
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from google.colab import files
import scipy.stats as stats
from scipy.stats import shapiro
from scipy.stats import boxcox
import math
import re
from scipy.stats import norm
from scipy.stats import chi2_contingency, ttest_ind, f_oneway, pearsonr
```

```
uploaded = files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
#
delhivery_data = pd.read_csv('delhivery_data.csv')
```

```
pd.set_option('display.max_columns', None)
```

```
delhivery_data.head()
```

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_cente
0	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AA
1	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AA
2	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AA
3	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AA
4	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AA

```
#
df = delhivery_data.copy()
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144867 entries, 0 to 144866
Data columns (total 24 columns):
 #   Column                          Non-Null Count   Dtype
---  ------                          --------------   -----
 0   data                            144867 non-null  object
 1   trip_creation_time              144867 non-null  object
 2   route_schedule_uuid             144867 non-null  object
 3   route_type                      144867 non-null  object
 4   trip_uuid                       144867 non-null  object
 5   source_center                   144867 non-null  object
 6   source_name                     144574 non-null  object
 7   destination_center              144867 non-null  object
 8   destination_name                144606 non-null  object
 9   od_start_time                   144867 non-null  object
 10  od_end_time                     144867 non-null  object
 11  start_scan_to_end_scan          144867 non-null  float64
 12  is_cutoff                       144867 non-null  bool
 13  cutoff_factor                   144867 non-null  int64
 14  cutoff_timestamp                144867 non-null  object
 15  actual_distance_to_destination  144867 non-null  float64
 16  actual_time                     144867 non-null  float64
 17  osrm_time                       144867 non-null  float64
 18  osrm_distance                   144867 non-null  float64
 19  factor                          144867 non-null  float64
 20  segment_actual_time             144867 non-null  float64
 21  segment_osrm_time               144867 non-null  float64
 22  segment_osrm_distance           144867 non-null  float64
 23  segment_factor                  144867 non-null  float64
dtypes: bool(1), float64(10), int64(1), object(12)
memory usage: 25.6+ MB
```

```
df.shape
```

```
(144867, 24)
```

```
df.columns
```

```
Index(['data', 'trip_creation_time', 'route_schedule_uuid', 'route_type',
       'trip_uuid', 'source_center', 'source_name', 'destination_center',
       'destination_name', 'od_start_time', 'od_end_time',
       'start_scan_to_end_scan', 'is_cutoff', 'cutoff_factor',
       'cutoff_timestamp', 'actual_distance_to_destination', 'actual_time',
       'osrm_time', 'osrm_distance', 'factor', 'segment_actual_time',
       'segment_osrm_time', 'segment_osrm_distance', 'segment_factor'],
      dtype='object')
```

```
1 df.isna().any()
```

	0
data	False
trip_creation_time	False
route_schedule_uuid	False
route_type	False
trip_uuid	False
source_center	False
source_name	True
destination_center	False
destination_name	True
od_start_time	False
od_end_time	False
start_scan_to_end_scan	False
is_cutoff	False
cutoff_factor	False
cutoff_timestamp	False
actual_distance_to_destination	False
actual_time	False
osrm_time	False
osrm_distance	False
factor	False
segment_actual_time	False
segment_osrm_time	False
segment_osrm_distance	False
segment_factor	False

dtype: bool

```
1 ((df.isna().sum() / len(df)) * 100).round(2)
```

	0
data	0.00
trip_creation_time	0.00
route_schedule_uuid	0.00
route_type	0.00
trip_uuid	0.00
source_center	0.00
source_name	0.20
destination_center	0.00
destination_name	0.18
od_start_time	0.00
od_end_time	0.00
start_scan_to_end_scan	0.00
is_cutoff	0.00
cutoff_factor	0.00
cutoff_timestamp	0.00
actual_distance_to_destination	0.00
actual_time	0.00
osrm_time	0.00
osrm_distance	0.00
factor	0.00
segment_actual_time	0.00
segment_osrm_time	0.00
segment_osrm_distance	0.00
segment_factor	0.00

dtype: float64

```
1 df.isna().sum()
```

	0
data	0
trip_creation_time	0
route_schedule_uuid	0
route_type	0
trip_uuid	0
source_center	0
source_name	293
destination_center	0
destination_name	261
od_start_time	0
od_end_time	0
start_scan_to_end_scan	0
is_cutoff	0
cutoff_factor	0
cutoff_timestamp	0
actual_distance_to_destination	0
actual_time	0
osrm_time	0
osrm_distance	0
factor	0
segment_actual_time	0
segment_osrm_time	0
segment_osrm_distance	0
segment_factor	0

dtype: int64

```
df[df.duplicated()]
```

data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_center	destination_name

```
df.describe().T
```

	count	mean	std	min	25%	50%	75%	max
start_scan_to_end_scan	144867.0	961.262986	1037.012769	20.000000	161.000000	449.000000	1634.000000	7898.000000
cutoff_factor	144867.0	232.926567	344.755577	9.000000	22.000000	66.000000	286.000000	1927.000000
actual_distance_to_destination	144867.0	234.073372	344.990009	9.000045	23.355874	66.126571	286.708875	1927.447705
actual_time	144867.0	416.927527	598.103621	9.000000	51.000000	132.000000	513.000000	4532.000000
osrm_time	144867.0	213.868272	308.011085	6.000000	27.000000	64.000000	257.000000	1686.000000
osrm_distance	144867.0	284.771297	421.119294	9.008200	29.914700	78.525800	343.193250	2326.199100
factor	144867.0	2.120107	1.715421	0.144000	1.604264	1.857143	2.213483	77.387097
segment_actual_time	144867.0	36.196111	53.571158	-244.000000	20.000000	29.000000	40.000000	3051.000000
segment_osrm_time	144867.0	18.507548	14.775960	0.000000	11.000000	17.000000	22.000000	1611.000000
segment_osrm_distance	144867.0	22.829020	17.860660	0.000000	12.070100	23.513000	27.813250	2191.403700
segment_factor	144867.0	2.218368	4.847530	-23.444444	1.347826	1.684211	2.250000	574.250000

```
df.describe(include=object).T
```

	count	unique	top	freq
data	144867	2	training	104858
trip_creation_time	144867	14817	2018-09-22 04:55:04.835022	101
route_schedule_uuid	144867	1504	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	1812
route_type	144867	2	FTL	99660
trip_uuid	144867	14817	trip-153759210483476123	101
source_center	144867	1508	IND000000ACB	23347
source_name	144574	1498	Gurgaon_Bilaspur_HB (Haryana)	23347
destination_center	144867	1481	IND000000ACB	15192
destination_name	144606	1468	Gurgaon_Bilaspur_HB (Haryana)	15192
od_start_time	144867	26369	2018-09-21 18:37:09.322207	81
od_end_time	144867	26369	2018-09-24 09:59:15.691618	81
cutoff_timestamp	144867	93180	2018-09-24 05:19:20	40

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

```
df["cutoff_timestamp"] = pd.to_datetime(df["cutoff_timestamp"],format ="mixed")
```

```
df.sample(5)
```

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destinati
34278	training	2018-09-16 19:19:01.957793	thanos::sroute:9235e090-a61d-4a3b-81a3-eb4f37d...	FTL	trip-153712554195755989	IND421302AAG	Bhiwandi_Mankoli_HB (Maharashtra)	IND5
40991	training	2018-09-15 23:10:22.830629	thanos::sroute:54a7c356-361d-4e74-9ee7-d420c37...	FTL	trip-153705302283040335	IND562132AAA	Bangalore_Nelmngla_H (Karnataka)	IND3
49530	test	2018-09-28 20:46:11.791131	thanos::sroute:6b53909c-62c8-4c16-8ea1-c746855...	FTL	trip-153816757179091270	IND842001AAA	Muzaffrpur_Bbganj_I (Bihar)	IND8
132146	training	2018-09-14 00:18:57.973357	thanos::sroute:64d4c6c9-ffb9-4794-b9f1-05f064c...	FTL	trip-153688433797310425	IND110037AAM	Delhi_Airport_H (Delhi)	IND4
136980	training	2018-09-17 17:29:26.034420	thanos::sroute:4e7e8e63-8b57-464c-9028-8d02069...	FTL	trip-153720536603406530	IND577002AAA	Davangere_Central_I_1 (Karnataka)	IND5

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144867 entries, 0 to 144866
Data columns (total 24 columns):
 #   Column                          Non-Null Count   Dtype
---  ------                          --------------   -----
 0   data                            144867 non-null  object
 1   trip_creation_time              144867 non-null  datetime64[ns]
 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  datetime64[ns]
 10  od_end_time                     144867 non-null  datetime64[ns]
 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  datetime64[ns]
 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), datetime64[ns](4), float64(10), int64(1), object(8)
memory usage: 25.6+ MB
```

```
df['year'] = df['trip_creation_time'].dt.year
df.insert(2, 'year', df.pop('year'))

df['month_name'] = df['trip_creation_time'].dt.month_name()
df.insert(3, 'month_name', df.pop('month_name'))

df['week_days'] = df['trip_creation_time'].dt.day_name()
df.insert(4, 'week_days', df.pop('week_days'))

df['hours'] = df['trip_creation_time'].dt.hour
df.insert(5, 'hours', df.pop('hours'))

df['weeks'] = df['trip_creation_time'].dt.isocalendar().week
df.insert(7, 'weeks', df.pop('weeks'))
```

```
# Converting the datatypes to category for columns like data and route_type as they have fixed value:
df['data'] = df['data'].astype('category')
df['year'] = df['year'].astype('category')
df['month_name'] = df['month_name'].astype('category')
df['week_days'] = df['week_days'].astype('category')
df['route_type'] = df['route_type'].astype('category')
```

```
df[df.columns[::]].sample(2)
```

	data	trip_creation_time	year	month_name	week_days	hours	route_schedule_uuid	weeks	route_type	trip_uuid	sou
103176	training	2018-09-24 19:03:06.678919	2018	September	Monday	19	thanos::sroute:bae3c09c-2500-4fbb-95b5-633f40e...	39	Carting	trip-153781578667865654	IND
58838	training	2018-09-14 18:53:01.364151	2018	September	Friday	18	thanos::sroute:17fc17ec-ffde-4f2a-8ad6-ff420a0...	37	FTL	trip-153695118137161432	IND

```
df['trip_uuid'] = df['trip_uuid'].str.strip().str.split('trip-').str.get(1)
```

```
df['source_center'] = df['source_center'].str.extract(r'(\d+)([A-Za-z]+)')\
                                                                .agg('-'.join, axis=1)
```

```
df['destination_center'] = df['destination_center'].str.extract(r'(\d+)([A-Za-z]+)')\
                                                                .agg('-'.join, axis=1)
```

```
df.head()
```

	data	trip_creation_time	year	month_name	week_days	hours	route_schedule_uuid	weeks	route_type	trip_uuid	source_c
0	training	2018-09-20 02:35:36.476840	2018	September	Thursday	2	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	38	Carting	153741093647649320	38812
1	training	2018-09-20 02:35:36.476840	2018	September	Thursday	2	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	38	Carting	153741093647649320	38812
2	training	2018-09-20 02:35:36.476840	2018	September	Thursday	2	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	38	Carting	153741093647649320	38812
3	training	2018-09-20 02:35:36.476840	2018	September	Thursday	2	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	38	Carting	153741093647649320	38812
4	training	2018-09-20 02:35:36.476840	2018	September	Thursday	2	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	38	Carting	153741093647649320	38812

```
# def extract_info(name):
#     if not isinstance(name, str):
#         return None, None, None

#     pattern = r'^(?P<city>[^\s_]+)_?(?P<place>[^\(\)]*)\s?\((?P<state>[A-Za-z\s&]+)\)$'
#     match = re.match(pattern, name)
#     if match:
#         city = match.group('city').strip()
#         place = match.group('place').strip() if match.group('place') else city
#         state = match.group('state').strip()
#         return city, place, state
#     else:
#         return None, None, None
```

```
# df[['source_city_name', 'source_place', 'source_state_name']] = df['source_name'].apply(lambda x: pd.Series(extract_info(x)))

# df.insert(11, 'source_state_name', df.pop('source_state_name'))
# df.insert(12, 'source_place', df.pop('source_place'))
# df.insert(13, 'source_city_name', df.pop('source_city_name'))
```

```
# df['source_place_name'] = df['source_place_name'].apply(lambda x: x.split('_')[0] if isinstance(x, str) and '_' in x else x)
```

```
# df['source_place_name'] = df['source_place'].apply(lambda x: x.strip().split('_')[0] if isinstance(x, str) else None)
# df.insert(12, 'source_place_name', df.pop('source_place_name'))
```

```
# df['source_location_type'] = df['source_place'].apply(lambda x: x.strip().split('_')[1] if isinstance(x, str) and '_' in x else None)
# df.insert(13, 'source_location_type', df.pop('source_location_type'))
```

```
# import pandas as pd

# # Sample data (Replace this with reading from your actual file)
# data = {
#     'source_name': [
#         'Bangalore_Nelmngla_H (Karnataka)',
#         'Bengaluru_Bomsndra_HB (Karnataka)',
#         'Anand_VUNagar_DC (Gujarat)',
#         'Una_Mamlatdr_DC (Gujarat)',
#         'Talala_SsnRdDPP_D (Gujarat)',
#         'Sonipat_Kundli_H (Haryana)',
#         'Roorkee_IOTCEncl_L (Uttarakhand)',
#         'MAA_Poonamallee_HB (Tamil Nadu)',
#         'Gurgaon_Begumpur_CP (Haryana)',
#         'Ajmer_FoySGRRD_I (Rajasthan)',
#         'Kanpur_Central_H_6 (Uttar Pradesh)',
#         'Ahmedabad_East_H_1 (Gujarat)',
#         'Vizag_Gajuwaka (Andhra Pradesh)',
#         'Vizag _NAD (Andhra Pradesh)',
#         'Dabhoi_Central_DPP_3 (Gujarat)',
#         'Delhi_Rohini_DPC (Delhi)'
#     ]
# }
```

```
# df['source_state_name'] = df['source_name'].str.extract(r'\((.*?)\)')
# df['clean_name'] = df['source_name'].str.extract(r'^(.*?)\s+\(')[0]
# tokens = df['clean_name'].str.strip().str.split(r'[_\s]+', expand=True)

# df['source_city_name'] = tokens[0]
# df['source_place_name'] = tokens[1]
# df['source_code_name'] = tokens[2]

# df['source_state_name'] = df['source_state_name'].fillna('Unkown')
# df['source_city_name'] = df['source_city_name'].fillna('Unkown')
# df['source_place_name'] = df['source_place_name'].fillna('Unkown')
# df['source_code_name'] = df['source_code_name'].fillna('Unkown')

# df.insert(12, 'source_state_name', df.pop('source_state_name'))
# df.insert(13, 'source_city_name', df.pop('source_city_name'))
# df.insert(14, 'source_place_name', df.pop('source_place_name'))
# df.insert(15, 'source_code_name', df.pop('source_code_name'))

# df.drop(columns=['clean_name'], inplace=True)
```

```
df.sample(5)
```

	data	trip_creation_time	year	month_name	week_days	hours	route_schedule_uuid	weeks	route_type	trip_uuid	sou
37155	test	2018-09-29 03:25:55.320169	2018	September	Saturday	3	thanos::sroute:01164881-301e-45f8-bacd-ee21c37...	39	FTL	153819155531990348	
33928	training	2018-09-18 05:58:15.075750	2018	September	Tuesday	5	thanos::sroute:54e37e7d-cf98-497d-bf5c-bceb104...	38	FTL	153725029507550932	
135298	test	2018-10-01 21:38:41.852974	2018	October	Monday	21	thanos::sroute:e387b964-5c3a-49b4-95b9-991f296...	40	Carting	153842992185274119	
29543	training	2018-09-20 22:33:19.518073	2018	September	Thursday	22	thanos::sroute:0f5c3b4b-5c1c-4a8f-abd4-98fcadb...	38	Carting	153748279951770211	
89495	training	2018-09-21 23:39:00.503554	2018	September	Friday	23	thanos::sroute:f60f8fd7-4c32-4656-b6fc-3fa9a79...	38	FTL	153757314050330118	

```
df['source_city_name'] = df["source_name"].str.extract(r'([^_]+)')
df['source_place_name'] = df["source_name"].str.split("_", n = 2, expand = True)[1]
df['source_code_name'] = (df["source_name"].str.split("_",n=2,expand = True)[2]).str.split(" ",n = 1, expand = True)[0]
df['source_state_name'] = df["source_name"].str.extract(r'.*\((.*)\).*')

pd.set_option('display.max_columns', None)
```

```
df['destination_city_name']= df["destination_name"].str.extract(r'([^_]+)')
df['destination_place_name'] = df["destination_name"].str.split("_", n = 2, expand = True)[1]
df['destination_code_name'] = (df["destination_name"].str.split("_",n=2,expand = True)[2]).str.split(" ",n = 1, expand = True)[0]
df['destination_state_name'] = df["destination_name"].str.extract(r'.*\((.*)\).*')

pd.set_option('display.max_columns', None)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144867 entries, 0 to 144866
Data columns (total 37 columns):
 #   Column                        Non-Null Count   Dtype
---  ------                        --------------   -----
 0   data                          144867 non-null  category
 1   trip_creation_time            144867 non-null  datetime64[ns]
 2   year                          144867 non-null  category
 3   month_name                    144867 non-null  category
 4   week_days                     144867 non-null  category
 5   hours                         144867 non-null  int32
 6   route_schedule_uuid           144867 non-null  object
 7   weeks                         144867 non-null  UInt32
 8   route_type                    144867 non-null  category
 9   trip_uuid                     144867 non-null  object
 10  source_center                 144867 non-null  object
```

```
 11  source_name                   144574 non-null  object
 12  destination_center            144867 non-null  object
 13  destination_name              144606 non-null  object
 14  od_start_time                 144867 non-null  datetime64[ns]
 15  od_end_time                   144867 non-null  datetime64[ns]
 16  start_scan_to_end_scan        144867 non-null  float64
 17  is_cutoff                     144867 non-null  bool
 18  cutoff_factor                 144867 non-null  int64
 19  cutoff_timestamp              144867 non-null  datetime64[ns]
 20  actual_distance_to_destination  144867 non-null  float64
 21  actual_time                   144867 non-null  float64
 22  osrm_time                     144867 non-null  float64
 23  osrm_distance                 144867 non-null  float64
 24  factor                        144867 non-null  float64
 25  segment_actual_time           144867 non-null  float64
 26  segment_osrm_time             144867 non-null  float64
 27  segment_osrm_distance         144867 non-null  float64
 28  segment_factor                144867 non-null  float64
 29  source_city_name              144574 non-null  object
 30  source_place_name             142467 non-null  object
 31  source_code_name              129924 non-null  object
 32  source_state_name             144574 non-null  object
 33  destination_city_name         144606 non-null  object
 34  destination_place_name        142165 non-null  object
 35  destination_code_name         129038 non-null  object
 36  destination_state_name        144606 non-null  object
dtypes: UInt32(1), bool(1), category(5), datetime64[ns](4), float64(10), int32(1), int64(1), object(14)
memory usage: 34.1+ MB
```

```
df['source_state_name'] = df['source_state_name'].fillna('Unkown')
df['source_city_name'] = df['source_city_name'].fillna('Unkown')
df['source_place_name'] = df['source_place_name'].fillna('Unkown')
df['source_code_name'] = df['source_code_name'].fillna('Unkown')

df['destination_state_name'] = df['destination_state_name'].fillna('Unkown')
df['destination_city_name'] = df['destination_city_name'].fillna('Unkown')
df['destination_place_name'] = df['destination_place_name'].fillna('Unkown')
df['destination_code_name'] = df['destination_code_name'].fillna('Unkown')
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144867 entries, 0 to 144866
Data columns (total 37 columns):
 #   Column                        Non-Null Count   Dtype
---  ------                        --------------   -----
 0   data                          144867 non-null  category
 1   trip_creation_time            144867 non-null  datetime64[ns]
 2   year                          144867 non-null  category
 3   month_name                    144867 non-null  category
 4   week_days                     144867 non-null  category
 5   hours                         144867 non-null  int32
 6   route_schedule_uuid           144867 non-null  object
 7   weeks                         144867 non-null  UInt32
 8   route_type                    144867 non-null  category
 9   trip_uuid                     144867 non-null  object
 10  source_center                 144867 non-null  object
 11  source_name                   144574 non-null  object
 12  destination_center            144867 non-null  object
 13  destination_name              144606 non-null  object
 14  od_start_time                 144867 non-null  datetime64[ns]
 15  od_end_time                   144867 non-null  datetime64[ns]
 16  start_scan_to_end_scan        144867 non-null  float64
 17  is_cutoff                     144867 non-null  bool
 18  cutoff_factor                 144867 non-null  int64
 19  cutoff_timestamp              144867 non-null  datetime64[ns]
 20  actual_distance_to_destination  144867 non-null  float64
 21  actual_time                   144867 non-null  float64
 22  osrm_time                     144867 non-null  float64
 23  osrm_distance                 144867 non-null  float64
 24  factor                        144867 non-null  float64
 25  segment_actual_time           144867 non-null  float64
 26  segment_osrm_time             144867 non-null  float64
 27  segment_osrm_distance         144867 non-null  float64
 28  segment_factor                144867 non-null  float64
 29  source_city_name              144867 non-null  object
 30  source_place_name             144867 non-null  object
 31  source_code_name              144867 non-null  object
 32  source_state_name             144867 non-null  object
 33  destination_city_name         144867 non-null  object
 34  destination_place_name        144867 non-null  object
 35  destination_code_name         144867 non-null  object
```

```
 36  destination_state_name          144867 non-null  object
dtypes: UInt32(1), bool(1), category(5), datetime64[ns](4), float64(10), int32(1), int64(1), object(14)
memory usage: 34.1+ MB
```

```
1 df['source_code_name'].value_counts()
```

source_code_name	count
HB	41177
D	30004
H	26880
Unkown	14943
I	8464
IP	2768
H_1	2536
L	2108
DC	1944
DPC	1586
H_6	1513
I_2	1490
PC	1283
H_2	1082
C	879
D_1	830
D_2	703
DPP_1	551
DPP_2	497
I_1	435
P	391
I_7	381
CP	371
I_4	276
Dc	177
I_3	171
D_3	158
M	157
RP	151
I_20	129
H_4	126
V	111
I_21	111
DPP_3	95
Pc	92
Nagar_DPC	65
D_5	51
D_4	41
D_7	33
R_11	22
D_12	21
D_9	18
L_8	17
DPP_4	8
D_15	7

R_8	6
D_8	4
D_20	2
D_10	2

dtype: int64

```
df['source_code_name'] = df['source_code_name'].str.replace(r'[_\d]+', '', regex=True)
df['source_code_name'].value_counts()
```

source_code_name	count
HB	41177
H	32137
D	31874
Unkown	14943
I	11457
IP	2768
L	2125
DC	1944
DPC	1586
PC	1283
DPP	1151
C	879
P	391
CP	371
Dc	177
M	157
RP	151
V	111
Pc	92
NagarDPC	65
R	28

dtype: int64

```
df['source_code_name'] = df['source_code_name'].str.upper()

code_mapping = {
    'HB': 'Delivery Hub',
    'H': 'Delivery Hub',
    'DPC': 'Delivery Hub',
    'NAGARDPC':'Delivery Hub',
    'D': 'Delivery Center',
    'DC': 'Distribution Center',
    'I': 'Inbound Area',
    'IP': 'Inbound Processing',
    'L': 'Local Center',
    'M': 'Main Distribution Center',
    'PC': 'Pickup Center',
    'P': 'Pickup Point',
    'CP': 'Collection Point',
    'DPP': 'Delivery Station',
    'C': 'Center',
    'RP': 'Regional Processing Center',
    'R': 'Regional Center',
    'V': 'Vendor Dispatch Point',
    'NAGAR': 'Locality'
```

```
}

df['source_location_type'] = df['source_code_name'].map(code_mapping).fillna('Unknown')
```

```
print(df[['source_code_name', 'source_location_type']].value_counts())
```

```
source_code_name  source_location_type
HB                Delivery Hub                41177
H                 Delivery Hub                32137
D                 Delivery Center             31874
UNKOWN            Unknown                     14943
I                 Inbound Area                11457
IP                Inbound Processing           2768
L                 Local Center                 2125
DC                Distribution Center          2121
DPC               Delivery Hub                 1586
PC                Pickup Center                1375
DPP               Delivery Station             1151
C                 Center                        879
P                 Pickup Point                  391
CP                Collection Point              371
M                 Main Distribution Center      157
RP                Regional Processing Center    151
V                 Vendor Dispatch Point         111
NAGARDPC          Delivery Hub                   65
R                 Regional Center                28
Name: count, dtype: int64
```

