▼ Delhivery - Feature Engineering



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 Data team builds 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.

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

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

#importing necessary packages for the analyses
import numpy as np
import pandas as pd
from scipy import stats
import matplotlib.pyplot as plt
import seaborn as sns

#downloading the .csv file
df = pd.read_csv("https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/551/original/delhivery_data.csv?1642751181")

Data checking

#initial data check
df.head()

		data	<pre>trip_creation_time</pre>	route_schedule_uuid	route_type	trip_uuid
	0	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3	Carting	trip- 153741093647649320
4E +-	:1/	`				

df.tail()

	data	trip_creation_time	route_schedule_uuid	route_type	trip_u
144862	training	2018-09-20 16:24:28.436231	thanos::sroute:f0569d2f- 4e20-4c31-8542- 67b86d5	Carting	153746066843555
144863	training	2018-09-20 16:24:28.436231	thanos::sroute:f0569d2f- 4e20-4c31-8542- 67b86d5	Carting	153746066843555
144864	training	2018-09-20 16:24:28.436231	thanos::sroute:f0569d2f- 4e20-4c31-8542- 67b86d5	Carting	153746066843555
144865	training	2018-09-20 16:24:28.436231	thanos::sroute:f0569d2f- 4e20-4c31-8542- 67b86d5	Carting	153746066843555
144866	training	2018-09-20 16:24:28.436231	thanos::sroute:f0569d2f- 4e20-4c31-8542- 67b86d5	Carting	153746066843555
5 rows × 24 columns					

```
# no of rows amd columns in dataset
print(f"# rows: {df.shape[0]} \n# columns: {df.shape[1]}")

# rows: 144867
# columns: 24
```

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144867 entries, 0 to 144866
Data columns (total 24 columns):

	columns (cocal 2+ columns).						
#	Column	Non-Nu	ll 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	<pre>actual_distance_to_destination</pre>	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			
dtype	<pre>dtypes: bool(1), float64(10), int64(1), object(12)</pre>						
memor	∽y usage: 25.6+ MB						

df.describe()

	start_scan_to_end_scan	cutoff_factor	${\tt actual_distance_to_destination}$	actua
count	144867.000000	144867.000000	144867.000000	144867.
mean	961.262986	232.926567	234.073372	416.

df.iloc[:, 1:].describe(include='all')

	<pre>trip_creation_time</pre>	route_schedule_uuid	route_type	trip_uuid	so		
count	144867	144867	144867	144867			
unique	14817	1504	2	14817			
top	2018-09-28 05:23:15.359220	thanos::sroute:4029a8a2- 6c74-4b7e-a6d8- f9e069f	FTL	trip- 153811219535896559	IN		
freq	101	1812	99660	101			
mean	NaN	NaN	NaN	NaN			
std	NaN	NaN	NaN	NaN			
min	NaN	NaN	NaN	NaN			
25%	NaN	NaN	NaN	NaN			
50%	NaN	NaN	NaN	NaN			
75%	NaN	NaN	NaN	NaN			
max	NaN	NaN	NaN	NaN			
11 rows × 23 columns							

detecting missing values in the dataset
df.isnull().sum()

```
data
                                     0
trip_creation_time
                                     0
route_schedule_uuid
route_type
                                     0
trip_uuid
source_center
                                     0
                                   293
source_name
destination_center
                                     a
destination_name
                                   261
od_start_time
                                     0
od_end_time
start_scan_to_end_scan
                                     0
\verb"is_cutoff"
cutoff_factor
cutoff_timestamp
actual_distance_to_destination
actual time
osrm time
osrm_distance
                                     0
factor
{\tt segment\_actual\_time}
                                     0
segment_osrm_time
                                      0
segment_osrm_distance
                                      0
segment_factor
dtype: int64
```

