Packages

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
import scipy.stats as st

pd.set_option("display.max_columns",50)
```

Loading Data

```
data=pd.read_csv("/content/delhivery_data.txt")
data.head()
```

e_to_destination	actual_time	osrm_time	osrm_distance	factor	segment_actual_time	segment_osrm_time	segment_osrm_(
10.435660	14.0	11.0	11.9653	1.272727	14.0	11.0	
18.936842	24.0	20.0	21.7243	1.200000	10.0	9.0	
36.118028	62.0	40.0	45.5620	1.550000	21.0	12.0	

Problem Statement:

Make the data suitable for building forecasting models on it by cleaning and doing feature engineering.

Exploratory Data Analysis

Shape of the data:

Number of rows and columns

```
print("Number of rows: ",data.shape[0])
print("Number of columns: ",data.shape[1])
```

```
Number of rows:  5460
Number of columns:  24
```

Summary statistics

```
data.describe()
```

	start_scan_to_end_scan	cutoff_factor	actual_distance_to_destination	actual_time	osrm_time	osrm_distance
count	5459.000000	5459.000000	5459.000000	5459.000000	5459.000000	5459.000000
mean	880.768273	215.867558	216.970249	381.978934	201.280821	265.342989
std	992.546724	336.202581	336.418659	565.798027	305.279616	414.603425
min	25.000000	9.000000	9.000267	9.000000	6.000000	9.202000
25%	148.000000	22.000000	22.948256	49.000000	26.000000	28.757800
50%	379.000000	54.000000	54.442149	116.000000	58.000000	70.677700
75%	1285.000000	242.000000	242.572677	439.500000	220.500000	288.167050
max	3230.000000	1690.000000	1690.302865	2873.000000	1549.000000	2095.672900

Every numerical column has outliers as there is a significant difference between **mean** and **median**(50% quartile)

The minimum value in **segment_actual_time** time taken by the subset of the package delivery is negative.It does not make sense that the time would be negative.

Also **segment_factor** contains negative values

```
# Count the number of rows having segment_actual_time is negative
print("Number of rows having segment_actual_time are negative: ",data[data['segment_actual_time']<0].shape[0])
```

```
Number of rows having segment_actual_time are negative:  3
```

```
# get the sense of negative data in segment_actual_time
data[data['segment_actual_time']<0]['segment_actual_time']
```

```
1805   -26.0
3761   -21.0
4040    -5.0
Name: segment_actual_time, dtype: float64
```

```
# convert the negative values in segment_actual_time into positive
data['segment_actual_time']=np.absolute(data['segment_actual_time'])
```

```
data[data['segment_factor']<0]['segment_factor']
```

```
47     -1.0
54     -1.0
90     -1.0
164    -1.0
224    -1.0
       ...
5222   -1.0
5264   -1.0
5268   -1.0
5310   -1.0
5420   -1.0
Name: segment_factor, Length: 88, dtype: float64
```

Data types of every column

```
print("Data types:\n",data.dtypes)
```

```
Data types:
 data                              object
trip_creation_time                object
route_schedule_uuid               object
route_type                        object
trip_uuid                         object
source_center                     object
source_name                       object
```

```
destination_center                 object
destination_name                   object
od_start_time                      object
od_end_time                        object
start_scan_to_end_scan            float64
is_cutoff                          object
cutoff_factor                     float64
cutoff_timestamp                   object
actual_distance_to_destination    float64
actual_time                       float64
osrm_time                         float64
osrm_distance                     float64
factor                            float64
segment_actual_time               float64
segment_osrm_time                 float64
segment_osrm_distance             float64
segment_factor                    float64
dtype: object
```

There are couple of attributes whose data type is object.We can convert them into category

Basic information of the dataset

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5460 entries, 0 to 5459
Data columns (total 24 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   data                            5460 non-null   object 
 1   trip_creation_time              5460 non-null   object 
 2   route_schedule_uuid             5460 non-null   object 
 3   route_type                      5459 non-null   object 
 4   trip_uuid                       5459 non-null   object 
 5   source_center                   5459 non-null   object 
```

```
 6   source_name                     5438 non-null   object
 7   destination_center              5459 non-null   object
 8   destination_name                5451 non-null   object
 9   od_start_time                   5459 non-null   object
 10  od_end_time                     5459 non-null   object
 11  start_scan_to_end_scan          5459 non-null   float64
 12  is_cutoff                       5459 non-null   object
 13  cutoff_factor                   5459 non-null   float64
 14  cutoff_timestamp                5459 non-null   object
 15  actual_distance_to_destination  5459 non-null   float64
 16  actual_time                     5459 non-null   float64
 17  osrm_time                       5459 non-null   float64
 18  osrm_distance                   5459 non-null   float64
 19  factor                          5459 non-null   float64
 20  segment_actual_time             5459 non-null   float64
 21  segment_osrm_time               5459 non-null   float64
 22  segment_osrm_distance           5459 non-null   float64
 23  segment_factor                  5459 non-null   float64
dtypes: float64(11), object(13)
memory usage: 1023.9+ KB
```

The memory usage of the data is more than 25 MB

Converting some attributes into "category" data type

```
data['route_type']=data['route_type'].astype("category")
data['is_cutoff']=data['is_cutoff'].astype("category")
```

Convert some of the attributes into date time object

```
cols_datetime=['trip_creation_time','od_start_time','od_end_time','cutoff_timestamp']
for col in cols_datetime:
```

```
    data[col]=pd.to_datetime(data[col],infer_datetime_format=True)
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5460 entries, 0 to 5459
Data columns (total 24 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   data                            5460 non-null   object
 1   trip_creation_time              5460 non-null   datetime64[ns]
 2   route_schedule_uuid             5460 non-null   object
 3   route_type                      5459 non-null   category
 4   trip_uuid                       5459 non-null   object
 5   source_center                   5459 non-null   object
 6   source_name                     5438 non-null   object
 7   destination_center              5459 non-null   object
 8   destination_name                5451 non-null   object
 9   od_start_time                   5459 non-null   datetime64[ns]
 10  od_end_time                     5459 non-null   datetime64[ns]
 11  start_scan_to_end_scan          5459 non-null   float64
 12  is_cutoff                       5459 non-null   category
 13  cutoff_factor                   5459 non-null   float64
 14  cutoff_timestamp                5459 non-null   datetime64[ns]
 15  actual_distance_to_destination  5459 non-null   float64
 16  actual_time                     5459 non-null   float64
 17  osrm_time                       5459 non-null   float64
 18  osrm_distance                   5459 non-null   float64
 19  factor                          5459 non-null   float64
 20  segment_actual_time             5459 non-null   float64
 21  segment_osrm_time               5459 non-null   float64
 22  segment_osrm_distance           5459 non-null   float64
 23  segment_factor                  5459 non-null   float64
dtypes: category(2), datetime64[ns](4), float64(11), object(7)
memory usage: 949.5+ KB
```

After converting into category data type the memory usage reduced to 20.5 MB

Detecting Missing Values

```
data.isna().sum()
```

```
data                               0
trip_creation_time                 0
route_schedule_uuid                0
route_type                         1
trip_uuid                          1
source_center                      1
source_name                       22
destination_center                 1
destination_name                   9
od_start_time                      1
od_end_time                        1
start_scan_to_end_scan             1
is_cutoff                          1
cutoff_factor                      1
cutoff_timestamp                   1
actual_distance_to_destination     1
actual_time                        1
osrm_time                          1
osrm_distance                      1
factor                             1
segment_actual_time                1
segment_osrm_time                  1
segment_osrm_distance              1
segment_factor                     1
dtype: int64
```

Two attributes have missing values.Namely **source_name** and **destination_name**

Missing value treatment:

Here some values in **source_name** and **destination_name** are missing.There are some rows where **source_name** is missing but **destination_name** is there.If we impute missing values using most frequent or other or something else.It does not make sense as the reason for missing values could be technical glitch.Therefore it is better to drop all the missing rows.IT will not hurt the dataset as the dataset has more than 100k data-points

```
data.dropna(how="any",inplace=True)
```

```
data.shape
```

```
(5430, 24)
```

The original dataset has 144867 rows whereas after removing rows that having missing values the size of the dataset reduced to 144316.So the data is almost not affected by na values removal.

Feature Creation and Merging of rows and aggregation of fields

Aggregation based on these attributes

1.Trip_uuid, Source ID(Source Center) and Destination ID(Destination Center)

2.Trip_uuid

```
# drop all the unknown fields
#is_cutoff – Unknown field
#cutoff_factor – Unknown field
```

```
#cutoff_timestamp – Unknown field
#factor – Unknown field
#segment_factor – Unknown field
# Also drop "data" column as we are not building a machine learning model ,therefore there is no need of keeping
# it
data.drop(["data","is_cutoff","cutoff_factor","cutoff_timestamp","factor","segment_factor"],axis=1,inplace=True)
```

Segment related attributes in group by should be summed up using cummulative sum as these are segments(sub-trip)

```
data['sub_trip_group']=data['trip_uuid']+data['source_center']+data['destination_center']
data['segment_actual_time_total']=data.groupby("sub_trip_group").agg({'segment_actual_time':np.cumsum})
data['segment_osrm_time_total']=data.groupby("sub_trip_group").agg({'segment_osrm_time':np.cumsum})
data['segment_osrm_distance_total']=data.groupby("sub_trip_group").agg({'segment_osrm_distance':np.cumsum})
```

Now group by and filter the whole dataset.Take the last value of new created columns as these are cummulative sum

```
data_sub_trip=data.groupby('sub_trip_group').agg({'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':'last',
```

```
                                             'actual_distance_to_destination':'last',
                                             'actual_time':'last',
                                             'osrm_time':'first',
                                             'osrm_distance':'first',
                                             'segment_actual_time_total':'last',
                                             'segment_osrm_time_total':'last',
                                             'segment_osrm_distance_total':'last'

}).reset_index(drop=True)
```

The time taken between od_start_time and od_end_time:

A new feature

```
# time taken in minutes
data_sub_trip['od_start_end_time_minute']=((data_sub_trip['od_end_time']-data_sub_trip['od_start_time']).dt.total_seconds
```

```
# there is no need of keeping attributes:
# od_start_time
# od_end_time
data_sub_trip.drop(['od_start_time','od_end_time'],axis=1,inplace=True)
```