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

source_location_type	count
Delivery Hub	74965
Delivery Center	31874
Unknown	14943
Inbound Area	11457
Inbound Processing	2768
Local Center	2125
Distribution Center	2121
Pickup Center	1375
Delivery Station	1151
Center	879
Pickup Point	391
Collection Point	371
Main Distribution Center	157
Regional Processing Center	151
Vendor Dispatch Point	111
Regional Center	28

dtype: int64

```
df[df['source_location_type'] == 'Unknown'].sample(8)
```

	data	trip_creation_time	year	month_name	week_days	hours	route_schedule_uuid	weeks	route_type	trip_uuid	sou
60183	training	2018-09-16 21:03:30.682448	2018	September	Sunday	21	thanos::sroute:95390c11-b18d-4f05-84c3-0e2e864...	37	FTL	153713181068220360	
11772	training	2018-09-24 15:25:06.973617	2018	September	Monday	15	thanos::sroute:fb4c42ab-bec0-4ea6-963e-a594f56...	39	Carting	153780270697335483	
113663	training	2018-09-17 22:31:18.413589	2018	September	Monday	22	thanos::sroute:fa83fd49-3327-4503-8e80-bf58ed6...	38	FTL	153722348992824420	
102700	test	2018-09-28 21:44:23.454783	2018	September	Friday	21	thanos::sroute:bcce7b68-e962-4a29-af24-167e3e9...	39	FTL	153817106345453699	
117307	test	2018-10-02 05:23:44.397739	2018	October	Tuesday	5	thanos::sroute:6f755c85-4bc8-45f0-8ad8-922cbbb...	40	Carting	153845782439747738	
112994	training	2018-09-16 10:48:41.778831	2018	September	Sunday	10	thanos::sroute:d4c1cb5b-d8ac-4f5a-b143-c4edcdc...	37	FTL	153709492316223315	
124097	training	2018-09-18 06:07:25.997486	2018	September	Tuesday	6	thanos::sroute:7c115632-8e81-4330-904a-9c7a6d6...	38	FTL	153725084599723069	
117928	training	2018-09-21 05:02:49.303239	2018	September	Friday	5	thanos::sroute:25dd334d-e30d-4cfa-b6e8-192bcfe...	38	FTL	153750616930299040	

```
df['source_location_type'].unique()

```

```
array(['Distribution Center', 'Delivery Center', 'Delivery Hub',
       'Unknown', 'Local Center', 'Collection Point', 'Inbound Area',
       'Center', 'Inbound Processing', 'Delivery Station',
       'Pickup Center', 'Regional Center', 'Vendor Dispatch Point',
       'Pickup Point', 'Main Distribution Center',
       'Regional Processing Center'], dtype=object)
```

```
df[df['source_location_type'] == 'Delivery Station']
```

	data	trip_creation_time	year	month_name	week_days	hours	route_schedule_uuid	weeks	route_type	trip_uuid	so
421	training	2018-09-14 19:56:55.742527	2018	September	Friday	19	thanos::sroute:ed5b80be-7abf-424d-b8cd-d81556a...	37	FTL	153695501574213014	
422	training	2018-09-14 19:56:55.742527	2018	September	Friday	19	thanos::sroute:ed5b80be-7abf-424d-b8cd-d81556a...	37	FTL	153695501574213014	
423	training	2018-09-14 19:56:55.742527	2018	September	Friday	19	thanos::sroute:ed5b80be-7abf-424d-b8cd-d81556a...	37	FTL	153695501574213014	
424	training	2018-09-14 19:56:55.742527	2018	September	Friday	19	thanos::sroute:ed5b80be-7abf-424d-b8cd-d81556a...	37	FTL	153695501574213014	
425	training	2018-09-14 19:56:55.742527	2018	September	Friday	19	thanos::sroute:ed5b80be-7abf-424d-b8cd-d81556a...	37	FTL	153695501574213014	
...	...	...	...	...	...	...	...	...	...	...	
144370	test	2018-10-03 07:03:32.343136	2018	October	Wednesday	7	thanos::sroute:147ddb06-42e6-4598-ae86-6cb0862...	40	Carting	153855021234288417	
144371	test	2018-10-03 07:03:32.343136	2018	October	Wednesday	7	thanos::sroute:147ddb06-42e6-4598-ae86-6cb0862...	40	Carting	153855021234288417	
144394	training	2018-09-19 03:28:16.636172	2018	September	Wednesday	3	thanos::sroute:ba13d833-af7e-4411-846a-04390e6...	38	Carting	153732769663592769	
144395	training	2018-09-19 03:28:16.636172	2018	September	Wednesday	3	thanos::sroute:ba13d833-af7e-4411-846a-04390e6...	38	Carting	153732769663592769	
144396	training	2018-09-19 03:28:16.636172	2018	September	Wednesday	3	thanos::sroute:ba13d833-af7e-4411-846a-04390e6...	38	Carting	153732769663592769	

1151 rows × 38 columns

```
# df[df['source_place_name'].str.contains('HB', na=False)]
```

```
# df[['destination_city_name', 'destination_place_name', 'destination_state_name']] = df['destination_name'].apply(lambda x: pd.Series(e

# state_col = df.pop('destination_state_name')
# place_col = df.pop('destination_place_name')
# city_col = df.pop('destination_city_name')

# df.insert(16, 'destination_state_name', state_col)
# df.insert(17, 'destination_place_name', place_col)
# df.insert(18, 'destination_city_name', city_col)
```

```
# df['destination_place_name'] = df['destination_place_name'].apply(lambda x: x.split('_')[0] if isinstance(x, str) and '_' in x else x)
```

```
df['destination_city_name'].sample(5)
```

	destination_city_name
18027	Baddi
110659	Gurgaon
140537	Jaipur
125877	Bhanvad
10132	Hyderabad

dtype: object

```
df.head()
```

	data	trip_creation_time	year	month_name	week_days	hours	route_schedule_uuid	weeks	route_type	trip_uuid	source_c
0	training	2018-09-20 02:35:36.476840	2018	September	Thursday	2	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	38	Carting	153741093647649320	38812
1	training	2018-09-20 02:35:36.476840	2018	September	Thursday	2	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	38	Carting	153741093647649320	38812
2	training	2018-09-20 02:35:36.476840	2018	September	Thursday	2	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	38	Carting	153741093647649320	38812
3	training	2018-09-20 02:35:36.476840	2018	September	Thursday	2	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	38	Carting	153741093647649320	38812
4	training	2018-09-20 02:35:36.476840	2018	September	Thursday	2	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	38	Carting	153741093647649320	38812

```
# df['source_state_name'] = df['source_name'].str.strip().str.split('(').str.get(1).str.split(')').str.get(0)
# df.insert(10, 'source_state_name', df.pop('source_state_name'))
```

```
# df['source_city_name'] = (
#     df['source_name']
#     .str.strip()
#     .str.split('(').str[0]
#     .str.split('-').str[0]
#     .str.replace('_', ' ')
#     .str.replace(r'\b(?:DC|FC|HB|Hub|H\s?\d*|I\s?\d*|D\s?\d*|H|D|I)\b\s*$', '', regex=True)
#     .str.replace(r'\s+', ' ', regex=True)
#     .str.strip()
# )
# df.insert(12, 'source_city_name', df.pop('source_city_name'))
```

```
# df['destination_state_name'] = df['destination_name'].str.strip().str.split('(').str.get(1).str.split(')').str.get(0)
# df.insert(11, 'destination_state_name', df.pop('destination_state_name'))
```

```
# df['destination_city_name'] = (
#     df['source_name']
#     .str.strip()
#     .str.split('(').str[0]
#     .str.split('-').str[0]
#     .str.replace('_', ' ')
#     .str.replace(r'\b(?:DC|FC|HB|Hub|H\s?\d*|I\s?\d*|D\s?\d*|H|D|I)\b\s*$', '', regex=True)
#     .str.replace(r'\s+', ' ', regex=True)
#     .str.strip()
# )
# df.insert(13, 'destination_city_name', df.pop('destination_city_name'))
```

```
df.drop(columns=['source_name', 'destination_name'], inplace=True)
```

```
df[df['source_city_name'].str.strip().str.contains('Bangalore', na=False)].sample(5)
```

	data	trip_creation_time	year	month_name	week_days	hours	route_schedule_uuid	weeks	route_type	trip_uuid	sou
84441	training	2018-09-16 13:49:03.943641	2018	September	Sunday	13	thanos::sroute:a1b25549-1e77-498f-8538-00292e5...	37	FTL	153710574394338691	
49723	training	2018-09-17 18:45:47.103654	2018	September	Monday	18	thanos::sroute:366da0f3-1979-4793-973f-27da635...	38	FTL	153720994710340958	
140874	training	2018-09-20 20:24:08.434699	2018	September	Thursday	20	thanos::sroute:76951383-1608-44e4-a284-46d92e8...	38	FTL	153747504843433031	
116570	training	2018-09-15 18:28:19.885391	2018	September	Saturday	18	thanos::sroute:2cb11ecd-7ac1-4c28-8781-af0ca81...	37	FTL	153703609988497817	
79347	training	2018-09-15 02:38:03.045869	2018	September	Saturday	2	thanos::sroute:2994b7ae-bb9c-4d7c-a30f-7882553...	37	FTL	153697908304560072	

```
df.loc[df.source_city_name == 'Bangalore','source_city_name'] = 'Bengaluru'
df.loc[df.destination_city_name == 'Bangalore','destination_city_name']='Bengaluru'
```

```
df[df['source_city_name'].str.strip().str.contains('Bengaluru', na=False)]
```

	data	trip_creation_time	year	month_name	week_days	hours	route_schedule_uuid	weeks	route_type	trip_uuid	sou
17	training	2018-09-13 20:44:19.424489	2018	September	Thursday	20	thanos::sroute:76951383-1608-44e4-a284-46d92e8...	37	FTL	153687145942424248	
18	training	2018-09-13 20:44:19.424489	2018	September	Thursday	20	thanos::sroute:76951383-1608-44e4-a284-46d92e8...	37	FTL	153687145942424248	
19	training	2018-09-13 20:44:19.424489	2018	September	Thursday	20	thanos::sroute:76951383-1608-44e4-a284-46d92e8...	37	FTL	153687145942424248	
20	training	2018-09-13 20:44:19.424489	2018	September	Thursday	20	thanos::sroute:76951383-1608-44e4-a284-46d92e8...	37	FTL	153687145942424248	
21	training	2018-09-13 20:44:19.424489	2018	September	Thursday	20	thanos::sroute:76951383-1608-44e4-a284-46d92e8...	37	FTL	153687145942424248	
...	...	...	...	...	...	...	...	...	...	...	
144600	training	2018-09-13 01:56:13.073644	2018	September	Thursday	1	thanos::sroute:16a02d06-e6b6-443b-bd98-0a9e4f4...	37	Carting	153680377307314823	
144601	training	2018-09-13 01:56:13.073644	2018	September	Thursday	1	thanos::sroute:16a02d06-e6b6-443b-bd98-0a9e4f4...	37	Carting	153680377307314823	
144602	training	2018-09-13 01:56:13.073644	2018	September	Thursday	1	thanos::sroute:16a02d06-e6b6-443b-bd98-0a9e4f4...	37	Carting	153680377307314823	
144603	training	2018-09-13 01:56:13.073644	2018	September	Thursday	1	thanos::sroute:16a02d06-e6b6-443b-bd98-0a9e4f4...	37	Carting	153680377307314823	
144604	training	2018-09-13 01:56:13.073644	2018	September	Thursday	1	thanos::sroute:16a02d06-e6b6-443b-bd98-0a9e4f4...	37	Carting	153680377307314823	

14341 rows × 36 columns

```
df.shape
```

```
(144867, 36)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144867 entries, 0 to 144866
Data columns (total 36 columns):
 #   Column                          Non-Null Count   Dtype
---  ------                          --------------   -----
 0   data                            144867 non-null  category
 1   trip_creation_time              144867 non-null  datetime64[ns]
 2   year                            144867 non-null  category
 3   month_name                      144867 non-null  category
 4   week_days                       144867 non-null  category
 5   hours                           144867 non-null  int32
 6   route_schedule_uuid             144867 non-null  object
 7   weeks                           144867 non-null  UInt32
 8   route_type                      144867 non-null  category
 9   trip_uuid                       144867 non-null  object
 10  source_center                   144867 non-null  object
 11  destination_center              144867 non-null  object
 12  od_start_time                   144867 non-null  datetime64[ns]
 13  od_end_time                     144867 non-null  datetime64[ns]
 14  start_scan_to_end_scan          144867 non-null  float64
 15  is_cutoff                       144867 non-null  bool
 16  cutoff_factor                   144867 non-null  int64
 17  cutoff_timestamp                144867 non-null  datetime64[ns]
 18  actual_distance_to_destination  144867 non-null  float64
 19  actual_time                     144867 non-null  float64
 20  osrm_time                       144867 non-null  float64
 21  osrm_distance                   144867 non-null  float64
 22  factor                          144867 non-null  float64
 23  segment_actual_time             144867 non-null  float64
 24  segment_osrm_time               144867 non-null  float64
 25  segment_osrm_distance           144867 non-null  float64
 26  segment_factor                  144867 non-null  float64
 27  source_city_name                144867 non-null  object
 28  source_place_name               144867 non-null  object
 29  source_code_name                144867 non-null  object
 30  source_state_name               144867 non-null  object
 31  destination_city_name           144867 non-null  object
 32  destination_place_name          144867 non-null  object
 33  destination_code_name           144867 non-null  object
 34  destination_state_name          144867 non-null  object
 35  source_location_type            144867 non-null  object
dtypes: UInt32(1), bool(1), category(5), datetime64[ns](4), float64(10), int32(1), int64(1), object(13)
memory usage: 33.0+ MB
```

```
df.head(2)
```

	data	trip_creation_time	year	month_name	week_days	hours	route_schedule_uuid	weeks	route_type	trip_uuid	source_c
0	training	2018-09-20 02:35:36.476840	2018	September	Thursday	2	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	38	Carting	153741093647649320	38812
1	training	2018-09-20 02:35:36.476840	2018	September	Thursday	2	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	38	Carting	153741093647649320	38812

```
df[df.columns[1:12:]].sample(2)
```

	trip_creation_time	year	month_name	week_days	hours	route_schedule_uuid	weeks	route_type	trip_uuid	source_cente
60281	2018-09-15 01:24:39.033033	2018	September	Saturday	1	thanos::sroute:df8d7098-cfd9-48f3-9bf3-a3144a4...	37	FTL	153697468300510917	411033-AA
86173	2018-09-15 13:59:15.494372	2018	September	Saturday	13	thanos::sroute:7af51efd-ae4d-49bc-9b68-	37	FTL	153701996256424406	562132-AA

```
# checking the unique values for columns
def unique_values_col(df):
  for col in df.columns:
    if col != 'datetime':
      print(f"Unique Values: {col} → {df[col].nunique()} ")

print(f"{unique_values_col(df)}")
```

```
Unique Values: data → 2
Unique Values: trip_creation_time → 14817
Unique Values: year → 1
```

```
Unique Values: month_name → 2
Unique Values: week_days → 7
Unique Values: hours → 24
Unique Values: route_schedule_uuid → 1504
Unique Values: weeks → 4
Unique Values: route_type → 2
Unique Values: trip_uuid → 14817
Unique Values: source_center → 1508
Unique Values: destination_center → 1481
Unique Values: od_start_time → 26369
Unique Values: od_end_time → 26369
Unique Values: start_scan_to_end_scan → 1915
Unique Values: is_cutoff → 2
Unique Values: cutoff_factor → 501
Unique Values: cutoff_timestamp → 93180
Unique Values: actual_distance_to_destination → 144515
Unique Values: actual_time → 3182
Unique Values: osrm_time → 1531
Unique Values: osrm_distance → 138046
Unique Values: factor → 45641
Unique Values: segment_actual_time → 747
Unique Values: segment_osrm_time → 214
Unique Values: segment_osrm_distance → 113799
Unique Values: segment_factor → 5675
Unique Values: source_city_name → 1262
Unique Values: source_place_name → 1179
Unique Values: source_code_name → 19
Unique Values: source_state_name → 32
Unique Values: destination_city_name → 1258
Unique Values: destination_place_name → 1155
Unique Values: destination_code_name → 49
Unique Values: destination_state_name → 33
Unique Values: source_location_type → 16
None
```

```
def value_count_col(df):
    for col in df.columns:
        if df[col].dtype in ['category', 'bool']:
            print(f"Total Values Count in the column '{col}':")
            print(df[col].value_counts().reset_index())
            print('-' * 50)

value_count_col(df)
```

```
Total Values Count in the column 'data':
       data   count
0  training  104858
1      test   40009
--------------------------------------------------
Total Values Count in the column 'year':
   year   count
0  2018  144867
--------------------------------------------------
Total Values Count in the column 'month_name':
  month_name   count
0  September  127349
1    October   17518
--------------------------------------------------
Total Values Count in the column 'week_days':
   week_days  count
0  Wednesday  26732
1   Thursday  20481
2     Friday  20242
3    Tuesday  19961
4   Saturday  19936
5     Monday  19645
6     Sunday  17870
--------------------------------------------------
Total Values Count in the column 'route_type':
  route_type  count
0        FTL  99660
1    Carting  45207
--------------------------------------------------
Total Values Count in the column 'is_cutoff':
   is_cutoff   count
0       True  118749
1      False   26118
--------------------------------------------------
```

```
def value_count_col(df, columns):
    for col in columns:
```

```
        if col in df.columns and df[col].dtype in ['object']:
            print(f"Total Value Counts in the column '{col}':")
            print(df[col].value_counts().reset_index().head(60))
            print('-' * 50)
```

```
value_count_col(df, ['route_schedule_uuid'])
```

```
Total Value Counts in the column 'route_schedule_uuid':
                                route_schedule_uuid  count
0   thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...   1812
1   thanos::sroute:0456b740-1dad-4929-bbe0-87d8843...   1608
2   thanos::sroute:dca6268f-741a-4d1a-b1b0-aab1309...   1605
3   thanos::sroute:a1b25549-1e77-498f-8538-00292e5...   1285
4   thanos::sroute:de5e208e-7641-45e6-8100-4d9fb1e...   1280
5   thanos::sroute:96a80600-40e1-436b-9161-fa68f9e...   1211
6   thanos::sroute:bcce7b68-e962-4a29-af24-167e3e9...   1162
7   thanos::sroute:69409580-4bf0-4bbf-96fe-9e7bc65...   1158
8   thanos::sroute:7af51efd-ae4d-49bc-9b68-345abe6...   1085
9   thanos::sroute:e2f5faaa-455a-494b-a501-549c3e3...   1069
10  thanos::sroute:162f9a67-5ebe-4338-8450-1c6d57d...   1046
11  thanos::sroute:14c55592-ba2e-4f72-820c-3a22334...   1039
12  thanos::sroute:6be6529b-f2ad-4714-b7ab-ac58f24...   1015
13  thanos::sroute:25dd334d-e30d-4cfa-b6e8-192bcfe...    978
14  thanos::sroute:396d96a3-e2f8-4c40-af0e-056e11f...    965
15  thanos::sroute:be1c03eb-fd2f-4455-a933-5e3d085...    954
16  thanos::sroute:67c77992-49e3-4594-9a75-9861ef0...    936
17  thanos::sroute:d44a95bc-1d78-49aa-a987-ea5763a...    924
18  thanos::sroute:2c33e360-7e52-4d2c-a9db-fe24996...    899
19  thanos::sroute:bc7dbb1d-9379-4674-b8d3-f9c3b96...    895
20  thanos::sroute:15c921f8-8a40-44cc-95ac-59f93d2...    853
21  thanos::sroute:a3414a57-5b1f-4cc0-bf8e-1a46456...    831
22  thanos::sroute:a4bf93af-8105-4dff-818e-cb79ddd...    818
23  thanos::sroute:64d4c6c9-ffb9-4794-b9f1-05f064c...    815
24  thanos::sroute:c094f55b-3c48-4ce4-b649-b99a4af...    810
25  thanos::sroute:6f20715d-5684-4595-a986-2836d48...    783
26  thanos::sroute:f01c8bbd-655d-42ea-9abf-60d5040...    775
27  thanos::sroute:3def24ea-f80d-4d49-b450-720dc5d...    773
28  thanos::sroute:cf2e63a5-87d6-4e39-a2d6-5555ed6...    770
29  thanos::sroute:fb308c0f-ea3a-48ef-a6c3-4776341...    732
30  thanos::sroute:870bead8-6c8a-458f-b4d8-658de44...    729
31  thanos::sroute:51d8aa58-9b5b-4bc2-81e9-bb284c6...    726
32  thanos::sroute:366da0f3-1979-4793-973f-27da635...    694
33  thanos::sroute:16f438c4-c258-4955-8358-bdb1e25...    667
34  thanos::sroute:828f0a4b-da11-4921-88df-5316ddb...    665
35  thanos::sroute:9d80b949-2d55-4578-b0ee-881d4bf...    658
36  thanos::sroute:65298ce5-d9ee-4614-80fe-0b619cf...    648
37  thanos::sroute:fa83fd49-3327-4503-8e80-bf58ed6...    639
38  thanos::sroute:19271c51-91cf-4bd7-8c7a-6e3f2d3...    636
39  thanos::sroute:951d77aa-4725-4c4e-882d-42acc35...    633
40  thanos::sroute:824ae884-8323-4beb-b955-27c6772...    617
41  thanos::sroute:f736bbd2-bccd-4649-a101-94b6a89...    616
42  thanos::sroute:2cb11ecd-7ac1-4c28-8781-af0ca81...    605
43  thanos::sroute:95390c11-b18d-4f05-84c3-0e2e864...    597
44  thanos::sroute:ef440d0b-5e79-4fe0-a7de-1cfa8c2...    580
45  thanos::sroute:f7de4133-6bd9-4367-a7f7-ab190b6...    568
46  thanos::sroute:caf62782-95cc-4d47-a071-d1c7038...    563
47  thanos::sroute:9ff9217a-3084-48e0-aab2-b340606...    557
48  thanos::sroute:cddde595-4764-4102-b5e2-2687cde...    531
49  thanos::sroute:34f33bf4-fb8c-476b-91fe-007dcdd...    503
50  thanos::sroute:3592c86e-c3d1-429b-917a-ebe9051...    498
51  thanos::sroute:adfe08d8-90c1-4170-aea7-04ce569...    486
52  thanos::sroute:54a7c356-361d-4e74-9ee7-d420c37...    484
53  thanos::sroute:36941a6b-0e90-4582-a95a-96666dc...    484
54  thanos::sroute:0f5c3b4b-5c1c-4a8f-abd4-98fcadb...    470
55  thanos::sroute:e798a910-1f3b-4eab-8dca-a18ec32...    458
```

```
value_count_col(df, ['trip_uuid'])
```

```
Total Value Counts in the column 'trip_uuid':
              trip_uuid  count
0   153759210483476123    101
1   153715938946690081    101
2   153784927255069118    101
3   153733005409156789    101
4   153811219535896559    101
5   153854305492910872    101
6   153837029526866991    101
7   153776597384821516    101
8   153846035308581166    101
9   153819749763881430    101
10  153793758186488532    101
11  153802363942560700    101
```

12	153741795740530104	101
13	153750670483274503	100
14	153814369747664517	100
15	153840656812932039	100
16	153805929645698249	100
17	153689939954743811	100
18	153788249820559505	99
19	153700734080145609	99
20	153845186341223055	95
21	153687903715256850	90
22	153844549250126648	90
23	153740782675825334	90
24	153851785421092561	90
25	153757183400969130	89
26	153713782709469234	89
27	153706159747270669	89
28	153860879439383883	89
29	153671043369099517	89
30	153722448294571122	89
31	153730228726629896	89
32	153680356130952302	88
33	153677936599367940	88
34	153789898080970939	88
35	153694983868521936	88
36	153747387300626701	88
37	153781308031132891	88
38	153850724778170196	88
39	153704214147054167	88
40	153773119907185732	88
41	153738682262223442	88
42	153859003271955591	88
43	153712971315208488	87
44	153762877083011555	87
45	153730278735722967	87
46	153721590035745248	87
47	153774373484687596	85
48	153764458438035894	85
49	153843116995748678	81
50	153799938034632401	81
51	153833321805533843	81
52	153705302283040335	81
53	153816749822118292	81
54	153790725871935220	81
55	153851500707048755	81

```
1 value_count_col(df, ['source_center'])
```

```
Total Value Counts in the column 'source_center':
```

	source_center	count
0	000000-ACB	23347
1	562132-AAA	9975
2	421302-AAG	9088
3	411033-AAA	4061
4	501359-AAE	3340
5	712311-AAA	2612
6	160002-AAC	2450
7	395023-AAA	2189
8	110037-AAM	2013
9	560099-AAB	1958
10	382430-AAB	1760
11	131028-AAB	1682
12	600056-AAB	1678
13	781018-AAB	1568
14	209304-AAA	1513
15	751002-AAB	1469
16	462022-AAA	1450
17	560300-AAA	1331
18	834002-AAB	1074
19	854326-AAB	1053
20	302014-AAA	791
21	110044-AAB	766
22	530012-AAA	711
23	400072-AAB	709
24	842001-AAA	709
25	000000-ACT	699
26	306401-AAB	622
27	121004-AAB	615
28	825409-AAA	614
29	821115-AAB	541
30	413002-AAA	507
31	416012-AAA	482
32	000000-ACA	464
33	444005-AAB	444
34	518002-AAA	405