There are some missing values in the source_name and destination_name column. However, these don't even constitute 1% of the total data. Hence we can ignore the same. Thus remove or drop null values from the data.

```
#removing null values
df = df.dropna(how='any')
df = df.reset_index(drop=True)
#rechecking data for null values
df.isnull().sum()
    trip creation time
    route_schedule_uuid
                                       0
     route_type
    trip_uuid
                                       0
                                       0
     source_center
                                       0
     source_name
     destination_center
                                       0
     destination_name
```

```
0
od_start_time
                                   0
od_end_time
start_scan_to_end_scan
                                   0
is_cutoff
cutoff_factor
                                   0
cutoff_timestamp
actual_distance_to_destination
actual_time
osrm_time
osrm_distance
factor
segment_actual_time
                                   0
segment_osrm_time
{\tt segment\_osrm\_distance}
                                   0
segment\_factor
dtype: int64
```

#converting datetime to pandas datetime

```
df["od_start_time"] = pd.to_datetime(df["od_start_time"])
df["od_end_time"] = pd.to_datetime(df["od_end_time"])
```

#using max columns to display all the columns
pd.set_option('display.max_columns', None)
df.head()

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid
0	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3	Carting	trip- 153741093647649320
1	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3	Carting	trip- 153741093647649320
2	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3	Carting	trip- 153741093647649320
3	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3	Carting	trip- 153741093647649320
4	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78- b351-4c0e-a951- fa3d5c3	Carting	trip- 153741093647649320

#column 9 and 10 shows dtype as datetime64 after change df.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 144316 entries, 0 to 144315 Data columns (total 24 columns):

#	Column	Non-Null Count	Dtype	
0	data	144316 non-null	object	
1	trip_creation_time	144316 non-null	object	
2	route_schedule_uuid	144316 non-null	object	
3	route_type	144316 non-null	object	
4	trip_uuid	144316 non-null	object	
5	source_center	144316 non-null	object	
6	source_name	144316 non-null	object	
7	destination_center	144316 non-null	object	
8	destination_name	144316 non-null	object	
9	od_start_time	144316 non-null	<pre>datetime64[ns]</pre>	
10	od_end_time	144316 non-null	datetime64[ns]	
11	start_scan_to_end_scan	144316 non-null	float64	
12	is_cutoff	144316 non-null	bool	
13	cutoff_factor	144316 non-null	int64	
14	cutoff_timestamp	144316 non-null	object	
15	<pre>actual_distance_to_destination</pre>	144316 non-null	float64	
16	actual_time	144316 non-null	float64	
17	osrm_time	144316 non-null	float64	
18	osrm_distance	144316 non-null	float64	
19	factor	144316 non-null	float64	
20	segment_actual_time	144316 non-null	float64	
21	segment_osrm_time	144316 non-null		
22	segment_osrm_distance	144316 non-null		
23	segment_factor	144316 non-null		
	es: bool(1), datetime64[ns](2),	float64(10), int6	4(1), object(10)	
memory usage: 25.5+ MB				

```
# grouping by sub-journey in the trip
df['segment_key'] = df['trip_uuid'] + df['source_center'] + df['destination_center']

segment_cols = ['segment_actual_time', 'segment_osrm_distance', 'segment_osrm_time']

#after the loop completes, df will have new columns for each original column specified in segment_cols, where the values represent the cu
for col in segment_cols:
    df[col + '_sum'] = df.groupby('segment_key')[col].cumsum()

df[[col + '_sum' for col in segment_cols]]
```

	segment_actual_time_sum	segment_osrm_distance_sum	segment_osrm_time_sum
0	14.0	11.9653	11.0
1	24.0	21.7243	20.0
2	40.0	32.5395	27.0
3	61.0	45.5619	39.0
4	67.0	49.4772	44.0
144311	92.0	65.3487	94.0
144312	118.0	82.7212	115.0
144313	138.0	103.4265	149.0
144314	155.0	122.3150	176.0
144315	423.0	131.1238	185.0

144316 rows × 3 columns

```
#aggregating at sub-journey level
```

create_segment_dict = {

```
'data' : 'first',
    'trip creation time' : 'first',
    'route_schedule_uuid' : 'first',
    'route_type' : 'first',
    'trip uuid' : 'first',
    'source_center' : 'first',
'source_name' : 'first',
    'destination_center' : 'last',
    'destination_name' : 'last',
    'od_start_time' : 'first',
    'od_end_time' : 'first',
    'start_scan_to_end_scan' : 'first',
    \verb|'actual_distance_to_destination': 'last',\\
    'actual_time' : 'last',
    'osrm_time' : 'last',
    'osrm distance' : 'last',
    'segment_actual_time_sum' : 'last',
    'segment_osrm_distance_sum' : 'last',
    'segment_osrm_time_sum' : 'last',
}
# grouping mini-trips, sorting by time
segment = df.groupby('segment_key').agg(create_segment_dict).reset_index()
segment = segment.sort_values(by=['segment_key','od_end_time'], ascending=True).reset_index()
segment
```

