data-processing-for-delhivery

September 18, 2024

Problem Statement:

Delhivery wants to understand and process data from its data engineering pipelines. The goal is to clean, manipulate, and make sense of raw data to help the data science team build forecasting models. Key tasks include cleaning, sanitizing, and feature extraction from raw fields, particularly focusing on the trip data and delivery operations.

Approach:

1. Exploratory Data Analysis (EDA):

-Shape and Data Types: Explore the structure of the dataset, identifying data types for each column.

-Missing Values: Identify columns with missing values and plan appropriate treatments such as imputation or dropping rows/columns with excessive missing values.

-Statistical Summary: Generate a summary of numeric features (mean, median, quartiles) and identify outliers for further treatment.

2. Feature Engineering:

-Extract Time Features: From trip_creation_time, extract month, year, day, and hour to capture seasonal and temporal trends.

-Distance Time Features: Create new features comparing actual_time and osrm_time, and calculate the time difference between od_start_time and od_end_time.

-Source and Destination Features: Split source_name and destination_name into city and state components for location-based analysis.

3. Data Aggregation:

-Merging Rows by trip_uuid: Use groupby on trip_uuid, source_center, and destination_center to combine multiple rows into single trips. For continuous fields, sum the values where relevant (e.g., actual_time, osrm_time). For fields where summing doesn't make sense, use the first or last values (e.g., route_type, source_name).

-Aggregation Functions: Apply relevant functions like sum(), mean(), and last() for various fields depending on their nature.

4. Outlier Treatment:

-Use IQR method to detect outliers in time-related variables like actual_time, segment_actual_time, and start_scan_to_end_scan. Visualize these outliers with boxplots and correct them by capping values or removing extreme rows.

-Hypothesis testing or visual analysis to validate these outliers and their business impact.

5. Hypothesis Testing and Comparison:

Perform hypothesis testing to compare aggregated time and distance fields:

-Actual Time vs OSRM Time: Use t-tests or ANOVA to check if there is a significant difference between the two times.

-Segment Times vs Aggregated Times: Compare segment-level times (segment_actual_time) with overall trip times to identify inconsistencies in delivery segments.

-Distance Comparisons: Visualize and compare osrm_distance vs segment_osrm_distance to detect discrepancies.

6. Categorical Value Encoding:

One-hot encode categorical variables like route_type and source_name to prepare the data for machine learning or predictive modeling.

7. Normalization/Standardization:

Apply MinMaxScaler or StandardScaler on continuous variables like actual_time, osrm_time, and actual_distance_to_destination to normalize the data, ensuring that different features are on a comparable scale.

[ ]:
```
!pip install matplotlib
```

[53]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
from sklearn.preprocessing import StandardScaler, MinMaxScaler
```

[54]:
```
data = pd.read_csv('https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/
↪000/001/551/original/delhivery_data.csv?1642751181')
```

[55]:
```
data.head()
```

[55]:
```
       data          trip_creation_time  \
0  training  2018-09-20 02:35:36.476840
1  training  2018-09-20 02:35:36.476840
2  training  2018-09-20 02:35:36.476840
3  training  2018-09-20 02:35:36.476840
4  training  2018-09-20 02:35:36.476840

                                 route_schedule_uuid route_type  \
0  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
1  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
2  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
3  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
```

```
4  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting

                 trip_uuid source_center                 source_name  \
0  trip-153741093647649320  IND388121AAA  Anand_VUNagar_DC (Gujarat)
1  trip-153741093647649320  IND388121AAA  Anand_VUNagar_DC (Gujarat)
2  trip-153741093647649320  IND388121AAA  Anand_VUNagar_DC (Gujarat)
3  trip-153741093647649320  IND388121AAA  Anand_VUNagar_DC (Gujarat)
4  trip-153741093647649320  IND388121AAA  Anand_VUNagar_DC (Gujarat)

  destination_center               destination_name  \
0       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
1       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
2       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
3       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
4       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)

                od_start_time  …            cutoff_timestamp  \
0  2018-09-20 03:21:32.418600  …         2018-09-20 04:27:55
1  2018-09-20 03:21:32.418600  …         2018-09-20 04:17:55
2  2018-09-20 03:21:32.418600  …  2018-09-20 04:01:19.505586
3  2018-09-20 03:21:32.418600  …         2018-09-20 03:39:57
4  2018-09-20 03:21:32.418600  …         2018-09-20 03:33:55

   actual_distance_to_destination  actual_time  osrm_time osrm_distance  \
0                       10.435660         14.0       11.0       11.9653
1                       18.936842         24.0       20.0       21.7243
2                       27.637279         40.0       28.0       32.5395
3                       36.118028         62.0       40.0       45.5620
4                       39.386040         68.0       44.0       54.2181

     factor  segment_actual_time  segment_osrm_time  segment_osrm_distance  \
0  1.272727                 14.0               11.0                11.9653
1  1.200000                 10.0                9.0                 9.7590
2  1.428571                 16.0                7.0                10.8152
3  1.550000                 21.0               12.0                13.0224
4  1.545455                  6.0                5.0                 3.9153

   segment_factor
0        1.272727
1        1.111111
2        2.285714
3        1.750000
4        1.200000

[5 rows x 24 columns]
```

[17]:
```python
# Basic Statistical Summary
summary = data.describe()
summary
```

[17]:

	start_scan_to_end_scan	cutoff_factor	actual_distance_to_destination
count	144867.000000	144867.000000	144867.000000
mean	961.262986	232.926567	234.073372
std	1037.012769	344.755577	344.990009
min	20.000000	9.000000	9.000045
25%	161.000000	22.000000	23.355874
50%	449.000000	66.000000	66.126571
75%	1634.000000	286.000000	286.708875
max	7898.000000	1927.000000	1927.447705

	actual_time	osrm_time	osrm_distance	factor
count	144867.000000	144867.000000	144867.000000	144867.000000
mean	416.927527	213.868272	284.771297	2.120107
std	598.103621	308.011085	421.119294	1.715421
min	9.000000	6.000000	9.008200	0.144000
25%	51.000000	27.000000	29.914700	1.604264
50%	132.000000	64.000000	78.525800	1.857143
75%	513.000000	257.000000	343.193250	2.213483
max	4532.000000	1686.000000	2326.199100	77.387097

	segment_actual_time	segment_osrm_time	segment_osrm_distance
count	144867.000000	144867.000000	144867.00000
mean	36.196111	18.507548	22.82902
std	53.571158	14.775960	17.86066
min	-244.000000	0.000000	0.00000
25%	20.000000	11.000000	12.07010
50%	29.000000	17.000000	23.51300
75%	40.000000	22.000000	27.81325
max	3051.000000	1611.000000	2191.40370

	segment_factor
count	144867.000000
mean	2.218368
std	4.847530
min	-23.444444
25%	1.347826
50%	1.684211
75%	2.250000
max	574.250000

[56]:
```python
#Step 1: EDA
# 1.1 Handle missing values in the data
# Check for missing values
```