35	580028-AAA	401
36	683511-AAA	399
37	515004-AAA	398
38	313001-AAB	387
39	302014-AAB	381
40	600032-AAB	355
41	474003-AAA	352
42	431136-AAC	334
43	403726-AAA	333
44	641062-AAD	327
45	532001-AAB	316
46	521225-AAB	309
47	585104-AAA	309
48	263153-AAB	295
49	144001-AAC	294
50	533106-AAA	289
51	400072-AAD	282
52	125001-AAA	269
53	211002-AAB	265
54	390022-AAA	263

```
1 value_count_col(df, ['destination_center'])
```

```
Total Value Counts in the column 'destination_center':
```

	destination_center	count
0	000000-ACB	15192
1	562132-AAA	11019
2	421302-AAG	5492
3	501359-AAE	5142
4	712311-AAA	4892
5	110037-AAM	3769
6	411033-AAA	3695
7	160002-AAC	2874
8	131028-AAB	2796
9	751002-AAB	2524
10	462022-AAA	2264
11	209304-AAA	2246
12	600056-AAB	2096
13	382430-AAB	1953
14	302014-AAA	1700
15	560099-AAB	1425
16	834002-AAB	1307
17	842001-AAA	1271
18	560300-AAA	1232
19	521225-AAB	1200
20	395023-AAA	988
21	821115-AAB	808
22	530012-AAA	680
23	781018-AAB	674
24	413002-AAA	622
25	400072-AAB	596
26	826004-AAA	559
27	683511-AAA	556
28	121004-AAB	556
29	444005-AAB	513
30	416012-AAA	489
31	305001-AAC	481
32	403726-AAA	480
33	000000-ACA	474
34	390022-AAA	457
35	518002-AAA	448
36	313001-AAB	411
37	401104-AAA	401
38	854326-AAB	394
39	585104-AAA	391
40	515004-AAA	377
41	580028-AAA	358
42	560043-AAC	358
43	533106-AAA	356
44	532001-AAB	342
45	121002-AAB	341
46	000000-AFT	333
47	211002-AAB	330
48	400015-AAA	328
49	422011-AAD	306
50	201301-AAM	304
51	641062-AAD	304
52	560058-AAB	302
53	713205-AAB	299
54	110064-AAA	289
55	431603-AAA	286

```
1 value_count_col(df, ['source_state_name'])
```

```
Total Value Counts in the column 'source_state_name':
         source_state_name  count
0                  Haryana  27499
1              Maharashtra  21401
2                Karnataka  19578
3               Tamil Nadu   7494
4                  Gujarat   7202
5             Uttar Pradesh   7137
6                Telangana   6496
7              West Bengal   5963
8           Andhra Pradesh   5539
9                Rajasthan   5267
10                 Punjab   4704
11                  Delhi   4398
12                  Bihar   4190
13          Madhya Pradesh   4021
14                  Assam   2875
15               Jharkhand   2597
16                 Kerala   2413
17                 Orissa   2094
18            Uttarakhand   1162
19       Himachal Pradesh    587
20                    Goa    514
21             Chandigarh    507
22                 Unkown    293
23      Arunachal Pradesh    245
24           Chhattisgarh    229
25         Jammu & Kashmir    226
26               Meghalaya     86
27             Pondicherry     49
28                Nagaland     40
29  Dadra and Nagar Haveli     30
30                 Mizoram     26
31                 Tripura      5
--------------------------------------------------
```

```
1 value_count_col(df, ['source_city_name'])
```

```
Total Value Counts in the column 'source_city_name':
             source_city_name  count
0                      Gurgaon  23665
1                    Bengaluru  14341
2                     Bhiwandi   9088
3                         Pune   4269
4                    Hyderabad   4023
5                        Delhi   3587
6                   Chandigarh   2953
7                      Kolkata   2844
8                        Surat   2362
9                    Ahmedabad   1850
10                     Sonipat   1795
11                    Guwahati   1678
12                         MAA   1678
13                      Mumbai   1618
14                      Kanpur   1581
15                      Bhopal   1542
16                Bhubaneshwar   1501
17                      Jaipur   1386
18                     Chennai   1188
19                      Ranchi   1074
20                      Purnia   1053
21                         Del    766
22              Visakhapatnam    748
23  Mumbai Hub (Maharashtra)    709
24                  Muzaffrpur   709
25                       Pali    622
26                        FBD    615
27                  JhumriTlya   614
28                       Noida   614
29                     Sasaram   541
30                    Ludhiana   518
31                     Solapur   507
32                    Kolhapur   505
33                   Jalandhar   498
34                       Akola   444
35                     Kurnool   405
36                         Goa   403
37                       Hubli   401
38                       Aluva   399
39                   Anantapur   398
40                     Udaipur   387
41                       Hisar   380
42                  Aurangabad   370
```

43	Coimbatore	352
44	Gwalior	352
45	Allahabad	322
46	Srikakulam	316
47	Vijayawada	309
48	Gulbarga	309
49	Rudrapur	295
50	Unkown	293
51	Rajamundry	289
52	Vadodara	264
53	Etawah	257
54	Dhanbad	247
55	Nellore	237

```
value_count_col(df, ['source_place_name'])
```

```
Total Value Counts in the column 'source_place_name':
```

	source_place_name	count
0	Bilaspur	23464
1	Nelmngla	10053
2	Mankoli	9088
3	Central	8989
4	Tathawde	4061
5	Shamshbd	3340
6	Dankuni	2612
7	Mehmdpur	2450
8	Unkown	2400
9	HUB (Gujarat)	2189
10	Airport	2013
11	East	2004
12	Bomsndra	1960
13	Kundli	1682
14	Poonamallee	1678
15	Hub (Assam)	1568
16	Hub (Orissa)	1469
17	Trnsport	1450
18	KGAirprt	1331
19	Hub (Jharkhand)	1074
20	Hub (Rajasthan)	791
21	DPC (Punjab)	782
22	Okhla	766
23	Gajuwaka	766
24	Bbganj	709
25	Gateway	699
26	DC (Gujarat)	676
27	Nayagaon	622
28	Balabhgarh	615
29	RadhaCpx	614
30	Shivaji	482
31	MilrGanj	464
32	Gaurkshn	444
33	AbbasNgr	405
34	Adargchi	401
35	Peedika	399
36	KamaStrt	398
37	Mangri	387
38	Hub (Tamil Nadu)	355
39	HrihrNgr	352
40	Hub (Goa)	333
41	Karayam	327
42	DC (Andhra Pradesh)	325
43	Kuslpram	316
44	Rynapadu	309
45	Nehrugnj	309
46	UdhamNgr	295
47	Sodal Road (Punjab)	294
48	AtoNgrRd	289
49	Chndivli	283
50	ModelTwn	269
51	Peenya	267
52	Karelibaug	264
53	North	261
54	MhraChng	257
55	Sector02	246

```
value_count_col(df, ['destination_state_name'])
```

```
Total Value Counts in the column 'destination_state_name':
```

	destination_state_name	count
0	Karnataka	21065
1	Haryana	20622
2	Maharashtra	18196
3	West Bengal	8499

```
4               Telangana   8205
5              Tamil Nadu   8058
6            Uttar Pradesh   7834
7                 Gujarat   6714
8               Rajasthan   6361
9           Andhra Pradesh   6265
10                  Delhi   5754
11                 Punjab   5105
12          Madhya Pradesh   4345
13                  Bihar   4238
14                 Orissa   3234
15               Jharkhand   2552
16                 Kerala   2230
17                  Assam   2000
18             Uttarakhand    893
19                    Goa    580
20        Himachal Pradesh    553
21              Chandigarh    389
22                  Unkown    261
23            Chhattisgarh    229
24       Arunachal Pradesh    211
25         Jammu & Kashmir    201
26             Pondicherry    154
27               Meghalaya     37
28  Dadra and Nagar Haveli     34
29                 Mizoram     31
30                 Tripura      9
31                Nagaland      7
32              Daman & Diu      1
--------------------------------------------------
```

```
1 value_count_col(df, ['destination_city_name'])
```

```
Total Value Counts in the column 'destination_city_name':
        destination_city_name  count
0                      Gurgaon  15393
1                    Bengaluru  15283
2                    Hyderabad   5838
3                     Bhiwandi   5586
4                        Delhi   5429
5                      Kolkata   5221
6                         Pune   3845
7                   Chandigarh   3271
8                      Sonipat   2913
9                 Bhubaneshwar   2524
10                      Kanpur   2365
11                      Mumbai   2308
12                      Jaipur   2295
13                      Bhopal   2276
14                         MAA   2096
15                   Ahmedabad   1953
16                     Chennai   1539
17                      Ranchi   1307
18                  Muzaffrpur   1271
19                  Vijayawada   1200
20                       Surat   1185
21                     Sasaram    808
22                    Guwahati    718
23               Visakhapatnam    706
24                       Noida    634
25                     Solapur    622
26   Mumbai Hub (Maharashtra)    596
27                     Dhanbad    566
28                         FBD    556
29                       Aluva    556
30                         Goa    539
31                       Akola    513
32                    Kolhapur    496
33                       Ajmer    481
34                    Ludhiana    474
35                    Vadodara    459
36                     Kurnool    448
37                     Udaipur    411
38                   Faridabad    407
39                      Purnia    394
40                    Gulbarga    391
41                   Anantapur    377
42                   Allahabad    373
43                       Hubli    363
44  HBR Layout PC (Karnataka)    358
45                  Rajamundry    356
46                  Srikakulam    342
47                  Coimbatore    322
```

48	Nashik	306
49	CCU	302
50	Durgapur	299
51	Nanded	286
52	Aurangabad	272
53	Jalandhar	271
54	Dibrugarh	268

```
value_count_col(df, ['destination_place_name'])
```

```
Total Value Counts in the column 'destination_place_name':
```

	destination_place_name	count
0	Bilaspur	15363
1	Nelmngla	11019
2	Central	9373
3	Mankoli	5586
4	Shamshbd	5309
5	Dankuni	4972
6	Airport	3769
7	Tathawde	3695
8	Kundli	2907
9	Mehmdpur	2886
10	Unkown	2702
11	Hub (Orissa)	2524
12	Trnsport	2264
13	East	2189
14	Poonamallee	2100
15	Hub (Rajasthan)	1700
16	Bomsndra	1432
17	Hub (Jharkhand)	1307
18	Bbganj	1271
19	KGAirprt	1232
20	Rynapadu	1200
21	HUB (Gujarat)	988
22	DPC (Punjab)	965
23	DC (Gujarat)	688
24	Gajuwaka	680
25	Hub (Assam)	674
26	Kalynpur	559
27	DC (Rajasthan)	558
28	Balabhgarh	556
29	Peedika	556
30	Chrompet	518
31	Gaurkshn	513
32	Shivaji	489
33	FoySGRRD	481
34	Hub (Goa)	480
35	MilrGanj	474
36	Karelibaug	459
37	AbbasNgr	448
38	Peenya	425
39	Mangri	411
40	MiraRd	401
41	Nehrugnj	391
42	KamaStrt	377
43	Adargchi	358
44	AtoNgrRd	356
45	DC (Punjab)	353
46	Kuslpram	342
47	Mthurard	341
48	Sanpada	334
49	CottonGreen	328
50	TgrniaRD	306
51	Sector63	304
52	Karayam	304
53	Mayapuri	289
54	Aswningr	286
55	DC (Haryana)	284

```
def group_by_count(df, col1, col2):
    group_by = df.groupby([col1, col2], observed=True).size().reset_index(name='Counts')
    sort_data = group_by.sort_values(by='Counts', ascending=False).head(20)
    print(f"Combinations Grouped by '{col1}' and '{col2}':")
    print(sort_data)
```

```
group_by_count(df, 'data', 'route_type')
```

```
Combinations Grouped by 'data' and 'route_type':
```

	data	route_type	Counts
3	training	FTL	73108
2	training	Carting	31750
1	test	FTL	26552

```
0      test    Carting   13457
```

```
group_by_count(df, 'year', 'data')
```

```
Combinations Grouped by 'year' and 'data':
   year      data  Counts
1  2018  training  104858
0  2018      test   40009
```

```
group_by_count(df, 'year', 'month_name')
```

```
Combinations Grouped by 'year' and 'month_name':
   year month_name  Counts
1  2018  September  127349
0  2018    October   17518
```

```
group_by_count(df, 'month_name', 'week_days')
```

```
Combinations Grouped by 'month_name' and 'week_days':
  month_name  week_days  Counts
9  September  Wednesday   20631
7  September   Thursday   20481
3  September     Friday   20242
5  September   Saturday   19936
6  September     Sunday   17870
8  September    Tuesday   14522
4  September     Monday   13667
2    October  Wednesday    6101
0    October     Monday    5978
1    October    Tuesday    5439
```

```
group_by_count(df, 'week_days', 'hours')
```

```
Combinations Grouped by 'week_days' and 'hours':
     week_days  hours  Counts
166  Wednesday     22    2513
163  Wednesday     19    1978
118   Thursday     22    1855
164  Wednesday     20    1805
142    Tuesday     22    1760
47      Monday     23    1755
145  Wednesday      1    1725
46      Monday     22    1722
23      Friday     23    1679
94      Sunday     22    1655
21      Friday     21    1642
140    Tuesday     20    1592
115   Thursday     19    1569
67    Saturday     19    1546
165  Wednesday     21    1536
116   Thursday     20    1527
144  Wednesday      0    1495
20      Friday     20    1462
91      Sunday     19    1461
167  Wednesday     23    1433
```

```
group_by_count(df, 'month_name', 'weeks')
```

```
Combinations Grouped by 'month_name' and 'weeks':
  month_name  weeks  Counts
2  September     38   49002
3  September     39   43379
1  September     37   34968
0    October     40   17518
```

```
group_by_count(df, 'trip_uuid', 'source_state_name')
```

```
Combinations Grouped by 'trip_uuid' and 'source_state_name':
                 trip_uuid source_state_name  Counts
7558   153755502932196495            Punjab      81
13776  153828700829921150           Haryana      79
14347  153837097390448401           Haryana      79
2662   153699138149593590           Haryana      79
7291   153751271053200074           Haryana      79
11032  153793999089967312           Haryana      79
1912   153690920439662353           Haryana      79
11813  153802876613714747           Haryana      79
15559  153854253003897121           Haryana      79
```

```
995    153681464570847135          Haryana      79
7405   153753420328505667        Karnataka      78
14875  153844549250126648        Karnataka      78
1542   153687903715256850        Karnataka      78
6391   153740782675825334        Karnataka      78
6728   153745694804626435        Karnataka      78
2813   153701996256424406        Karnataka      78
5878   153736437104067671        Karnataka      78
11925  153805395578070317        Karnataka      78
11182  153796781323528185        Karnataka      78
12588  153813931982659430        Karnataka      78
```

```
group_by_count(df, 'source_center', 'destination_center')
```

```
Combinations Grouped by 'source_center' and 'destination_center':
     source_center destination_center  Counts
59      000000-ACB         562132-AAA    4976
1753    562132-AAA         000000-ACB    3316
61      000000-ACB         712311-AAA    2862
57      000000-ACB         501359-AAE    1639
54      000000-ACB         421302-AAG    1617
1142    421302-AAG         000000-ACB    1269
2511    781018-AAB         110037-AAM    1137
1168    421302-AAG         562132-AAA    1131
53      000000-ACB         411033-AAA    1120
60      000000-ACB         600056-AAB    1015
1755    562132-AAA         302014-AAA     978
1144    421302-AAG         110037-AAM     965
966     395023-AAA         562132-AAA     935
1068    411033-AAA         000000-ACB     924
2769    854326-AAB         000000-ACB     899
62      000000-ACB         751002-AAB     853
1787    562132-AAA         751002-AAB     818
118     110037-AAM         421302-AAG     815
959     395023-AAA         110037-AAM     773
211     131028-AAB         000000-ACB     760
```

```
group_by_count(df, 'source_state_name', 'destination_state_name')
```

```
Combinations Grouped by 'source_state_name' and 'destination_state_name':
    source_state_name destination_state_name  Counts
103       Maharashtra            Maharashtra   11876
75          Karnataka              Karnataka   11107
135        Tamil Nadu             Tamil Nadu    6549
162     Uttar Pradesh          Uttar Pradesh    4978
49            Haryana              Karnataka    4976
46            Haryana                Haryana    4508
36            Gujarat                Gujarat    4491
129         Rajasthan              Rajasthan    4380
172       West Bengal            West Bengal    4004
143         Telangana              Telangana    3804
0       Andhra Pradesh         Andhra Pradesh    3755
74          Karnataka                Haryana    3394
124            Punjab                 Punjab    2985
99        Maharashtra                Haryana    2934
60            Haryana            West Bengal    2862
15              Bihar                  Bihar    2770
51            Haryana            Maharashtra    2737
25              Delhi                Haryana    2051
90     Madhya Pradesh         Madhya Pradesh    1989
86             Kerala                 Kerala    1943
```

```
group_by_count(df, 'source_state_name', 'destination_city_name')
```

```
Combinations Grouped by 'source_state_name' and 'destination_city_name':
     source_state_name destination_city_name  Counts
468          Karnataka             Bengaluru    5888
336            Haryana             Bengaluru    4976
500          Karnataka               Gurgaon    3394
373            Haryana               Kolkata    2862
721        Maharashtra              Bhiwandi    2323
767        Maharashtra                Mumbai    2308
742        Maharashtra               Gurgaon    2193
365            Haryana             Hyderabad    1639
338            Haryana              Bhiwandi    1617
1150         Telangana             Hyderabad    1612
347            Haryana                 Delhi    1563
359            Haryana               Gurgaon    1550
1032        Tamil Nadu               Chennai    1539
232              Delhi               Gurgaon    1526
719        Maharashtra             Bengaluru    1469
```

788	Maharashtra	Pune	1420
880	Punjab	Chandigarh	1210
1286	Uttar Pradesh	Gurgaon	1157
171	Bihar	Gurgaon	1156
744	Maharashtra	Hyderabad	1152

```
group_by_count(df, 'source_city_name', 'destination_city_name')
```

Combinations Grouped by 'source_city_name' and 'destination_city_name':

	source_city_name	destination_city_name	Counts
243	Bengaluru	Bengaluru	5071
806	Gurgaon	Bengaluru	4976
251	Bengaluru	Gurgaon	3394
829	Gurgaon	Kolkata	2862
824	Gurgaon	Hyderabad	1639
807	Gurgaon	Bhiwandi	1617
813	Gurgaon	Delhi	1345
327	Bhiwandi	Gurgaon	1269
848	Guwahati	Delhi	1137
323	Bhiwandi	Bengaluru	1131
331	Bhiwandi	Mumbai	1130
836	Gurgaon	Pune	1120
574	Delhi	Gurgaon	1073
830	Gurgaon	MAA	1015
258	Bengaluru	Jaipur	978
955	Hyderabad	Hyderabad	969
326	Bhiwandi	Delhi	965
2157	Surat	Bengaluru	935
1806	Pune	Gurgaon	924
1824	Purnia	Gurgaon	899

```
group_by_count(df, 'source_city_name', 'source_place_name')
```

Combinations Grouped by 'source_city_name' and 'source_place_name':

	source_city_name	source_place_name	Counts
529	Gurgaon	Bilaspur	23464
161	Bengaluru	Nelmngla	10053
200	Bhiwandi	Mankoli	9088
1150	Pune	Tathawde	4061
593	Hyderabad	Shamshbd	3340
781	Kolkata	Dankuni	2612
277	Chandigarh	Mehmdpur	2450
1351	Surat	HUB (Gujarat)	2189
373	Delhi	Airport	2013
154	Bengaluru	Bomsndra	1960
9	Ahmedabad	East	1760
1329	Sonipat	Kundli	1682
841	MAA	Poonamallee	1678
536	Guwahati	Hub (Assam)	1568
704	Kanpur	Central	1559
207	Bhubaneshwar	Hub (Orissa)	1469
205	Bhopal	Trnsport	1450
157	Bengaluru	KGAirprt	1331
1191	Ranchi	Hub (Jharkhand)	1074
1154	Purnia	Central	1053

```
group_by_count(df, 'destination_city_name', 'destination_place_name')
```

Combinations Grouped by 'destination_city_name' and 'destination_place_name':

	destination_city_name	destination_place_name	Counts
510	Gurgaon	Bilaspur	15363
159	Bengaluru	Nelmngla	11019
197	Bhiwandi	Mankoli	5586
568	Hyderabad	Shamshbd	5309
760	Kolkata	Dankuni	4972
355	Delhi	Airport	3769
1125	Pune	Tathawde	3695
1307	Sonipat	Kundli	2907
267	Chandigarh	Mehmdpur	2886
204	Bhubaneshwar	Hub (Orissa)	2524
682	Kanpur	Central	2288
201	Bhopal	Trnsport	2264
818	MAA	Poonamallee	2096
10	Ahmedabad	East	1953
589	Jaipur	Hub (Rajasthan)	1700
152	Bengaluru	Bomsndra	1432
1167	Ranchi	Hub (Jharkhand)	1307
949	Muzaffrpur	Bbganj	1271
155	Bengaluru	KGAirprt	1232
1420	Vijayawada	Rynapadu	1200

```
def group_by_count(df, col1, col2, col3,):
    group_by = df.groupby([col1, col2, col3], observed=True).size().reset_index(name='Counts')
    sort_data = group_by.sort_values(by='Counts', ascending=False).head(20)
    print(f"Combinations Grouped by '{col1}' and '{col2}':")
    print(sort_data)
```

```
group_by_count(df, 'data', 'month_name', 'week_days')
```

```
Combinations Grouped by 'data' and 'month_name':
        data month_name  week_days  Counts
13  training  September  Wednesday   20631
12  training  September    Tuesday   14522
7   training  September     Friday   14448
11  training  September   Thursday   14391
9   training  September   Saturday   14249
8   training  September     Monday   13667
10  training  September     Sunday   12950
2       test    October  Wednesday    6101
6       test  September   Thursday    6090
0       test    October     Monday    5978
3       test  September     Friday    5794
4       test  September   Saturday    5687
1       test    October    Tuesday    5439
5       test  September     Sunday    4920
```

```
group_by_count(df, 'route_type', 'month_name', 'week_days')
```

```
Combinations Grouped by 'route_type' and 'month_name':
   route_type month_name  week_days  Counts
19        FTL  September  Wednesday   14360
17        FTL  September   Thursday   13726
13        FTL  September     Friday   13676
15        FTL  September   Saturday   13535
16        FTL  September     Sunday   13002
18        FTL  September    Tuesday   10045
14        FTL  September     Monday    9609
7     Carting  September   Thursday    6755
3     Carting  September     Friday    6566
5     Carting  September   Saturday    6401
9     Carting  September  Wednesday    6271
6     Carting  September     Sunday    4868
8     Carting  September    Tuesday    4477
4     Carting  September     Monday    4058
12        FTL    October  Wednesday    4018
10        FTL    October     Monday    4008
11        FTL    October    Tuesday    3681
2     Carting    October  Wednesday    2083
0     Carting    October     Monday    1970
1     Carting    October    Tuesday    1758
```

```
group_by_count(df, 'week_days', 'source_state_name', 'destination_state_name')
```

```
Combinations Grouped by 'week_days' and 'source_state_name':
     week_days source_state_name destination_state_name  Counts
966  Wednesday       Maharashtra            Maharashtra    2371
939  Wednesday         Karnataka              Karnataka    1969
239     Monday       Maharashtra            Maharashtra    1685
668   Thursday       Maharashtra            Maharashtra    1682
817    Tuesday       Maharashtra            Maharashtra    1655
90      Friday       Maharashtra            Maharashtra    1644
386   Saturday       Maharashtra            Maharashtra    1644
65      Friday         Karnataka              Karnataka    1635
214     Monday         Karnataka              Karnataka    1605
642   Thursday         Karnataka              Karnataka    1583
789    Tuesday         Karnataka              Karnataka    1541
361   Saturday         Karnataka              Karnataka    1503
500     Sunday         Karnataka              Karnataka    1271
994  Wednesday        Tamil Nadu             Tamil Nadu    1204
524     Sunday       Maharashtra            Maharashtra    1195
119     Friday        Tamil Nadu             Tamil Nadu    1088
263     Monday        Tamil Nadu             Tamil Nadu    1008
905  Wednesday           Gujarat                Gujarat     940
843    Tuesday        Tamil Nadu             Tamil Nadu     931
694   Thursday        Tamil Nadu             Tamil Nadu     915
```

```
group_by_count(df, 'hours', 'source_state_name', 'destination_state_name')
```

```
Combinations Grouped by 'hours' and 'source_state_name':
      hours source_state_name destination_state_name  Counts
1018     18          Haryana             Karnataka    1282
```