Now aggregate based on trip_uuid to get the information for each trip

```
data_trip=data_sub_trip.groupby('trip_uuid').agg({'trip_creation_time':'first',
                                             'route_schedule_uuid':'first',
                                             'route_type':'first',
                                             'source_center':'first',
                                             'source_name':'first',
                                             'destination_center':'last',
                                             'destination_name':'last',
```

```
                                    'start_scan_to_end_scan':np.sum,
                                    'od_start_end_time_minute':np.sum,
                                    'actual_distance_to_destination':np.sum,
                                    'actual_time':np.sum,
                                    'osrm_time':np.sum,
                                    'osrm_distance':np.sum,
                                    'segment_actual_time_total':np.sum,
                                    'segment_osrm_time_total':np.sum,
                                    'segment_osrm_distance_total':np.sum

}).reset_index(drop=True)

data_trip.head()
```

	trip_creation_time	route_schedule_uuid	route_type	source_center	source_name	destination_center	dest
0	2018-09-12 00:25:19.499696	thanos::sroute:0ac760f3-96cb-4046-bfd0-8bc4678...	FTL	IND487001AAB	Narsinghpur_KndliDPP_D (Madhya Pradesh)	IND464668AAA	Bar (M
1	2018-09-12 00:32:55.970840	thanos::sroute:db0f8027-8ade-4411-9aff-b26adaa...	Carting	IND785690AAB	Sonari_Central_DPP_1 (Assam)	IND785682AAA	Sivasa
2	2018-09-12 00:46:48.079257	thanos::sroute:8c5ab716-198a-4395-b83f-5672773...	Carting	IND121004AAB	FBD_Balabhgarh_DPC (Haryana)	IND121004AAB	FBD_E
3	2018-09-12 01:24:59.938573	thanos::sroute:82facc11-0f66-496b-9d39-fa3891f...	FTL	IND384205AAA	Mehsana_Panchot_IP (Gujarat)	IND384205AAA	Mehs
4	2018-09-12 01:33:48.711350	thanos::sroute:5f7d8d49-ae14-430e-9333-37361e1...	Carting	IND362001AAA	Junagadh_DPC (Gujarat)	IND362560AAA	Ur

Feature creation based on the attributes **Destination Name,Source Name,Trip_creation_time**

```
data_trip['destination_name'][data_trip['destination_name'].str.split("_").str.len()==1] # checking how destination look
```

```
7                       Erode (Tamil Nadu)
10                Mumbai Hub (Maharashtra)
14                      Palwal (Haryana)
31        Bhopal MP Nagar (Madhya Pradesh)
37                Mumbai Hub (Maharashtra)
53                  Meerut (Uttar Pradesh)
65                     Janakpuri (Delhi)
98                Mumbai Hub (Maharashtra)
120           PNQ Pashan DPC (Maharashtra)
124                     Patiala (Punjab)
162             HBR Layout PC (Karnataka)
172               Mumbai Hub (Maharashtra)
187                    Janakpuri (Delhi)
188     PNQ Vadgaon Sheri DPC (Maharashtra)
195                     Erode (Tamil Nadu)
204               Mumbai Hub (Maharashtra)
222               Mumbai Hub (Maharashtra)
226               Mumbai Hub (Maharashtra)
273               Mumbai Hub (Maharashtra)
289               Mumbai Hub (Maharashtra)
291       Bhopal MP Nagar (Madhya Pradesh)
298                   Jaipur (Rajasthan)
305               Bareilly (Uttar Pradesh)
319           PNQ Pashan DPC (Maharashtra)
340     PNQ Vadgaon Sheri DPC (Maharashtra)
449               Mumbai Hub (Maharashtra)
475             HBR Layout PC (Karnataka)
510                     Palwal (Haryana)
552     PNQ Vadgaon Sheri DPC (Maharashtra)
563                     Palwal (Haryana)
```

```
576                       Karnal (Haryana)
Name: destination_name, dtype: object
```

```
data_trip['destination_name'][data_trip['destination_name'].str.split("_").str.len()==2] # checking how destination look
```

```
23       Chennai_Hub (Tamil Nadu)
45          Amritsar_DPC (Punjab)
63       Chennai_Hub (Tamil Nadu)
107        Jaipur_Hub (Rajasthan)
135      Chennai_Hub (Tamil Nadu)
139            GGN_DPC (Haryana)
144            Surat_HUB (Gujarat)
151             Raikot_DC (Punjab)
156           Guwahati_Hub (Assam)
205            Surat_HUB (Gujarat)
211            Tonk_DC (Rajasthan)
221              GGN_DPC (Haryana)
224          Amritsar_DPC (Punjab)
236         Amdavad_East (Gujarat)
268       Hooghly_DC (West Bengal)
272        Ambabadi_DC (Rajasthan)
292              Bhuj_DC (Gujarat)
296              GGN_DPC (Haryana)
301          Bhatinda_DPC (Punjab)
311       Bharatpur_DC (Rajasthan)
313           Guwahati_Hub (Assam)
323             Anjar_DC (Gujarat)
358            Surat_HUB (Gujarat)
367      Bhubaneshwar_Hub (Orissa)
371                  Goa_Hub (Goa)
373       Chennai_Hub (Tamil Nadu)
401         AMD_Memnagar (Gujarat)
425       Guwahati_Sixmile (Assam)
427       Chennai_Hub (Tamil Nadu)
455             Dahod_DC (Gujarat)
470                 OK_RPC (Delhi)
474              Moga_DPC (Punjab)
485             Raikot_DC (Punjab)
493              GGN_DPC (Haryana)
527     Rishikesh_DC (Uttarakhand)
535       Hooghly_DC (West Bengal)
```

```
542          Guwahati_Hub (Assam)
543                OK_RPC (Delhi)
Name: destination_name, dtype: object
```

```
data_trip['destination_name'][data_trip['destination_name'].str.split("_").str.len()==3] # checking how destination look
```

```
0       Bareli_SourvDPP_D (Madhya Pradesh)
1             Sivasagar_Babupaty_D (Assam)
2             FBD_Balabhgarh_DPC (Haryana)
3             Mehsana_Panchot_IP (Gujarat)
4                Una_Mamlatdr_DC (Gujarat)
                      ...
577         Nedumangad_Arsprmbu_D (Kerala)
578            Muzaffrpur_Bbganj_I (Bihar)
580         Radhanpur_Santalpr_D (Gujarat)
581    Chalisgaon_BhadgDPP_D (Maharashtra)
583       Chennai_Thiruvlr_DC (Tamil Nadu)
Name: destination_name, Length: 457, dtype: object
```

```
data_trip['source_name'][data_trip['source_name'].str.split("_").str.len()==1] # checking how destination look likes
```

```
16                Mumbai Hub (Maharashtra)
31         Bhopal MP Nagar (Madhya Pradesh)
34     PNQ Vadgaon Sheri DPC (Maharashtra)
105               HBR Layout PC (Karnataka)
115                Mumbai Hub (Maharashtra)
124                        Patiala (Punjab)
149                      Jaipur (Rajasthan)
176            Vijayawada (Andhra Pradesh)
189                     Faridabad (Haryana)
197                Mumbai Hub (Maharashtra)
330               HBR Layout PC (Karnataka)
349                Mumbai Hub (Maharashtra)
350                     Faridabad (Haryana)
352                      Salem (Tamil Nadu)
380                Mumbai Hub (Maharashtra)
390                Mumbai Hub (Maharashtra)
412                        Patiala (Punjab)
512                      Vadodara (Gujarat)
```

```
554                Mumbai Hub (Maharashtra)
Name: source_name, dtype: object
```

```
data_trip['source_name'][data_trip['source_name'].str.split("_").str.len()==2] # checking how destination look likes
```

```
4                Junagadh_DPC (Gujarat)
36              Chennai_Hub (Tamil Nadu)
63              Chennai_Hub (Tamil Nadu)
70           LowerParel_CP (Maharashtra)
88      Chennai_Poonamallee (Tamil Nadu)
154             Chennai_Hub (Tamil Nadu)
156              Guwahati_North (Assam)
166          Chittaurgarh_DC (Rajasthan)
172          LowerParel_CP (Maharashtra)
174         Kakinada_DC (Andhra Pradesh)
202                Pune_PC (Maharashtra)
206         Kakinada_DC (Andhra Pradesh)
223                Pune_PC (Maharashtra)
225              Ranchi_Hub (Jharkhand)
233         Kakinada_DC (Andhra Pradesh)
236                AMD_Rakhial (Gujarat)
259                        Goa_Hub (Goa)
287      Bhubaneshwar_Nayapalli (Orissa)
292                   Anjar_DC (Gujarat)
304          LowerParel_CP (Maharashtra)
323                    Bhuj_DC (Gujarat)
329                    GGN_DPC (Haryana)
341              Jaipur_Hub (Rajasthan)
362          LowerParel_CP (Maharashtra)
372              Jaipur_Hub (Rajasthan)
374              Ranchi_Hub (Jharkhand)
400             Gandhinagar_DC (Gujarat)
401               AMD_Memnagar (Gujarat)
408             Chennai_Hub (Tamil Nadu)
425                Guwahati_Hub (Assam)
444             Chennai_Hub (Tamil Nadu)
452              Jaipur_Hub (Rajasthan)
472              Jaipur_Hub (Rajasthan)
474                    Moga_DPC (Punjab)
```

```
476      Jalandhar_Sodal Road (Punjab)
526             Jaipur_Hub (Rajasthan)
535           Hooghly_DC (West Bengal)
542               Guwahati_Hub (Assam)
545          Bhubaneshwar_Hub (Orissa)
547             CCU_Hub (West Bengal)
548             Jaipur_Hub (Rajasthan)
551                  GGN_DPC (Haryana)
571         Ganga Nagar_DC (Rajasthan)
573        LowerParel_CP (Maharashtra)
576               Panipat_PC (Haryana)
580                 Unjha_DC (Gujarat)
Name: source_name, dtype: object
```

```
data_trip['source_name'][data_trip['source_name'].str.split("_").str.len()==3] # checking how destination look likes
```

```
0      Narsinghpur_KndliDPP_D (Madhya Pradesh)
2                 FBD_Balabhgarh_DPC (Haryana)
3                 Mehsana_Panchot_IP (Gujarat)
5                      Delhi_Airport_H (Delhi)
6             Dinhata_WrdN4DPP_D (West Bengal)
                        ...
578                Muzaffrpur_Bbganj_I (Bihar)
579                Ahmedabad_Paldi_D (Gujarat)
581             Dhule_MIDCAvdn_I (Maharashtra)
582           Hapur_Swargash_D (Uttar Pradesh)
583             Chennai_Porur_DPC (Tamil Nadu)
Name: source_name, Length: 470, dtype: object
```

```
# utility functions to extract state,city,place,and code
def extract_state(x):
  # x is a string
  # eg: x is like "Kanpur_Central_H_6 (Uttar Pradesh)"
  idx=x.index("(") # index of "("
  state=x[idx+1:-1] # removing )
  return state

def extract_city(x):
```

```
    # x is a string like "Kanpur_Central_H_6 (Uttar Pradesh)"
    # it can also be like PNQ Rahatani DPC (Maharashtra)
      x=x[:x.index("(")].strip() # removing state and extra space
      x=x.split("_") # split based on "_"
      if len(x)==1:
        if x[0].lower()=='pnq vadgaon sheri dpc':
          return 'Vadgaonsheri'
        if x[0].lower() in ['pnq pashan dpc','pnq rahatani dpc', 'pune balaji nagar']:
          return "Pune"
        if x[0].lower()=='hbr layout pc':
          return "Bengaluru"
        if x[0].lower()=="bhopal mp nagar":
          return "Bhopal"
        if x[0].lower()=="mumbai antop hill":
          return "Mumbai"
        return x[0]
      return x[0]


  def extract_place(x):
    x=x[:x.index("(")].strip() # remove state and extra space
    x=x.split("_")
    # no city name
    if len(x)==1:
      return x[0]

    if len(x)>=3:
      return x[1]
    # city name and place name same
    if len(x)==2:
      return x[0]

  def extract_code(x):
    x=x[:x.index("(")].strip() # remove state and extra space
    x=x.split("_")

    if len(x)>=2:
```

```
        return x[-1]
    return "none" # no code
```