```
missing_values = data.isnull().sum()
#missing_percentage = (missing_values / len(data)) * 100
missing_values
```

[56]:
```
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
```

[59]:
```
# Fill missing values with appropriate strategies (mean for numerical, mode for␣
↪categorical)
for column in data.columns:
    if data[column].dtype == 'object':
        data[column].fillna(data[column].mode()[0], inplace=True)
    else:
        data[column].fillna(data[column].mean(), inplace=True)
```

[61]:
```
# 1.2 Analyze the structure of the data
data_info = data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144867 entries, 0 to 144866
Data columns (total 24 columns):
 #   Column                          Non-Null Count   Dtype
---  ------                          --------------   -----
 0   data                            144867 non-null  object
```

```
 1   trip_creation_time              144867 non-null  object
 2   route_schedule_uuid             144867 non-null  object
 3   route_type                      144867 non-null  object
 4   trip_uuid                       144867 non-null  object
 5   source_center                   144867 non-null  object
 6   source_name                     144867 non-null  object
 7   destination_center              144867 non-null  object
 8   destination_name                144867 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
```

[62]:
```
# 1.3 Merging rows using `trip_uuid`, `source_center`, and `destination_center`
grouped_data = data.groupby(['trip_uuid', 'source_center',␣
 ↪'destination_center']).agg({
    'actual_time': 'sum',
    'osrm_time': 'sum',
    'actual_distance_to_destination': 'sum',
    'segment_actual_time': 'sum',
    'segment_osrm_time': 'sum',
    'segment_osrm_distance': 'sum',
    'source_name': 'first',
    'destination_name': 'last',
    'route_type': 'first',
    'trip_creation_time': 'first',
    'od_start_time': 'first',
    'od_end_time': 'last'
}).reset_index()
```

[63]:
```
grouped_data.head()
```

[63]:
```
                 trip_uuid source_center destination_center  actual_time  \
0  trip-153671041653548748   IND209304AAA       IND000000ACB       6484.0
```

```
1  trip-153671041653548748  IND462022AAA       IND209304AAA       9198.0
2  trip-153671042288605164  IND561203AAB       IND562101AAA         96.0
3  trip-153671042288605164  IND572101AAA       IND561203AAB        303.0
4  trip-153671043369099517  IND000000ACB       IND160002AAC       2601.0

   osrm_time  actual_distance_to_destination  segment_actual_time  \
0     3464.0                     3778.765471                728.0
1     4323.0                     5082.046634                820.0
2       55.0                       53.310332                 46.0
3      155.0                      186.897974                 95.0
4     1427.0                     1725.590250                608.0

   segment_osrm_time  segment_osrm_distance  \
0              534.0               670.6205
1              474.0               649.8528
2               26.0                28.1995
3               39.0                55.9899
4              231.0               317.7408

                        source_name                    destination_name  \
0  Kanpur_Central_H_6 (Uttar Pradesh)      Gurgaon_Bilaspur_HB (Haryana)
1  Bhopal_Trnsport_H (Madhya Pradesh)  Kanpur_Central_H_6 (Uttar Pradesh)
2   Doddablpur_ChikaDPP_D (Karnataka)   Chikblapur_ShntiSgr_D (Karnataka)
3       Tumkur_Veersagr_I (Karnataka)   Doddablpur_ChikaDPP_D (Karnataka)
4       Gurgaon_Bilaspur_HB (Haryana)     Chandigarh_Mehmdpur_H (Punjab)

  route_type          trip_creation_time              od_start_time  \
0        FTL  2018-09-12 00:00:16.535741  2018-09-12 16:39:46.858469
1        FTL  2018-09-12 00:00:16.535741  2018-09-12 00:00:16.535741
2    Carting  2018-09-12 00:00:22.886430  2018-09-12 02:03:09.655591
3    Carting  2018-09-12 00:00:22.886430  2018-09-12 00:00:22.886430
4        FTL  2018-09-12 00:00:33.691250  2018-09-14 03:40:17.106733

                 od_end_time
0  2018-09-13 13:40:23.123744
1  2018-09-12 16:39:46.858469
2  2018-09-12 03:01:59.598855
3  2018-09-12 02:03:09.655591
4  2018-09-14 17:34:55.442454
```

Insights: Basic Data Cleaning and Exploration

1. Handling Missing Values:

We identified missing values and filled them using appropriate methods. Numerical fields were filled with the mean, and categorical fields with the mode.

Insight: Missing data can cause inconsistencies in analysis. Filling them ensures complete data is available for analysis.

2. Analyzing the Structure of the Data:

The info() function shows the data types, missing values, and column details.

Insight: It's crucial to know the structure of the data before performing operations like aggregation or transformation.

3. Merging Rows:

Data was grouped by trip_uuid, source_center, and destination_center to aggregate important columns such as time, distance, and source/destination details.

Insight: This gives us a complete picture of each trip by summing up segment times and distances, making the data ready for feature extraction.

[64]:
```
# Step 2: Feature Extraction
# 2.1 & 2.2 Split destination_name and source_name to extract city and state
grouped_data['destination_city'] = grouped_data['destination_name'].
  ↪apply(lambda x: x.split('_')[0])
grouped_data['destination_state'] = grouped_data['destination_name'].
  ↪apply(lambda x: x.split('(')[-1].strip(')'))


