the null hypothesis")
    print("There is no significance difference between 'actual_time' and␣
↪'osrm_time'")
  else:
    print("Reject the null hypothesis")
    print("There is a significant difference between 'actual_time' and␣
↪'osrm_time'")
```

[1963]:
```
test(carting_data[['actual_time', 'osrm_time']])
```

```
Reject the null hypothesis
There is a significant difference between 'actual_time' and 'osrm_time'
```

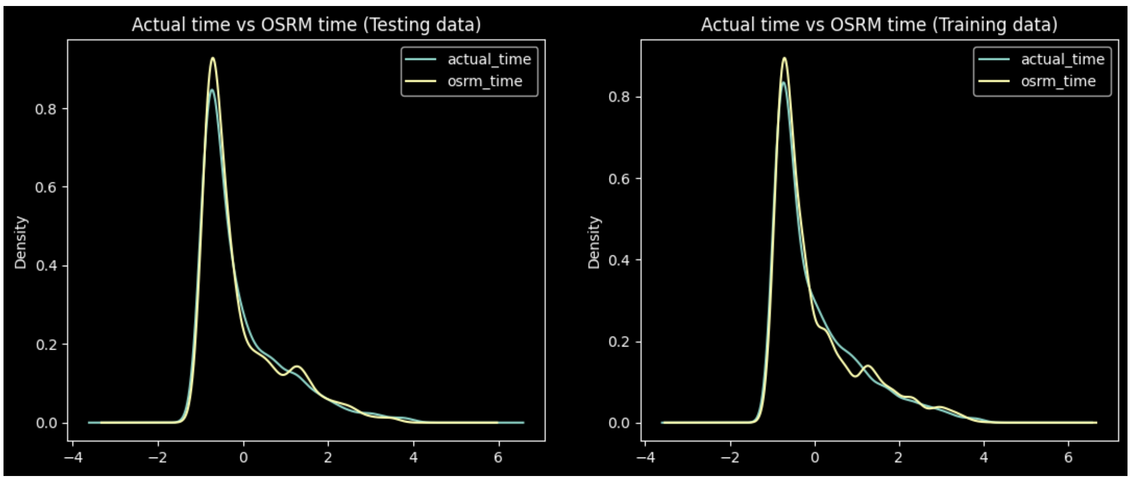
[1964]:
```
test(ftl_data[['actual_time','osrm_time']])
```

```
Reject the null hypothesis
There is a significant difference between 'actual_time' and 'osrm_time'
```

Type of data(training vs Test)

[1965]:
```
#checking on basis of data(Testing vs Training)
train_data = df.loc[df['data'] == 'training']
test_data = df.loc[df['data'] == 'test']
```

[1966]:
```
_,ax = plt.subplots(1,2,figsize = (13,5))
cols = ['actual_time','osrm_time']
test_data[cols].plot(kind = 'density',ax= ax[0],title = 'Actual time vs OSRM␣
↪time (Testing data)')
train_data[cols].plot(kind = 'density',ax= ax[1],title = 'Actual time vs OSRM␣
↪time (Training data)')
plt.show()
```



[1967]:
```
test(test_data[['actual_time', 'osrm_time']])
```

```
Accept the null hypothesis
There is no significance difference between 'actual_time' and 'osrm_time'
```

[1968]:
```
test(train_data[['actual_time', 'osrm_time']])
```

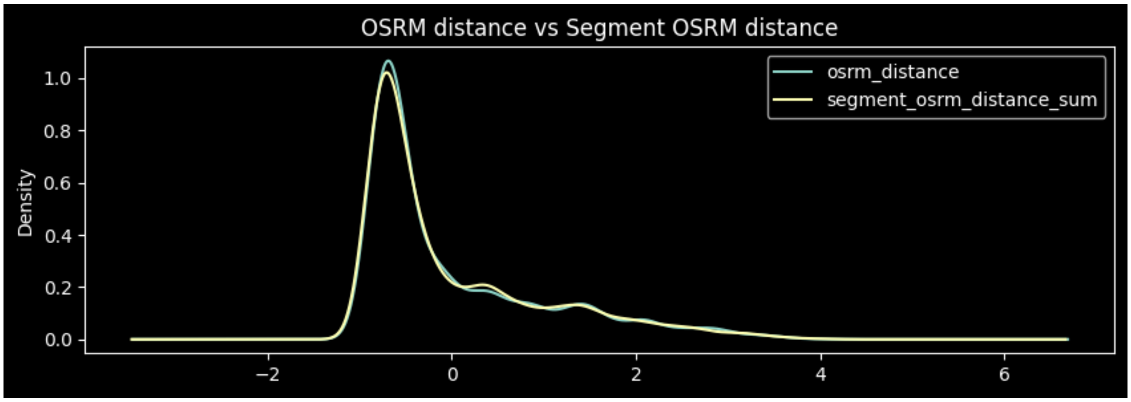
```
Accept the null hypothesis
There is no significance difference between 'actual_time' and 'osrm_time'
```

- There is no significincat difference between features ‘actual_time’ and ‘osrm_time’ for test and train data.

0.0.4 OSRM distance aggregated value and segment OSRM distance

[1969]:
```
cols = ['osrm_distance','segment_osrm_distance_sum']
df[cols].plot(kind = 'density',figsize = (10,3),title = 'OSRM distance vs␣
↪Segment OSRM distance')
```

```
plt.show()
```



From above EDA analysis, OSRM distance and Segment OSRM distance are strongly correlated and similar distribution.

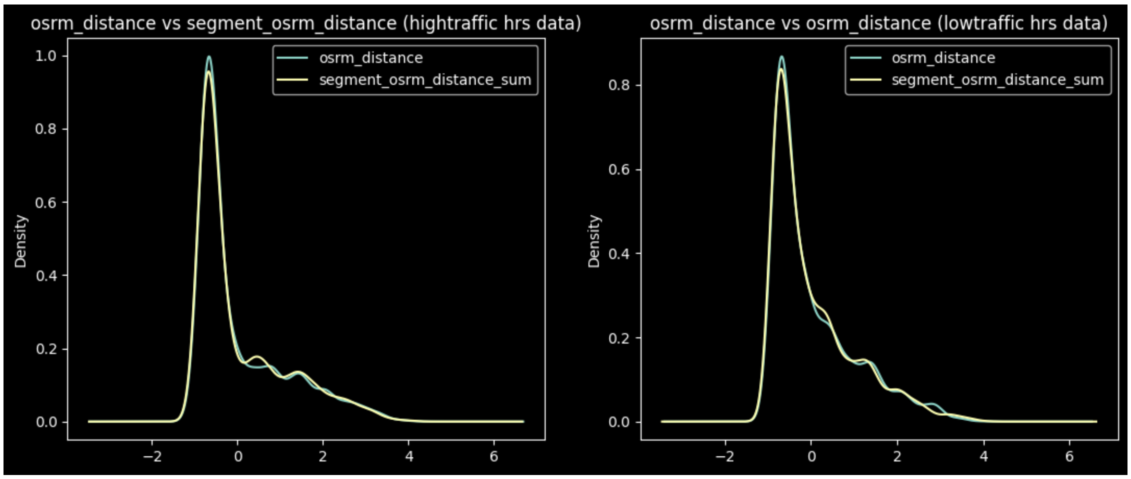
[1970]:
```
#Statistical test
Spearman_coefficent,_ = stats.
 ↪spearmanr(df['osrm_distance'],df['segment_osrm_distance_sum'])
print(np.round(Spearman_coefficent,2),' OSRM distance and Segment OSRM distance␣
 ↪are strongly correlated')