Destination Name:

```
data_trip['destination_state']=data_trip['destination_name'].apply(extract_state)
data_trip['destination_city']=data_trip['destination_name'].apply(extract_city)
data_trip['destination_place']=data_trip['destination_name'].apply(extract_place)
data_trip['destination_code']=data_trip['destination_name'].apply(extract_code)
```

```
data_trip[['destination_name','destination_state','destination_city','destination_place','destination_code']].head()
```

	destination_name	destination_state	destination_city	destination_place	destination_code
0	Bareli_SourvDPP_D (Madhya Pradesh)	Madhya Pradesh	Bareli	SourvDPP	D
1	Sivasagar_Babupaty_D (Assam)	Assam	Sivasagar	Babupaty	D
2	FBD_Balabhgarh_DPC (Haryana)	Haryana	FBD	Balabhgarh	DPC
3	Mehsana_Panchot_IP (Gujarat)	Gujarat	Mehsana	Panchot	IP
4	Una_Mamlatdr_DC (Gujarat)	Gujarat	Una	Mamlatdr	DC

Source Name

```
data_trip['source_state']=data_trip['source_name'].apply(extract_state)
data_trip['source_city']=data_trip['source_name'].apply(extract_city)
data_trip['source_place']=data_trip['source_name'].apply(extract_place)
```

```
data_trip['source_code']=data_trip['source_name'].apply(extract_code)
```

```
data_trip[['source_name','source_state','source_city','source_place','source_code']].head()
```

	source_name	source_state	source_city	source_place	source_code
0	Narsinghpur_KndliDPP_D (Madhya Pradesh)	Madhya Pradesh	Narsinghpur	KndliDPP	D
1	Sonari_Central_DPP_1 (Assam)	Assam	Sonari	Central	1
2	FBD_Balabhgarh_DPC (Haryana)	Haryana	FBD	Balabhgarh	DPC
3	Mehsana_Panchot_IP (Gujarat)	Gujarat	Mehsana	Panchot	IP
4	Junagadh_DPC (Gujarat)	Gujarat	Junagadh	Junagadh	DPC

Trip_creation_time: Extract features like month, year and day etc

```
data_trip['trip_creation_year']=data_trip['trip_creation_time'].dt.year
data_trip['trip_creation_month']=data_trip['trip_creation_time'].dt.month
data_trip['trip_creation_day']=data_trip['trip_creation_time'].dt.day
data_trip['trip_creation_week']=data_trip['trip_creation_time'].dt.isocalendar().week
data_trip['trip_creation_dayofweek']=data_trip['trip_creation_time'].dt.dayofweek
```

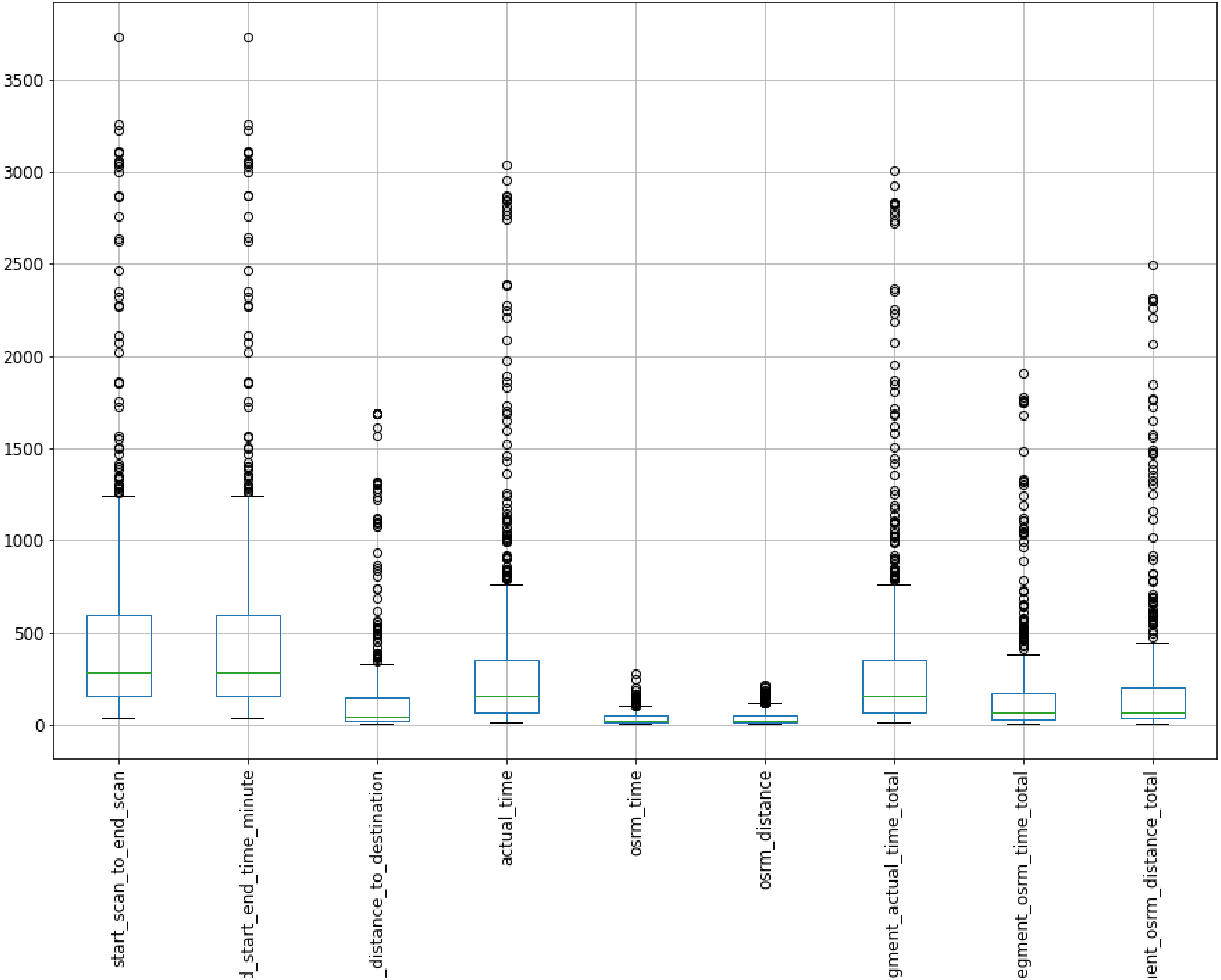
```
# drop columns trip_creation_time,destination_name,source_name
data_trip.drop(['trip_creation_time','source_name','destination_name'],axis=1,inplace=True)
```

```
data_trip.head()
```

	route_schedule_uuid	route_type	source_center	destination_center	start_scan_to_end_scan	od_start_end_time_minu
0	thanos::sroute:0ac760f3-96cb-4046-bfd0-8bc4678...	FTL	IND487001AAB	IND464668AAA	290.0	290.6622
1	thanos::sroute:db0f8027-8ade-4411-9aff-b26adaa...	Carting	IND785690AAB	IND785682AAA	252.0	252.0769
2	thanos::sroute:8c5ab716-198a-4395-b83f-5672773...	Carting	IND121004AAB	IND121004AAB	259.0	260.4358
3	thanos::sroute:82facc11-0f66-496b-9d39-fa3891f...	FTL	IND384205AAA	IND384205AAA	562.0	563.8168
4	thanos::sroute:5f7d8d49-ae14-430e-9333-37361e1...	Carting	IND362001AAA	IND362560AAA	473.0	475.1951

Outliers detection using boxplot and removing them using IQR:

```
cols_with_outliers=['start_scan_to_end_scan',
       'od_start_end_time_minute', 'actual_distance_to_destination',
       'actual_time', 'osrm_time', 'osrm_distance',
       'segment_actual_time_total', 'segment_osrm_time_total',
       'segment_osrm_distance_total']
fig,ax=plt.subplots(figsize=(15,10))
data_trip[cols_with_outliers].boxplot(rot=90,ax=ax,fontsize='large')
plt.show()
```


3500
3000
2500
2000
1500
1000
500
0
start_scan_to_end_scan
d_start_end_time_minute
_distance_to_destination
actual_time
osrm_time
osrm_distance
gment_actual_time_total
egment_osrm_time_total
ıent_osrm_distance_total

According to box-plot all the numerical columns have outliers

```
# handling outliers
Q1 = data_trip[cols_with_outliers].quantile(0.25) # first quantile
Q3 = data_trip[cols_with_outliers].quantile(0.75) # third quantile

IQR = Q3 - Q1 # inter-quantile range

data_trip = data_trip[~((data_trip[cols_with_outliers] < (Q1 - 1.5 * IQR)) | (data_trip[cols_with_outliers] > (Q3 + 1.5 *
```