grouped_data['source_city'] = grouped_data['source_name'].apply(lambda x: x.
  ↪split('_')[0])
grouped_data['source_state'] = grouped_data['source_name'].apply(lambda x: x.
  ↪split('(')[-1].strip(')'))
```

[65]:
```
# 2.3 Extract features from trip_creation_time (month, year, day, hour)
grouped_data['trip_creation_time'] = pd.
  ↪to_datetime(grouped_data['trip_creation_time'])
grouped_data['month'] = grouped_data['trip_creation_time'].dt.month
grouped_data['year'] = grouped_data['trip_creation_time'].dt.year
grouped_data['day'] = grouped_data['trip_creation_time'].dt.day
grouped_data['hour'] = grouped_data['trip_creation_time'].dt.hour
```

[66]:
```
grouped_data.head()
```

[66]:
```
                   trip_uuid source_center destination_center  actual_time  \
0  trip-153671041653548748   IND209304AAA       IND000000ACB       6484.0
1  trip-153671041653548748   IND462022AAA       IND209304AAA       9198.0
2  trip-153671042288605164   IND561203AAB       IND562101AAA         96.0
3  trip-153671042288605164   IND572101AAA       IND561203AAB        303.0
4  trip-153671043369099517   IND000000ACB       IND160002AAC       2601.0

   osrm_time  actual_distance_to_destination  segment_actual_time  \
0     3464.0                     3778.765471                728.0
1     4323.0                     5082.046634                820.0
2       55.0                       53.310332                 46.0
3      155.0                      186.897974                 95.0
```

```
4     1427.0                    1725.590250              608.0

   segment_osrm_time  segment_osrm_distance  \
0              534.0               670.6205
1              474.0               649.8528
2               26.0                28.1995
3               39.0                55.9899
4              231.0               317.7408

                         source_name  …              od_start_time  \
0  Kanpur_Central_H_6 (Uttar Pradesh)  …  2018-09-12 16:39:46.858469
1  Bhopal_Trnsport_H (Madhya Pradesh)  …  2018-09-12 00:00:16.535741
2   Doddablpur_ChikaDPP_D (Karnataka)  …  2018-09-12 02:03:09.655591
3       Tumkur_Veersagr_I (Karnataka)  …  2018-09-12 00:00:22.886430
4       Gurgaon_Bilaspur_HB (Haryana)  …  2018-09-14 03:40:17.106733

                 od_end_time destination_city destination_state source_city  \
0  2018-09-13 13:40:23.123744          Gurgaon           Haryana      Kanpur
1  2018-09-12 16:39:46.858469           Kanpur     Uttar Pradesh      Bhopal
2  2018-09-12 03:01:59.598855        Chikblapur         Karnataka  Doddablpur
3  2018-09-12 02:03:09.655591        Doddablpur         Karnataka      Tumkur
4  2018-09-14 17:34:55.442454        Chandigarh            Punjab     Gurgaon

     source_state month  year day  hour
0   Uttar Pradesh     9  2018  12     0
1  Madhya Pradesh     9  2018  12     0
2       Karnataka     9  2018  12     0
3       Karnataka     9  2018  12     0
4         Haryana     9  2018  12     0

[5 rows x 23 columns]
```

Insights on Feature Extraction

1. Splitting Source and Destination Names:

The source_name and destination_name were split into city and state components.

Insight: Breaking down locations into city and state provides deeper insights for regional analysis, which helps in optimizing routes.

2. Extracting Features from Trip Creation Time:

We extracted month, year, day, and hour from trip_creation_time.

Insight: These time-based features allow us to analyze trends based on time, like identifying high traffic periods or seasonal delays.

[67]:
```
# Step 3: In-depth analysis and feature engineering
# 3.1 Calculate the time taken between od_start_time and od_end_time
```

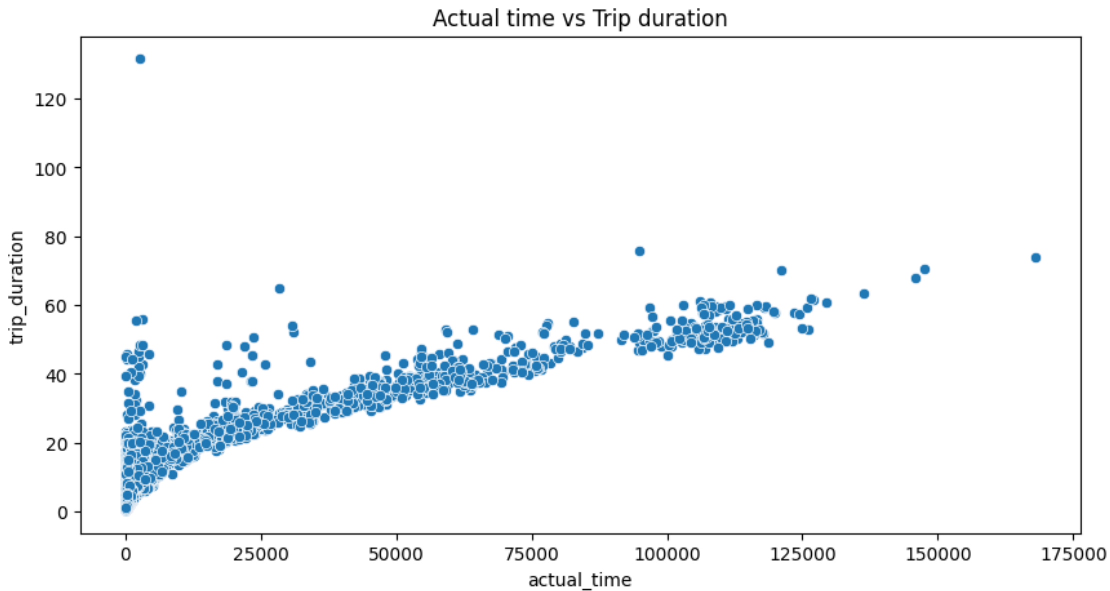
```
grouped_data['od_start_time'] = pd.to_datetime(grouped_data['od_start_time'])
grouped_data['od_end_time'] = pd.to_datetime(grouped_data['od_end_time'])
grouped_data['trip_duration'] = (grouped_data['od_end_time'] -
↪grouped_data['od_start_time']).dt.total_seconds() / 3600