def ttest_independent(data):
  #Hypothesis testing
  #H0 : 'osrm_distance' and 'segment_osrm_distance' are similiar.
  #H1 : 'osrm_distance' and 'segment_osrm_distance' are different.
  _,p_value = stats.
 ↪ttest_ind(data['osrm_distance'],data['segment_osrm_distance_sum'])
  if p_value > 0.05:
    print("Accept the null hypothesis")
    print("There is no significance difference between 'osrm_distance' and␣
 ↪'segment_osrm_distance_sum'")
  else:
    print("Reject the null hypothesis")
    print("There is a significant difference between 'osrm_distance' and␣
 ↪'segment_osrm_distance_sum'")


print()

ttest_independent(df[['osrm_distance','segment_osrm_distance_sum']])
```

```
0.99  OSRM distance and Segment OSRM distance are strongly correlated
```

```
Accept the null hypothesis
There is no significance difference between 'osrm_distance' and
'segment_osrm_distance_sum'
```

hightraffic hrs and low traffic hrs segmented data

[1971]:
```
_,ax=plt.subplots(1,2,figsize=(13,5))
cols = ['osrm_distance','segment_osrm_distance_sum']
hts_data[cols].plot(kind = 'density',title = 'osrm_distance vs␣
↪segment_osrm_distance (hightraffic hrs data)',ax=ax[0])
lts_data[cols].plot(kind = 'density',title = 'osrm_distance vs osrm_distance␣
↪(lowtraffic hrs data)',ax=ax[1])
plt.show()
```



- Distribution of OSRM distance and segment OSRM distance looks similar for both datasets.

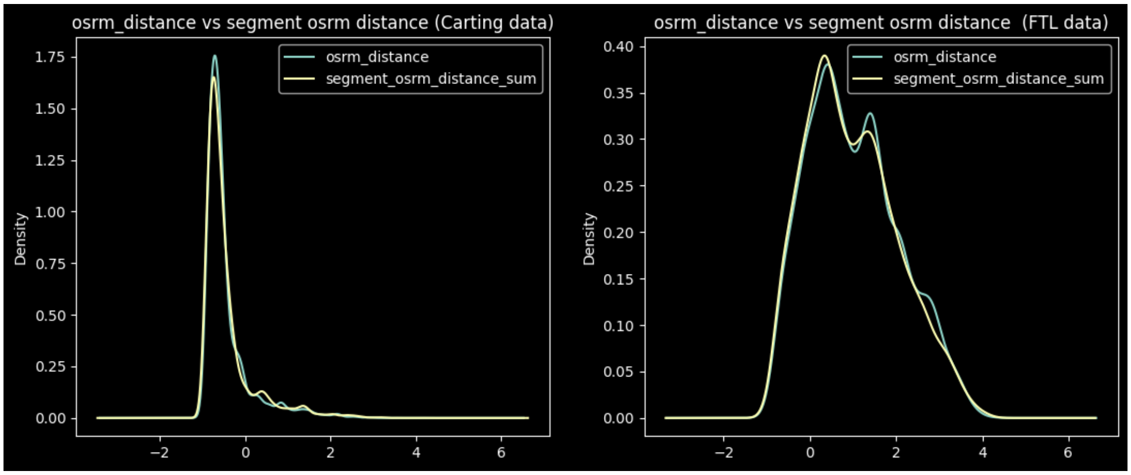
[1972]:
```
#checking though statistical method

#Hypothesis testing
#H0 : 'osrm_distance' and 'segment_osrm_distance' are similar.
#H1 : 'osrm_distance' and 'segment_osrm_distance' are different.

print('Hypothesis during High Trafic Hours','\n')
_,p_value = stats.
↪ttest_ind(hts_data['osrm_distance'],hts_data['segment_osrm_distance_sum'])
if p_value > 0.05:
  print("Accept the null hypothesis")
  print("There is no significance difference between 'osrm_distance' and␣
↪'segment_osrm_distance_sum'")
else:
  print("Reject the null hypothesis")
```

```
  print("There is a significant difference between 'osrm_distance' and␣
↪'segment_osrm_distance_sum'")

print('Hypothesis during Low Trafic Hours','\n')

_,p_value = stats.
↪ttest_ind(lts_data['osrm_distance'],lts_data['segment_osrm_distance_sum'])
if p_value > 0.05:
  print("Accept the null hypothesis")
  print("There is no significance difference between 'osrm_distance' and␣
↪'segment_osrm_distance_sum'")
else:
  print("Reject the null hypothesis")
  print("There is a significant difference between 'osrm_distance' and␣
↪'segment_osrm_distance_sum'")
```

```
Hypothesis during High Trafic Hours

Accept the null hypothesis
There is no significance difference between 'osrm_distance' and
'segment_osrm_distance_sum'
Hypothesis during Low Trafic Hours