Range of values for some of the attributes

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

```
FTL        3714
Carting    1716
Name: route_type, dtype: int64
```

```
sns.countplot(x='route_type',data=data_trip)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f08aedf21d0>
```

There are only two types of route.**FTL** being in heighest number.

```
data_trip.describe()
```

	start_scan_to_end_scan	od_start_end_time_minute	actual_distance_to_destination	actual_time	osrm_time	osrm_
count	477.000000	477.000000	477.000000	477.000000	477.000000	
mean	290.121593	290.921408	63.867098	160.368973	26.834382	
std	211.280554	211.514831	61.398939	135.660856	21.752906	
min	34.000000	34.522275	9.169091	13.000000	6.000000	
25%	138.000000	138.528613	21.264406	62.000000	12.000000	
50%	225.000000	225.162093	36.008738	112.000000	18.000000	
75%	393.000000	394.080267	93.965201	227.000000	34.000000	
max	1216.000000	1218.061670	308.977925	761.000000	101.000000	

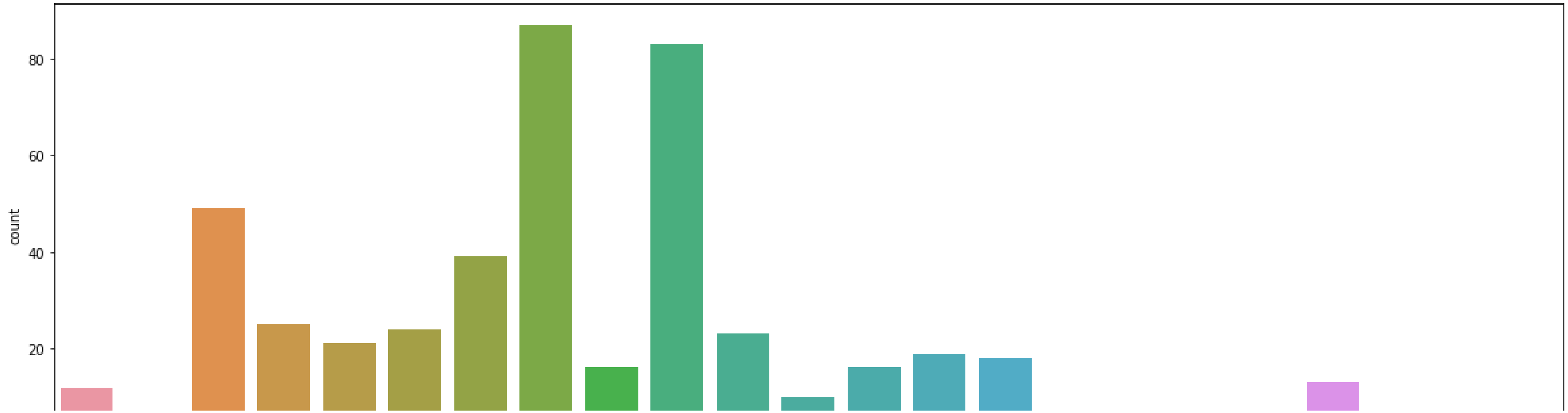
The minimum amd maximum times for start_scan_to_end_scan are 34 and 3230 respectively.So there is a huge gap between these two values.On the other hand the min and max values for od_start_end_time_minute are very close to the scan times.

```
data_trip['destination_state'].value_counts()
```

```
Maharashtra        87
Karnataka          83
```

```
Haryana            49
Tamil Nadu         39
Gujarat            25
West Bengal        24
Delhi              23
Uttar Pradesh      21
Punjab             19
Telangana          18
Rajasthan          16
Andhra Pradesh     16
Kerala             13
Madhya Pradesh     12
Bihar              10
Assam               6
Jharkhand           4
Orissa              4
Chhattisgarh        2
Uttarakhand         2
Goa                 2
Jammu & Kashmir     1
Chandigarh          1
Name: destination_state, dtype: int64
```

```
fig,ax=plt.subplots(figsize=(20,6))
ax=sns.countplot(x='destination_state',data=data_trip)
plt.xticks(rotation=90)
plt.show()
```



Business Insights:

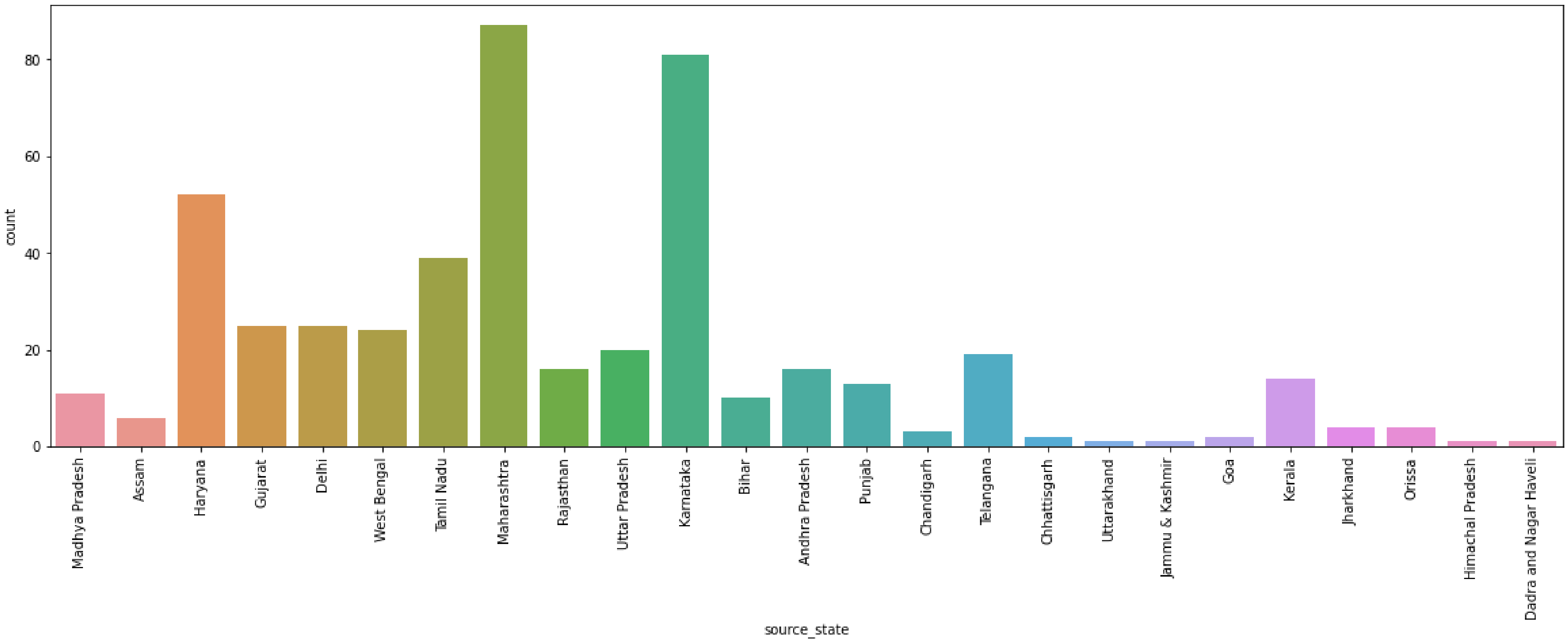
1. Maharashtra being heighest in terms of delivery then followed by Karnataka.Lowest is the chhattisgarh.
2. The north,west and south corridors have heavy trafic of orders.
3. On the other hand the central corridor,east and north eastern (states like Delhi,Chhattisgarh,Uttrakhand,Goa,etc) have less traffic of orders.

```
data_trip['trip_creation_year'].value_counts()
```

```
2018    477
Name: trip_creation_year, dtype: int64
```

The delivery are only from the year **2018**

```
fig,ax=plt.subplots(figsize=(20,6))
ax=sns.countplot(x='source_state',data=data_trip)
plt.xticks(rotation=90)
plt.show()
```

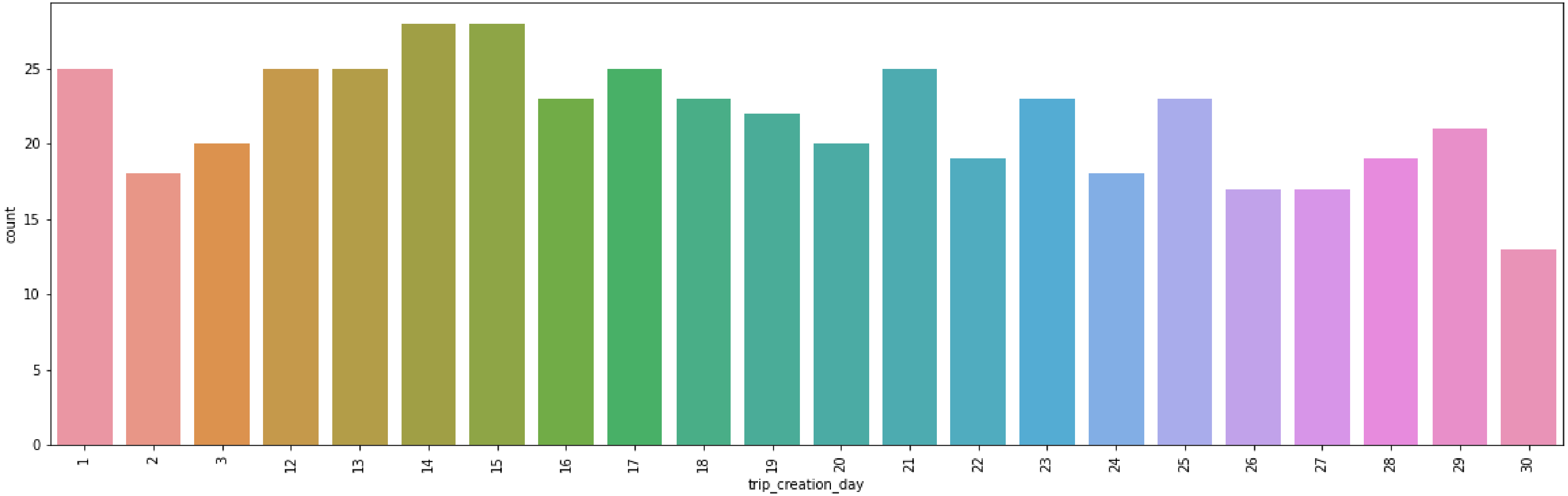


Business Insights:

1. **Maharashtra** being heighest in terms of producing products.
2. There are many states (Uttrakhand,Himachal Pradesh,Goa,etc) with very less of presence of products.