# Drop original columns if necessary
grouped_data.drop(columns=['od_start_time', 'od_end_time'], inplace=True)
```

[68]:
```
grouped_data.head()
```

[68]:
```
                 trip_uuid source_center destination_center  actual_time  \
0  trip-153671041653548748  IND209304AAA       IND000000ACB       6484.0
1  trip-153671041653548748  IND462022AAA       IND209304AAA       9198.0
2  trip-153671042288605164  IND561203AAB       IND562101AAA         96.0
3  trip-153671042288605164  IND572101AAA       IND561203AAB        303.0
4  trip-153671043369099517  IND000000ACB       IND160002AAC       2601.0

   osrm_time  actual_distance_to_destination  segment_actual_time  \
0     3464.0                     3778.765471                728.0
1     4323.0                     5082.046634                820.0
2       55.0                       53.310332                 46.0
3      155.0                      186.897974                 95.0
4     1427.0                     1725.590250                608.0

   segment_osrm_time  segment_osrm_distance  \
0              534.0               670.6205
1              474.0               649.8528
2               26.0                28.1995
3               39.0                55.9899
4              231.0               317.7408

                        source_name  …           trip_creation_time  \
0  Kanpur_Central_H_6 (Uttar Pradesh)  … 2018-09-12 00:00:16.535741
1  Bhopal_Trnsport_H (Madhya Pradesh)  … 2018-09-12 00:00:16.535741
2   Doddablpur_ChikaDPP_D (Karnataka)  … 2018-09-12 00:00:22.886430
3       Tumkur_Veersagr_I (Karnataka)  … 2018-09-12 00:00:22.886430
4       Gurgaon_Bilaspur_HB (Haryana)  … 2018-09-12 00:00:33.691250

  destination_city destination_state source_city    source_state month  year  \
0          Gurgaon           Haryana      Kanpur   Uttar Pradesh     9  2018
1           Kanpur     Uttar Pradesh      Bhopal  Madhya Pradesh     9  2018
2        Chikblapur         Karnataka  Doddablpur       Karnataka     9  2018
3        Doddablpur         Karnataka      Tumkur       Karnataka     9  2018
4        Chandigarh            Punjab     Gurgaon         Haryana     9  2018

   day  hour  trip_duration
0   12     0      21.010074
```

```
1   12      0       16.658423
2   12      0        0.980540
3   12      0        2.046325
4   12      0       13.910649

[5 rows x 22 columns]
```

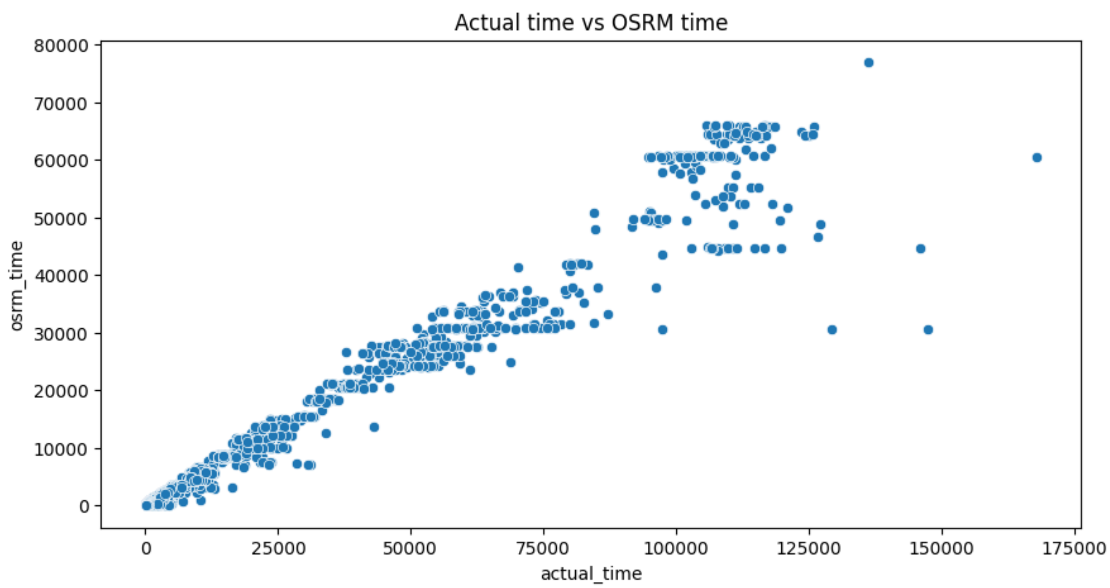
[69]:
```
# 3.2 Hypothesis Testing and Visual Analysis
# Compare actual_time with start_scan_to_end_scan using visual analysis
plt.figure(figsize=(10, 5))
sns.scatterplot(x=grouped_data['actual_time'], y=grouped_data['trip_duration'])
plt.title('Actual time vs Trip duration')
plt.show()
```



[26]:
```
# Hypothesis testing
t_stat, p_value = stats.ttest_rel(grouped_data['actual_time'],␣
 ↪grouped_data['trip_duration'])
print(f'T-statistic: {t_stat}, P-value: {p_value}')
```