Accept the null hypothesis
There is no significance difference between 'osrm_distance' and
'segment_osrm_distance_sum'
```

route type segmented data.

[1973]:
```
#checking based on route type
_,ax=plt.subplots(1,2,figsize=(13,5))
cols = ['osrm_distance','segment_osrm_distance_sum']
carting_data[cols].plot(kind = 'density',ax=ax[0],title = 'osrm_distance vs␣
↪segment osrm distance (Carting data)')
ftl_data[cols].plot(kind = 'density',ax = ax[1],title = 'osrm_distance vs␣
↪segment osrm distance  (FTL data)')
plt.show()
```



- Carting and FTL data distribution between osrm_distance and segment osrm distance looks similar.

[1974]:
```
ttest_independent(carting_data[['osrm_distance','segment_osrm_distance_sum']])
```

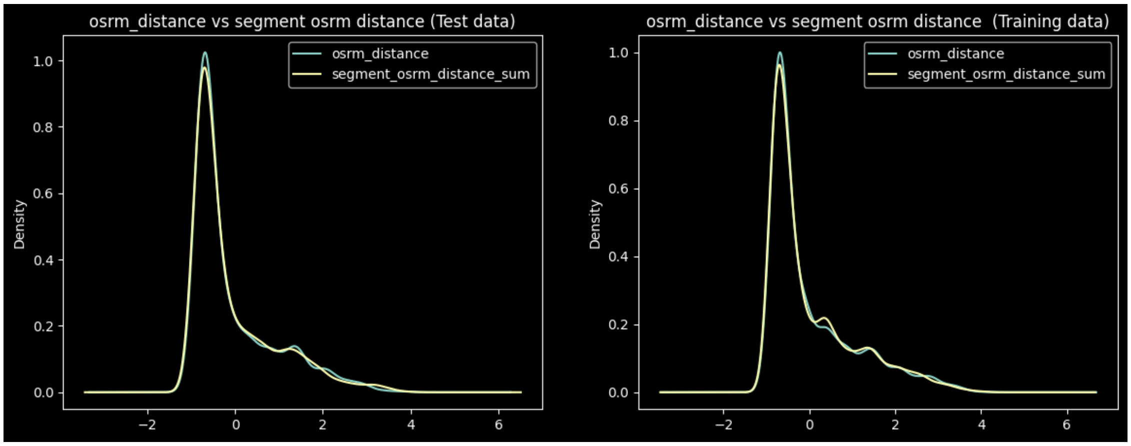
```
Reject the null hypothesis
There is a significant difference between 'osrm_distance' and
'segment_osrm_distance_sum'
```

[1975]:
```
ttest_independent(ftl_data[['osrm_distance','segment_osrm_distance_sum']])
```

```
Accept the null hypothesis
There is no significance difference between 'osrm_distance' and
'segment_osrm_distance_sum'
```

Type of data(training vs Test)

[1976]:
```
#checking based on data type
_,ax=plt.subplots(1,2,figsize=(14,5))
cols = ['osrm_distance','segment_osrm_distance_sum']
test_data[cols].plot(kind = 'density',ax = ax[0],title = 'osrm_distance vs␣
↪segment osrm distance (Test data)')
train_data[cols].plot(kind = 'density',ax=ax[1],title = 'osrm_distance vs␣
↪segment osrm distance  (Training data)')
plt.show()
```



[1977]:
```
ttest_independent(test_data[['osrm_distance','segment_osrm_distance_sum']])
```

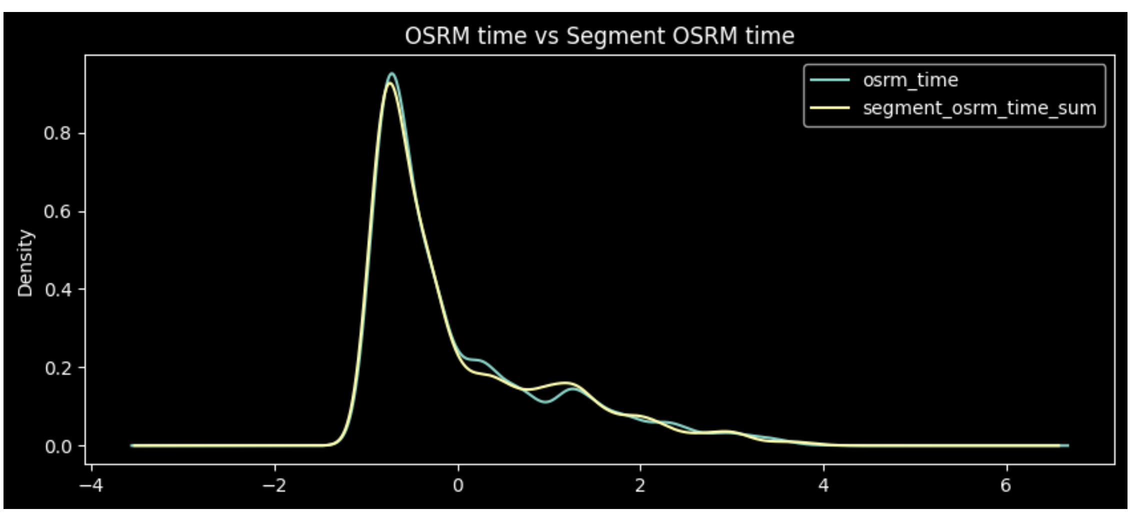
```
Accept the null hypothesis
There is no significance difference between 'osrm_distance' and
'segment_osrm_distance_sum'
```

[1978]:
```
ttest_independent(train_data[['osrm_distance','segment_osrm_distance_sum']])
```

```
Accept the null hypothesis
There is no significance difference between 'osrm_distance' and
'segment_osrm_distance_sum'
```

0.0.5 OSRM time aggregated value and segment OSRM time aggregated value

[1979]:
```
cols = ['osrm_time','segment_osrm_time_sum']
df[cols].plot(kind = 'density',figsize = (10,4),title = 'OSRM time vs Segment␣
↪OSRM time')
plt.show()
```



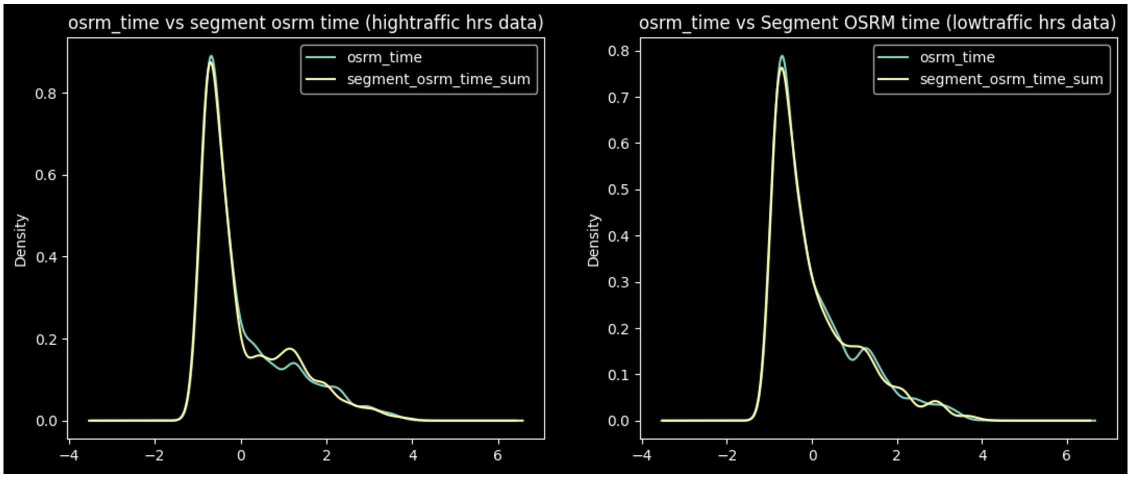
From above EDA analysis, OSRM time and Segment OSRM time are strongly correlated and similar distribution

[1980]:
```
#Statistical test
Spearman_coefficent,_ = stats.
 ↪spearmanr(df['osrm_time'],df['segment_osrm_time_sum'])
print(np.round(Spearman_coefficent,2),'OSRM time and Segment OSRM time are␣
 ↪strongly correlated')