44	0	Maharashtra	Maharashtra	1199
360	5	Haryana	Karnataka	1152
93	1	Gujarat	Gujarat	1111
1459	23	Uttar Pradesh	Uttar Pradesh	1085
1122	19	Maharashtra	Maharashtra	979
31	0	Karnataka	Karnataka	930
1192	20	Karnataka	Karnataka	885
321	4	Maharashtra	Maharashtra	811
1269	21	Karnataka	Karnataka	801
1340	22	Karnataka	Karnataka	790
1221	20	Tamil Nadu	Tamil Nadu	766
1285	21	Maharashtra	Maharashtra	766
1093	19	Haryana	Maharashtra	765
1437	23	Maharashtra	Maharashtra	761
69	0	Uttar Pradesh	Uttar Pradesh	757
956	17	Haryana	Karnataka	748
1449	23	Tamil Nadu	Tamil Nadu	743
108	1	Karnataka	Karnataka	691
116	1	Maharashtra	Maharashtra	682

```
group_by_count(df, 'month_name', 'source_state_name', 'destination_state_name')
```

```
Combinations Grouped by 'month_name' and 'source_state_name':
```

	month_name	source_state_name	destination_state_name	Counts
232	September	Maharashtra	Maharashtra	10424
204	September	Karnataka	Karnataka	9834
263	September	Tamil Nadu	Tamil Nadu	5876
290	September	Uttar Pradesh	Uttar Pradesh	4306
179	September	Haryana	Karnataka	4206
176	September	Haryana	Haryana	4080
166	September	Gujarat	Gujarat	3931
257	September	Rajasthan	Rajasthan	3787
300	September	West Bengal	West Bengal	3452
271	September	Telangana	Telangana	3346
131	September	Andhra Pradesh	Andhra Pradesh	3223
203	September	Karnataka	Haryana	3084
252	September	Punjab	Punjab	2673
228	September	Maharashtra	Haryana	2627
190	September	Haryana	West Bengal	2502
146	September	Bihar	Bihar	2395
181	September	Haryana	Maharashtra	2339
156	September	Delhi	Haryana	1901
219	September	Madhya Pradesh	Madhya Pradesh	1726
215	September	Kerala	Kerala	1633

```
group_by_count(df, 'route_type', 'source_state_name', 'destination_state_name')
```

```
Combinations Grouped by 'route_type' and 'source_state_name':
```

	route_type	source_state_name	destination_state_name	Counts
29	Carting	Karnataka	Karnataka	8117
34	Carting	Maharashtra	Maharashtra	6892
150	FTL	Maharashtra	Maharashtra	4984
96	FTL	Haryana	Karnataka	4976
43	Carting	Tamil Nadu	Tamil Nadu	4705
22	Carting	Haryana	Haryana	3464
121	FTL	Karnataka	Haryana	3394
208	FTL	Uttar Pradesh	Uttar Pradesh	3169
122	FTL	Karnataka	Karnataka	2990
146	FTL	Maharashtra	Haryana	2934
107	FTL	Haryana	West Bengal	2862
175	FTL	Rajasthan	Rajasthan	2775
98	FTL	Haryana	Maharashtra	2737
52	Carting	West Bengal	West Bengal	2710
67	FTL	Bihar	Bihar	2660
170	FTL	Punjab	Punjab	2513
189	FTL	Telangana	Telangana	2438
53	FTL	Andhra Pradesh	Andhra Pradesh	2316
83	FTL	Gujarat	Gujarat	2306
20	Carting	Gujarat	Gujarat	2185

```
group_by_count(df, 'week_days', 'source_state_name', 'destination_state_name')
```

```
Combinations Grouped by 'week_days' and 'source_state_name':
```

	week_days	source_state_name	destination_state_name	Counts
966	Wednesday	Maharashtra	Maharashtra	2371
939	Wednesday	Karnataka	Karnataka	1969
239	Monday	Maharashtra	Maharashtra	1685
668	Thursday	Maharashtra	Maharashtra	1682
817	Tuesday	Maharashtra	Maharashtra	1655
90	Friday	Maharashtra	Maharashtra	1644
386	Saturday	Maharashtra	Maharashtra	1644

```
65      Friday         Karnataka             Karnataka    1635
214     Monday         Karnataka             Karnataka    1605
642   Thursday         Karnataka             Karnataka    1583
789    Tuesday         Karnataka             Karnataka    1541
361   Saturday         Karnataka             Karnataka    1503
500     Sunday         Karnataka             Karnataka    1271
994  Wednesday        Tamil Nadu            Tamil Nadu    1204
524     Sunday       Maharashtra           Maharashtra    1195
119     Friday        Tamil Nadu            Tamil Nadu    1088
263     Monday        Tamil Nadu            Tamil Nadu    1008
905  Wednesday           Gujarat               Gujarat     940
843    Tuesday        Tamil Nadu            Tamil Nadu     931
694   Thursday        Tamil Nadu            Tamil Nadu     915
```

```
group_by_count(df, 'data', 'source_state_name', 'destination_city_name')
```

```
Combinations Grouped by 'data' and 'source_state_name':
          data source_state_name destination_city_name  Counts
1541  training         Karnataka             Bengaluru    4271
1417  training           Haryana             Bengaluru    3338
1573  training         Karnataka               Gurgaon    2662
1451  training           Haryana               Kolkata    2022
1809  training       Maharashtra               Gurgaon    1788
1789  training       Maharashtra              Bhiwandi    1716
246       test           Haryana             Bengaluru    1638
349       test         Karnataka             Bengaluru    1617
1834  training       Maharashtra                Mumbai    1389
1418  training           Haryana              Bhiwandi    1274
1437  training           Haryana               Gurgaon    1222
1854  training       Maharashtra                  Pune    1220
1318  training             Delhi               Gurgaon    1216
2202  training         Telangana             Hyderabad    1190
1443  training           Haryana             Hyderabad    1183
1426  training           Haryana                 Delhi    1174
1787  training       Maharashtra             Bengaluru    1128
2086  training        Tamil Nadu               Chennai    1069
1118  training    Andhra Pradesh             Hyderabad     982
1940  training            Punjab            Chandigarh     981
```

```
group_by_count(df, 'source_state_name', 'source_center', 'destination_center')
```

```
Combinations Grouped by 'source_state_name' and 'source_center':
     source_state_name source_center destination_center  Counts
642            Haryana    000000-ACB         562132-AAA    4976
900          Karnataka    562132-AAA         000000-ACB    3316
644            Haryana    000000-ACB         712311-AAA    2862
640            Haryana    000000-ACB         501359-AAE    1639
637            Haryana    000000-ACB         421302-AAG    1617
1458       Maharashtra    421302-AAG         000000-ACB    1269
164              Assam    781018-AAB         110037-AAM    1137
1484       Maharashtra    421302-AAG         562132-AAA    1131
636            Haryana    000000-ACB         411033-AAA    1120
643            Haryana    000000-ACB         600056-AAB    1015
902          Karnataka    562132-AAA         302014-AAA     978
1460       Maharashtra    421302-AAG         110037-AAM     965
582            Gujarat    395023-AAA         562132-AAA     935
1384       Maharashtra    411033-AAA         000000-ACB     924
349              Bihar    854326-AAB         000000-ACB     899
645            Haryana    000000-ACB         751002-AAB     853
934          Karnataka    562132-AAA         751002-AAB     818
413              Delhi    110037-AAM         421302-AAG     815
575            Gujarat    395023-AAA         110037-AAM     773
713            Haryana    131028-AAB         000000-ACB     760
```

```
group_by_count(df, 'source_state_name', 'source_city_name', 'source_place_name')
```

```
Combinations Grouped by 'source_state_name' and 'source_city_name':
     source_state_name source_city_name source_place_name  Counts
338            Haryana          Gurgaon          Bilaspur   23464
441          Karnataka        Bengaluru          Nelmngla   10053
683        Maharashtra         Bhiwandi           Mankoli    9088
770        Maharashtra             Pune          Tathawde    4061
1147         Telangana        Hyderabad          Shamshbd    3340
1429       West Bengal          Kolkata           Dankuni    2612
856              Punjab       Chandigarh          Mehmdpur    2450
306            Gujarat            Surat     HUB (Gujarat)    2189
217              Delhi            Delhi           Airport    2013
434          Karnataka        Bengaluru          Bomsndra    1960
248            Gujarat        Ahmedabad              East    1760
367            Haryana          Sonipat            Kundli    1682
1052        Tamil Nadu              MAA       Poonamallee    1678
```

```
108             Assam         Guwahati       Hub (Assam)    1568
1277    Uttar Pradesh           Kanpur           Central    1559
817            Orissa      Bhubaneshwar      Hub (Orissa)    1469
614     Madhya Pradesh           Bhopal          Trnsport    1450
437          Karnataka        Bengaluru          KGAirprt    1331
416          Jharkhand           Ranchi   Hub (Jharkhand)    1074
183              Bihar           Purnia           Central    1053
```

```
group_by_count(df, 'destination_state_name', 'destination_city_name', 'destination_place_name')
```

```
Combinations Grouped by 'destination_state_name' and 'destination_city_name':
     destination_state_name destination_city_name destination_place_name  \
332                 Haryana               Gurgaon               Bilaspur
432               Karnataka             Bengaluru               Nelmngla
671             Maharashtra              Bhiwandi                Mankoli
1118              Telangana             Hyderabad               Shamshbd
1400            West Bengal               Kolkata                Dankuni
209                   Delhi                 Delhi                Airport
757             Maharashtra                  Pune               Tathawde
360                 Haryana               Sonipat                 Kundli
840                  Punjab            Chandigarh               Mehmdpur
806                  Orissa          Bhubaneshwar           Hub (Orissa)
1247          Uttar Pradesh                Kanpur                Central
603          Madhya Pradesh                Bhopal               Trnsport
1030             Tamil Nadu                   MAA            Poonamallee
243                 Gujarat             Ahmedabad                   East
916               Rajasthan                Jaipur        Hub (Rajasthan)
425               Karnataka             Bengaluru                Bomsndra
407               Jharkhand                Ranchi        Hub (Jharkhand)
169                   Bihar             Muzaffrpur                 Bbganj
428               Karnataka             Bengaluru               KGAirprt
68            Andhra Pradesh            Vijayawada               Rynapadu

      Counts
332    15363
432    11019
671     5586
1118    5309
1400    4972
209     3769
757     3695
360     2907
840     2886
806     2524
1247    2288
603     2264
1030    2096
243     1953
916     1700
425     1432
407     1307
169     1271
428     1232
68      1200
```

```
df.head(1)
```

	data	trip_creation_time	year	month_name	week_days	hours	route_schedule_uuid	weeks	route_type	trip_uuid	source_c
0	training	2018-09-20 02:35:36.476840	2018	September	Thursday	2	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	38	Carting	153741093647649320	38812

✅ 1. Descriptive Analysis:

```
def average_stats(df, group_col, col1, col2, col3):
    average_col = df.groupby(group_col, observed=True)[[col1, col2, col3]].mean().reset_index().round(2)
    print(average_col)
```

The average actual_time, osrm_time, and factor for each route_type:

```
average_stats(df, 'data', 'actual_time', 'osrm_time', 'factor')
```

```
       data  actual_time  osrm_time  factor
0      test       434.26     222.06    2.14
```

```
1  training       410.31     210.74    2.11
```

```
average_stats(df, 'year', 'actual_time', 'osrm_time', 'factor')
```

```
   year  actual_time  osrm_time  factor
0  2018       416.93     213.87    2.12
```

```
average_stats(df, 'month_name', 'actual_time', 'osrm_time', 'factor')
```

```
  month_name  actual_time  osrm_time  factor
0    October       436.61     224.12    2.11
1  September       414.22     212.46    2.12
```

```
average_stats(df, 'week_days', 'actual_time', 'osrm_time', 'factor')
```

```
    week_days  actual_time  osrm_time  factor
0     Friday       413.49     212.64    2.12
1     Monday       413.71     213.21    2.11
2   Saturday       420.10     215.50    2.15
3     Sunday       419.54     220.17    2.06
4   Thursday       412.61     208.29    2.14
5    Tuesday       410.41     211.74    2.11
6  Wednesday       425.96     215.71    2.14
```

```
average_stats(df, 'route_type', 'actual_time', 'osrm_time', 'factor')
```

```
  route_type  actual_time  osrm_time  factor
0    Carting        70.64      30.45    2.41
1        FTL       574.01     297.07    1.99
```

```
average_stats(df, 'is_cutoff', 'actual_time', 'osrm_time', 'factor')
```

```
   is_cutoff  actual_time  osrm_time  factor
0      False       202.34      91.39    2.56
1       True       464.13     240.81    2.02
```

Segment Wise Analyze:

```
dd = df.copy()
```

```
dd.head(2)
```

	data	trip_creation_time	year	month_name	week_days	hours	route_schedule_uuid	weeks	route_type	trip_uuid	source_c
0	training	2018-09-20 02:35:36.476840	2018	September	Thursday	2	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	38	Carting	153741093647649320	38812
1	training	2018-09-20 02:35:36.476840	2018	September	Thursday	2	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	38	Carting	153741093647649320	38812

```
df = dd.copy()
```

Merging of rows and aggregation of fields

```
# Grouping by segment
# Creating a unique identifier for each segment of a trip

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

df['segment_key'] = df['trip_uuid'] + ' + ' + df['source_center'] + ' + ' + df['destination_center']

for col in segment_cols:
    df[col + '_sum'] = df.groupby('segment_key')[col].cumsum()

df[['segment_key', 'segment_actual_time', 'segment_actual_time_sum','segment_osrm_distance', 'segment_osrm_distance_sum','segment_osrm_t
```

	segment_key	segment_actual_time	segment_actual_time_sum	segment_osrm_distance	segment_osrm_distance_sum	segment_osrm
0	153741093647649320 + 388121-AAA + 388620-AAB	14.0	14.0	11.9653	11.9653	
1	153741093647649320 + 388121-AAA + 388620-AAB	10.0	24.0	9.7590	21.7243	
2	153741093647649320 + 388121-AAA + 388620-AAB	16.0	40.0	10.8152	32.5395	
3	153741093647649320 + 388121-AAA + 388620-AAB	21.0	61.0	13.0224	45.5619	
4	153741093647649320 + 388121-AAA + 388620-AAB	6.0	67.0	3.9153	49.4772	
...	...	...	...	...	...	
144862	153746066843555182 + 131028-AAB + 000000-ACB	12.0	92.0	8.1858	65.3487	
144863	153746066843555182 + 131028-AAB + 000000-ACB	26.0	118.0	17.3725	82.7212	
144864	153746066843555182 + 131028-AAB + 000000-ACB	20.0	138.0	20.7053	103.4265	
144865	153746066843555182 + 131028-AAB + 000000-ACB	17.0	155.0	18.8885	122.3150	
144866	153746066843555182 + 131028-AAB + 000000-ACB	268.0	423.0	8.8088	131.1238	

144867 rows × 7 columns

```
df.head(2)
```

	data	trip_creation_time	year	month_name	week_days	hours	route_schedule_uuid	weeks	route_type	trip_uuid	source_c
0	training	2018-09-20 02:35:36.476840	2018	September	Thursday	2	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	38	Carting	153741093647649320	388121
1	training	2018-09-20 02:35:36.476840	2018	September	Thursday	2	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	38	Carting	153741093647649320	388121

```
# Aggregating at segment level & Creating a dictionary for aggregation at segment level
 # year, month_name, week_days, source_state_name, destination_city_name,

segment_dict = {
  'trip_uuid' : 'first',
  'data': 'first',
  'route_type': 'first',
  'trip_creation_time': 'first',
  'year': 'first',
  'month_name': 'first',
  'week_days': 'first',
  'hours': 'first',
  'weeks': 'first',
  'source_state_name': 'first',
  'source_city_name': 'first',
  'source_place_name': 'first',
  'destination_state_name': 'last',
  'destination_city_name': 'last',
  'destination_place_name': 'last',
  'od_start_time': 'first',
  'od_end_time': 'last',
```

```
  'start_scan_to_end_scan': 'first',
  'actual_distance_to_destination': 'last',
  'actual_time': 'last',
  'osrm_time': 'last',
  'osrm_distance': 'last',
  'segment_actual_time' : 'sum',
  'segment_osrm_time' : 'sum',
  'segment_osrm_distance' : 'sum',
  'segment_actual_time_sum': 'last',
  'segment_osrm_time_sum': 'last',
  'segment_osrm_distance_sum': 'last',
}

# Grouping by segment_key and aggregating
df = df.groupby('segment_key').agg(segment_dict).reset_index()
df = df.sort_values(by=['segment_key','od_end_time'])
df.head(2)
```

	segment_key	trip_uuid	data	route_type	trip_creation_time	year	month_name	week_days	hours	weeks	source_sta
0	153671041653548748 + 209304-AAA + 000000-ACB	153671041653548748	training	FTL	2018-09-12 00:00:16.535741	2018	September	Wednesday	0	37	Uttar
1	153671041653548748 + 462022-AAA + 209304-AAA	153671041653548748	training	FTL	2018-09-12 00:00:16.535741	2018	September	Wednesday	0	37	Madhya

```
# 1. Calculating time difference between od_start_time and od_end_time
df['od_total_time'] = (df['od_end_time'] - df['od_start_time'])
df['od_time_diff_hour'] = (df['od_total_time']).dt.total_seconds()/3600
df.head()
```

	segment_key	trip_uuid	data	route_type	trip_creation_time	year	month_name	week_days	hours	weeks	source_sta
0	153671041653548748 + 209304-AAA + 000000-ACB	153671041653548748	training	FTL	2018-09-12 00:00:16.535741	2018	September	Wednesday	0	37	Uttar
1	153671041653548748 + 462022-AAA + 209304-AAA	153671041653548748	training	FTL	2018-09-12 00:00:16.535741	2018	September	Wednesday	0	37	Madhya
2	153671042288605164 + 561203-AAB + 562101-AAA	153671042288605164	training	Carting	2018-09-12 00:00:22.886430	2018	September	Wednesday	0	37	K
3	153671042288605164 + 572101-AAA + 561203-AAB	153671042288605164	training	Carting	2018-09-12 00:00:22.886430	2018	September	Wednesday	0	37	K
4	153671043369099517 + 000000-ACB + 160002-AAC	153671043369099517	training	FTL	2018-09-12 00:00:33.691250	2018	September	Wednesday	0	37	

```
df['source_state_name'].value_counts().to_frame().style.background_gradient(cmap='Reds')
```

source_state_name	count
Maharashtra	3565
Karnataka	3453
Tamil Nadu	2130
Haryana	2056
Uttar Pradesh	1832
Telangana	1484
Gujarat	1401
West Bengal	1368
Andhra Pradesh	1310
Rajasthan	1176
Bihar	1060
Punjab	1052
Delhi	821
Kerala	762
Madhya Pradesh	742
Assam	484
Uttarakhand	369
Jharkhand	301
Orissa	248
Himachal Pradesh	223
Chandigarh	160
Goa	86
Unkown	66
Chhattisgarh	52
Arunachal Pradesh	48
Jammu & Kashmir	47
Pondicherry	30
Dadra and Nagar Haveli	15
Meghalaya	13
Mizoram	8
Nagaland	5
Tripura	1

Detect Outliers

```
df.head(1)
```

	segment_key	trip_uuid	data	route_type	trip_creation_time	year	month_name	week_days	hours	weeks	source_sta
0	153671041653548748 + 209304-AAA + 000000-ACB	153671041653548748	training	FTL	2018-09-12 00:00:16.535741	2018	September	Wednesday	0	37	Uttar

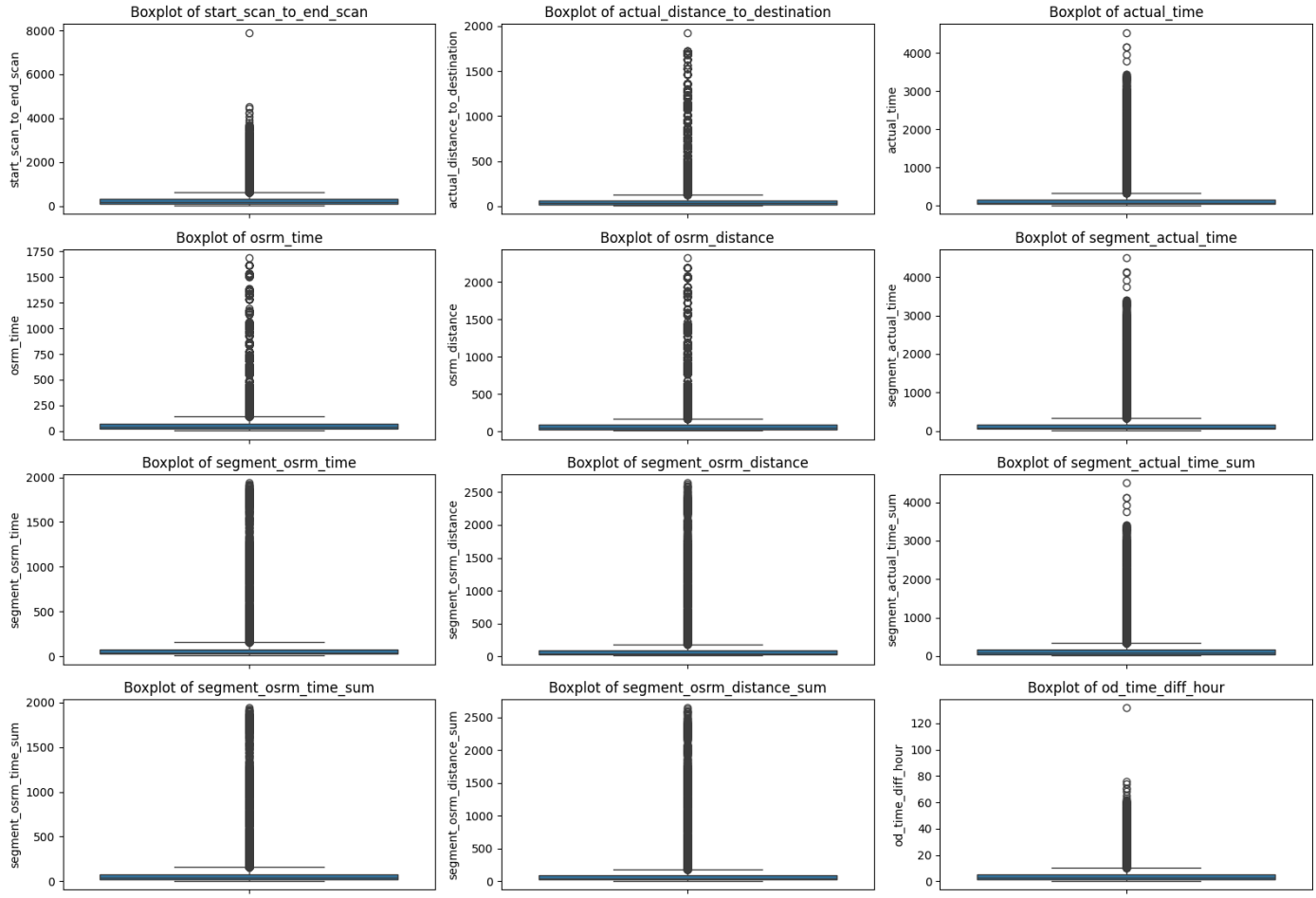
```
outlire_df = [
    'start_scan_to_end_scan', 'actual_distance_to_destination', 'actual_time',
    'osrm_time', 'osrm_distance', 'segment_actual_time',
    'segment_osrm_time', 'segment_osrm_distance',
    'segment_actual_time_sum', 'segment_osrm_time_sum',
```

```
    'segment_osrm_distance_sum', 'od_time_diff_hour'
]
```

```
# Calculate IQR for each numeric column in the list
Q1 = df[outlire_df].quantile(0.25)
Q3 = df[outlire_df].quantile(0.75)
IQR = Q3 - Q1

print(IQR)
```