```
T-statistic: 33.043648828681604, P-value: 1.174190798469266e-234
```

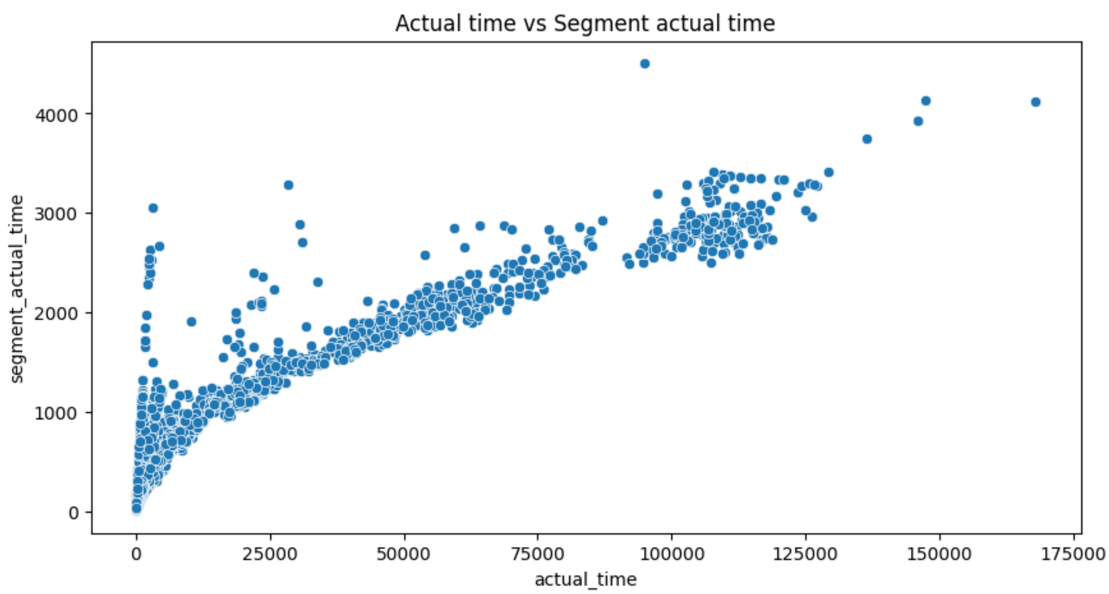
[70]:
```
# 3.3 Visual analysis and hypothesis testing for other comparisons
# Aggregated actual_time vs osrm_time
plt.figure(figsize=(10, 5))
sns.scatterplot(x=grouped_data['actual_time'], y=grouped_data['osrm_time'])
plt.title('Actual time vs OSRM time')
plt.show()
```



[28]:
```
t_stat_osrm, p_value_osrm = stats.ttest_rel(grouped_data['actual_time'],␣
↪grouped_data['osrm_time'])
print(f'T-statistic (OSRM): {t_stat_osrm}, P-value: {p_value_osrm}')
```

```
T-statistic (OSRM): 33.05610864906825, P-value: 7.904151560985772e-235
```

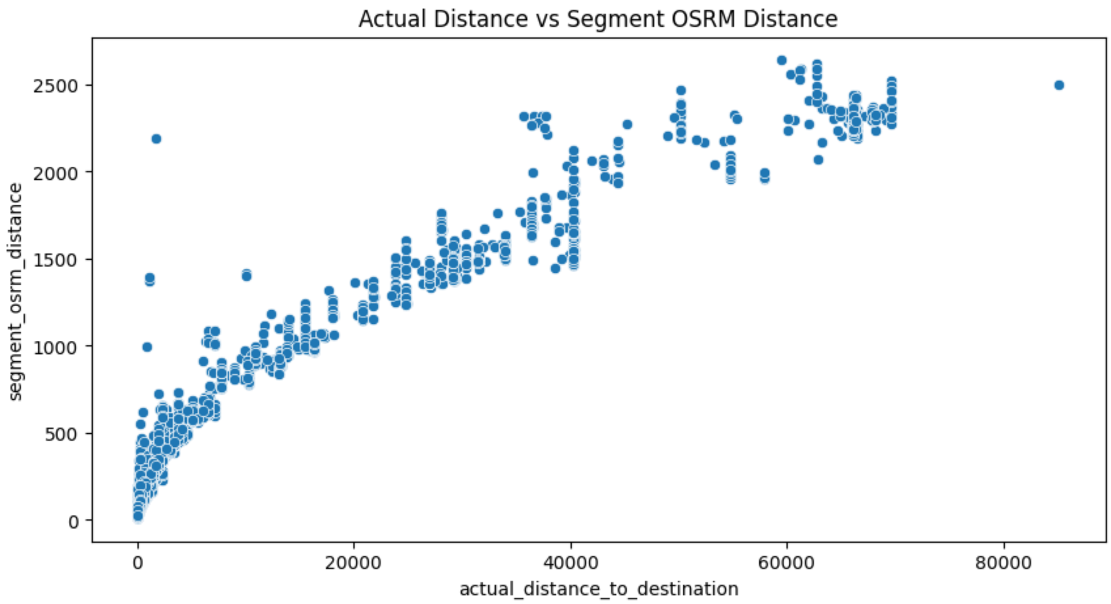
[71]:
```
# 3.4 Hypothesis testing and visual analysis
# Compare between actual_time and segment actual time aggregated value
plt.figure(figsize=(10,5))
sns.scatterplot(x=grouped_data['actual_time'],␣
↪y=grouped_data['segment_actual_time'])
plt.title('Actual time vs Segment actual time')
plt.show()
```



[33]:
```
t_stat, p_value = stats.ttest_rel(grouped_data['actual_time'],␣
    ↪grouped_data['segment_actual_time'])
print(f'T-statistic: {t_stat}, P-value: {p_value}')
```

```
T-statistic: 31.17395993579855, P-value: 1.5289517066693378e-209
```

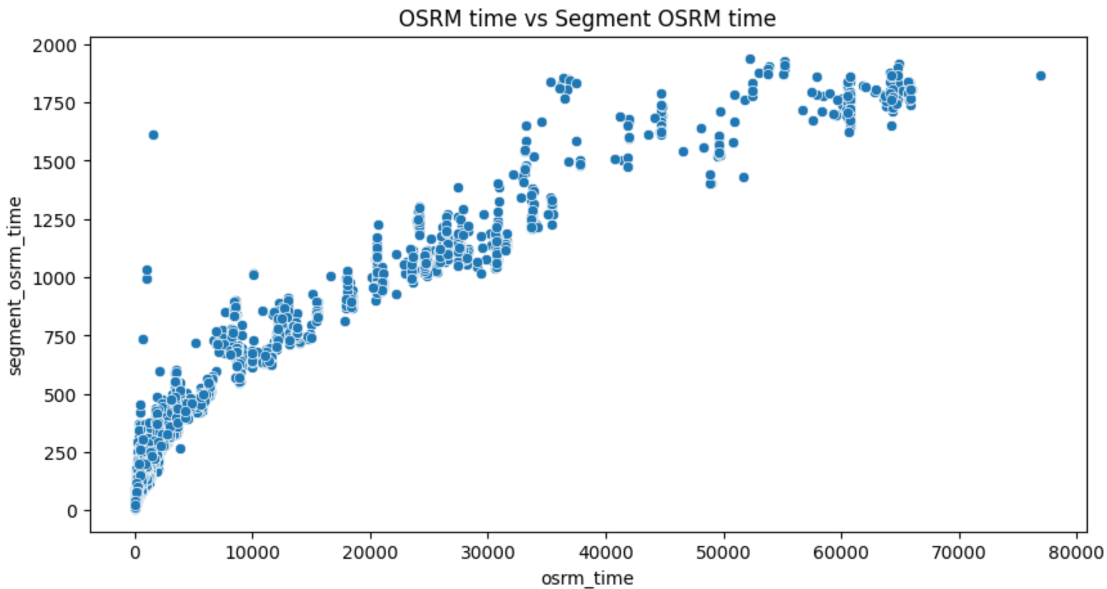
[72]:
```
# 3.5 Aggregated osrm_distance vs segment_osrm_distance
plt.figure(figsize=(10, 5))
sns.scatterplot(x=grouped_data['actual_distance_to_destination'],␣
    ↪y=grouped_data['segment_osrm_distance'])
plt.title('Actual Distance vs Segment OSRM Distance')
plt.show()
```



[35]:
```
t_stat, p_value = stats.
 ↪ttest_rel(grouped_data['actual_distance_to_destination'],␣
 ↪grouped_data['segment_osrm_distance'])
print(f'T-statistic: {t_stat}, P-value: {p_value}')
```