def ttest_independent_test(data):
  #Hypothesis testing
  #H0 : 'osrm_time' and 'segment_osrm_time' are similiar.
  #H1 : 'osrm_time' and 'segment_osrm_time' are different.
  _,p_value = stats.ttest_ind(data['osrm_time'],data['segment_osrm_time_sum'])
  if p_value > 0.05:
    print("Accept the null hypothesis")
    print("There is no significance difference between 'osrm_time' and␣
 ↪'segment_osrm_time_sum'")
  else:
    print("Reject the null hypothesis")
    print("There is a significant difference between 'osrm_time' and␣
 ↪'segment_osrm_time_sum'")


print()

ttest_independent_test(df[['osrm_time','segment_osrm_time_sum']])
```

```
0.99 OSRM time and Segment OSRM time are strongly correlated

Accept the null hypothesis
There is no significance difference between 'osrm_time' and
'segment_osrm_time_sum'
```

hightraffic hrs and low traffic hrs segmented data

[1981]:
```
# checkingg for highttrffic hrs and lowTraffic hrs segments.
_,ax=plt.subplots(1,2,figsize=(13,5))
cols = ['osrm_time','segment_osrm_time_sum']
hts_data[cols].plot(kind = 'density',title = 'osrm_time vs segment osrm time␣
 ↪(hightraffic hrs data)',ax=ax[0])
lts_data[cols].plot(kind = 'density',title = 'osrm_time vs Segment OSRM time␣
 ↪(lowtraffic hrs data)',ax=ax[1])
plt.show()
```

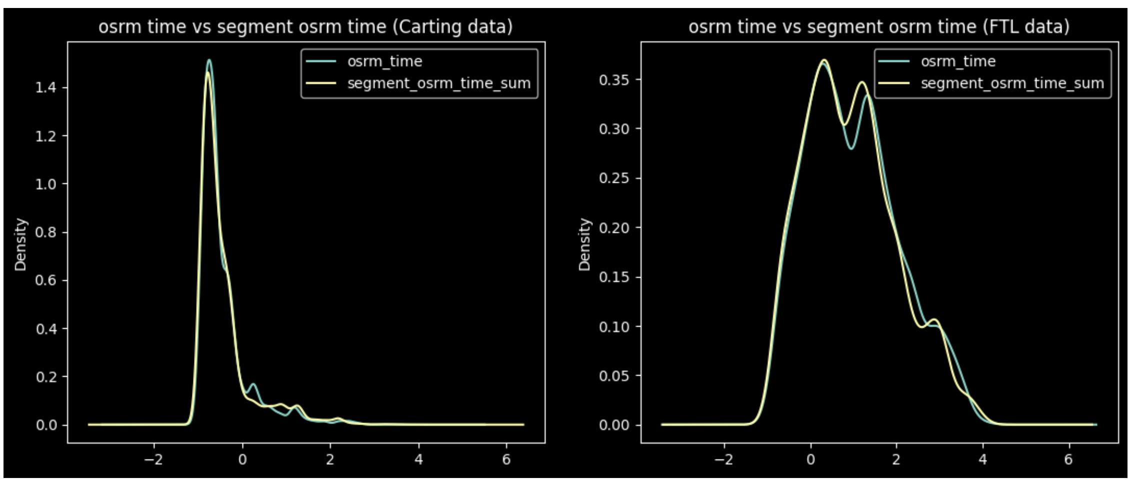


[1982]:
```python
#checking though statistical method

#Hypothesis testing
#H0 : 'osrm_distance' and 'segment_osrm_distance' are similar.
#H1 : 'osrm_distance' and 'segment_osrm_distance' are different.

print('Hypothesis during High Trafic Hours','\n')
_,p_value = stats.
↪ttest_ind(hts_data['osrm_time'],hts_data['segment_osrm_time_sum'])
if p_value > 0.05:
  print("Accept the null hypothesis")
  print("There is no significance difference between 'osrm_time' and␣
↪'segment_osrm_time'")
else:
  print("Reject the null hypothesis")
  print("There is a significant difference between 'osrm_time' and␣
↪'segment_osrm_time'")

print('Hypothesis during Low Trafic Hours','\n')

_,p_value = stats.
↪ttest_ind(lts_data['osrm_time'],lts_data['segment_osrm_time_sum'])
if p_value > 0.05:
  print("Accept the null hypothesis")
  print("There is no significance difference between 'osrm_time' and␣
↪'segment_osrm_time'")
else:
  print("Reject the null hypothesis")
  print("There is a significant difference between 'osrm_time' and␣
↪'segment_osrm_time'")
```

```
Hypothesis during High Trafic Hours

Accept the null hypothesis
There is no significance difference between 'osrm_time' and 'segment_osrm_time'
Hypothesis during Low Trafic Hours

Accept the null hypothesis
There is no significance difference between 'osrm_time' and 'segment_osrm_time'
```

route type segmented data.

[1983]:
```
#checking based on route type
_,ax=plt.subplots(1,2,figsize=(13,5))
cols = ['osrm_time','segment_osrm_time_sum']
carting_data[cols].plot(kind = 'density',ax=ax[0],title = 'osrm time vs segment␣
 ↪osrm time (Carting data)')
ftl_data[cols].plot(kind = 'density',ax=ax[1],title = 'osrm time vs segment␣
 ↪osrm time (FTL data)')
plt.show()
```



[1984]:
```
ttest_independent_test(carting_data[['osrm_time','segment_osrm_time_sum']])
```

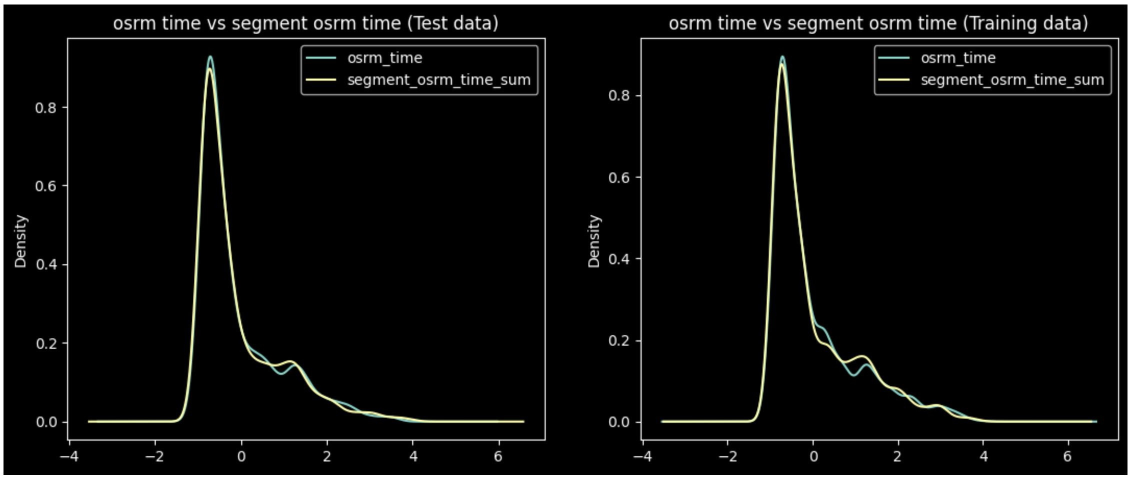
```
Reject the null hypothesis
There is a significant difference between 'osrm_time' and
'segment_osrm_time_sum'
```

[1985]:
```
ttest_independent_test(ftl_data[['osrm_time','segment_osrm_time_sum']])
```