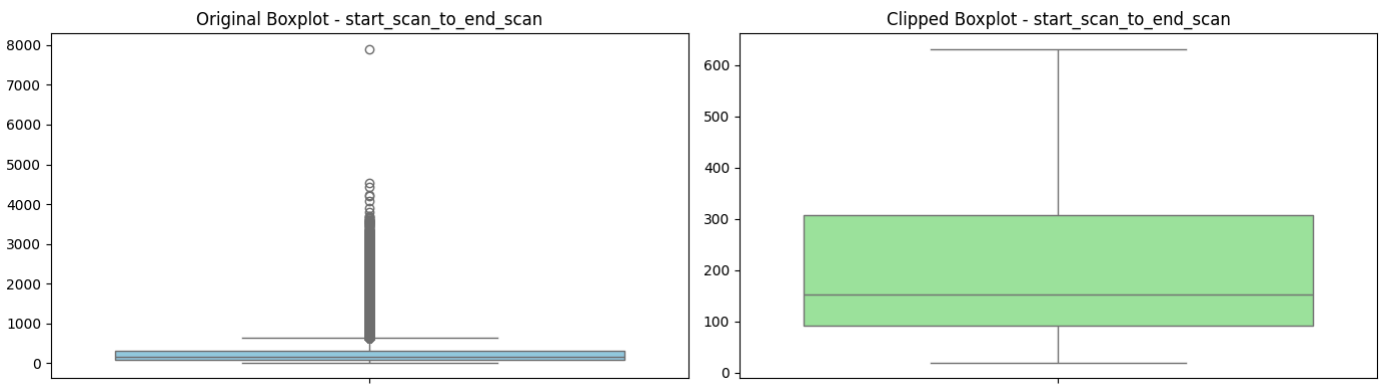
```
start_scan_to_end_scan            216.000000
actual_distance_to_destination     44.066307
actual_time                       117.000000
osrm_time                          47.000000
osrm_distance                      57.802250
segment_actual_time               116.000000
segment_osrm_time                  54.000000
segment_osrm_distance              62.880675
segment_actual_time_sum           116.000000
segment_osrm_time_sum              54.000000
segment_osrm_distance_sum          62.880675
od_time_diff_hour                   3.601070
dtype: float64
```

```
plt.figure(figsize=(16, 11))

for i in range(len(outlire_df)):
    plt.subplot(4, 3, i + 1)
    sns.boxplot(y=df[outlire_df[i]])
    plt.title(f'Boxplot of {outlire_df[i]}')
    plt.tight_layout()

plt.show()
```

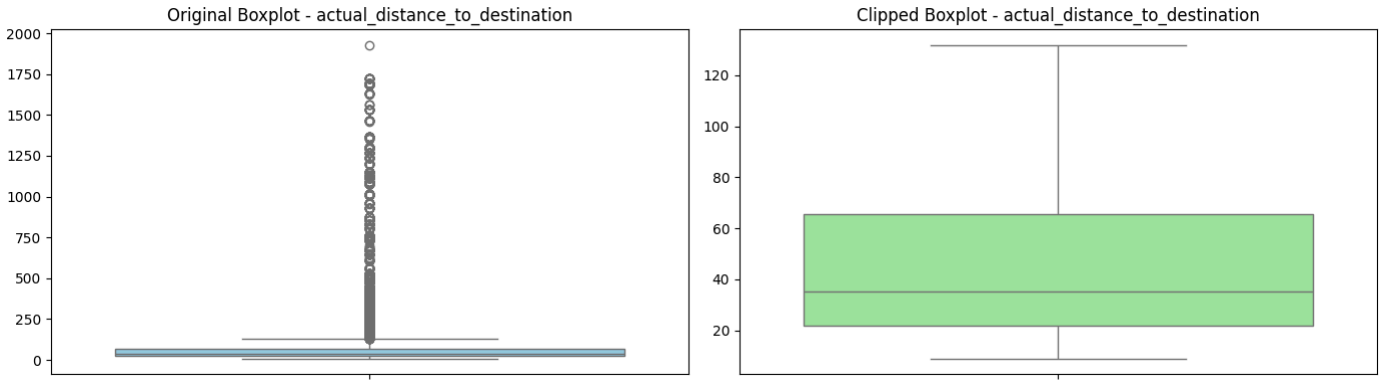



```
def compare_original_clipped(df, column_list):
    for col in column_list:
        data = df[col]

        # Calculate IQR
        Q1 = np.percentile(data, 25)
        Q3 = np.percentile(data, 75)
        IQR = Q3 - Q1
        lower_bound = Q1 - (1.5 * IQR)
        upper_bound = Q3 + (1.5 * IQR)
        clipped_data = np.clip(data, lower_bound, upper_bound)

        fig, axes = plt.subplots(1, 2, figsize=(14, 4))
        sns.boxplot(y=data, ax=axes[0], color='skyblue')
        axes[0].set_title(f'Original Boxplot - {col}')
        axes[0].set_ylabel('')

        sns.boxplot(y=clipped_data, ax=axes[1], color='lightgreen')
        axes[1].set_title(f'Clipped Boxplot - {col}')
        axes[1].set_ylabel('')

        plt.tight_layout()
        plt.show()
```

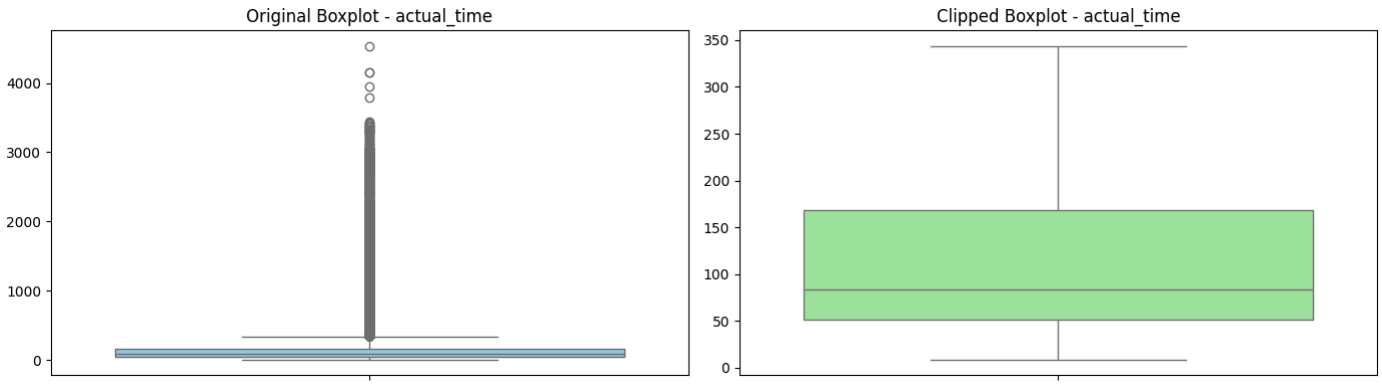
```
compare_original_clipped(df, ['start_scan_to_end_scan'])
```



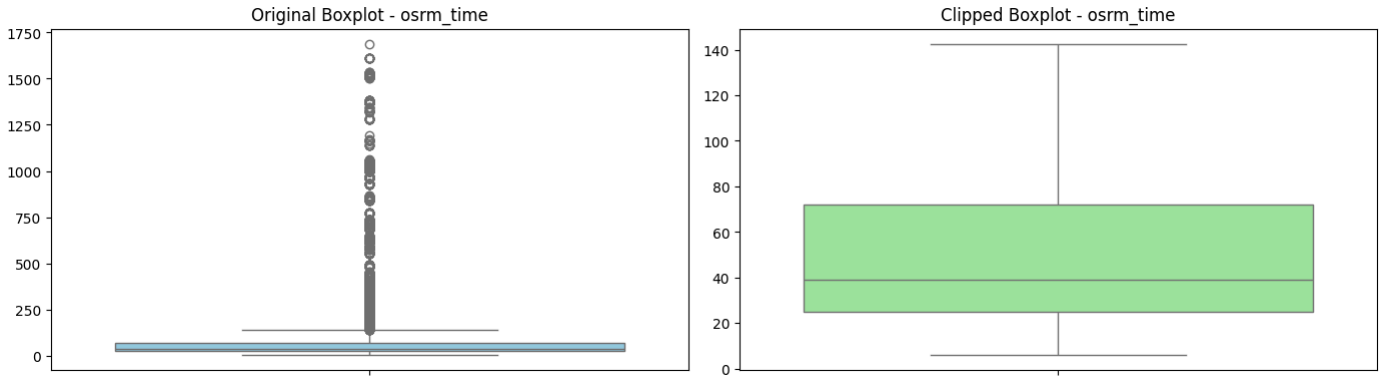

```
compare_original_clipped(df, ['actual_distance_to_destination'])
```



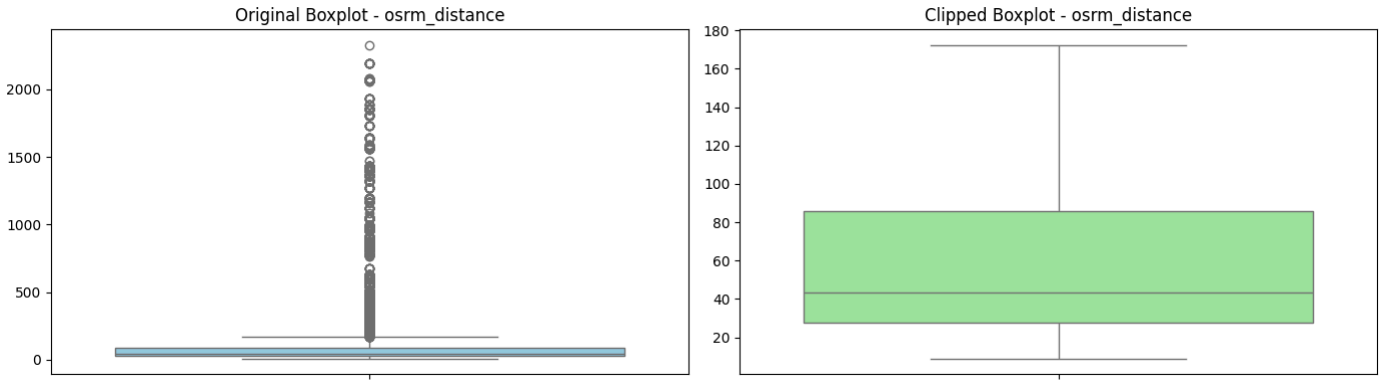

```
compare_original_clipped(df, ['actual_time'])
```



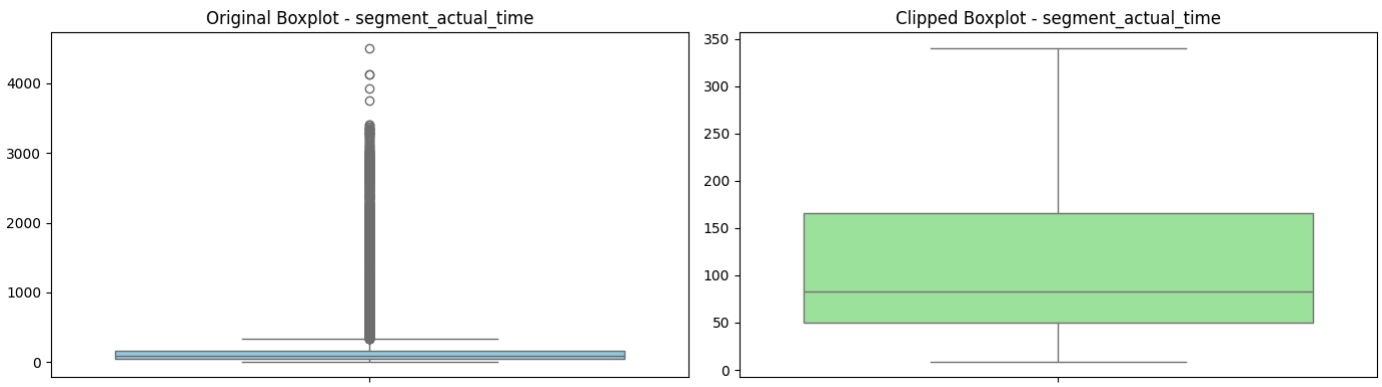

```
compare_original_clipped(df, ['osrm_time'])
```



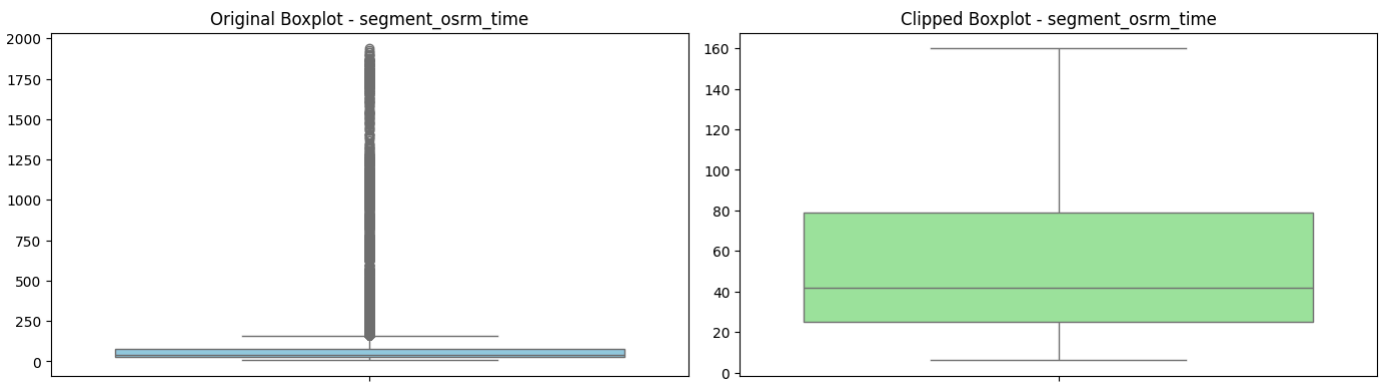

```
compare_original_clipped(df, ['osrm_distance'])
```



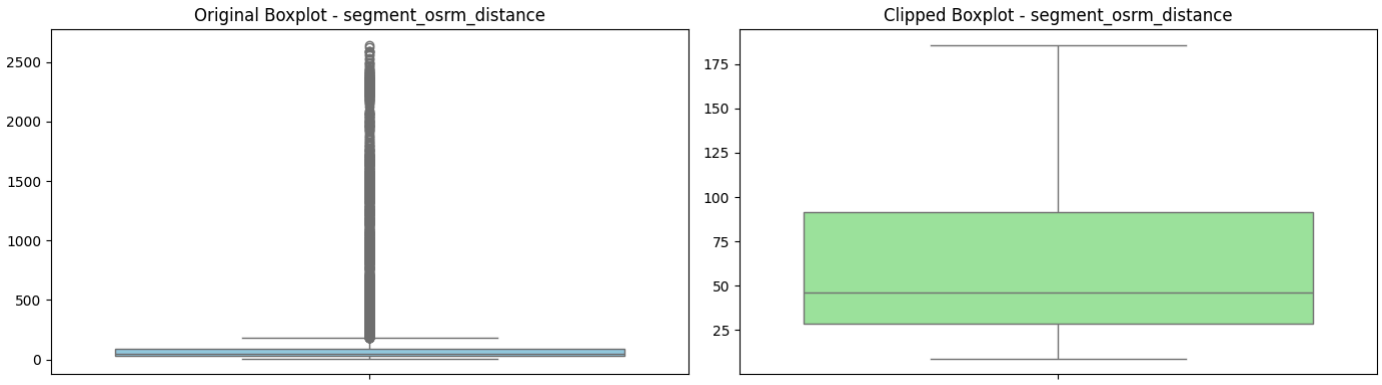

```
compare_original_clipped(df, ['segment_actual_time'])
```



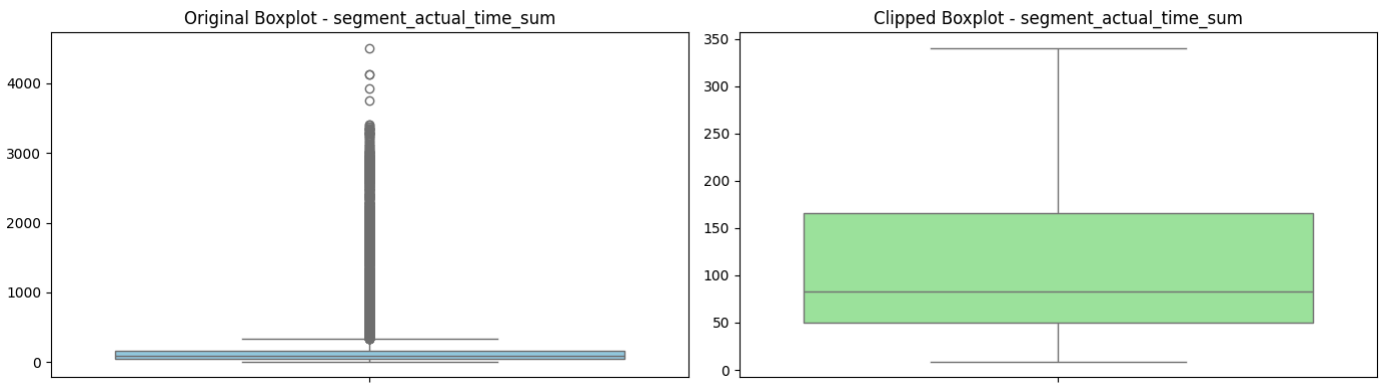

```
compare_original_clipped(df, ['segment_osrm_time'])
```



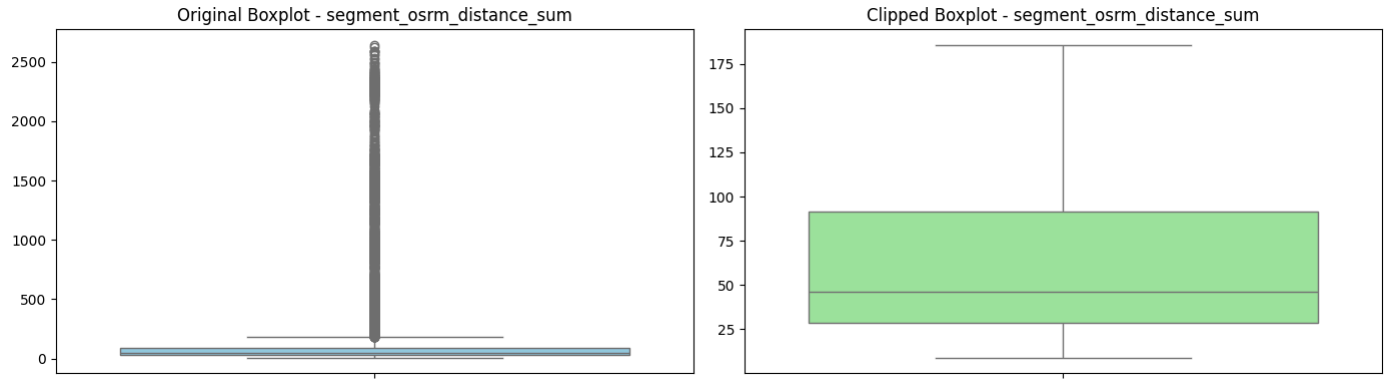

```
compare_original_clipped(df, ['segment_osrm_distance'])
```



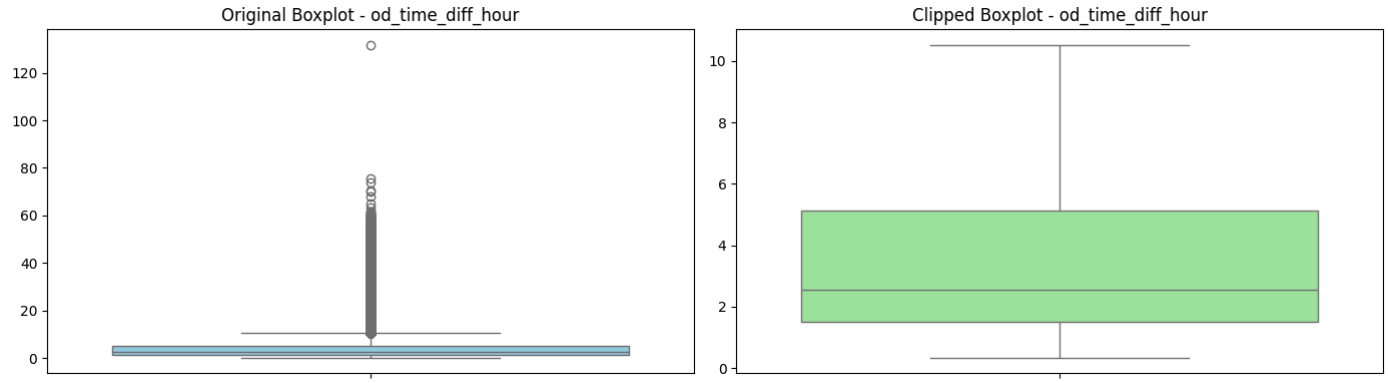

```
compare_original_clipped(df, ['segment_actual_time_sum'])
```




```
compare_original_clipped(df, ['segment_osrm_distance_sum'])
```




```
compare_original_clipped(df, ['od_time_diff_hour'])
```




```
Q1 = np.percentile(df[outlire_df], 25)
Q3 = np.percentile(df[outlire_df], 75)
IQR = Q3 - Q1

lower_bound = Q1 - (1.5 * IQR)
upper_bound = Q3 + (1.5 * IQR)
clipped_num_df = np.clip(df[outlire_df], lower_bound, upper_bound)

filtered_num_df = df[outlire_df][(df[outlire_df] >= lower_bound) | (df[outlire_df] <= upper_bound)]
filtered_num_df
```

	start_scan_to_end_scan	actual_distance_to_destination	actual_time	osrm_time	osrm_distance	segment_actual_time	segment_osrm_
0	1260.0	383.759164	732.0	329.0	446.5496	728.0	
1	999.0	440.973689	830.0	388.0	544.8027	820.0	
2	58.0	24.644021	47.0	26.0	28.1994	46.0	
3	122.0	48.542890	96.0	42.0	56.9116	95.0	
4	834.0	237.439610	611.0	212.0	281.2109	608.0	
...	...	...	...	...	...	...	
26363	62.0	33.627182	51.0	41.0	42.5213	49.0	
26364	91.0	33.673835	90.0	48.0	40.6080	89.0	
26365	44.0	12.661945	30.0	14.0	16.0185	29.0	
26366	287.0	40.546740	233.0	42.0	52.5303	233.0	
26367	66.0	25.534793	42.0	26.0	28.0484	41.0	

26368 rows × 12 columns

```
clipped_df_corr = clipped_num_df.corr()
clipped_df_corr
```