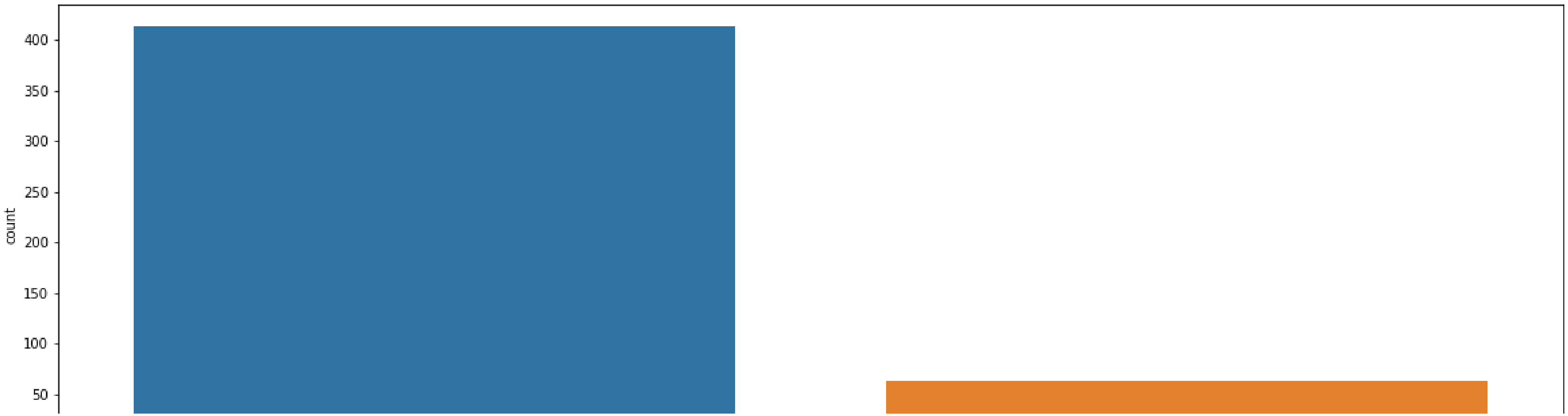
```
fig,ax=plt.subplots(figsize=(20,6))
ax=sns.countplot(x='trip_creation_day',data=data_trip)
```

```
plt.xticks(rotation=90)
plt.show()
```



Business Insights: Its surprising that the most of the trip(deliveries) created bteween day 12 and day 30

```
fig,ax=plt.subplots(figsize=(20,6))
ax=sns.countplot(x='trip_creation_month',data=data_trip)
plt.xticks(rotation=90)
plt.show()
```

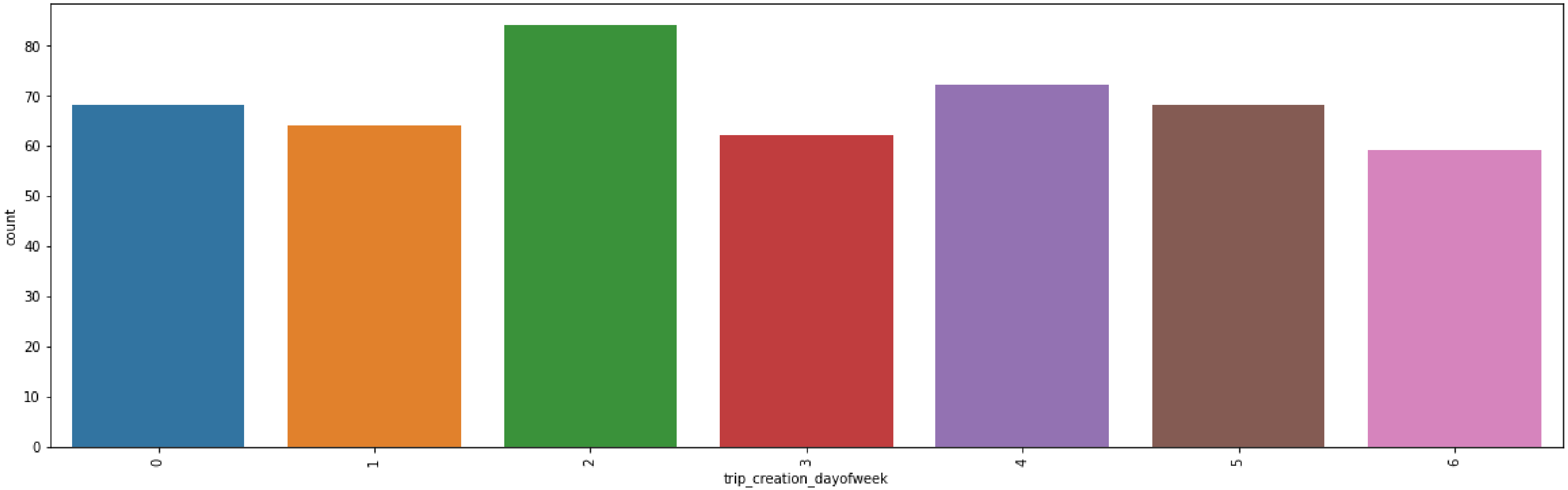


Business Insights:This is strange the most of the deliveries made on september

```
fig,ax=plt.subplots(figsize=(20,6))
ax=sns.countplot(x='trip_creation_week',data=data_trip)
plt.xticks(rotation=90)
plt.show()
```

Business Insights: Its surprising that the weeks other than 37,38,39,and 40 no deliveries made.This could be due to the fact of collection of data.

```
fig,ax=plt.subplots(figsize=(20,6))
ax=sns.countplot(x='trip_creation_dayofweek',data=data_trip)
plt.xticks(rotation=90)
plt.show()
```



Business Insights: Everyday of a week more or less has same number of deliveries

Handling Categorical Values:

Hnadling some of the attributes like destination_state,route_type,source_state,etc

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

```
# converting destination state into numerical values
# using probability frequency
dest_dict=data_trip['destination_state'].value_counts().to_dict()
total_count=sum(dest_dict.values())
for key in dest_dict:
  dest_dict[key]=dest_dict[key]/total_count # calculate probability
data_trip['destination_state_encoded']=data_trip['destination_state'].map(dest_dict)
```

```
# similarly do for source state
source_dict=data_trip['source_state'].value_counts().to_dict()
total_count=sum(source_dict.values())
for key in source_dict:
  source_dict[key]=source_dict[key]/total_count # calculate probability
data_trip['source_state_encoded']=data_trip['source_state'].map(source_dict)
```

```
data_trip.destination_state_encoded.head()
```

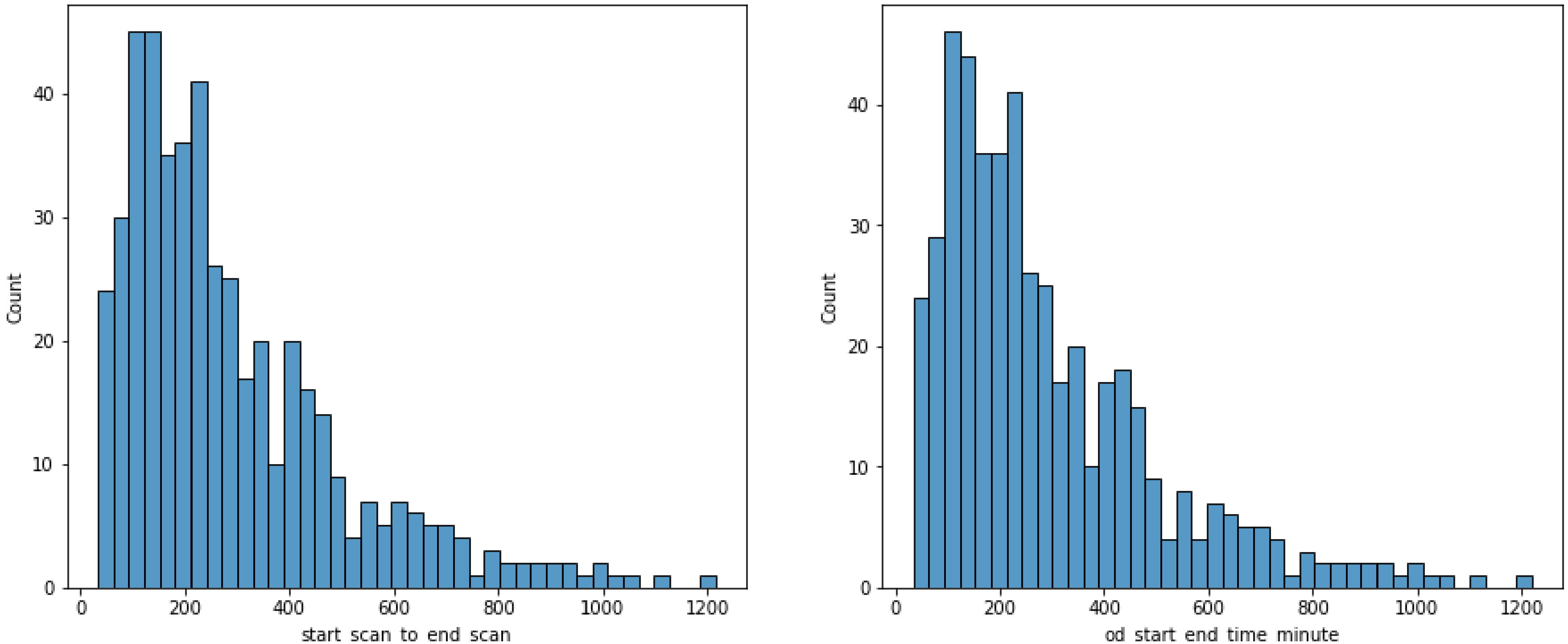
```
0    0.025157
1    0.012579
2    0.102725
3    0.052411
4    0.052411
Name: destination_state_encoded, dtype: float64
```

Checking relationship between aggregated fields and hypothesis testing

Hypothesis testing between start_scan_to_end_scan and time difference of od_start_time and od_end_time