	index	segment_key	data	trip_creation_ti
0	0	trip- 153671041653548748IND209304AAAIND000000ACB	training	2018-09-1 00:00:16.53574
1	1	trip- 153671041653548748IND462022AAAIND209304AAA	training	2018-09- ⁻ 00:00:16.5357 ²
2	2	trip- 153671042288605164IND561203AABIND562101AAA	training	2018-09- ² 00:00:22.8864 ²
3	3	trip- 153671042288605164IND572101AAAIND561203AAB	training	2018-09- ² 00:00:22.8864 ²
4	4	trip- 153671043369099517IND000000ACBIND160002AAC	training	2018-09- ² 00:00:33.6912
26217	26217	trip- 153861115439069069IND628204AAAIND627657AAA	test	2018-10-(23:59:14.3909
26218	26218	trip- 153861115439069069IND628613AAAIND627005AAA	test	2018-10-(23:59:14.3909
26219	26219	trip- 153861115439069069IND628801AAAIND628204AAA	test	2018-10-(23:59:14.3909

#example of filtering segment by trip_uuid
segment[segment['trip_uuid']=='trip-153671041653548748']

<class 'pandas.core.frame.DataFrame'>

	index	segment_key	data	trip_creation_time	
0	0	trip- 153671041653548748IND209304AAAIND000000ACB	training	2018-09-12 00:00:16.535741	tl
1	1	trip- 153671041653548748IND462022AAAIND209304AAA	training	2018-09-12 00:00:16.535741	tl

segment.info()

```
RangeIndex: 26222 entries, 0 to 26221
Data columns (total 21 columns):
# Column
                                    Non-Null Count Dtype
0
    index
                                    26222 non-null int64
    segment_key
                                    26222 non-null object
1
                                    26222 non-null object
2
    data
    trip_creation_time
                                   26222 non-null object
26222 non-null object
3
    route_schedule_uuid
    route_type
                                    26222 non-null object
6
    trip_uuid
                                    26222 non-null object
    source_center
                                    26222 non-null object
8
    source_name
                                    26222 non-null object
                                  26222 non-null object
    destination_center
10 destination_name
                                    26222 non-null object
                                   26222 non-null datetime64[ns]
11 od_start_time
12 od end time
                                    26222 non-null datetime64[ns]
                                    26222 non-null float64
13 start_scan_to_end_scan
14 actual_distance_to_destination 26222 non-null float64
                                    26222 non-null float64
15 actual time
16 osrm_time
                                    26222 non-null float64
17
    osrm_distance
                                    26222 non-null float64
18 segment_actual_time_sum
                                    26222 non-null float64
    segment_osrm_distance_sum
                                    26222 non-null
                                                   float64
20 segment_osrm_time_sum
                                    26222 non-null float64
dtypes: datetime64[ns](2), float64(8), int64(1), object(10)
memory usage: 4.2+ MB
```

#calculating time taken between od_start_time and od_end_time and keep it as a feature
segment['time_diff_hours'] = (segment['od_end_time'] - segment['od_start_time']).dt.total_seconds()/60
segment['time_diff_hours']

- 0 1260.604421 1 999.505379
- 2 58.832388

```
3 122.779486

4 834.638929

...

26217 62.115193

26218 91.087797

26219 44.174403

26220 287.474007

26221 66.933565

Name: time_diff_hours, Length: 26222, dtype: float64
```