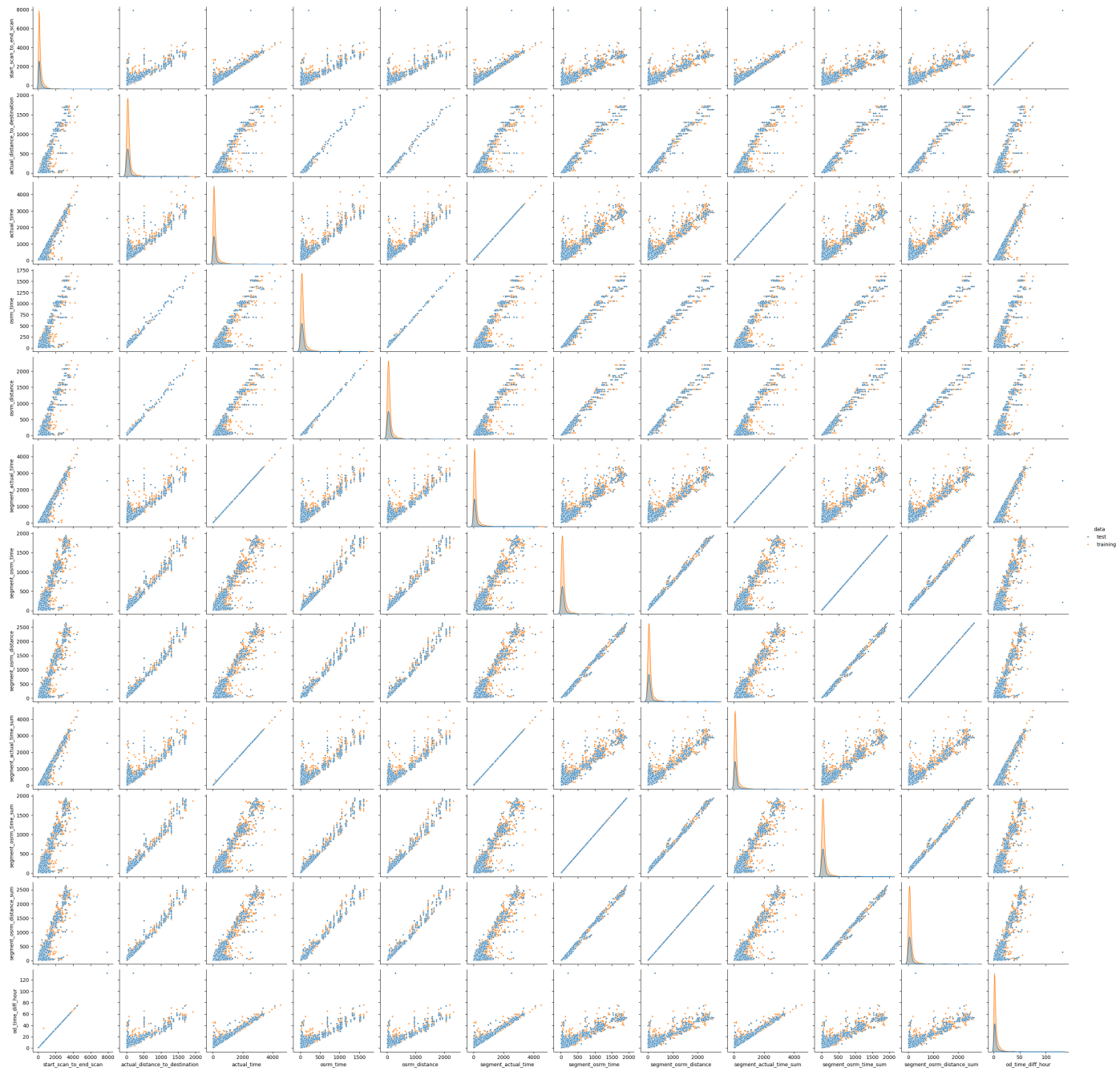
	start_scan_to_end_scan	actual_distance_to_destination	actual_time	osrm_time	osrm_distance	segment_actu
start_scan_to_end_scan	1.000000	0.576313	0.779462	0.589446	0.615214	
actual_distance_to_destination	0.576313	1.000000	0.791448	0.975538	0.981424	
actual_time	0.779462	0.791448	1.000000	0.799141	0.832446	
osrm_time	0.589446	0.975538	0.799141	1.000000	0.978984	
osrm_distance	0.615214	0.981424	0.832446	0.978984	1.000000	
segment_actual_time	0.778106	0.792490	0.999916	0.800123	0.833117	
segment_osrm_time	0.607306	0.949089	0.813944	0.977561	0.963846	
segment_osrm_distance	0.629866	0.962223	0.842914	0.961829	0.984144	
segment_actual_time_sum	0.778106	0.792490	0.999916	0.800123	0.833117	
segment_osrm_time_sum	0.607306	0.949089	0.813944	0.977561	0.963846	
segment_osrm_distance_sum	0.629866	0.962223	0.842914	0.961829	0.984144	
od_time_diff_hour	0.531849	0.716977	0.604997	0.724513	0.683889	

```
filtered_df_corr = filtered_num_df.corr()
filtered_df_corr
```

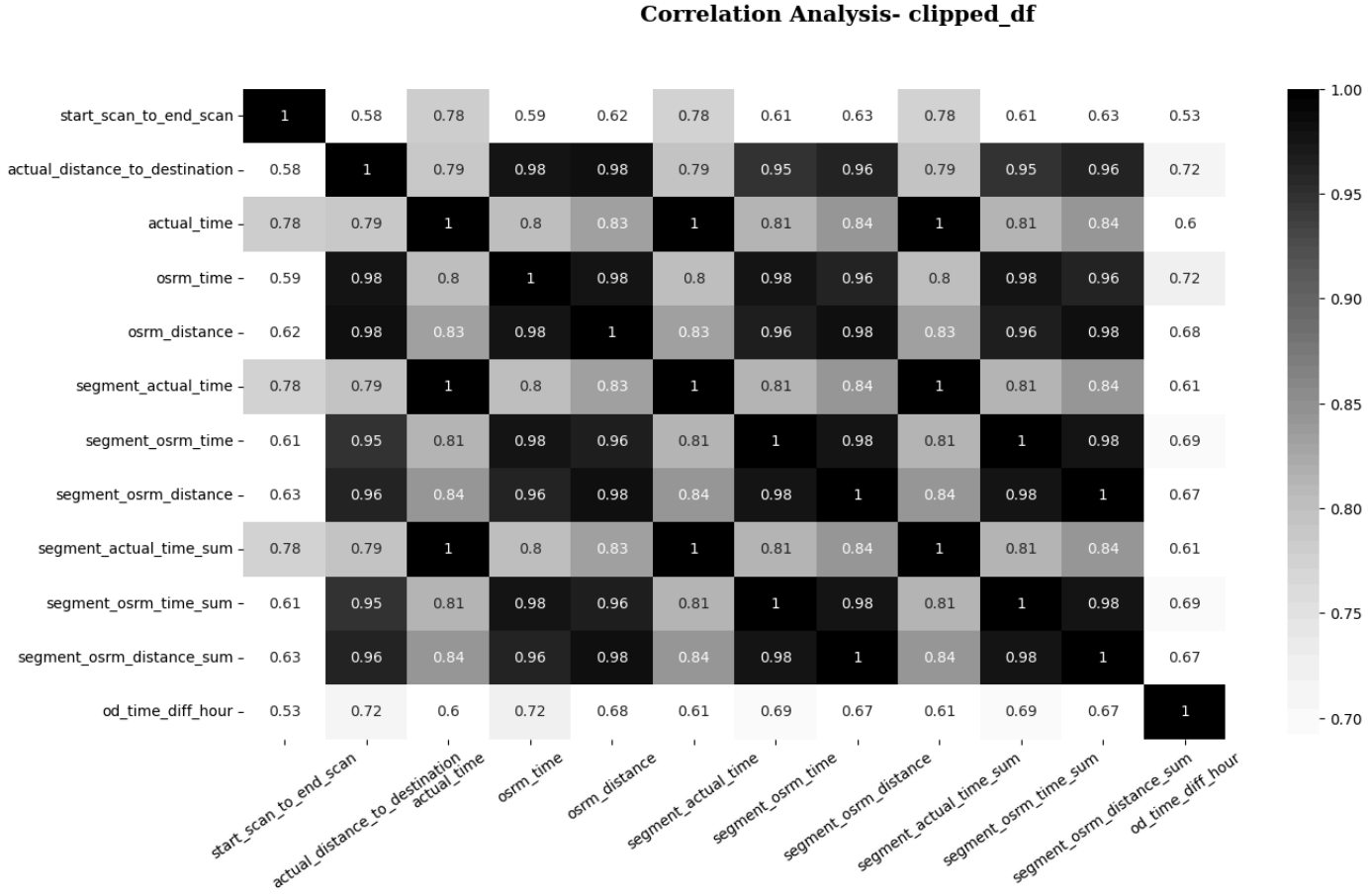
	start_scan_to_end_scan	actual_distance_to_destination	actual_time	osrm_time	osrm_distance	segment_actu
start_scan_to_end_scan	1.000000	0.906266	0.954473	0.911197	0.911361	
actual_distance_to_destination	0.906266	1.000000	0.948995	0.994893	0.997217	
actual_time	0.954473	0.948995	1.000000	0.953152	0.953845	
osrm_time	0.911197	0.994893	0.953152	1.000000	0.998384	
osrm_distance	0.911361	0.997217	0.953845	0.998384	1.000000	
segment_actual_time	0.954460	0.947989	0.999988	0.952218	0.952905	
segment_osrm_time	0.904397	0.987161	0.947958	0.992269	0.990975	
segment_osrm_distance	0.908123	0.992742	0.952183	0.992677	0.994311	
segment_actual_time_sum	0.954460	0.947989	0.999988	0.952218	0.952905	
segment_osrm_time_sum	0.904397	0.987161	0.947958	0.992269	0.990975	
segment_osrm_distance_sum	0.908123	0.992742	0.952183	0.992677	0.994311	
od_time_diff_hour	0.999796	0.905960	0.954179	0.910880	0.911049	

```
plt.figure(figsize=(14,0.05))
plt.axis('off')
plt.title(f' Pairplot Analysis', fontfamily = 'serif', fontweight = 'bold', fontsize = 15, backgroundcolor = 'crimson')
sns.pairplot(data = df, vars = outlire_df, hue ='data',markers = '.')
plt.show()
```

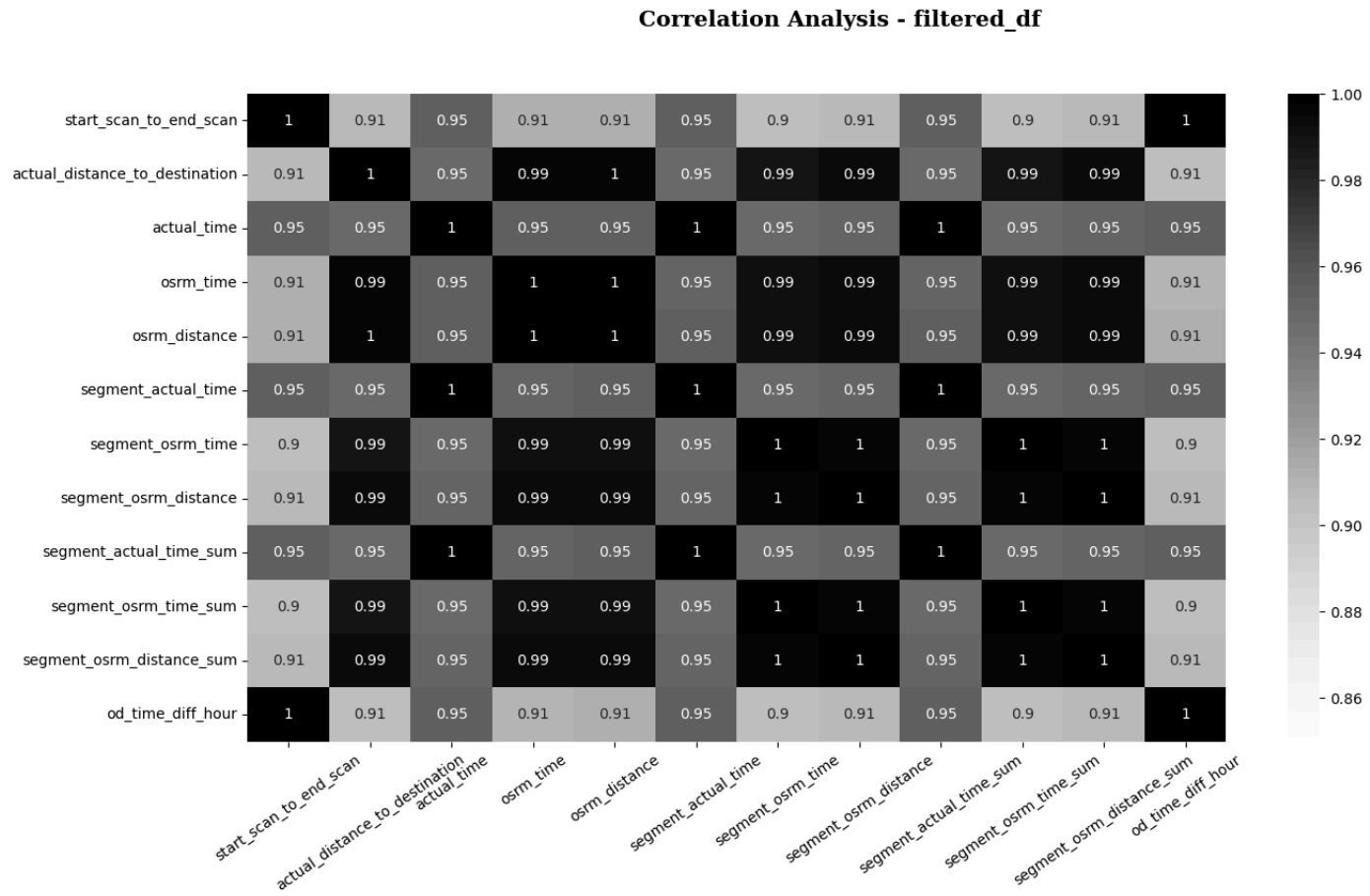
Pairplot Analysis




```
plt.figure(figsize = (15,8))
plt.suptitle(f'Correlation Analysis- clipped_df', fontfamily = 'serif', fontweight = 'bold', fontsize = 15)
sns.heatmap(data = clipped_df_corr, vmin = 0.69, annot = True, cmap = 'Greys')
plt.xticks(rotation = 35)
plt.show()
```




```
plt.figure(figsize=(15, 8))
plt.suptitle('Correlation Analysis - filtered_df', fontfamily='serif', fontweight='bold', fontsize=15)
sns.heatmap(data = filtered_df_corr, vmin = 0.85, annot = True, cmap = 'Greys')
plt.xticks(rotation = 35)
plt.show()
```



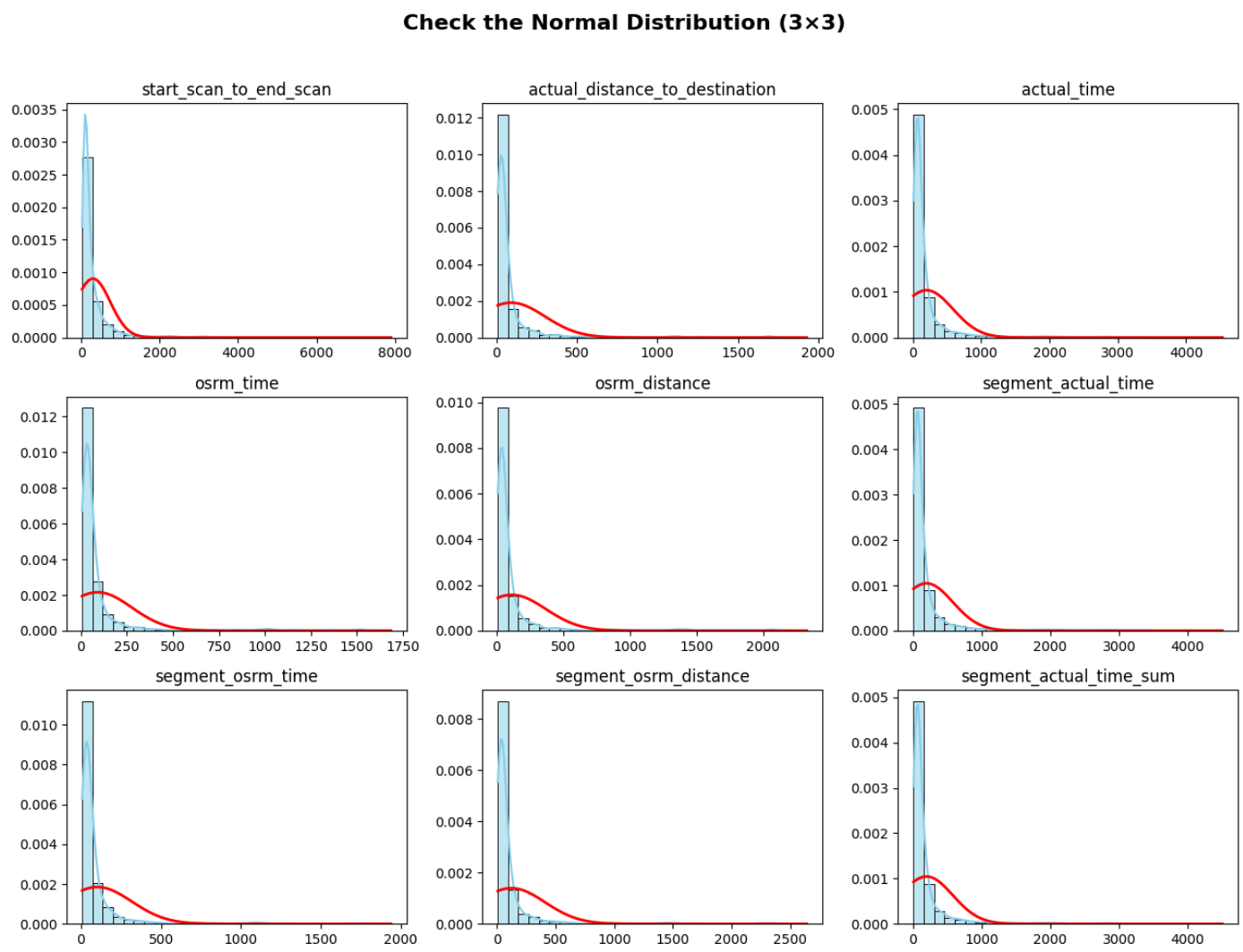

```
num_col = df.select_dtypes(include=['int64', 'float64'])
num_col.skew()
```

	0
start_scan_to_end_scan	4.214109
actual_distance_to_destination	5.162747
actual_time	4.775808
osrm_time	5.115344
osrm_distance	5.155178
segment_actual_time	4.771217
segment_osrm_time	5.231527
segment_osrm_distance	5.286599
segment_actual_time_sum	4.771217
segment_osrm_time_sum	5.231527
segment_osrm_distance_sum	5.286599
od_time_diff_hour	4.212476

dtype: float64

```
def plot_all_bell_curves(trip_df):
    cols = num_col.columns[:9]
    fig, axes = plt.subplots(3, 3, figsize=(13, 10))
    axes = axes.flatten()
```

```
    for i, col in enumerate(cols):
        data = num_col[col].dropna()
        x = np.linspace(data.min(), data.max(), 100)
        sns.histplot(data, bins=30, kde=True, stat='density', color='skyblue', ax=axes[i])
        axes[i].plot(x, norm.pdf(x, data.mean(), data.std()), color='red', lw=2)
        axes[i].set_title(col, fontsize=12)
        axes[i].set_xlabel('')
        axes[i].set_ylabel('')

    fig.suptitle("Check the Normal Distribution", fontsize=16, fontweight='bold')
    plt.tight_layout(rect=[0, 0, 1, 0.96])
    plt.show()

plot_all_bell_curves(df)
```



1 one-hot encoding

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26368 entries, 0 to 26367
Data columns (total 31 columns):
 #   Column                          Non-Null Count  Dtype
```

```
 ---  ------                          --------------  -----
  0   segment_key                     26368 non-null  object
  1   trip_uuid                       26368 non-null  object
  2   data                            26368 non-null  category
  3   route_type                      26368 non-null  category
  4   trip_creation_time              26368 non-null  datetime64[ns]
  5   year                            26368 non-null  category
  6   month_name                      26368 non-null  category
  7   week_days                       26368 non-null  category
  8   hours                           26368 non-null  int32
  9   weeks                           26368 non-null  UInt32
  10  source_state_name               26368 non-null  object
  11  source_city_name                26368 non-null  object
  12  source_place_name               26368 non-null  object
  13  destination_state_name          26368 non-null  object
  14  destination_city_name           26368 non-null  object
  15  destination_place_name          26368 non-null  object
  16  od_start_time                   26368 non-null  datetime64[ns]
  17  od_end_time                     26368 non-null  datetime64[ns]
  18  start_scan_to_end_scan          26368 non-null  float64
  19  actual_distance_to_destination  26368 non-null  float64
  20  actual_time                     26368 non-null  float64
  21  osrm_time                       26368 non-null  float64
  22  osrm_distance                   26368 non-null  float64
  23  segment_actual_time             26368 non-null  float64
  24  segment_osrm_time               26368 non-null  float64
  25  segment_osrm_distance           26368 non-null  float64
  26  segment_actual_time_sum         26368 non-null  float64
  27  segment_osrm_time_sum           26368 non-null  float64
  28  segment_osrm_distance_sum       26368 non-null  float64
  29  od_total_time                   26368 non-null  timedelta64[ns]
  30  od_time_diff_hour               26368 non-null  float64
dtypes: UInt32(1), category(5), datetime64[ns](3), float64(12), int32(1), object(8), timedelta64[ns](1)
memory usage: 5.2+ MB
```

```
# Display Full Array in NumPy Console Output
np.set_printoptions(threshold=np.inf)
```

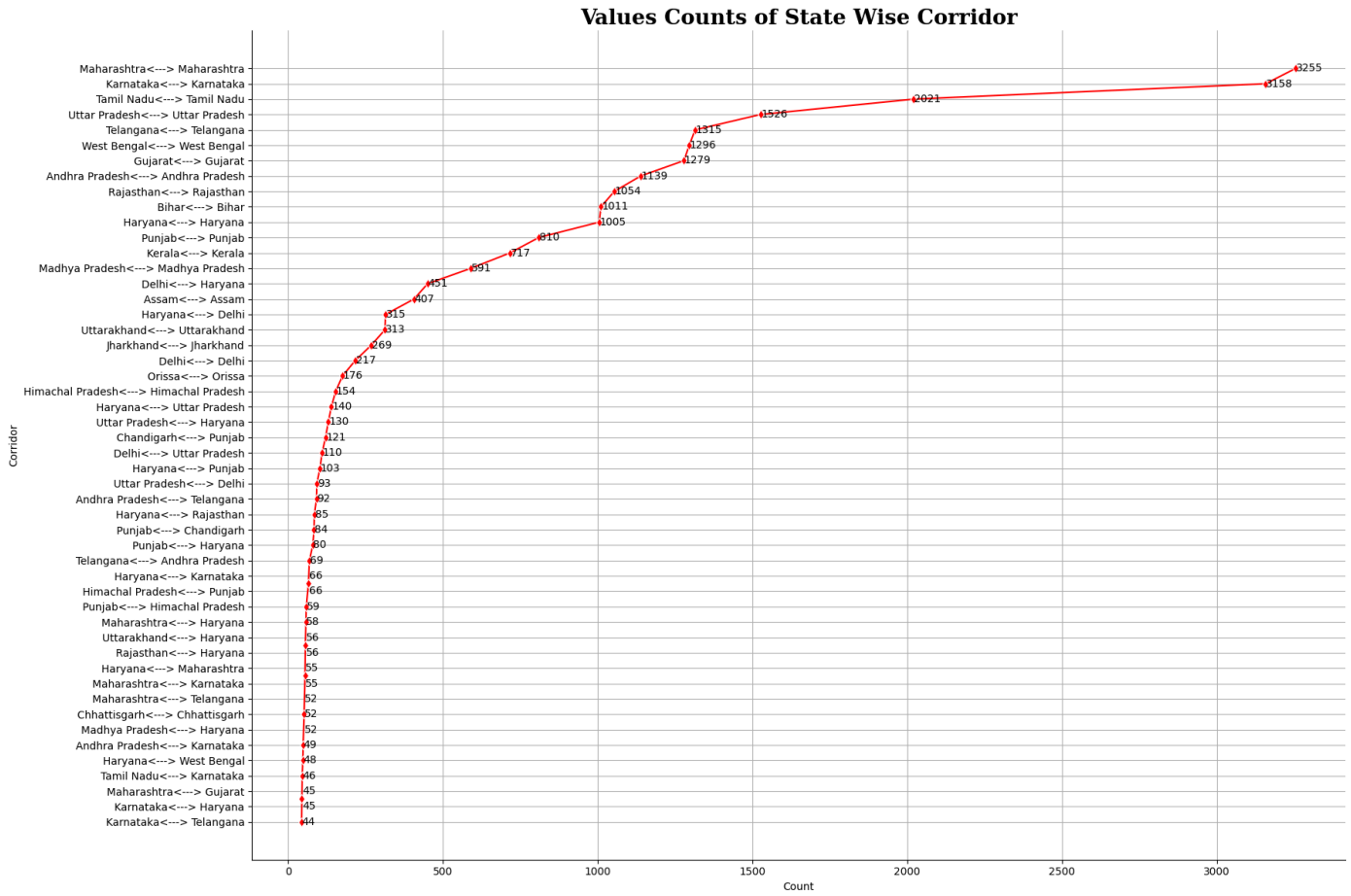
```
df['state_corridor'] = df['source_state_name'] + '<---> ' + df['destination_state_name']
df['state_corridor'].value_counts().head(10)
```

state_corridor	count
Maharashtra<---> Maharashtra	3255
Karnataka<---> Karnataka	3158
Tamil Nadu<---> Tamil Nadu	2021
Uttar Pradesh<---> Uttar Pradesh	1526
Telangana<---> Telangana	1315
West Bengal<---> West Bengal	1296
Gujarat<---> Gujarat	1279
Andhra Pradesh<---> Andhra Pradesh	1139
Rajasthan<---> Rajasthan	1054
Bihar<---> Bihar	1011

dtype: int64