```
T-statistic: 30.18088244031722, P-value: 9.390085051829893e-197
```

[73]:
```
# 3.6 Aggregated osrm time vs segment osrm time
plt.figure(figsize=(10, 5))
sns.scatterplot(x=grouped_data['osrm_time'],␣
 ↪y=grouped_data['segment_osrm_time'])
plt.title('OSRM time vs Segment OSRM time')
plt.show()
```



[37]:
```python
t_stat, p_value = stats.ttest_rel(grouped_data['osrm_time'],␣
 ↪grouped_data['segment_osrm_time'])
print(f'T-statistic: {t_stat}, P-value: {p_value}')
```

```
T-statistic: 30.616387259869175, P-value: 2.5813253598938318e-202
```

[74]:
```python
# 3.7 Outlier Detection using IQR method
def detect_outliers(df, col):
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1
    return df[((df[col] < (Q1 - 1.5 * IQR)) | (df[col] > (Q3 + 1.5 * IQR)))]

outliers = detect_outliers(grouped_data, 'actual_time')
print("Outliers in actual_time:")
outliers[['trip_uuid', 'actual_time']]
```

```
Outliers in actual_time:
```

[74]:

	trip_uuid	actual_time
0	trip-153671041653548748	6484.0
1	trip-153671041653548748	9198.0
4	trip-153671043369099517	2601.0
5	trip-153671043369099517	109624.0
23	trip-153671121411074590	3383.0
…	…	…
26266	trip-153860879439383883	114932.0

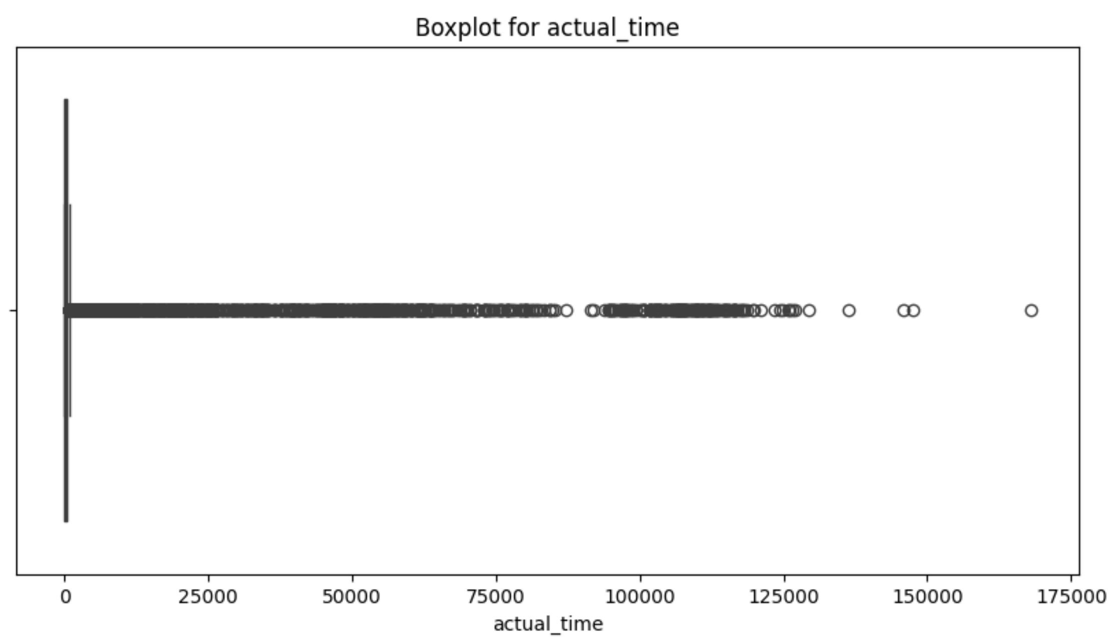
```
26316  trip-153860998196116365      1034.0
26329  trip-153861007249500192      2330.0
26330  trip-153861014185597051      3658.0
26333  trip-153861014185597051      9682.0