segment

	index	segment_key	data	trip_creation_tin	
0	0	trip- 153671041653548748IND209304AAAIND000000ACB	training	2018-09-′ 00:00:16.5357₄	
1	1	trip- 153671041653548748IND462022AAAIND209304AAA	training	2018-09- [/] 00:00:16.5357 [/]	
2	2	trip- 153671042288605164IND561203AABIND562101AAA	training	2018-09- [/] 00:00:22.8864(
3	3	trip- 153671042288605164IND572101AAAIND561203AAB	training	2018-09-′ 00:00:22.8864′	
4	4	trip- 153671043369099517IND000000ACBIND160002AAC	training	2018-09- ² 00:00:33.6912	
26217	26217	trip- 153861115439069069IND628204AAAIND627657AAA	test	2018-10-(23:59:14.3909	
26218	26218	trip- 153861115439069069IND628613AAAIND627005AAA	test	2018-10-(23:59:14.3909	
26219	26219	trip- 153861115439069069IND628801AAAIND628204AAA	test	2018-10-(23:59:14.3909(
26220	26220	trip- 153861118270144424IND583119AAAIND583101AAA	test	2018-10-(23:59:42.7016(
26221	26221	trip- 153861118270144424IND583201AAAIND583119AAA	test	2018-10-(23:59:42.7016(
26222 rd	26222 rows × 22 columns				

```
create_trip_dict = {
    'data' : 'first',
    'trip_creation_time' : 'first',
    'route_schedule_uuid' : 'first',
    'route_type' : 'first',
'trip_uuid' : 'first',
    'source_center' : 'first',
    'source_name' : 'first',
    'destination_center' : 'last',
    'destination_name' : 'last',
    'start_scan_to_end_scan' : 'sum',
    'time_diff_hours' : 'sum',
    'actual_distance_to_destination' : 'sum',
    'actual_time' : 'sum',
    'osrm_time' : 'sum',
    'osrm_distance' : 'sum',
    'segment_actual_time_sum' : 'sum',
    'segment_osrm_distance_sum' : 'sum',
    'segment_osrm_time_sum' : 'sum',
}
```

trip = segment.groupby("trip_uuid").agg(create_trip_dict).reset_index(drop=True)
trip

	data	trip_creation_time	route_schedule_uuid	route_type	trip_u	
0	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba- a29b-4a0b-b2f4- 288cdc6	FTL	153671041653548	
1	training	2018-09-12 00:00:22.886430	thanos::sroute:3a1b0ab2- bb0b-4c53-8c59- eb2a2c0	Carting	153671042288605	
2	training	2018-09-12 00:00:33.691250	thanos::sroute:de5e208e- 7641-45e6-8100- 4d9fb1e	FTL	153671043369099	
3	training	2018-09-12 00:01:00.113710	thanos::sroute:f0176492- a679-4597-8332- bbd1c7f	Carting	153671046011330	
4	training	2018-09-12 00:02:09.740725	thanos::sroute:d9f07b12- 65e0-4f3b-bec8- df06134	FTL	153671052974046	
14782	test	2018-10-03 23:55:56.258533	thanos::sroute:8a120994- f577-4491-9e4b- b7e4a14	Carting	153861095625827	
14783	test	2018-10-03 23:57:23.863155	thanos::sroute:b30e1ec3- 3bfa-4bd2-a7fb- 3b75769	Carting	153861104386292	
14784	test	2018-10-03 23:57:44.429324	thanos::sroute:5609c268- e436-4e0a-8180- 3db4a74	Carting	153861106442901	
14785	test	2018-10-03 23:59:14.390954	thanos::sroute:c5f2ba2c- 8486-4940-8af6- d1d2a6a	Carting	153861115439069	
14786	test	2018-10-03 23:59:42.701692	thanos::sroute:412fea14- 6d1f-4222-8a5f- a517042	FTL	153861118270144	
14787 rows × 18 columns						

trip[['actual_time','segment_actual_time_sum']]

	actual_time	segment_actual_time_sum
0	1562.0	1548.0
1	143.0	141.0
2	3347.0	3308.0
3	59.0	59.0
4	341.0	340.0
14782	83.0	82.0
14783	21.0	21.0
14784	282.0	281.0
14785	264.0	258.0
14786	275.0	274.0

14787 rows × 2 columns

#example of filtering by trip_uuid
trip[trip['trip_uuid'].isin(['trip-153671042288605164','trip-153671052974046625'])]

trip[['actual_distance_to_destination','osrm_distance']]