```
corridor_counts = df['state_corridor'].value_counts()[:50]

plt.figure(figsize=(18,12))

sns.lineplot(y=corridor_counts.index, x = corridor_counts.values, marker = 'd', color = 'r')
plt.title('Values Counts of State Wise Corridor', fontsize = 20,fontfamily = 'serif',fontweight = 'bold')
plt.ylabel('Corridor')
plt.xlabel('Count')
plt.tight_layout()
sns.despine()
plt.grid(True)

for i, count in enumerate(corridor_counts.values):
    plt.text(count+1.5, corridor_counts.index[i], str(count), ha = 'left', va = 'center')
```

```
15
16 plt.show()
```



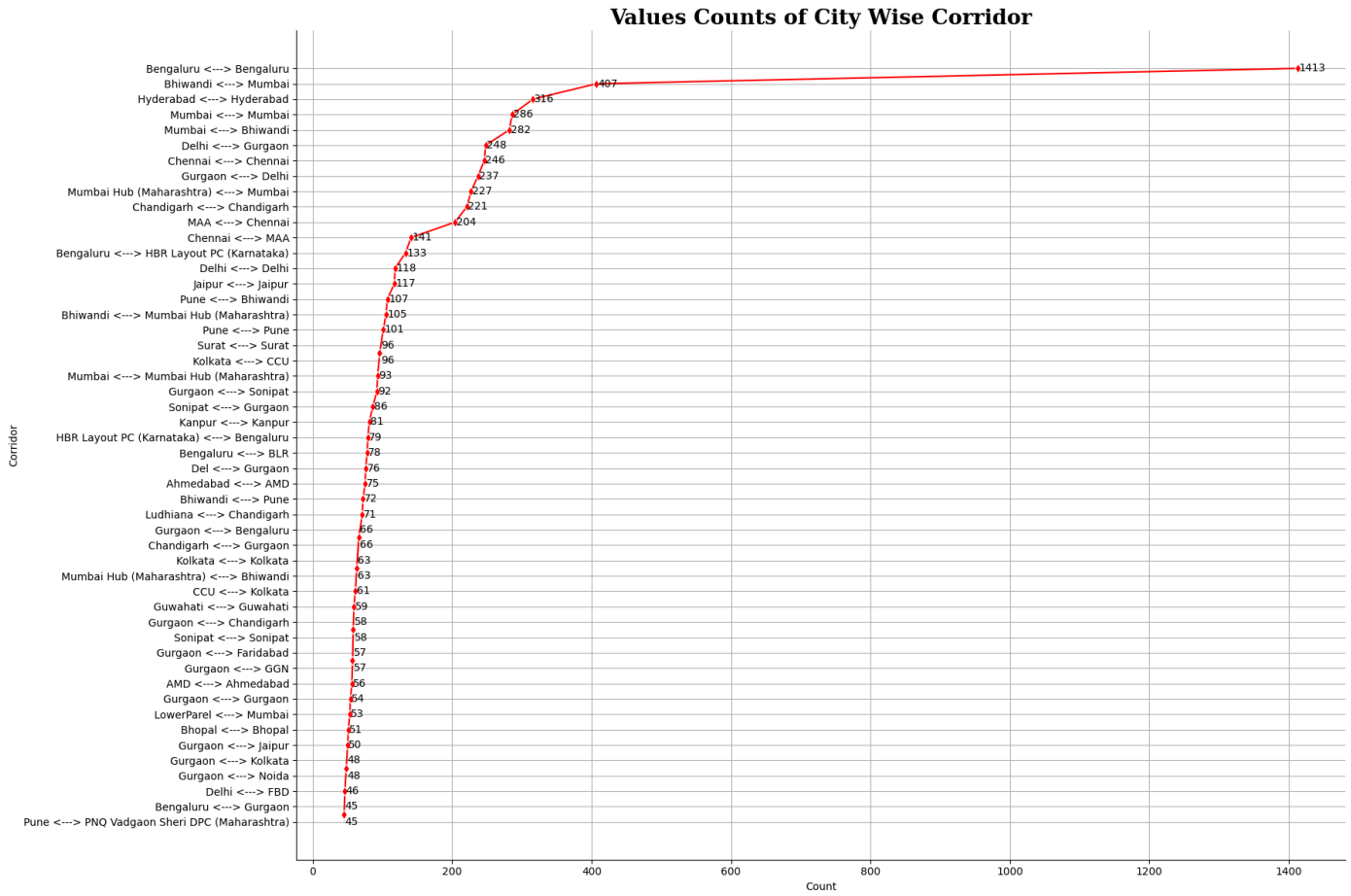

```
1 df['city_corridor'] = df['source_city_name'] +' <---> '+ df['destination_city_name']
2 df['city_corridor'].value_counts().head(10)
```

city_corridor	count
Bengaluru <---> Bengaluru	1413
Bhiwandi <---> Mumbai	407
Hyderabad <---> Hyderabad	316
Mumbai <---> Mumbai	286
Mumbai <---> Bhiwandi	282
Delhi <---> Gurgaon	248
Chennai <---> Chennai	246
Gurgaon <---> Delhi	237
Mumbai Hub (Maharashtra) <---> Mumbai	227
Chandigarh <---> Chandigarh	221

dtype: int64

```
1 corridor_counts = df['city_corridor'].value_counts()[:50]
2
3 plt.figure(figsize=(18,12))
```

```
4
5 sns.lineplot(y=corridor_counts.index, x = corridor_counts.values, marker = 'd', color = 'r')
6 plt.title('Values Counts of City Wise Corridor', fontsize = 20,fontfamily = 'serif',fontweight = 'bold')
7 plt.ylabel('Corridor')
8 plt.xlabel('Count')
9 plt.tight_layout()
10 sns.despine()
11 plt.grid(True)
12
13 for i, count in enumerate(corridor_counts.values):
14     plt.text(count+1.5, corridor_counts.index[i], str(count), ha = 'left', va = 'center')
15
16 plt.show()
```

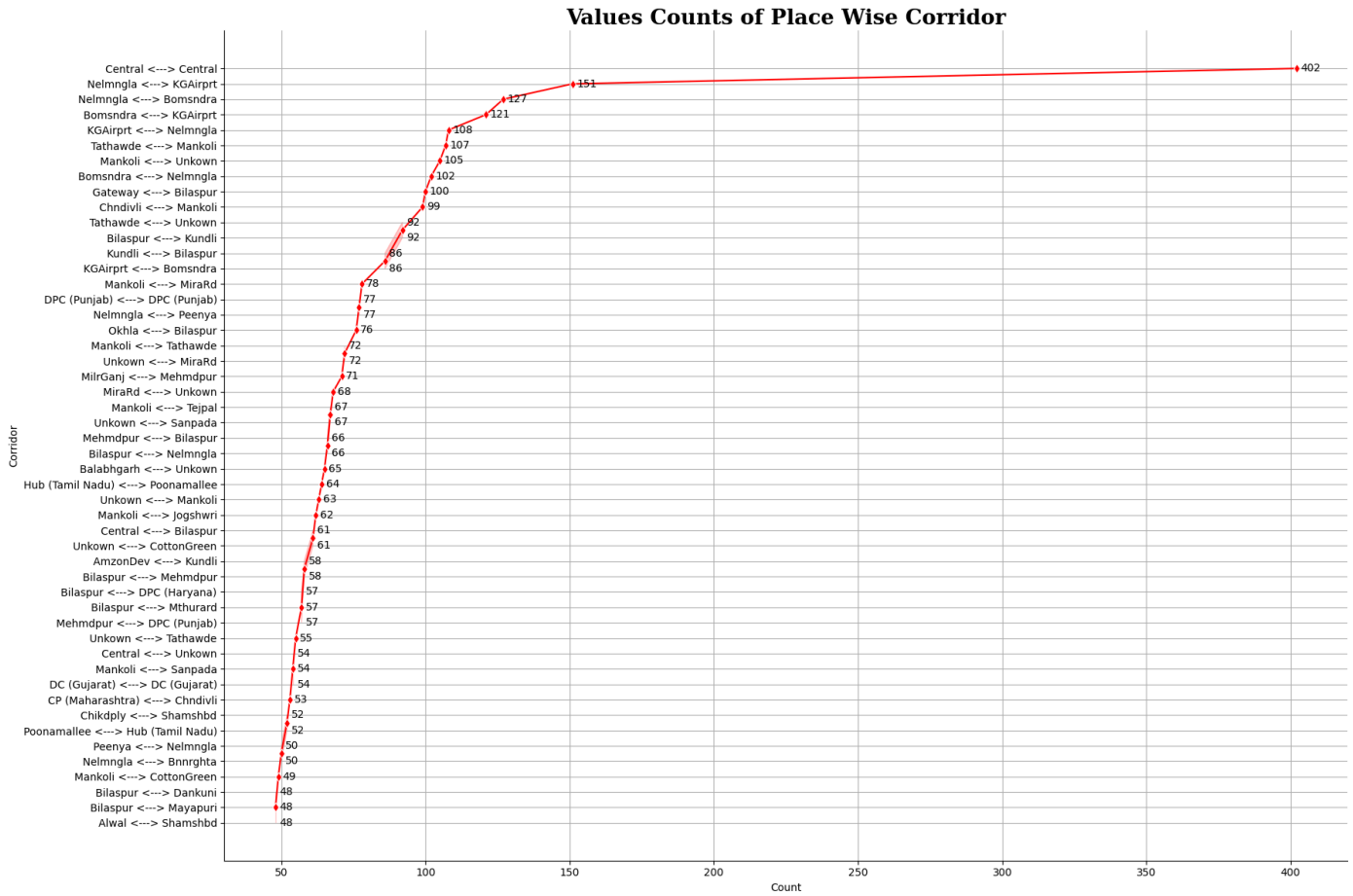



```
1 df['place_corridor'] = df['source_place_name'] +' <---> '+ df['destination_place_name']
2 df['place_corridor'].value_counts().head(10)
```

place_corridor	count
Central <---> Central	402
Nelmngla <---> KGAirprt	151
Nelmngla <---> Bomsndra	127
Bomsndra <---> KGAirprt	121
KGAirprt <---> Nelmngla	108
Tathawde <---> Mankoli	107
Mankoli <---> Unkown	105
Bomsndra <---> Nelmngla	102
Gateway <---> Bilaspur	100
Chndivli <---> Mankoli	99

dtype: int64

```
corridor_counts = df['place_corridor'].value_counts()[:50]

plt.figure(figsize=(18,12))

sns.lineplot(y=corridor_counts.index, x = corridor_counts.values, marker = 'd', color = 'r')
plt.title('Values Counts of Place Wise Corridor', fontsize = 20,fontfamily = 'serif',fontweight = 'bold')
plt.ylabel('Corridor')
plt.xlabel('Count')
plt.tight_layout()
sns.despine()
plt.grid(True)

for i, count in enumerate(corridor_counts.values):
    plt.text(count+1.5, corridor_counts.index[i], str(count), ha = 'left', va = 'center')

plt.show()
```




```
1 df.head()
```

	segment_key	trip_uuid	data	route_type	trip_creation_time	year	month_name	week_days	hours	weeks	source_sta
0	153671041653548748 + 209304-AAA + 000000-ACB	153671041653548748	training	FTL	2018-09-12 00:00:16.535741	2018	September	Wednesday	0	37	Uttar
1	153671041653548748 + 462022-AAA + 209304-AAA	153671041653548748	training	FTL	2018-09-12 00:00:16.535741	2018	September	Wednesday	0	37	Madhya
2	153671042288605164 + 561203-AAB + 562101-AAA	153671042288605164	training	Carting	2018-09-12 00:00:22.886430	2018	September	Wednesday	0	37	K
3	153671042288605164 + 572101-AAA + 561203-AAB	153671042288605164	training	Carting	2018-09-12 00:00:22.886430	2018	September	Wednesday	0	37	K
4	153671043369099517 + 000000-ACB + 160002-AAC	153671043369099517	training	FTL	2018-09-12 00:00:33.691250	2018	September	Wednesday	0	37	

```
1 #
2 create_trip_dict={
3   'data' : 'first', # data
4   'route_type' : 'first', #  route_type
5   'od_start_time':'first', # , 'od_start_time'
6   'od_end_time':'last', # od_end_time
7   'od_total_time':'last', # od_total_time
8   'od_time_diff_hour' : 'sum', # od_time_diff_hour
```

```
  'trip_creation_time' : 'first', # trip_creation_time
  'month_name' : 'first', # month_name
  'year' : 'first', # year
  'hours' : 'first', # hours
  'week_days' : 'first', # week_days
  'weeks' : 'first', # weeks
  'start_scan_to_end_scan' : 'sum', # start_scan_to_end_scan
  'actual_distance_to_destination' : 'sum', # actual_distance_to_destination
  'actual_time' : 'sum', # actual_time
  'osrm_time' : 'sum', # osrm_time
  'osrm_distance' : 'sum', # osrm_distance
  'segment_actual_time': 'sum', # segment_actual_time
  'segment_osrm_time': 'sum', # segment_osrm_time
  'segment_osrm_distance': 'sum', # segment_osrm_distance
  'segment_actual_time_sum': 'sum', # segment_actual_time_sum
  'segment_osrm_time_sum': 'sum', # segment_osrm_time_sum
  'segment_osrm_distance_sum': 'sum', # segment_osrm_distance_sum
  'source_state_name': 'first', # source_state_name
  'source_city_name':'first', # source_city_name
  'source_place_name':'first', # source_place_name
  'destination_state_name': 'first', # destination_state_name
  'destination_city_name':'first', # destination_city_name
  'destination_place_name':'first', # destination_place_name
  'state_corridor':'first', # state_corridor
  'city_corridor':'first', # city_corridor
  'place_corridor':'first' # city_corridor
  }

agg_df = df.groupby('trip_uuid').agg(create_trip_dict).reset_index()
agg_df.head()
```

	trip_uuid	data	route_type	od_start_time	od_end_time	od_total_time	od_time_diff_hour	trip_creation_time	month_n
0	153671041653548748	training	FTL	2018-09-12 16:39:46.858469	2018-09-12 16:39:46.858469	0 days 16:39:30.322728	37.668497	2018-09-12 00:00:16.535741	Septem
1	153671042288605164	training	Carting	2018-09-12 02:03:09.655591	2018-09-12 02:03:09.655591	0 days 02:02:46.769161	3.026865	2018-09-12 00:00:22.886430	Septem
2	153671043369099517	training	FTL	2018-09-14 03:40:17.106733	2018-09-14 03:40:17.106733	2 days 03:39:43.415483	65.572709	2018-09-12 00:00:33.691250	Septem
3	153671046011330457	training	Carting	2018-09-12 00:01:00.113710	2018-09-12 01:41:29.809822	0 days 01:40:29.696112	1.674916	2018-09-12 00:01:00.113710	Septem
4	153671052974046625	training	FTL	2018-09-12 00:02:09.740725	2018-09-12 03:54:43.114421	0 days 01:20:32.598828	11.972484	2018-09-12 00:02:09.740725	Septem

Feature Engineering

```
# 1. Calculating time difference between od_start_time and od_end_time
df['od_total_time'] = (df['od_end_time'] - df['od_start_time'])
df['od_time_diff_hour'] = (df['od_total_time']).dt.total_seconds()/3600
df.head(2)
```

	segment_key	trip_uuid	data	route_type	trip_creation_time	year	month_name	week_days	hours	weeks	source_sta
0	153671041653548748 + 209304-AAA + 000000-ACB	153671041653548748	training	FTL	2018-09-12 00:00:16.535741	2018	September	Wednesday	0	37	Uttar
1	153671041653548748 + 462022-AAA + 209304-AAA	153671041653548748	training	FTL	2018-09-12 00:00:16.535741	2018	September	Wednesday	0	37	Madhya

```
np.set_printoptions(threshold=np.inf)
```

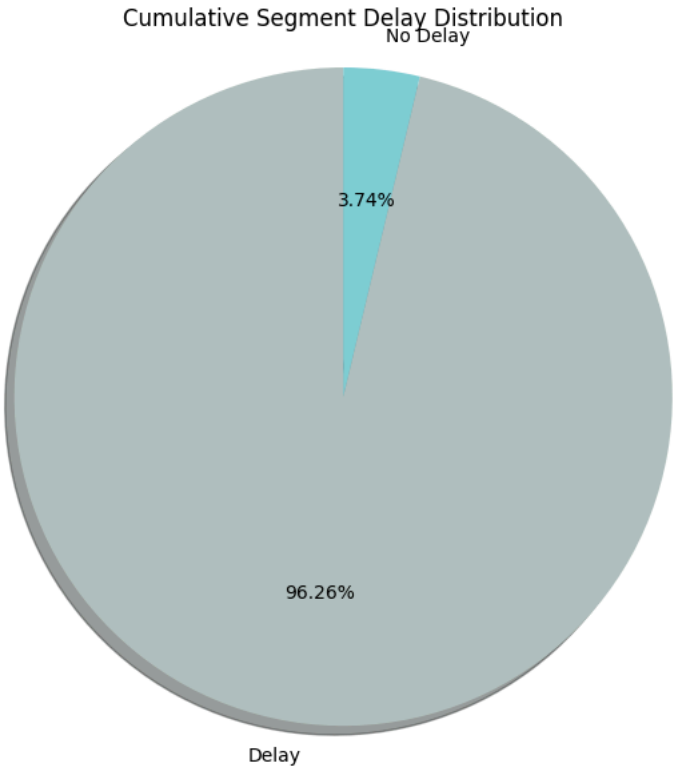
Analyze Delay

```
df['segment_cumulative_delay'] = df['segment_actual_time_sum'] - df['segment_osrm_time_sum']
```

```
delay_flag = df['segment_cumulative_delay'].apply(lambda x: 'Delay' if x > 0 else 'No Delay')
delay_counts = delay_flag.value_counts()
delay_counts.reset_index()
```

	segment_cumulative_delay	count
0	Delay	25382
1	No Delay	986

```
plt.figure(figsize=(7, 7))
plt.pie(delay_counts, labels=delay_counts.index, autopct='%1.2f%%', startangle=90, colors=['#b2c2bf', '#80ced6'], shadow=True)
plt.title('Cumulative Segment Delay Distribution')
plt.axis('equal')
plt.show()
```




```
# 📅 Time-Based Patterns
weekly = df.groupby('week_days', observed=True)['segment_cumulative_delay'].mean().sort_values().reset_index().round(2)
weekly
```

	week_days	segment_cumulative_delay
0	Tuesday	91.69
1	Friday	94.64
2	Thursday	97.38
3	Wednesday	97.84
4	Monday	99.08
5	Sunday	100.00
6	Saturday	100.12

```
# 📅 Time-Based Patterns
df.groupby('month_name', observed=True)['segment_cumulative_delay'].mean().sort_values().reset_index().round(2)
```

	month_name	segment_cumulative_delay
0	October	93.41
1	September	97.70

```
df['segment_delay'] = df['segment_actual_time'] - df['segment_osrm_time']
df['segment_delay'].head()
```

	segment_delay
0	194.0
1	346.0
2	20.0
3	56.0
4	377.0

dtype: float64

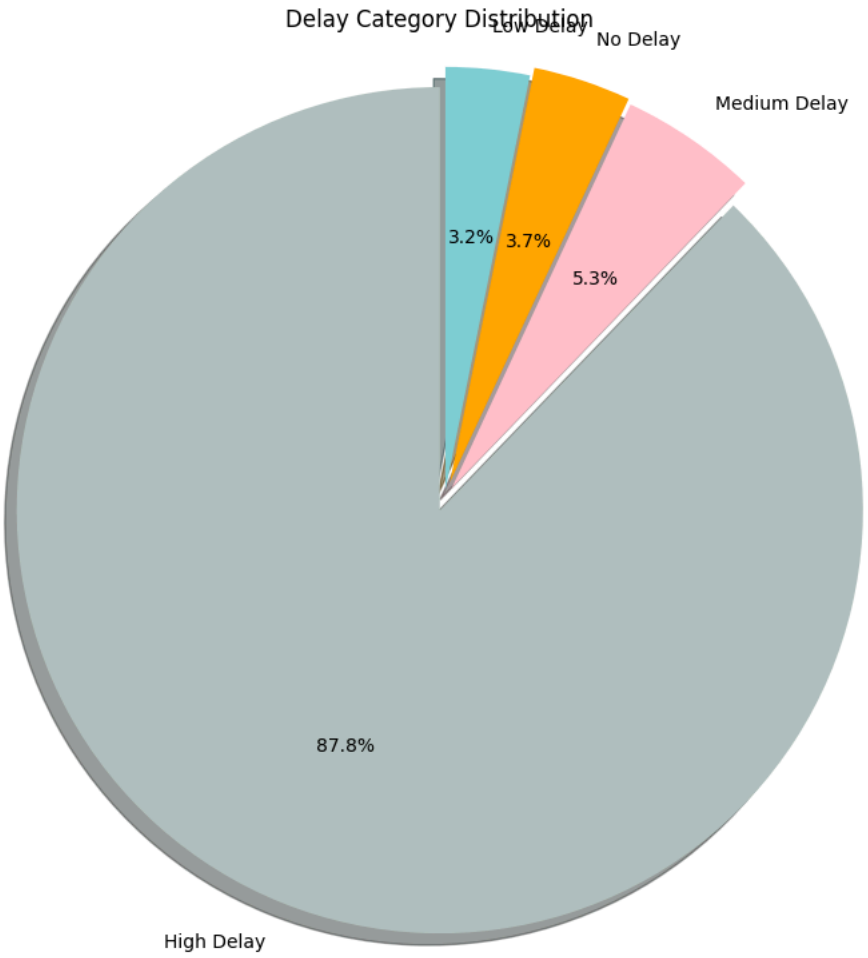
```
print("Mean Delay:", df['segment_delay'].mean())
print("Median Delay:", df['segment_delay'].median())
print("Max Delay:", df['segment_delay'].max())
print("Min Delay:", df['segment_delay'].min())
```

```
Mean Delay: 97.18177336165049
Median Delay: 39.0
Max Delay: 3006.0
Min Delay: -210.0
```

```
def delay_category(x):
    if x <= 0:
        return 'No Delay'
    elif x <= 5:
        return 'Low Delay'
    elif x <= 10:
        return 'Medium Delay'
    else:
        return 'High Delay'

df['delay_category'] = df['segment_delay'].apply(delay_category)
df['delay_category'].value_counts().reset_index()
```

	delay_category	count
0	High Delay	23151
1	Medium Delay	1386
2	No Delay	986
3	Low Delay	845

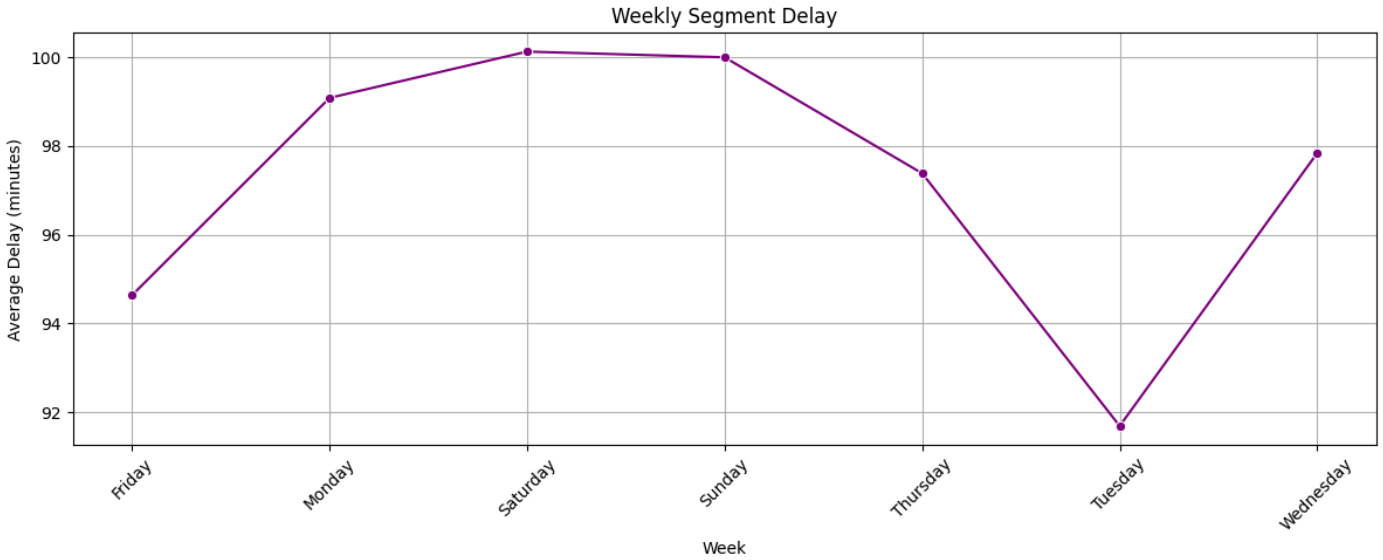
```
delay_counts = df['delay_category'].value_counts()

plt.figure(figsize=(9, 9))
plt.pie(delay_counts,
        labels=delay_counts.index,
        autopct='%1.1f%%',
        startangle=90,
        colors=['#b2c2bf', 'pink', 'orange', '#80ced6'],
        explode=(0.03, 0.03, 0.04, 0.02),
        shadow=True)

plt.title('Delay Category Distribution')
plt.axis('equal')
plt.show()
```




```
weekly_delay = df.groupby('week_days', observed=True)['segment_delay'].mean().reset_index()
weekly_delay
```

	week_days	segment_delay
0	Friday	94.637216
1	Monday	99.080966
2	Saturday	100.124480
3	Sunday	99.995504
4	Thursday	97.382052
5	Tuesday	91.690948
6	Wednesday	97.838250

```
plt.figure(figsize=(12,5))
sns.lineplot(data=weekly_delay, x='week_days', y='segment_delay', marker='o', color='purple')
plt.title("Weekly Segment Delay")
plt.xlabel("Week")
plt.ylabel("Average Delay (minutes)")
plt.xticks(rotation=45)
plt.grid(True)
plt.tight_layout()
plt.show()
```




```
monthly_delay = df.groupby('month_name', observed=True)['segment_delay'].mean().round(2).reset_index()
monthly_delay
```

	month_name	segment_delay
0	October	93.41
1	September	97.70

```
np.random.seed(42)
sample_df = pd.DataFrame({
    'segment_cumulative_delay': np.random.normal(loc=15, scale=5, size=1000),
    'week_days': np.random.choice(['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday'], 1000),
    'source_state_name': np.random.choice(['Delhi', 'Maharashtra', 'Karnataka', 'Tamil Nadu'], 1000),
    'segment_osrm_time': np.random.normal(loc=10, scale=2, size=1000)
})
sample_df.head(2)
```

	segment_cumulative_delay	week_days	source_state_name	segment_osrm_time
0	17.483571	Sunday	Tamil Nadu	8.328092
1	14.308678	Thursday	Maharashtra	9.794246

Chi-Square Test: Delay vs Weekdays

```
H0 = 'Delay occurrence is independent of the day of the week.'
Ha = 'Delay occurrence depends on the day of the week.'

sample_df['delay_flag'] = sample_df['segment_cumulative_delay'].apply(lambda x: 'Delay' if x > 0 else 'No Delay')

contingency_table = pd.crosstab(sample_df['week_days'], sample_df['delay_flag'])
alpha = 0.05

# Perform Chi-Square test
chi2, p_value, dof, expected = chi2_contingency(contingency_table)

print("Chi-Square Statistic:", chi2)
print("p-value:", p_value)

print(f"Reject Null Hypothesis: {Ha}" if p_value < alpha else f"Fail to Reject: {H0}")
```

```
Chi-Square Statistic: 6.04830182294971
p-value: 0.4178011040012267
Fail to Reject: Delay occurrence is independent of the day of the week.
```

T-Test: Weekday vs Weekend Delay

```
H0 = 'Average delay on Weekdays = Average delay on Weekends.'
Ha = 'Average delay on Weekdays ≠ Average delay on Weekends.'