```
Reject the null hypothesis
There is a significant difference between 'osrm_time' and
'segment_osrm_time_sum'
```

Type of data(training vs Test)

[1986]:
```
#checking based on data type
_,ax=plt.subplots(1,2,figsize=(13,5))
cols = ['osrm_time','segment_osrm_time_sum']
test_data[cols].plot(kind = 'density',ax=ax[0],title = 'osrm time vs segment␣
↪osrm time (Test data)')
train_data[cols].plot(kind = 'density',ax=ax[1],title = 'osrm time vs segment␣
↪osrm time (Training data)')
plt.show()
```



[1987]:
```
ttest_independent_test(test_data[['osrm_time','segment_osrm_time_sum']])
```

```
Accept the null hypothesis
There is no significance difference between 'osrm_time' and
'segment_osrm_time_sum'
```

[1988]:
```
ttest_independent_test(train_data[['osrm_time','segment_osrm_time_sum']])
```

```
Accept the null hypothesis
There is no significance difference between 'osrm_time' and
'segment_osrm_time_sum'
```

0.0.6 Observed Patterns

[1989]:
```
temp = df['trip_creation_time'].dt.month.value_counts().reset_index()
temp.columns = ['month','count']
temp.loc[temp['month'] == 9,'count'] = (temp.loc[temp['month'] == 9,'count']/
↪18).round(2)
temp.loc[temp['month'] == 10,'count'] = (temp.loc[temp['month'] == 10,'count']/
↪3).round(2)
temp
```

[1989]:
```
   month   count
0      9  620.67
1     10  517.00
```

- September month has high deliveries comparing to october month

[1990]:
```
df['trip_creation_dayname'].value_counts()
```

[1990]:
```
trip_creation_dayname
Wednesday    2352
Saturday     1836
Thursday     1819
Friday       1774
Tuesday      1766
Monday       1697
Sunday       1479
Name: count, dtype: int64
```

[1991]:
```
temp = (np.round(100*df['source_state'].value_counts()/
 ↪len(df['source_state']),3))
temp.name = '% of source_state'
temp.head()
```

[1991]:
```
source_state
maharashtra    18.077
karnataka      16.003
haryana        10.461
tamil nadu      8.213
delhi           5.242
Name: % of source_state, dtype: float64
```

- Most orders are placed from Maharastra and Karnataka

[1992]:
```
temp = 100*df[['source_state','destination_state']].value_counts()/
 ↪len(df['source_state'])
temp.name = '% of orders'
temp.head()
```

[1992]:
```
source_state  destination_state
maharashtra   maharashtra          17.849564
karnataka     karnataka            15.562367
tamil nadu    tamil nadu            7.946239
haryana       haryana               6.177788
telangana     telangana             4.959522
Name: % of orders, dtype: float64
```

- Most orders are within the state of maharastra, karnataka, tamil nadu, haryana.

[1993]:
```
temp = pd.DataFrame(100*df[['source_city','destination_city']].value_counts()/
↪len(df))
temp.columns = ['% of orders']
temp.head()
```

[1993]:
```
                             % of orders
source_city destination_city
bangalore   bangalore          12.072624
mumbai      mumbai              4.708009
chennai     chennai             4.354319
bhiwandi    mumbai              3.426865
hyderabad   hyderabad           2.978857
```

- Most orders are within the city of bangalore, mumbai, chennai.
- There is significant orders from bhiwandi to mumbai.

[1994]:
```
cols = ['source_city','source_place','destination_city','destination_place']
arr = df[cols].value_counts().head(10).reset_index().iloc[:,0:-1].values
```

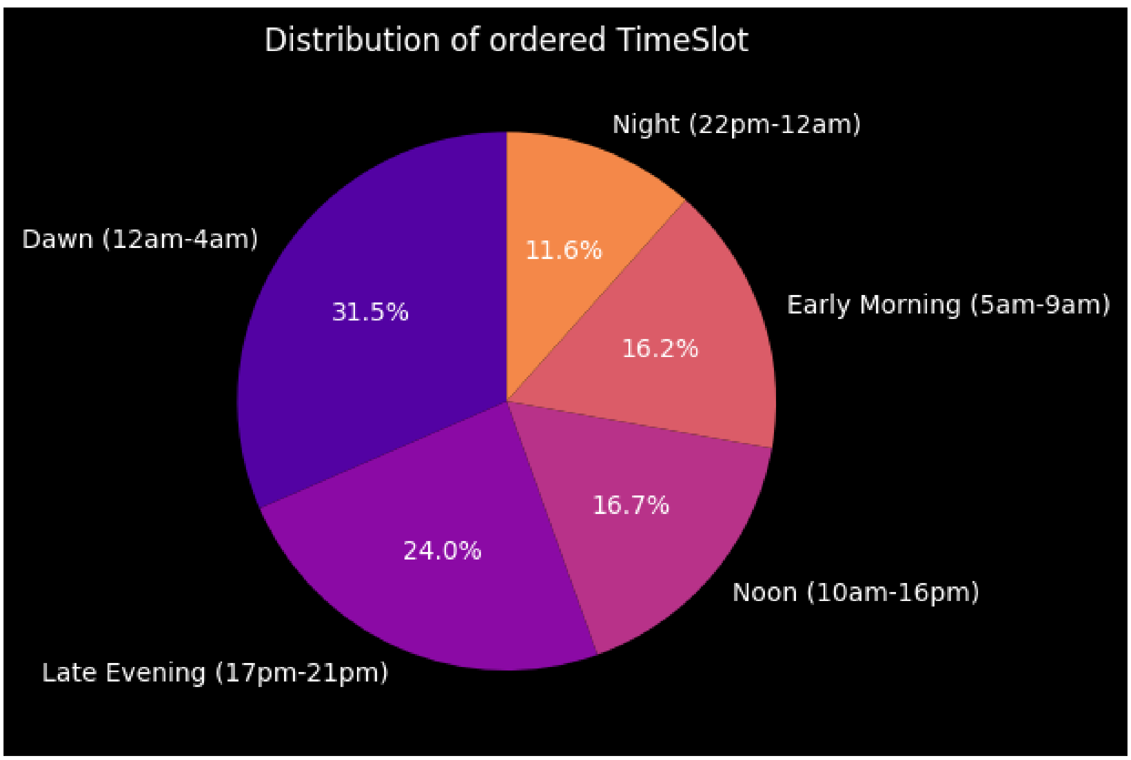
[1995]:
```
a1 = list()
for s_city,s_place,d_city,d_place in arr:
  temp = data.loc[(df['source_place'] == s_place) & (df['source_city'] ==␣
↪s_city) & (df['destination_place'] == d_place) & (df['destination_city'] ==␣
↪d_city)]
  temp['actual_time'].mean(),temp['actual_distance_to_destination'].mean()
  a1+=[[s_city,s_place,d_city,d_place,np.round(temp['actual_time'].mean()),
        np.round(temp['actual_distance_to_destination'].mean()),np.
↪round(temp['osrm_distance'].mean()),
        np.round(temp['osrm_time'].mean())]]
```

[1996]:
```
cols = ['source_city','source_place','destination_city','destination_place',
       ␣
↪'avg_actual_time','avg_actual_distance','avg_osrm_distance','avg_osrm_time']
pd.DataFrame(a1,columns = cols)
```

[1996]:
```
  source_city source_place destination_city destination_place  \
0   bangalore     nelmngla        bangalore          kgairprt
1  chandigarh     mehmdpur       chandigarh          mehmdpur
2   bangalore     bomsndra        bangalore          kgairprt
3    bhiwandi      mankoli         bhiwandi           mankoli
4   bangalore     kgairprt        bangalore          nelmngla
5   ahmedabad         east        ahmedabad              east
6    bhiwandi      mankoli           mumbai            mumbai
7      mumbai     chndivli         bhiwandi           mankoli
8   bangalore     nelmngla        bangalore          bomsndra
9     gurgaon     bilaspur          sonipat            kundli
```