And visualization: histogram

```
fig,ax=plt.subplots(nrows=1,ncols=2,figsize=(15,6))
ax=ax.flatten()
sns.histplot(x='start_scan_to_end_scan',data=data_trip,ax=ax[0],bins=40)
sns.histplot(x='od_start_end_time_minute',data=data_trip,ax=ax[1],bins=40)
plt.show()
```



Great resemblance between the two histograms.From histogram it is clear that the data has still some sort of outliers.But we can live this.

confidence interval for both **scan time and od time**

```
# find confidence interval
means_scan=[]
means_od=[]
nsim=1000 # 100 bootstrap simulations
sample_size=100 # sample size is 100
for _ in range(nsim):
  sample=data_trip['start_scan_to_end_scan'].sample(sample_size)
  means_scan.append(sum(sample)/len(sample))

  sample=data_trip['od_start_end_time_minute'].sample(sample_size)
  means_od.append(sum(sample)/len(sample))


# confidence interval for means
interval_scan=[np.percentile(means_scan,2.5),np.percentile(means_scan,97.5)] # 2.5th and 97.5th percentiles ,with 5% leve
interval_od=[np.percentile(means_od,2.5),np.percentile(means_od,97.5)]

print("Confidence interval for the mean of scan time: ",interval_scan)

print("Confidence interval for the mean of od time: ",interval_od)
```

```
Confidence interval for the mean of scan time:  [255.33325, 326.495]
Confidence interval for the mean of od time:  [254.23816766421683, 332.2286531487792]
```

The 95% confidence interval for both scan time and od time is almost same. This tells that there is no significance difference between scan time and od time

Applying t-test on the right skewd distributed data would be misleading as means heavily affected by outliers,we will remove the outliers(using IQR) and then carry out the test.

H0:Means of scan time and od time are equal

H1: otherwise

```
# removing outliers for both scan time and od time
Q1=data_trip['start_scan_to_end_scan'].quantile(0.25)
Q3=data_trip['start_scan_to_end_scan'].quantile(0.75)
IQR=Q3-Q1
scan=data_trip['start_scan_to_end_scan']
logical=((Q1-1.5*IQR)<scan ) & (scan<(Q3+1.5*IQR))
scan_data=data_trip['start_scan_to_end_scan'][logical]

# similarly do for od time
Q1=data_trip['od_start_end_time_minute'].quantile(0.25)
Q3=data_trip['od_start_end_time_minute'].quantile(0.75)
IQR=Q3-Q1
od=data_trip['od_start_end_time_minute']
logical=((Q1-1.5*IQR)<od ) & (od<(Q3+1.5*IQR))
od_data=data_trip['od_start_end_time_minute'][logical]


# hypothesis testing for equality of means
# paired t-test: as the both time depends on the delivery.

test_statistics,p_value=st.ttest_rel(scan_data,od_data) # two-sided paired t-test

print("Test-statistics:",test_statistics)
print("P-value:",p_value)
```

```
Test-statistics: -29.615008802193312
P-value: 2.2461833908056246e-108
```

If we consider 5% level of significance,the **p-value** is way less than 0.05.Therefore null hypothesis must i.e the mean of **scan time** and the mean of **od time** are not equal.

hypothesis test between actual_time aggregated value and OSRM time aggregated value

```
fig,ax=plt.subplots(nrows=1,ncols=2,figsize=(15,6))
ax=ax.flatten()
sns.histplot(x='actual_time', data=data_trip,ax=ax[0],bins=40) # aggregate actual time
ax[0].set_xlabel("Actual time aggregated")
sns.histplot(x='osrm_time',data=data_trip,ax=ax[1],bins=40) # OSRM aggregated time
ax[1].set_xlabel("OSRM aggregated time")
plt.show()
```

Both actual and osrm aggregated time are right skewd distribution.ANOVA can't be applied here because the data are not normal

confidence interval of means for both the actual time(aggregated) and osrm time(aggregated)

```
# find confidence interval
means_actual=[]
means_osrm=[]
nsim=1000 # 100 bootstrap simulations
sample_size=100 # sample size is 100
for _ in range(nsim):
  sample=data_trip['actual_time'].sample(sample_size)
  means_actual.append(sum(sample)/len(sample))

  sample=data_trip['osrm_time'].sample(sample_size)
  means_osrm.append(sum(sample)/len(sample))


# confidence interval for means
interval_actual=[np.percentile(means_actual,2.5),np.percentile(means_actual,97.5)] # 2.5th and 97.5th percentiles ,with 5
interval_osrm=[np.percentile(means_osrm,2.5),np.percentile(means_osrm,97.5)]

print("Confidence interval for actual time(aggregated): ",interval_actual)
print("Confidence interval for OSRM time(aggregated): ",interval_osrm)
```

```
Confidence interval for actual time(aggregated):  [137.24775, 185.79325]
Confidence interval for OSRM time(aggregated):  [23.13, 30.850250000000003]
```

There is no overlap between the intervals.According to confidence intervals there is no relation between actual time taken to deliver a product and osrm time(machine genrated time).

It proves machine generated time is not accordance with the actual time

H0:Means of actual time and OSRM time are equal

H1: otherwise

Actual time depends on the delivery whereas OSRM time is machine generated,therefore we will do independent t-test for hypothesis test

```
# first remove outliers
Q1=data_trip['actual_time'].quantile(0.25)
Q3=data_trip['actual_time'].quantile(0.75)
IQR=Q3-Q1
actual=data_trip['actual_time']
logical=((Q1-1.5*IQR)<actual ) & (actual<(Q3+1.5*IQR))
actual_data=data_trip['actual_time'][logical]

# similarly do for od time
Q1=data_trip['osrm_time'].quantile(0.25)
Q3=data_trip['osrm_time'].quantile(0.75)
IQR=Q3-Q1
osrm=data_trip['osrm_time']
logical=((Q1-1.5*IQR)<osrm ) & (osrm<(Q3+1.5*IQR))
osrm_data=data_trip['osrm_time'][logical]
test_statistics,p_value=st.ttest_ind(osrm_data,actual_data,
                                     equal_var=True, random_state=2022, alternative='two-sided')
print("Test-statistics:",test_statistics)
print("P-value:",p_value)
```

```
Test-statistics: -23.723659699899443
P-value: 8.465203154007822e-97
```

Again the p-values is very low ,way less than 5% level of significance.Therefore the null hypothesis must that is the mean of actual time is not

Hypothesis tesing between actual_time aggregated value and segment actual time aggregated value.

H0: Means of actual time(aggregated) and actual segement time(aggregated) are equal

H1:otherwise

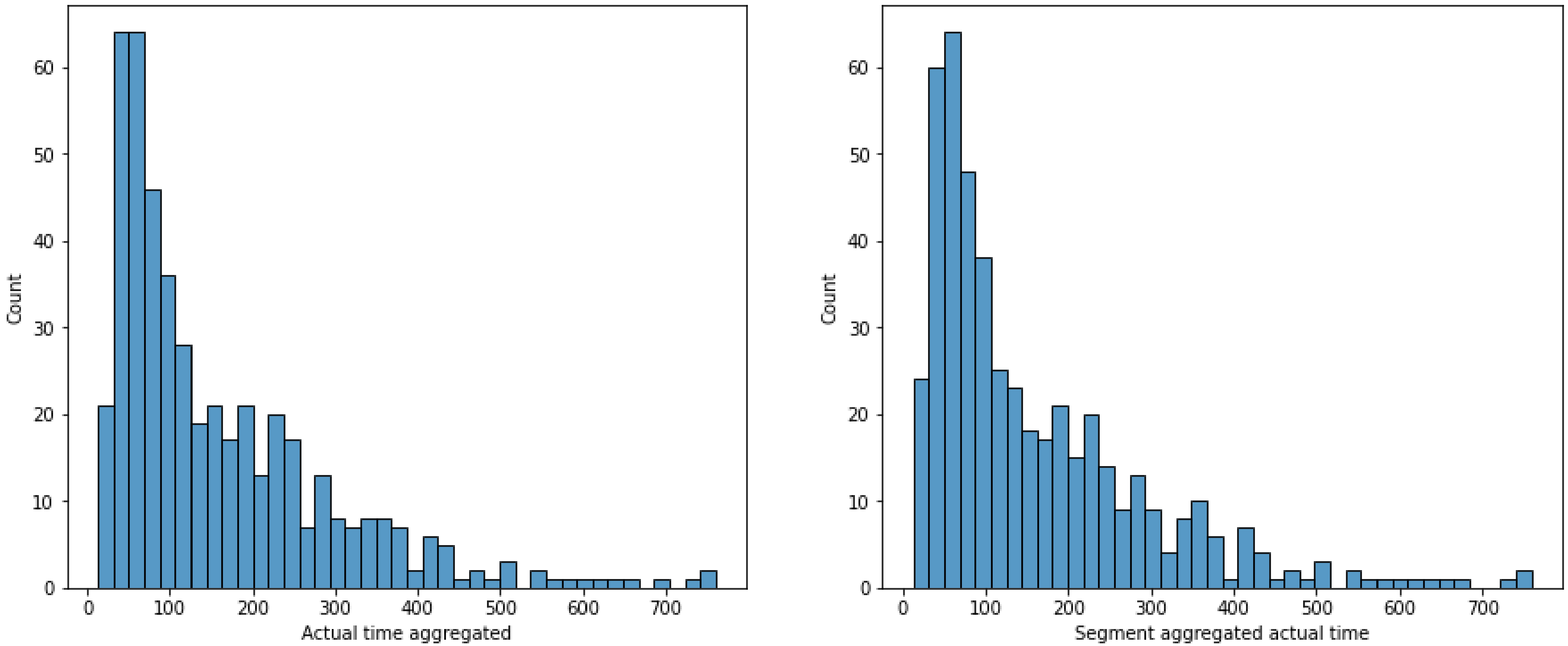
Confidence interval of actual time(aggregated) and segment_time(aggregated)

```
# find confidence interval
means_actual=[]
means_actual_seg=[]
nsim=1000 # 100 bootstrap simulations
sample_size=100 # sample size is 100
for _ in range(nsim):
  sample=data_trip['actual_time'].sample(sample_size)
  means_actual.append(sum(sample)/len(sample))

  sample=data_trip['segment_actual_time_total'].sample(sample_size)
  means_actual_seg.append(sum(sample)/len(sample))


# confidence interval for means
interval_actual=[np.percentile(means_actual,2.5),np.percentile(means_actual,97.5)] # 2.5th and 97.5th percentiles ,with 5
interval_actual_seg=[np.percentile(means_actual_seg,2.5),np.percentile(means_actual_seg,97.5)]

print("Confidence interval for actual time(aggregated): ",interval_actual)
print("Confidence interval for actual segment time(aggregated): ",interval_osrm)
```

```
Confidence interval for actual time(aggregated):  [137.67925, 184.40075000000002]
Confidence interval for actual segment time(aggregated):  [23.13, 30.850250000000003]
```