	${\tt actual_distance_to_destination}$	osrm_distance
0	824.732854	991.3523
1	73.186911	85.1110
2	1927.404273	2354.0665
3	17.175274	19.6800
4	127.448500	146.7918
14782	57.762332	73.4630
14783	15.513784	16.0882
14784	38.684839	58.9037
14785	134.723836	171.1103
14786	66.081533	80.5787

14787 rows × 2 columns

▼ Hypothesis testing

trip.head()

trip_uuid	route_type	route_schedule_uuid	<pre>trip_creation_time</pre>	data	
trip- 153671041653548748	FTL	thanos::sroute:d7c989ba- a29b-4a0b-b2f4- 288cdc6	2018-09-12 00:00:16.535741	training	0
trip- 153671042288605164	Carting	thanos::sroute:3a1b0ab2- bb0b-4c53-8c59- eb2a2c0	2018-09-12 00:00:22.886430	training	1
trip- 153671043369099517	FTL	thanos::sroute:de5e208e- 7641-45e6-8100- 4d9fb1e	2018-09-12 00:00:33.691250	training	2
trip- 153671046011330457	Carting	thanos::sroute:f0176492- a679-4597-8332- bbd1c7f	2018-09-12 00:01:00.113710	training	3
trip- 153671052974046625	FTL	thanos::sroute:d9f07b12- 65e0-4f3b-bec8- df06134	2018-09-12 00:02:09.740725	training	4

```
trip['destination_name'] = trip['destination_name'].str.lower() # lowering all columns
trip['source_name'] = trip['source_name']
def place2state(x):
    # transform "gurgaon_bilaspur_hb (haryana)" into "haryana"
   state = x.split('(')[1]
   return state[:-1] #removing ')' from ending
def place2city(x):
    #we remove state in this step
   city = x.split(' (')[0]
   city = city.split('_')[0]
   # now dealing with edge cases
   if city == 'pnq vadgaon sheri dpc': return 'vadgaonsheri'
   # ['PNQ Pashan DPC', 'Bhopal MP Nagar', 'HBR Layout PC',
    # 'PNQ Rahatani DPC', 'Pune Balaji Nagar', 'Mumbai Antop Hill']
    if city in ['pnq pashan dpc','pnq rahatani dpc', 'pune balaji nagar']:
       return 'pune
    if city == 'hbr layout pc' :
       return 'bengaluru'
```

```
if city == 'bhopal mp nagar':
        return 'bhopal'
    if city == 'mumbai antop hill':
        return 'mumbai'
    return city
def place2city_place(x):
    # we will remove state
    x = x.split('(')[0]
    len_ = len(x.split('_'))
    if len_ >= 3:
        return x.split('_')[1]
    # small cities have same city and place name
    if len_ == 2:
        return x.split('_')[0]
    \ensuremath{\text{\#}} now we need to deal with edge cases or improper name convention
    # if len(x.split('_')) == 2:
    return x.split(' ')[0]
def place2code(x):
    # we will remove state
    x = x.split('(')[0]
    if len(x.split('_')) >= 3:
        return x.split('_')[-1]
    return 'none'
trip['destination_state'] = trip['destination_name'].apply(lambda x: place2state(x))
trip['destination_city'] = trip['destination_name'].apply(lambda x: place2city(x))
trip['destination_place'] = trip['destination_name'].apply(lambda x: place2city_place(x))
trip['destination_code'] = trip['destination_name'].apply(lambda x: place2code(x))
trip['destination_name'].head()
     0
          kanpur_central_h_6 (uttar pradesh)
           doddablpur_chikadpp_d (karnataka)
     1
     2
              gurgaon_bilaspur_hb (haryana)
     3
              mumbai_mirard_ip (maharashtra)
     4
               sandur_wrdn1dpp_d (karnataka)
     Name: destination_name, dtype: object
trip[['destination_state','destination_city','destination_place','destination_code']]
```

	destination_state	${\tt destination_city}$	destination_place	destination_code
0	uttar pradesh	kanpur	central	6
1	karnataka	doddablpur	chikadpp	d
2	haryana	gurgaon	bilaspur	hb
3	maharashtra	mumbai	mirard	ip
4	karnataka	sandur	wrdn1dpp	d
14782	punjab	chandigarh	mehmdpur	h
14783	haryana	faridabad	blbgarh	dc
14784	uttar pradesh	kanpur	govndngr	dc
14785	tamil nadu	tirchchndr	shnmgprm	d
14786	karnataka	sandur	wrdn1dpp	d