```
   avg_actual_time  avg_actual_distance  avg_osrm_distance  avg_osrm_time
0             88.0                 28.0               38.0           48.0
1            337.0                154.0              190.0          161.0
2            115.0                 42.0               53.0           57.0
3            241.0                 85.0              108.0           83.0
4            105.0                 28.0               41.0           50.0
5            124.0                 39.0               46.0           39.0
6             61.0                 21.0               27.0           22.0
7             81.0                 20.0               26.0           21.0
8             95.0                 40.0               50.0           50.0
9            216.0                 70.0               98.0           97.0
```

[1997]:
```
clr = sns.color_palette('plasma')
plt.pie(x = df['order_timeslot'].value_counts(),labels = df['order_timeslot'].
 ↪value_counts().index,autopct = '%1.1f%%',startangle=90,colors = clr)
plt.title('Distribution of ordered TimeSlot')
plt.show()
```



[1998]:
```
temp = pd.DataFrame(np.round(100*df[['source_city','order_timeslot']].
 ↪value_counts()/len(df),2))
temp.columns = ['% of orders']
temp.head(12)
```

[1998]:

```
                                          % of orders
source_city order_timeslot
bangalore   Late Evening (17pm-21pm)         3.73
            Dawn (12am-4am)                  2.82
            Early Morning (5am-9am)          2.74
            Noon (10am-16pm)                 2.69
mumbai      Dawn (12am-4am)                  2.15
gurgaon     Late Evening (17pm-21pm)         2.12
mumbai      Late Evening (17pm-21pm)         2.11
delhi       Late Evening (17pm-21pm)         1.70
gurgaon     Noon (10am-16pm)                 1.52
            Dawn (12am-4am)                  1.45
bhiwandi    Noon (10am-16pm)                 1.38
            Late Evening (17pm-21pm)         1.38
```

- Most delhiveries shipping are intiated during dawn & late night.
- Banglore and Mumbai has highest percent in orders. Most of them were shipped in During late evening and dawn hours.

[1999]:

```
# weekend column

df['is_weekend'].value_counts()
```

[1999]:

```
is_weekend
0    9408
1    3315
Name: count, dtype: int64
```

[2000]:

```
100*pd.crosstab(df['order_timeslot'],df['is_weekend'],normalize = True).
↪sort_values(by=[0,1],ascending = [False,False])
```

[2000]:

```
is_weekend                        0         1
order_timeslot
Dawn (12am-4am)           22.919123  8.590741
Late Evening (17pm-21pm)  17.841704  6.122770
Noon (10am-16pm)          12.481333  4.252142
Early Morning (5am-9am)   11.946868  4.275721
Night (22pm-12am)          8.755797  2.813802
```

- Most of the shipments were done at Dawn and Late Evening irrespective of day.

is_weekend, shipment_timeslot feature effects on OSRM and Actual time

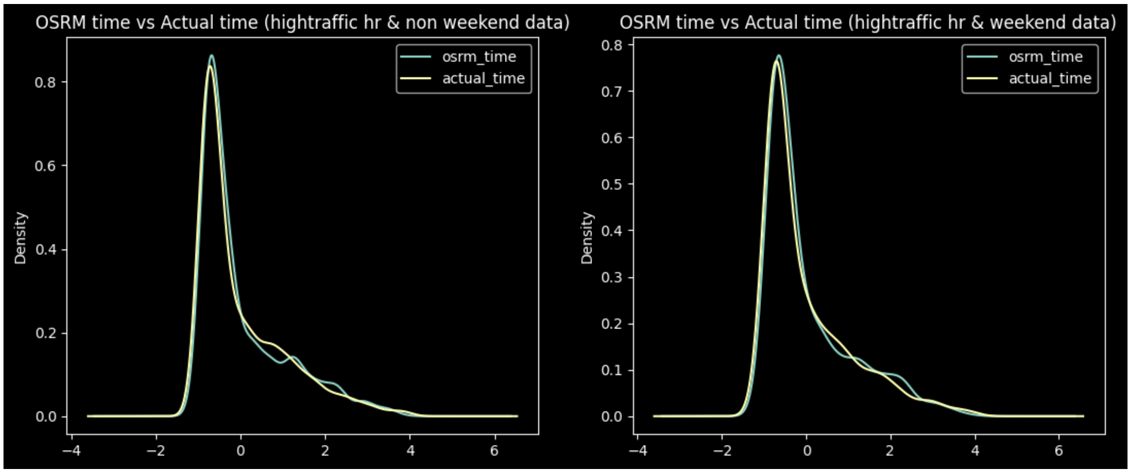
[2001]:

```
#OSRM time, #Actual Time, #is_weekend, #shipment_timeslot

w0= df.loc[df['is_weekend'] == 0]
w1 = df.loc[df['is_weekend'] == 1]
```

[2002]:
```
hts_w0_data = w0.loc[df['order_timeslot'].isin(['Noon (10am-16pm)','Late Evening (17pm-21pm)'])]
lts_w0_data = w0.loc[df['order_timeslot'].isin(['Dawn (12am-4am)','Night (22pm-12am)'])]


hts_w1_data = w1.loc[df['order_timeslot'].isin(['Noon (10am-16pm)','Late Evening (17pm-21pm)'])]
lts_w1_data = w1.loc[df['order_timeslot'].isin(['Dawn (12am-4am)','Night (22pm-12am)'])]
```

[2003]:
```
def hypothesis_test(df,val,col):
  print()
  print('Hypothesis during '+val+' Hours')
  _,p_value = stats.ttest_rel(df[col[0]],df[col[1]])
  print()
  if p_value > 0.05:
    print("Accept the null hypothesis")
    print("There is no significance difference between '"+col[0]+"' and '"+col[1]+"'")
  else:
    print("Reject the null hypothesis")
    print("There is a significant difference between '"+col[0]+"' and '"+col[1]+"'")
```

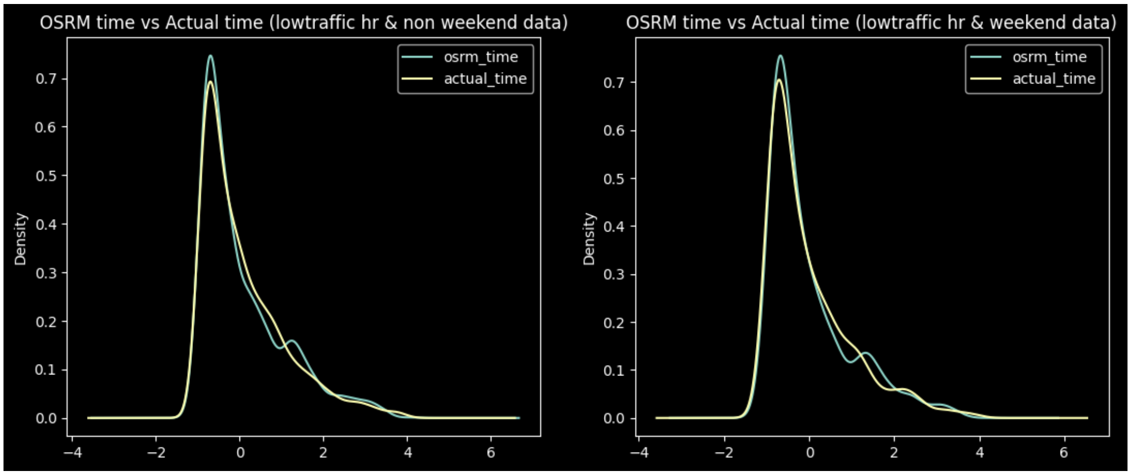
[2004]:
```
_,ax = plt.subplots(1,2,figsize=(13,5))
cols = ['osrm_time','actual_time']
hts_w0_data[cols].plot(kind = 'density',ax=ax[0],title = 'OSRM time vs Actual time (hightraffic hr & non weekend data)')
hts_w1_data[cols].plot(kind = 'density',ax = ax[1],title = 'OSRM time vs Actual time (hightraffic hr & weekend data)')
plt.show()

hypothesis_test(hts_w0_data, 'hightraffic hr & non weekend data', ['osrm_time','actual_time'])
hypothesis_test(hts_w1_data, 'hightraffic hr & weekend data', ['osrm_time','actual_time'])
```




```
Hypothesis during hightraffic hr & non weekend data Hours

Reject the null hypothesis
There is a significant difference between 'osrm_time' and 'actual_time'

Hypothesis during hightraffic hr & weekend data Hours

Reject the null hypothesis
There is a significant difference between 'osrm_time' and 'actual_time'
```

[2005]:

```
_,ax = plt.subplots(1,2,figsize=(13,5))
cols = ['osrm_time','actual_time']
lts_w0_data[cols].plot(kind = 'density',ax=ax[0],title = 'OSRM time vs Actual␣
↪time (lowtraffic hr & non weekend data)')
lts_w1_data[cols].plot(kind = 'density',ax = ax[1],title = 'OSRM time vs Actual␣
↪time (lowtraffic hr & weekend data)')
plt.show()


hypothesis_test(lts_w0_data, 'lowtraffic hr & non weekend data',␣
↪['osrm_time','actual_time'])
hypothesis_test(lts_w1_data, 'lowtraffic hr & weekend data',␣
↪['osrm_time','actual_time'])
```



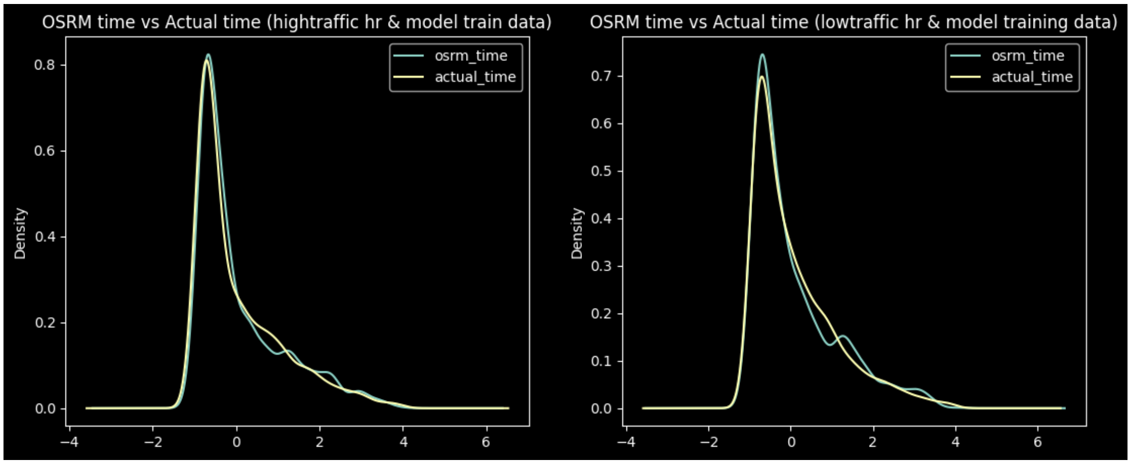

```
Hypothesis during lowtraffic hr & non weekend data Hours

Accept the null hypothesis
There is no significance difference between 'osrm_time' and 'actual_time'