# Separate delay data for weekdays and weekends
weekday_delay = sample_df[sample_df['week_days'].isin(['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday'])]['segment_cumulative_del
weekend_delay = sample_df[sample_df['week_days'].isin(['Saturday', 'Sunday'])]['segment_cumulative_delay']

# Perform independent T-test
t_stat, p_value = ttest_ind(weekday_delay, weekend_delay, equal_var=False)
alpha = 0.05

print("T-statistic:", t_stat)
print("p-value:", p_value)

print(f"Reject Null Hypothesis: {Ha}" if p_value < alpha else f"Fail to Reject: {H0}")
```

```
T-statistic: 0.349652934922979
p-value: 0.7267373359252989
Fail to Reject: Average delay on Weekdays = Average delay on Weekends.
```

ANOVA: Delay Across States

```
H0 = 'Mean delay is the same for all states.'
Ha = 'At least one state’s mean delay is different.'

groups = [group['segment_cumulative_delay'].values for name, group in df.groupby('source_state_name')]

# Perform one-way ANOVA
f_stat, p_value = f_oneway(*groups)
alpha = 0.05


print("F-statistic:", f_stat)
print("p-value:", p_value)

print(f"Reject Null Hypothesis: {Ha}" if p_value < alpha else f"Fail to Reject: {H0}")
```

```
F-statistic: 47.31337148249564
p-value: 5.662451569361929e-281
Reject Null Hypothesis: At least one state’s mean delay is different.
```

Pearson Correlation: OSRM Time vs Actual Delay

```
sample_df.sample(2)
```

	segment_cumulative_delay	week_days	source_state_name	segment_osrm_time	delay_flag
2	18.238443	Monday	Maharashtra	11.596508	Delay
766	14.825058	Sunday	Delhi	12.892389	Delay

```
H0 = 'There is no linear correlation between segment_osrm_time and segment_cumulative_delay.'
Ha = 'There is a linear correlation between segment_osrm_time and segment_cumulative_delay.'

corr_coef, p_value = pearsonr(sample_df['segment_osrm_time'], sample_df['segment_cumulative_delay'])
alpha = 0.05

print("Pearson correlation coefficient:", corr_coef)
print("p-value:", p_value)

print(f"Reject Null Hypothesis: {Ha}" if p_value < alpha else f"Fail to Reject: {H0}")
```

```
Pearson correlation coefficient: 0.0191563571682874
p-value: 0.5451291200016899
Fail to Reject: There is no linear correlation between segment_osrm_time and segment_cumulative_delay.
```

Statistical Test: Use a one-way ANOVA to compare delivery counts across weekdays for September.

```
df_september = df[df['month_name'] == 'September'].copy()
df_september['date'] = df_september['trip_creation_time'].dt.date
daily_counts = (df_september.groupby(['date', 'week_days'], observed=True).size().reset_index(name='count'))
daily_counts.sample(5)
```

	date	week_days	count
1	2018-09-13	Thursday	1320
14	2018-09-26	Wednesday	1274
7	2018-09-19	Wednesday	1155
2	2018-09-14	Friday	1296
3	2018-09-15	Saturday	1293

```
H0 = 'Mean trip counts are the same across all weekdays.'
Ha = 'At least one weekday has a different mean trip count.'

groups = []
for weekday in daily_counts['week_days'].cat.categories:
    arr = daily_counts.loc[daily_counts['week_days'] == weekday, 'count'].values
    if len(arr) > 1: groups.append(arr)

# (5) Perform One-Way ANOVA
f_stat, p_value = stats.f_oneway(*groups)
alpha = 0.05

print("ANOVA Test Result:")
print(f"  F-statistic: {f_stat:.2f}")
print(f"  p-value:     {p_value:.2e}")

print(f"Reject Null Hypothesis: {Ha}" if p_value < alpha else f"Fail to Reject: {H0}")
```

```
ANOVA Test Result:
  F-statistic: 2.12
  p-value:     1.26e-01
Fail to Reject: Mean trip counts are the same across all weekdays.
```

Does the average number of delivery data (actual_time) significantly differ across different delays conditions?

```
H0 = "The average actual delivery time is the same across all delay categories."
Ha = "At least one delay category has a significantly different average actual delivery time."

Hight_Delay = df[df['delay_category'] == 'High Delay']['actual_time']
Medium_Delay = df[df['delay_category'] == 'Medium Delay']['actual_time']
Low_Delay = df[df['delay_category'] == 'Low Delay']['actual_time']
No_Delay = df[df['delay_category'] == 'No Delay']['actual_time']
alpha = 0.05

# One-Way ANOVA & Independent Test:
t_stats, p_value = stats.f_oneway(Hight_Delay, Medium_Delay, Low_Delay, No_Delay)

print("T-statistic:", t_stats)
print("P-value:", p_value)

print(f"Reject Null Hypothysis: {H0}" if p_value < alpha else f"Fail to Reject Null Hypothesis: {Ha}")
```

```
T-statistic: 182.52690906505723
P-value: 3.80066043599476e-117
Reject Null Hypothysis: The average actual delivery time is the same across all delay categories.
```

Is there a significant difference in average actual_time data on test vs. training?

```
Ha = "There is no significant difference in the average actual delivery time between test and training."
H0 = "There is a significant difference in the average actual delivery time between between test and training."

test = df[df['data'] == 'test']['actual_time']
training = df[df['data'] == 'training']['actual_time']
alpha = 0.05
```

```
# Perform independent t-test
t_stats, p_value = stats.ttest_ind(test, training)

print("T-statistic:", t_stats)
print("P-value:", p_value)

print(f"Reject Null Hypothysis: {H0}" if p_value < alpha else f"Fail to Reject Null Hypothysis: {Ha}")
```

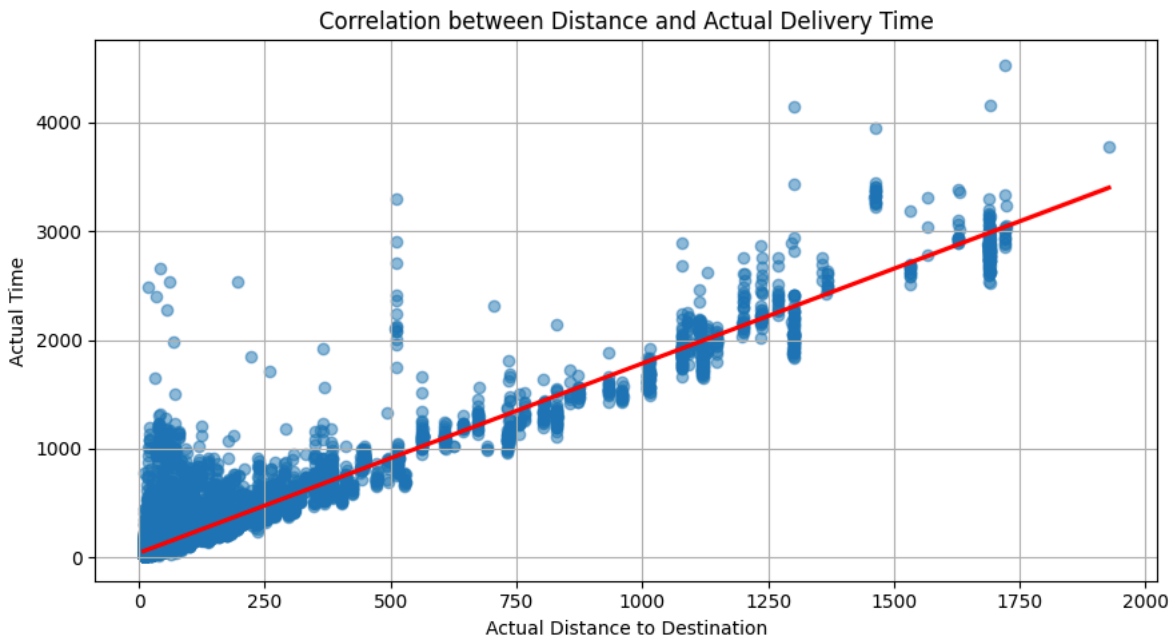
```
T-statistic: -1.7576494022088893
P-value: 0.07881878530111958
Fail to Reject Null Hypothysis: There is no significant difference in the average actual delivery time between test and training.
```

Is there a linear relationship between the actual delivery time and the actual distance to the destination?

```
H0 = "There is no linear correlation between actual delivery time and distance."
Ha = "There is a significant linear correlation between actual delivery time and distance."

alpha = 0.05

# Calculate Pearson's correlation between temp and count:
corr_coef, p_value = pearsonr(df['actual_distance_to_destination'], df['actual_time'])

print(f"Pearson's Correlation Coefficient: {corr_coef}")
print(f"P-value: {p_value}")

print(f"Reject Null Hypothesis: {Ha}" if p_value < alpha else f"Fail to Reject Null Hypothesis: {H0}")
```

```
Pearson's Correlation Coefficient: 0.9489953548287535
P-value: 0.0
Reject Null Hypothesis: There is a significant linear correlation between actual delivery time and distance.
```

```
plt.figure(figsize=(9, 5))
sns.regplot(x='actual_distance_to_destination', y='actual_time', data=df, line_kws={'color': 'red'}, scatter_kws={'alpha':0.5})
plt.title('Correlation between Distance and Actual Delivery Time')
plt.xlabel('Actual Distance to Destination')
plt.ylabel('Actual Time')
plt.grid(True)
plt.tight_layout()
plt.show()
```



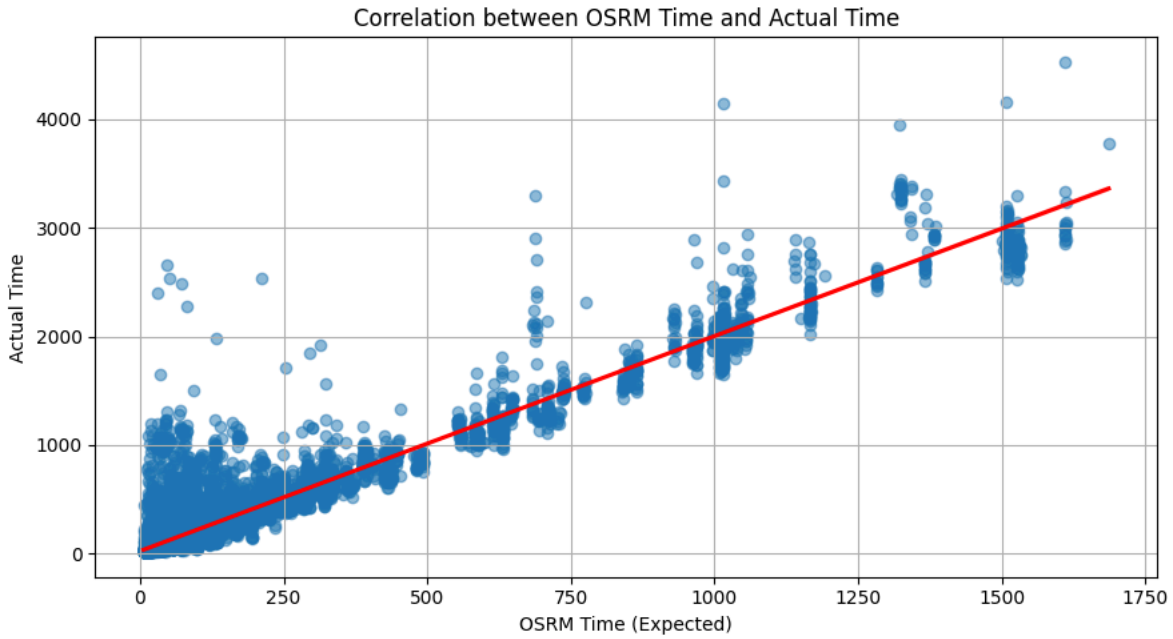
Is there a correlation between osrm_time and actual_time?

- Explanation: If OSRM (expected route planner time) predictions are close to real time.

```
H0 = "No significant correlation between osrm_time and actual_time."
Ha = "Significant correlation exists between osrm_time and actual_time."

corr_value, p_value = pearsonr(df['osrm_time'], df['actual_time'])
alpha = 0.05

print(f"Pearson Correlation Coefficient: {corr_value}")
print(f"P-value: {p_value}")

print(f"Reject Null Hypothesis: {Ha}" if p_value < alpha else f"Fail to Reject Null Hypothesis: {H0}")
```

```
Pearson Correlation Coefficient: 0.9531524416313518
P-value: 0.0
Reject Null Hypothesis: Significant correlation exists between osrm_time and actual_time.
```

```
plt.figure(figsize=(9, 5))
sns.regplot(x='osrm_time', y='actual_time', data=df, line_kws={'color': 'red'}, scatter_kws={'alpha':0.5})
plt.title("Correlation between OSRM Time and Actual Time")
plt.xlabel("OSRM Time (Expected)")
plt.ylabel("Actual Time")
plt.grid(True)
plt.tight_layout()
plt.show()
```



Is segment_osrm_distance_sum correlated with segment_actual_time_sum?

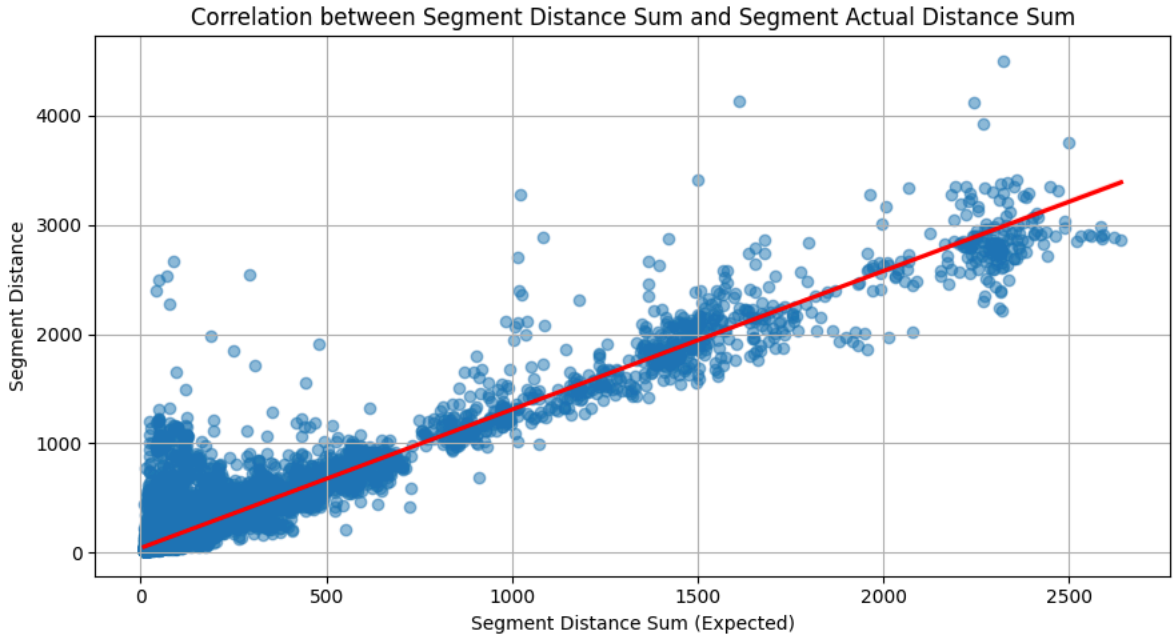
- Explanation: To analyze whether total segment distance predicts total segment time.

```
H0 = 'No significant correlation found between segment_osrm_distance_sum and segment_actual_time_sum.'
Ha = 'Significant correlation exists between segment_osrm_distance_sum and segment_actual_time_sum.'

corr_value, p_value = pearsonr(df['segment_osrm_distance_sum'], df['segment_actual_time_sum'])

print(f"Pearson Correlation Coefficient: {corr_value}")
print(f"P-value: {p_value}")
alpha = 0.05

print(f"Reject Null Hypothesis: {Ha}" if p_value < alpha else f"Fail to Reject Null Hypothesis: {H0}")
```

```
Pearson Correlation Coefficient: 0.9512547626622143
P-value: 0.0
Reject Null Hypothesis: Significant correlation exists between segment_osrm_distance_sum and segment_actual_time_sum.
```

```
plt.figure(figsize=(9, 5))
sns.regplot(x='segment_osrm_distance_sum', y='segment_actual_time_sum', data=df, line_kws={'color': 'red'}, scatter_kws={'alpha':0.5})
```

```
plt.title("Correlation between Segment Distance Sum and Segment Actual Distance Sum")
plt.xlabel("Segment Distance Sum (Expected)")
plt.ylabel("Segment Distance")
plt.grid(True)
plt.tight_layout()
plt.show()
```



Is there a correlation between segment_factor and segment_delay?

- Explanation: Segment factor is a performance ratio — check if poor factor correlates with delay.

```
corr = df['segment_factor'].corr(df['segment_delay'])
print("Correlation between segment_factor and segment_delay:", corr)

```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
/usr/local/lib/python3.11/dist-packages/pandas/core/indexes/base.py in get_loc(self, key)
   3804         try:
-> 3805             return self._engine.get_loc(casted_key)
   3806         except KeyError as err:

index.pyx in pandas._libs.index.IndexEngine.get_loc()

index.pyx in pandas._libs.index.IndexEngine.get_loc()

pandas/_libs/hashtable_class_helper.pxi in pandas._libs.hashtable.PyObjectHashTable.get_item()

pandas/_libs/hashtable_class_helper.pxi in pandas._libs.hashtable.PyObjectHashTable.get_item()

KeyError: 'segment_factor'

The above exception was the direct cause of the following exception:

KeyError                                  Traceback (most recent call last)
                                          2 frames
/usr/local/lib/python3.11/dist-packages/pandas/core/indexes/base.py in get_loc(self, key)
   3810             ):
   3811                 raise InvalidIndexError(key)
-> 3812             raise KeyError(key) from err
   3813         except TypeError:
   3814             # If we have a listlike key, _check_indexing_error will raise

KeyError: 'segment_factor'
```

Does cutoff_factor correlate with segment_cumulative_delay?

- Explanation: Check if higher cutoff buffer time is associated with delays.

```
H0 = 'No significant correlation found between cutoff_factor and segment_cumulative_delay.'
Ha = 'Significant correlation exists between cutoff_factor and segment_cumulative_delay.'

corr_value, p_value = pearsonr(df['cutoff_factor'], df['segment_cumulative_delay'])

print(f"Pearson Correlation Coefficient: {corr_value}")
print(f"P-value: {p_value}")
alpha = 0.05

print(f"Reject Null Hypothesis: {Ha}" if p_value < alpha else f"Fail to Reject Null Hypothesis: {H0}")
```

```
plt.figure(figsize=(9, 5))
sns.regplot(x='cutoff_factor', y='segment_cumulative_delay', data=df, line_kws={'color': 'red'}, scatter_kws={'alpha':0.5})
plt.title("Cutoff Factor vs Segment Cumulative Delay")
plt.xlabel("Cutoff Factor")
plt.ylabel("Segment Cumulative Delay")
plt.grid(True)
plt.show()
```

🔷 Z-Test (for Known Population Standard Deviation)

Do more than 80% of rides happen on route_type (FTL)?

```
# Define Hypothesis
H0 = "Proportion of delivery on route_type = 0.80"
Ha = "Proportion of delivery on route_type > 0.80"

Sample_Length = len(df)
FTL_Count = df[df['route_type'] == 'FTL'].shape[0]
Sample_Proportion = FTL_Count / Sample_Length
Population_Proportion = 0.80
Alpha = 0.05

# Z-test for proportions (Right Tail Test)
Z_Score = (Sample_Proportion - Population_Proportion) / np.sqrt((Population_Proportion * (1 - Population_Proportion)) / Sample_Length)
P_Value = 1 - stats.norm.cdf(Z_Score)

print("Sample Proportion (p̂):", Sample_Proportion)
print("Z-Score:", Z_Score)
print("P-Value:", P_Value)

print(f"Reject Null Hypothesis: {Ha}" if P_Value < Alpha else f"Fail to Reject: {H0}")
```

```
# Plot the normal distribution with Z critical value and Z score
z_critical = stats.norm.ppf(1 - Alpha)

x = np.linspace(-4, 4, 1000)
y = stats.norm.pdf(x, 0, 1)

plt.figure(figsize=(10, 5))
plt.plot(x, y, label='Standard Normal Distribution', color='blue')

# Shade the rejection region
plt.fill_between(x, 0, y, where=(x >= z_critical), color='red', alpha=0.4, label='Rejection Region (α=0.05)')

# Plot Z-score
plt.axvline(Z_Score, color='green', linestyle='--', label=f'Z-Score = {Z_Score:.2f}')
plt.axvline(z_critical, color='red', linestyle='--', label=f'Critical Z = {z_critical:.2f}')

plt.title("One-Tailed Z-Test for Proportion (FTL > 0.80)")
plt.xlabel("Z-Score")
plt.ylabel("Probability Density")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
df.sample(2)
```

😕💭Business Insights & Recommendations💭😕

Peak Days (Wednesday & Thursday):

- Deliveries are highest on Wednesdays and Thursdays. Action: Increase staffing and allocate more trucks on those days to handle the volume efficiently.

Low Activity Days (Sunday & Monday):

- Sundays and Mondays show lower delivery activity. Action: Schedule warehouse maintenance or staff training on those days to make productive use of slower periods.

Busy Month (September):

- September shows noticeably higher totals than October. This may indicate a seasonal spike—perhaps due to festivals or end-of-quarter demand. Action: Plan for additional resources (drivers, vehicles, temporary staff) in September to meet the higher demand without delays.

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Start coding or generate with AI.
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