There is a significant difference between the confidence intervals.segment actual time is faster than the actual time.

```
fig,ax=plt.subplots(nrows=1,ncols=2,figsize=(15,6))
ax=ax.flatten()
sns.histplot(x='actual_time', data=data_trip,ax=ax[0],bins=40) # aggregate actual time
ax[0].set_xlabel("Actual time aggregated")
sns.histplot(x='segment_actual_time_total',data=data_trip,ax=ax[1],bins=40) # segment aggregated actual time
ax[1].set_xlabel("Segment aggregated actual time")
plt.show()
```



Again the data distribution are right skewed.The data has outliers we will remove and then carry out t-test

```
# first remove outliers
```

```
Q1=data_trip['actual_time'].quantile(0.25)
Q3=data_trip['actual_time'].quantile(0.75)
IQR=Q3-Q1
actual=data_trip['actual_time']
logical=((Q1-1.5*IQR)<actual ) & (actual<(Q3+1.5*IQR))
actual_data=data_trip['actual_time'][logical]

# similarly do for od time
Q1=data_trip['segment_actual_time_total'].quantile(0.25)
Q3=data_trip['segment_actual_time_total'].quantile(0.75)
IQR=Q3-Q1
segment=data_trip['segment_actual_time_total']
logical=((Q1-1.5*IQR)&lt;segment ) & (segment<(Q3+1.5*IQR))
segment_data=data_trip['segment_actual_time_total'][logical]
test_statistics,p_value=st.ttest_rel(segment_data,actual_data)
print("Test-statistics:",test_statistics)
print("P-value:",p_value)
```

```
Test-statistics: -10.10555078775598
P-value: 8.12425753694926e-22
```

The p-value is way less than the 5% level of significance.Therefore the mean actual time is different from mean segment time

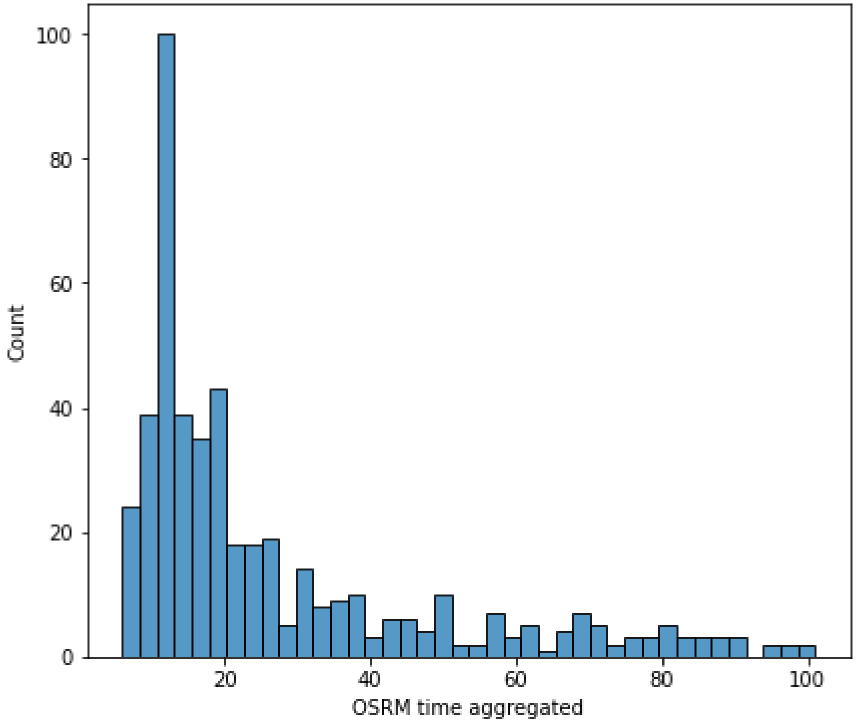
Hypothesis testing between osrm time aggregated value and segment osrm time aggregated value and visualization

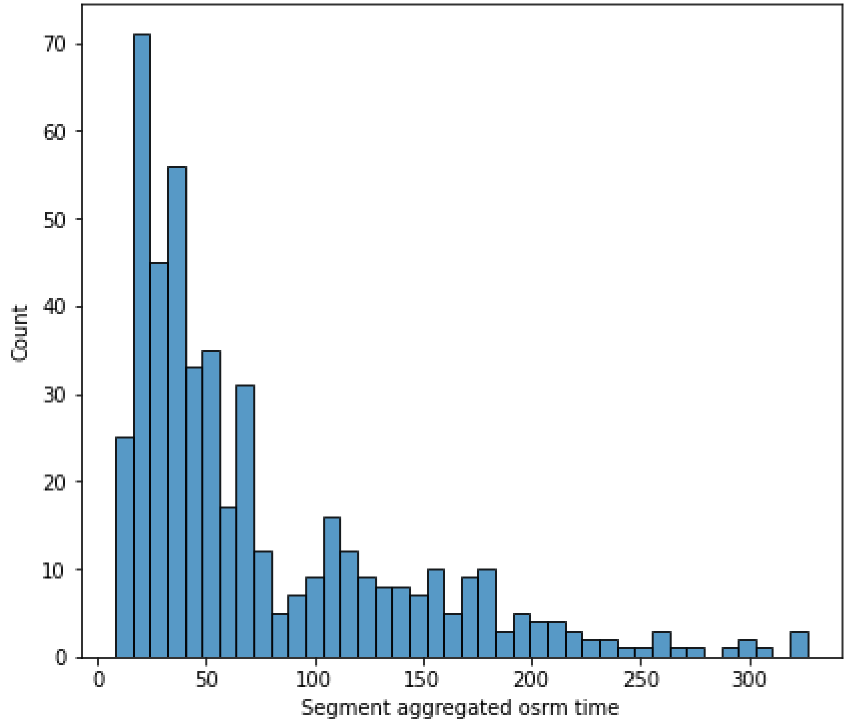
HO:mean of osrm time(aggregated) is same as mean of segment osrm time(aggregated)

H1:otherwise

```
fig,ax=plt.subplots(nrows=1,ncols=2,figsize=(15,6))
ax=ax.flatten()
sns.histplot(x='osrm_time', data=data_trip,ax=ax[0],bins=40) # aggregate OSRM time
ax[0].set_xlabel("OSRM time aggregated")
sns.histplot(x='segment_osrm_time_total',data=data_trip,ax=ax[1],bins=40) # segment aggregated osrm time
ax[1].set_xlabel("Segment aggregated osrm time")
```

```
plt.show()
```





The distributions are rightly skewed.The data contains outliers.The distribution are almost same

Confidence interval of osrm time aggregated and segement osrm time aggregated

```
# find confidence interval
means_segment=[]
means_osrm=[]
nsim=1000 # 100 bootstrap simulations
sample_size=100 # sample size is 100
for _ in range(nsim):
  sample=data_trip['segment_osrm_time_total'].sample(sample_size)
  means_segment.append(sum(sample)/len(sample))
```

```
  sample=data_trip['osrm_time'].sample(sample_size)
  means_osrm.append(sum(sample)/len(sample))


# confidence interval for means
interval_segment=[np.percentile(means_segment,2.5),np.percentile(means_segment,97.5)] # 2.5th and 97.5th percentiles ,witl
interval_osrm=[np.percentile(means_osrm,2.5),np.percentile(means_osrm,97.5)]

print("Confidence interval for segment osrm time(aggregated): ",interval_segment)
print("Confidence interval for OSRM time(aggregated): ",interval_osrm)
```

```
Confidence interval for segment osrm time(aggregated):  [65.00775, 86.153]
Confidence interval for OSRM time(aggregated):  [23.0595, 30.730999999999998]
```

Confidence intervals are not.Time taken by delivery as per segment OSRM time is way less than the time taken by delivery as per osrm time.

```
# first remove outliers
Q1=data_trip['segment_osrm_time_total'].quantile(0.25)
Q3=data_trip['segment_osrm_time_total'].quantile(0.75)
IQR=Q3-Q1
segment=data_trip['segment_osrm_time_total']
logical=((Q1-1.5*IQR)&lt;segment ) & (segment<(Q3+1.5*IQR))
segment_data=data_trip['segment_osrm_time_total'][logical]

# similarly do for od time
Q1=data_trip['osrm_time'].quantile(0.25)
Q3=data_trip['osrm_time'].quantile(0.75)
IQR=Q3-Q1
osrm=data_trip['osrm_time']
logical=((Q1-1.5*IQR)<osrm ) & (osrm<(Q3+1.5*IQR))
osrm_data=data_trip['osrm_time'][logical]
test_statistics,p_value=st.ttest_ind(osrm_data,segment_data,
                                     equal_var=True, random_state=2022, alternative='two-sided')
print("Test statistics:",test_statistics)
```

```
print("Test-statistics:",test_statistics)
print("P-value:",p_value)
```

```
Test-statistics: -17.56295705456822
P-value: 1.6290285454404585e-59
```

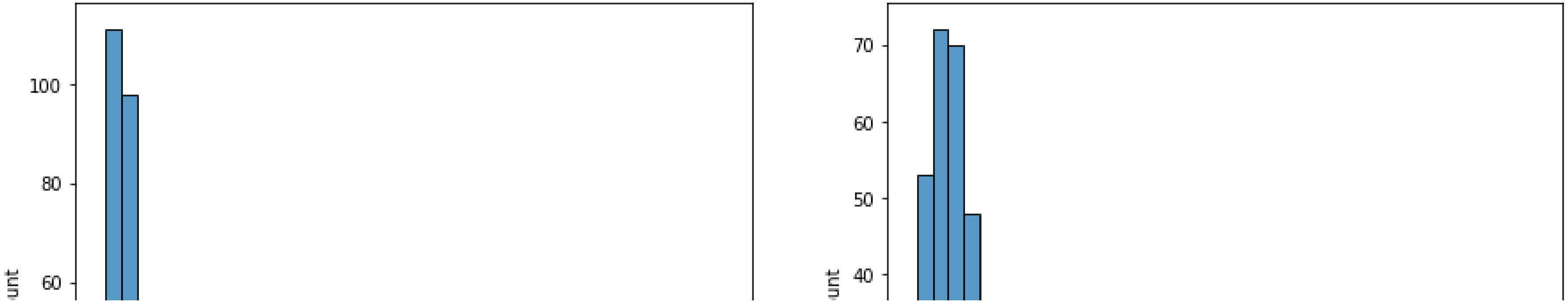
According to p-value the means are not same.