Hypothesis during lowtraffic hr & weekend data Hours

Accept the null hypothesis
There is no significance difference between 'osrm_time' and 'actual_time'
```

- Model predicts less time comparing to actual time in all days during High trafic Hrs.

[2006]:
```
# Comparing the actual_time and osrm_time with test and train data under␣
↪different ordered timeslots


hts_train_data = train_data.loc[train_data['order_timeslot'].isin(['Noon␣
↪(10am-16pm)','Late Evening (17pm-21pm)'])]
lts_train_data = train_data.loc[train_data['order_timeslot'].isin(['Dawn␣
↪(12am-4am)','Night (22pm-12am)'])]
```

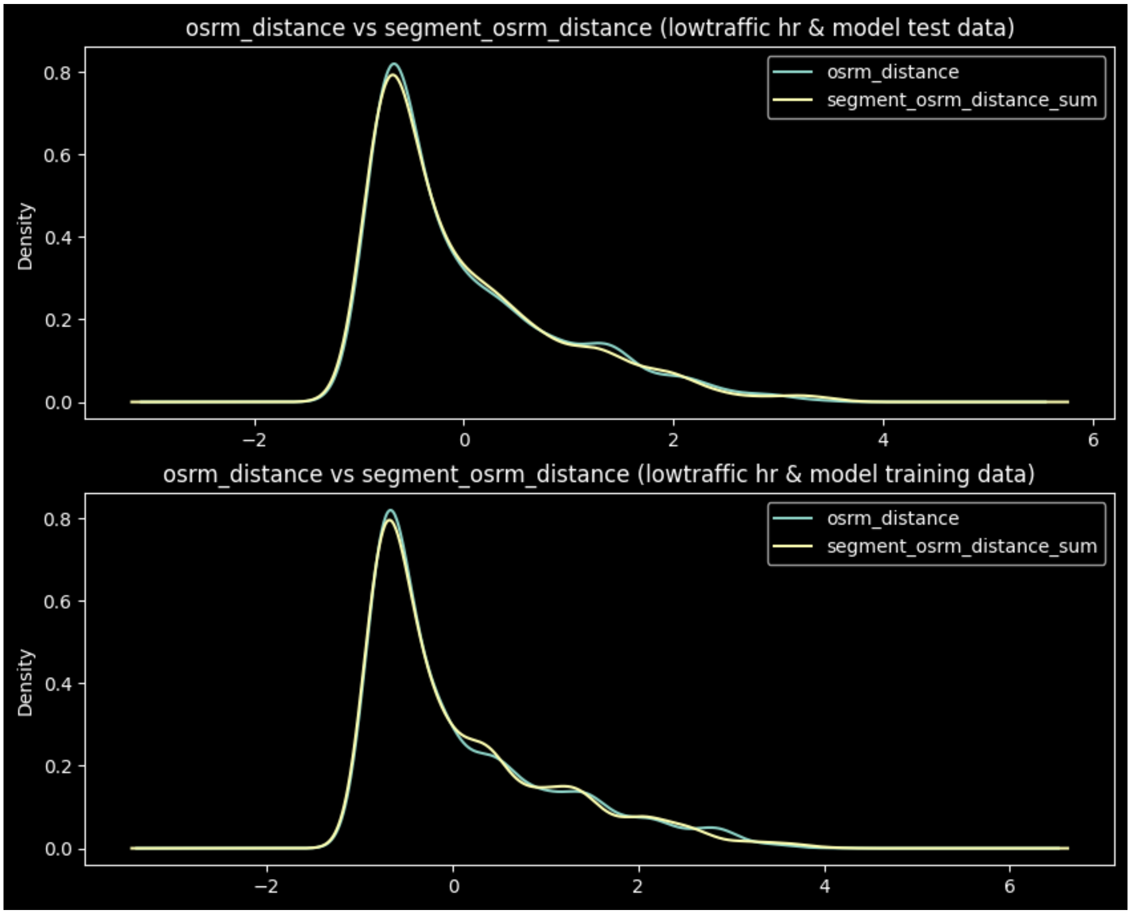
[2007]:
```
_,ax = plt.subplots(1,2,figsize=(13,5))
cols = ['osrm_time','actual_time']
hts_train_data[cols].plot(kind = 'density',ax=ax[0],title = 'OSRM time vs␣
↪Actual time (hightraffic hr & model train data)')
lts_train_data[cols].plot(kind = 'density',ax = ax[1],title = 'OSRM time vs␣
↪Actual time (lowtraffic hr & model training data)')
plt.show()
```

```
hypothesis_test(hts_train_data, 'hightraffic hr & model train data',␣
  ↪['osrm_time','actual_time'])
hypothesis_test(lts_train_data, 'lowtraffic hr & model train data',␣
  ↪['osrm_time','actual_time'])
```




```
Hypothesis during hightraffic hr & model train data Hours

Reject the null hypothesis
There is a significant difference between 'osrm_time' and 'actual_time'

Hypothesis during lowtraffic hr & model train data Hours

Accept the null hypothesis
There is no significance difference between 'osrm_time' and 'actual_time'
```

[2008]:
```
_,ax = plt.subplots(2,1,figsize=(10,8))
cols = ['osrm_distance','segment_osrm_distance_sum']
lts_test_data[cols].plot(kind = 'density',ax=ax[0],title = 'osrm_distance vs␣
  ↪segment_osrm_distance (lowtraffic hr & model test data)')

lts_train_data[cols].plot(kind = 'density',ax = ax[1],title = 'osrm_distance vs␣
  ↪segment_osrm_distance (lowtraffic hr & model training data)')
plt.show()


hypothesis_test(lts_test_data, 'lowtraffic hr & model test data',␣
  ↪['osrm_distance','segment_osrm_distance_sum'])
hypothesis_test(lts_train_data, 'lowtraffic hr & model training data',␣
  ↪['osrm_distance','segment_osrm_distance_sum'])
```




```
Hypothesis during lowtraffic hr & model test data Hours

Accept the null hypothesis
There is no significance difference between 'osrm_distance' and
'segment_osrm_distance_sum'

Hypothesis during lowtraffic hr & model training data Hours

Reject the null hypothesis
There is a significant difference between 'osrm_distance' and
'segment_osrm_distance_sum'
```

0.0.7 Observations

- During High traffic hrs., model time prediction is slightly deviating from actual hours.
- No significance difference between actual time and osrm time during low traffic hours.
- OSRM and Segment OSRM distance and time has no significance difference.
- Actual and OSRM time ,OSRM and Segment OSRM time has significant changes for different route types.

- Most orders are placed and delivered with in states of Maharashtra and Karnataka, Tamil-Nadu.
- More orders inflow with in capitals Bangalore, Mumbai, Chennai (Possibility to the high inflow of air logistics and urbanization demand). *Lot of delhivery orders created or shipped at late evenings,night and early morning timeslots.(It could strategy day delivery service).
- Most orders created/shipping are initiated during dawn ,late evenings & late night (It could strategy day delivery service). *Bangalore ,Mumbai, Gurgaon and Delhi has highest percent in orders. Most of them were shipped in During late evening and dawn hours irrespective of day.
- OSRM and Segment OSRM distance and time are highly corelated to each other.

0.0.8 Recommendations

- Training data showing the significant difference of prediction in time and distance. Refine the training data, to predict the actual time and segment orsm distance properly.
- Improve route planning algorithms and enhancing the delivery process experience for high traffic routes and warehouse/shipment cities.
- Offer flexible delivery options such as express delivery, weekend deliveries, and pick-up stations.