trip['trip_creation_time'] = pd.to_datetime(trip['trip_creation_time']) trip['trip_year'] = trip['trip_creation_time'].dt.year trip['trip_month'] = trip['trip_creation_time'].dt.month trip['trip_day'] = trip['trip_creation_time'].dt.day

trip['trip_hour'] = trip['trip_creation_time'].dt.hour

14787 rows × 4 columns

trip['trip_week'] = trip['trip_creation_time'].dt.isocalendar().week
trip['day_of_week'] = trip['trip_creation_time'].dt.dayofweek

trip[['trip_year','trip_month','trip_day','trip_hour','trip_week','day_of_week']]

	trip_year	trip_month	trip_day	trip_hour	trip_week	day_of_week
0	2018	9	12	0	37	2
1	2018	9	12	0	37	2
2	2018	9	12	0	37	2
3	2018	9	12	0	37	2
4	2018	9	12	0	37	2
14782	2018	10	3	23	40	2
14783	2018	10	3	23	40	2
14784	2018	10	3	23	40	2
14785	2018	10	3	23	40	2
14786	2018	10	3	23	40	2

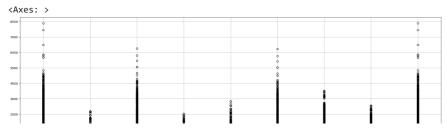
14787 rows × 6 columns

trip.head()

	data	<pre>trip_creation_time</pre>	route_schedule_uuid	route_type	trip_uuid
0	training	2018-09-12 00:00:16.535741	thanos::sroute:d7c989ba- a29b-4a0b-b2f4- 288cdc6	FTL	trip- 153671041653548748
1	training	2018-09-12 00:00:22.886430	thanos::sroute:3a1b0ab2- bb0b-4c53-8c59- eb2a2c0	Carting	trip- 153671042288605164
2	training	2018-09-12 00:00:33.691250	thanos::sroute:de5e208e- 7641-45e6-8100- 4d9fb1e	FTL	trip- 153671043369099517
3	training	2018-09-12 00:01:00.113710	thanos::sroute:f0176492- a679-4597-8332- bbd1c7f	Carting	trip- 153671046011330457
4	training	2018-09-12 00:02:09.740725	thanos::sroute:d9f07b12- 65e0-4f3b-bec8- df06134	FTL	trip- 153671052974046625

▼ Find outliers in numericals variable and visualize it using visual analysis

```
trip[num_cols].boxplot(rot=25, figsize=(25,8))
```

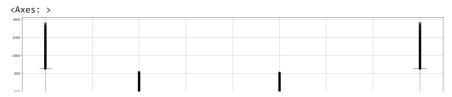


▼ Handle the outliers using IQR method

```
Q1 = trip[num_cols].quantile(0.25)
Q3 = trip[num_cols].quantile(0.75)
IQR = Q3 - Q1
IQR
      start_scan_to_end_scan
                                               483.000000
      \verb|actual_distance_to_destination||\\
                                               140.814159
      actual_time
                                               300.000000
      osrm_time
                                               139.000000
      osrm_distance
                                               175.887300
      segment_actual_time_sum
                                               298.000000
      segment_osrm_distance_sum
                                               183.981750
      segment_osrm_time_sum
time_diff_hours
                                               154.000000
                                               483.839201
     dtype: float64
 \label{trip}  \mbox{trip} = \mbox{trip}[-((\mbox{trip}[\mbox{num_cols}] < (\mbox{Q1 - 1.5 * IQR})) \ | \ (\mbox{trip}[\mbox{num_cols}] > (\mbox{Q3 + 1.5 * IQR}))).any(\mbox{axis=1})] 
trip = trip.reset_index(drop=True)
trip.head()
```