Hypothesis testing between osrm distance aggregated value and segment osrm distance aggregated value and visualization.

Ho: osrm mean distance is same as osrm segmented distance

H1:otherwise

```
fig,ax=plt.subplots(nrows=1,ncols=2,figsize=(15,6))
ax=ax.flatten()
sns.histplot(x='osrm_distance', data=data_trip,ax=ax[0],bins=40) # aggregate OSRM distance
ax[0].set_xlabel("OSRM distance aggregated")
sns.histplot(x='segment_osrm_distance_total',data=data_trip,ax=ax[1],bins=40) # segment aggregated osrm distance
ax[1].set_xlabel("Segment aggregated osrm distance")
plt.show()
```



right skewd distributions.Have outliers.we will remove them before carrying any t-test.

Confidence interval of osrm distance aggregated and segement osrm distance aggregated

```
# find confidence interval
means_segment=[]
means_osrm=[]
nsim=1000 # 100 bootstrap simulations
sample_size=100 # sample size is 100
for _ in range(nsim):
  sample=data_trip['segment_osrm_distance_total'].sample(sample_size)
  means_segment.append(sum(sample)/len(sample))

  sample=data_trip['osrm_time'].sample(sample_size)
  means_osrm.append(sum(sample)/len(sample))


# confidence interval for means
interval_segment=[np.percentile(means_segment,2.5),np.percentile(means_segment,97.5)] # 2.5th and 97.5th percentiles ,wit
interval_osrm=[np.percentile(means_osrm,2.5),np.percentile(means_osrm,97.5)]

print("Confidence interval for segment osrm distance(aggregated): ",interval_segment)
print("Confidence interval for OSRM distance(aggregated): ",interval_osrm)
```

```
Confidence interval for segment osrm distance(aggregated):  [71.52735435000002, 100.67660464999999]
Confidence interval for OSRM distance(aggregated):  [23.17975, 30.34]
```

The mean OSRM distance is relatively less than the mean segment osrm distance

```
# first remove outliers
Q1=data_trip['segment_osrm_distance_total'].quantile(0.25)
Q3=data_trip['segment_osrm_distance_total'].quantile(0.75)
IQR=Q3-Q1
segment=data_trip['segment_osrm_distance_total']
logical=((Q1-1.5*IQR)&lt;segment ) & (segment<(Q3+1.5*IQR))
segment_data=data_trip['segment_osrm_distance_total'][logical]

# similarly do for od time
Q1=data_trip['osrm_distance'].quantile(0.25)
Q3=data_trip['osrm_distance'].quantile(0.75)
IQR=Q3-Q1
osrm=data_trip['osrm_distance']
logical=((Q1-1.5*IQR)<osrm ) & (osrm<(Q3+1.5*IQR))
osrm_data=data_trip['osrm_distance'][logical]
test_statistics,p_value=st.ttest_ind(osrm_data,segment_data,
                                     equal_var=True, random_state=2022, alternative='two-sided')
print("Test-statistics:",test_statistics)
print("P-value:",p_value)
```

```
Test-statistics: -16.971438595307465
P-value: 4.137727991255941e-56
```

According to p-value mean distances are not same as p-value is way less than 5% level of significance.

Comparison & Visualization of time and distance fields:

actual_distance_to_destination, actual_time, osrm_time, osrm_distance, segment_actual_time_total, segment_osrm_time_total, segment_osrm_distance_total

The relation between time and distance is distance=time*speed Here we can treat speed as a parameter.

We can have scatter plot as well as correlation

actual_distance_to_destination vs actual_time

```
# calcualting a linear fit
p=np.polyfit(data_trip['actual_time'],data_trip['actual_distance_to_destination'],deg=1) # fitting a simple linear regres:
distance_pred=np.polyval(p,data_trip['actual_time']) # predicted distance

plt.scatter(data_trip['actual_time'],data_trip['actual_distance_to_destination'])
plt.plot(data_trip['actual_time'],distance_pred,color='r')
plt.xlabel('time[minute]')
plt.ylabel('distance[km]')
plt.title("time vs distance")
plt.show()
```

There are some distances(less than 50km) taken longest time.This might be due to the fault in the delivery or technical glitch.

osrm_time vs osrm_distance

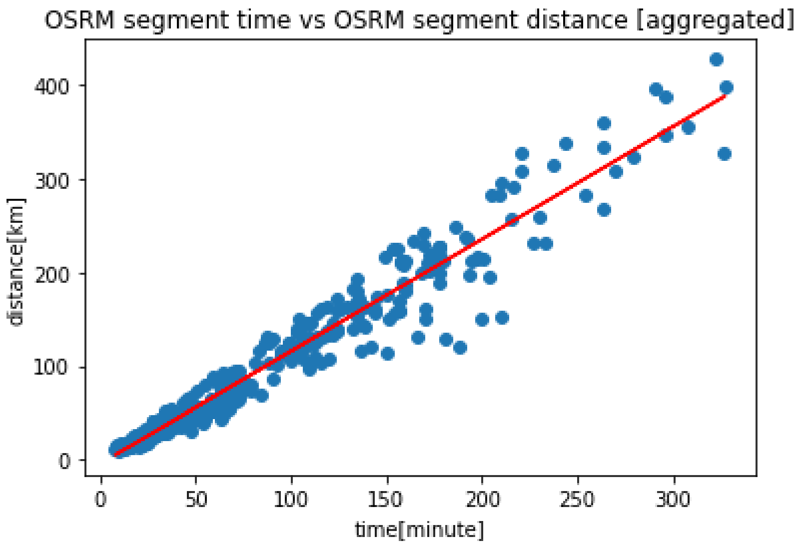
```
# calcualting a linear fit
p=np.polyfit(data_trip['osrm_time'],data_trip['osrm_distance'],deg=1) # fitting a simple linear regression
distance_pred=np.polyval(p,data_trip['osrm_time']) # predicted distance

plt.scatter(data_trip['osrm_time'],data_trip['osrm_distance'])
plt.plot(data_trip['osrm_time'],distance_pred,color='r')
plt.xlabel('time[minute]')
plt.ylabel('distance[km]')
plt.title("OSRM time vs OSRM distance")
plt.show()
```

OSRM time vs OSRM distance

The line almost perfectly fit the data.More time taken,more distance to cover.

segment_osrm_time_total vs segment_osrm_distance_total

```
# calcualting a linear fit
p=np.polyfit(data_trip['segment_osrm_time_total'],data_trip['segment_osrm_distance_total'],deg=1) # fitting a simple linea
distance_pred=np.polyval(p,data_trip['segment_osrm_time_total']) # predicted distance

plt.scatter(data_trip['segment_osrm_time_total'],data_trip['segment_osrm_distance_total'])
plt.plot(data_trip['segment_osrm_time_total'],distance_pred,color='r')
plt.xlabel('time[minute]')
plt.ylabel('distance[km]')
plt.title("OSRM segment time vs OSRM segment distance [aggregated]")
plt.show()
```



Here also the line almost perfectly the data.More segment time,more segment distance to cover.

Column Normalization /Column Standardization using StandardScaler:

StandardScaler normalize the data so that mean of each column(attributes) becomes zero and variance becomes 1

```
cols_to_standarized=['start_scan_to_end_scan',
       'od_start_end_time_minute', 'actual_distance_to_destination',
       'actual_time', 'osrm_time', 'osrm_distance',
       'segment_actual_time_total', 'segment_osrm_time_total',
       'segment_osrm_distance_total']

scaler=StandardScaler()
data_scaled=scaler.fit_transform(data_trip[cols_to_standarized])
data_scaled
```

```
array([[-5.76110513e-04, -1.22644075e-03,  5.88713848e-01, ...,
         6.91425797e-01,  8.59330823e-01,  6.71684125e-01],
       [-1.80620579e-01, -1.83841438e-01, -3.97347755e-01, ...,
         6.02245751e-01, -4.02978713e-01, -3.63428751e-01],
       [-1.47454492e-01, -1.44280784e-01,  2.01589614e-01, ...,
        -1.26057958e-01, -3.11727421e-01, -7.45048332e-02],
       ...,
       [-6.73373860e-01, -6.75596835e-01, -2.30452223e-01, ...,
        -2.37533016e-01, -4.33395810e-01, -2.27711657e-01],
       [-6.73373860e-01, -6.72652145e-01, -3.22180719e-01, ...,
        -2.82123039e-01, -3.87770164e-01, -4.64441824e-01],
       [-5.17019454e-01, -5.13527397e-01, -6.00903971e-01, ...,
        -7.28023269e-01, -6.46315491e-01, -6.48967122e-01]])
```

```
data_scaled.mean(axis=0)
```

```
array([-5.21362594e-17, -2.27165130e-16, -1.07996537e-16,  8.19284077e-17,
        4.84122409e-17,  3.72401853e-18,  1.06134528e-16, -7.07563521e-17,
        7.44803706e-17])
```

```
data_scaled.var(axis=0)
```

```
array([1., 1., 1., 1., 1., 1., 1., 1., 1.])
```

Recommendation:

1. There is a huge discrepency between OSRM and actual parameters thats need to be investigated.
2. There are distances(less than 50km) takes lot of time to deliver the product.Investigation is needed.
3. Sotuh,North and west have heavy presence but on the other hand east,central corridors have less presence.It would be worth if we increase our presense in these regions.
4. Maharash being heighest in terms of production as well as deliveries followed by Karnataka.
5. Unfortunately Delhi being capital city has less presence compared to Maharashtra,Karnataka.We need to our increase in Delhi.
6. We have very limited presence in states like Uttrakhand,Chhatisgarh,Goa,Jammu and Kashmir.It would be worth if we increase our presence.

```
Thats All until next time
```