[3811 rows x 2 columns]
```

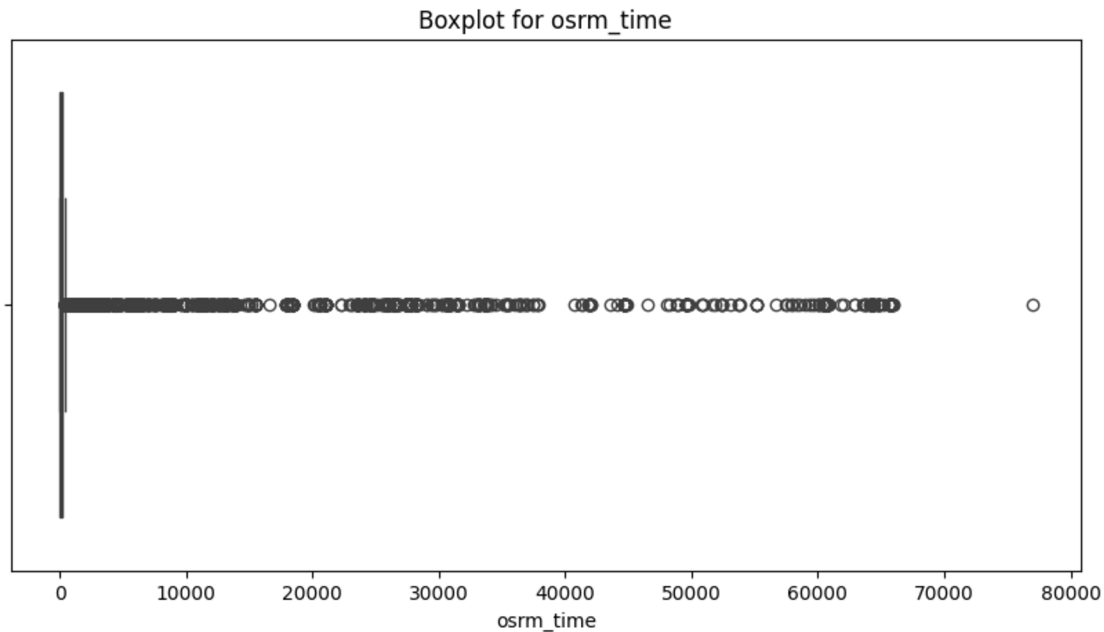
[75]:

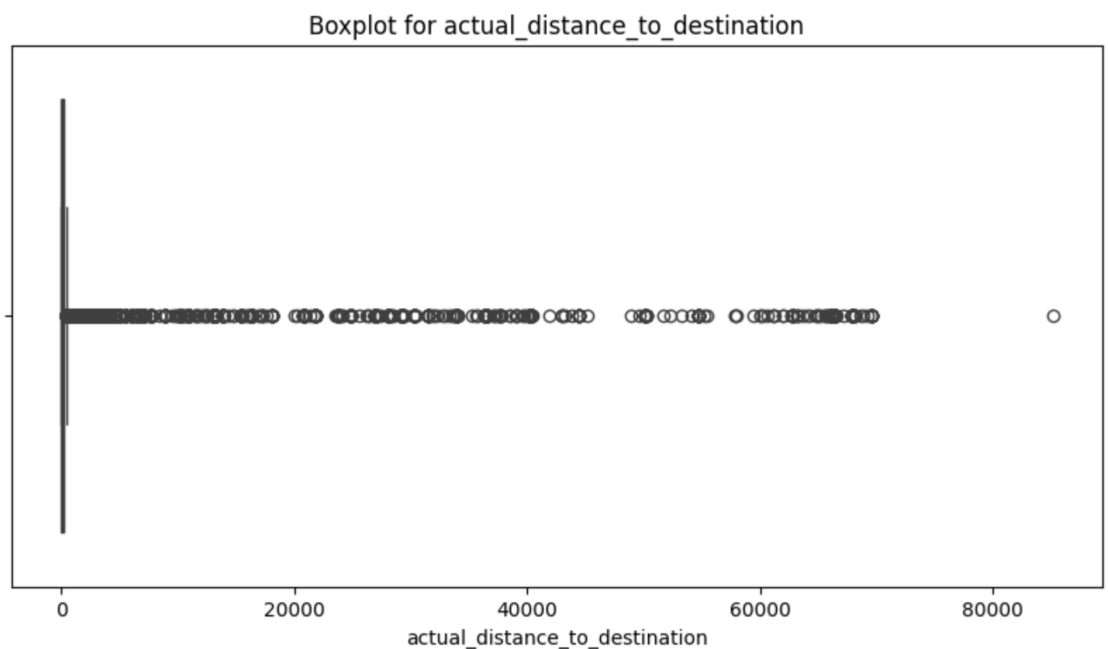
```
# Detect outliers for each numerical variable
numerical_columns = ['actual_time', 'osrm_time',␣
 ↪'actual_distance_to_destination', 'trip_duration']

outliers_dict = {}
for col in numerical_columns:
    outliers = detect_outliers(grouped_data, col)
    outliers_dict[col] = outliers
```

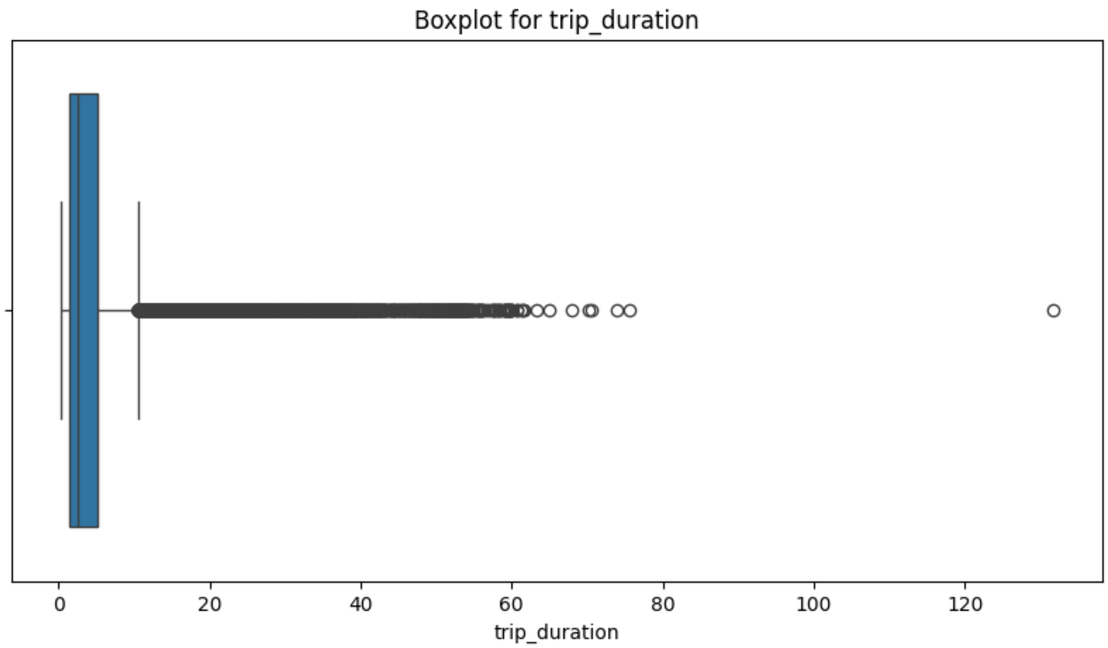
[76]:

```
# Visualizing outliers using boxplots for numerical variables
for col in numerical_columns:
    plt.figure(figsize=(10,5))
    sns.boxplot(x=grouped_data[col])
    plt.title(f'Boxplot for {col}')
    plt.show()
```




Boxplot for osrm_time
0
10000
20000
30000
40000
50000
60000
70000
80000
osrm_time


Boxplot for actual_distance_to_destination
0
20000
40000
60000
80000
actual_distance_to_destination



[82]:
```
# 3.5 Handling Outliers by capping them
Q1 = grouped_data['actual_time'].quantile(0.25)
Q3 = grouped_data['actual_time'].quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
grouped_data['actual_time'] = np.where(grouped_data['actual_time'] >
 ↪upper_bound, upper_bound,
                                       np.where(grouped_data['actual_time'] <
 ↪lower_bound, lower_bound, grouped_data['actual_time']))
```

[83]:
```
# 3.8 One-hot encoding for categorical columns
grouped_data_encoded = pd.get_dummies(grouped_data, columns=['route_type',
 ↪'source_city', 'destination_city'])
grouped_data_encoded.head()
```

[83]:
```
                  trip_uuid source_center destination_center  actual_time  \
0  trip-153671041653548748  IND209304AAA       IND000000ACB        988.5
1  trip-153671041653548748  IND462022AAA       IND209304AAA        988.5
2  trip-153671042288605164  IND561203AAB       IND562101AAA         96.0
3  trip-153671042288605164  IND572101AAA       IND561203AAB        303.0
4  trip-153671043369099517  IND000000ACB       IND160002AAC        988.5

   osrm_time  actual_distance_to_destination  segment_actual_time  \
0     3464.0                     3778.765471                728.0
```

```
1    4323.0                    5082.046634                 820.0
2      55.0                      53.310332                  46.0
3     155.0                     186.897974                  95.0
4    1427.0                    1725.590250                 608.0

   segment_osrm_time  segment_osrm_distance  \
0              534.0               670.6205
1              474.0               649.8528
2               26.0                28.1995
3               39.0                55.9899
4              231.0               317.7408

                         source_name  … destination_city_Wai  \
0  Kanpur_Central_H_6 (Uttar Pradesh)  …                False
1  Bhopal_Trnsport_H (Madhya Pradesh)  …                False
2   Doddablpur_ChikaDPP_D (Karnataka)  …                False
3       Tumkur_Veersagr_I (Karnataka)  …                False
4       Gurgaon_Bilaspur_HB (Haryana)  …                False

  destination_city_Wanaparthy destination_city_Wankaner  \
0                       False                     False
1                       False                     False
2                       False                     False
3                       False                     False
4                       False                     False

  destination_city_Warangal  destination_city_YamunaNagar  \
0                     False                         False
1                     False                         False
2                     False                         False
3                     False                         False
4                     False                         False

   destination_city_Yavatmal  destination_city_Yellandu  \
0                      False                      False
1                      False                      False
2                      False                      False
3                      False                      False
4                      False                      False

   destination_city_Yellareddy  destination_city_Zahirabad  \
0                        False                       False
1                        False                       False
2                        False                       False
3                        False                       False
4                        False                       False
```

```
   destination_city_Zirakpur
0                      False
1                      False
2                      False
3                      False
4                      False

[5 rows x 2541 columns]
```

[84]:
```
# 3.9 Normalize/Standardize numerical features
scaler = StandardScaler()
scaled_columns = ['actual_time', 'osrm_time', 'actual_distance_to_destination',␣
 ↪'trip_duration']
grouped_data_encoded[scaled_columns] = scaler.
 ↪fit_transform(grouped_data_encoded[scaled_columns])
grouped_data_encoded[scaled_columns].head()
```

[84]:
```
   actual_time  osrm_time  actual_distance_to_destination  trip_duration
0     2.002549   0.388408                        0.382766       2.182447
1     2.002549   0.534167                        0.582886       1.589963
2    -0.719251  -0.190047                       -0.189283      -0.544606
3    -0.087977  -0.173079                       -0.168770      -0.399498
4     2.002549   0.042760                        0.067498       1.215849
```

Insights on In-depth Analysis and Feature Engineering

1. Calculating Trip Duration:

The time difference between od_start_time and od_end_time was calculated and stored as a new feature trip_duration.

Insight: Trip duration helps in understanding the efficiency of deliveries and identifying delays.

2. Hypothesis Testing and Visual Analysis:

We visually compared actual_time vs trip_duration and ran a t-test to see if the two are statistically different.

Insight: If the p-value is low, it suggests that the actual times and calculated durations differ significantly, indicating potential inefficiencies.

We also compared actual_time vs osrm_time and actual_distance_to_destination vs segment_osrm_distance.

Insight: These comparisons help in identifying discrepancies between actual and estimated values, which can guide route optimizations.

3. Outlier Detection Using the IQR Method:

Outliers in actual_time were detected using the IQR method.

Insight: Outliers can distort analysis by skewing averages and trends. Detecting them helps in handling anomalies and improving data quality.

4. Handling Outliers by Capping:

Outliers were capped by setting values above the upper bound to the upper bound and below the lower bound to the lower bound.

Insight: Capping outliers ensures they don't influence the overall results too much while still retaining the data.

5. One-Hot Encoding for Categorical Columns:

We performed one-hot encoding on categorical variables like route_type, source_city, and destination_city.

Insight: Converting categorical variables into numerical form allows them to be used in machine learning models.

6. Normalization and Standardization:

We normalized and standardized continuous features using StandardScaler.

Insight: Standardization brings all numeric variables to a similar scale, ensuring that features with larger ranges don't dominate the model training process.

Recommendations:

Fix Missing Data: Always ensure that missing values are handled properly, either by filling them or removing them, to avoid incomplete analysis.

Analyze Time-Based Trends: Look into delivery times by month, day, or hour to identify periods where deliveries slow down and find ways to speed them up.

Check for Inconsistent Data: Regularly compare actual and predicted times (like actual_time vs osrm_time) to find gaps where estimates are off.

Handle Outliers: Remove or cap outliers that could skew your analysis. They can come from unexpected delays or data entry errors.

Standardize Your Data: Make sure all your data is on the same scale, so different features don't overpower each other when doing any kind of analysis.

Automate Feature Extraction: Features like month, year, and city should be automatically extracted from date or text columns for easy analysis and modeling.

[ ]:

```

```