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid
0	training	2018-09-12 00:00:22.886430	thanos::sroute:3a1b0ab2- bb0b-4c53-8c59- eb2a2c0	Carting	trip- 153671042288605164
1	training	2018-09-12 00:01:00.113710	thanos::sroute:f0176492- a679-4597-8332- bbd1c7f	Carting	trip- 153671046011330457
2	training	2018-09-12 00:02:09.740725	thanos::sroute:d9f07b12- 65e0-4f3b-bec8- df06134	FTL	trip- 153671052974046625
3	training	2018-09-12 00:02:34.161600	thanos::sroute:9bf03170- d0a2-4a3f-aa4d- 9aaab3d	Carting	trip- 153671055416136166
4	training	2018-09-12 00:04:22.011653	thanos::sroute:a97698cc- 846e-41a7-916b- 88b1741	Carting	trip- 153671066201138152

trip[num_cols].boxplot(rot=25, figsize=(25,8))



▼ Handling Categorical Variables

```
trip['route_type'].value_counts()

Carting    8812
FTL     3911
    Name: route_type, dtype: int64

trip['route_type'] = trip['route_type'].map({'FTL':0, 'Carting':1})
```

▼ Normalize/Standarize the numerical features using MinMaxScaler or StandardScaler

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
scaler.fit(trip[num_cols])

v StandardScaler
StandardScaler()

trip[num_cols] = scaler.transform(trip[num_cols])

trip[num_cols]
```

	start_scan_to_end_scan	${\tt actual_distance_to_destination}$	actual_time	osrm_time
0	-0.548546	0.012060	-0.217856	-0.144341
1	-0.861602	-0.765152	-0.749015	-0.87708
2	1.552838	0.764988	1.034163	0.533102
3	-0.513328	-0.662169	-0.736369	-0.766482
4	-0.869428	-0.877197	-0.970332	-0.904736
12718	-0.247231	-0.201970	-0.597255	-0.227293
12719	-1.018130	-0.788207	-0.989302	-0.918561
12720	0.394533	-0.466688	0.661086	-0.420848
12721	0.104957	0.865940	0.547267	1.390274
12722	0.128436	-0.086534	0.616823	-0.144341
12723 rd	ows × 9 columns			

trip[num_cols].describe()

	start_scan_to_end_scan	${\tt actual_distance_to_destination}$	actual_time	osrm_time	osrm_distance	segment_actual_time_sum
count	1.272300e+04	1.272300e+04	1.272300e+04	1.272300e+04	1.272300e+04	1.272300e+04
mean	-1.619566e-17	-7.371818e-17	-8.041983e-17	4.467769e-17	3.797603e-17	-3.127438e-17
std	1.000039e+00	1.000039e+00	1.000039e+00	1.000039e+00	1.000039e+00	1.000039e+00
min	-1.162918e+00	-8.785574e-01	-1.065181e+00	-1.001514e+00	-9.229378e-01	-1.061764e+00
25%	-7.207269e-01	-7.065920e-01	-7.363685e-01	-7.111809e-01	-7.077649e-01	-7.371165e-01
50%	-3.411472e-01	-4.689012e-01	-4.012322e-01	-3.931975e-01	-4.836339e-01	-3.997380e-01
75%	4.023595e-01	4.073375e-01	4.650634e-01	4.224989e-01	4.419548e-01	4.596223e-01
max	4.049455e+00	4.178358e+00	4.031419e+00	4.113871e+00	4.150641e+00	4.037107e+00

Recommendation:

· Routing Engine Discrepancies:

The data indicates a noticeable variance between the output from the Open Source Routing Machine (OSRM) and the actual parameters. It is imperative to review the input information provided to the routing engine for trip planning. Additionally, a thorough examination of potential disparities with transporters is recommended to ensure the routing engine is configured for optimal results.

• Traffic Disparities Across Zones:

Analyzing the traffic patterns reveals significant order flow in the North, South, and West Zones, while the Central, Eastern, and North-Eastern zones exhibit comparatively lower activity. While this observation may need validation over a more extended period, it suggests an opportunity to explore and enhance our presence in these less-explored regions.

• Strategic Resource Allocation:

State-wise analysis highlights Maharashtra as a region with heavy order traffic, closely followed by Karnataka. This insight serves as a strategic indicator, emphasizing the need for prioritized resource planning and on-ground presence in these two states, particularly during festive seasons.