Business Case: Delhivery - Feature Engineering

Problem Statement and Exploratory Data Analysis

The main objective is to help Delhivery process, clean, and analyze data generated from their logistics operations. The goal is to make sense of this raw data, engineer useful features, and assist the data science team in building forecasting models for improved efficiency, quality, and profitability of deliveries. Specifically, we will clean, sanitize, and manipulate the data and build useful features to merge various trip segments. These features will be critical for understanding the time, distance, and other operational metrics involved in each delivery.

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

delhivery_data = pd.read_csv("/content/delhivery.csv")

# Display the shape of the data
print("Shape of the dataset:", delhivery_data.shape)
```

```
Shape of the dataset: (144867, 24)
```

```
# Display the data types of all attributes
print("Data types of the attributes:\n", delhivery_data.dtypes)
```

```
Data types of the attributes:
 data                                     object
trip_creation_time                       object
route_schedule_uuid                      object
route_type                               object
trip_uuid                                object
source_center                            object
source_name                              object
destination_center                       object
destination_name                         object
od_start_time                            object
od_end_time                              object
start_scan_to_end_scan                  float64
is_cutoff                                  bool
cutoff_factor                             int64
cutoff_timestamp                         object
actual_distance_to_destination          float64
actual_time                             float64
osrm_time                               float64
osrm_distance                           float64
factor                                  float64
```

```
segment_actual_time                  float64
segment_osrm_time                    float64
segment_osrm_distance                float64
segment_factor                       float64
dtype: object
```

```python
# Convert object type columns that represent categories to 'category' data type
categorical_columns = ['data', 'route_type', 'trip_uuid', 'source_center', 'destination_center']

for col in categorical_columns:
    delhivery_data[col] = delhivery_data[col].astype('category')

print("Updated Data Types:\n", delhivery_data.dtypes)
```

```
Updated Data Types:
 data                              category
trip_creation_time                  object
route_schedule_uuid                 object
route_type                        category
trip_uuid                         category
source_center                     category
source_name                         object
destination_center                category
destination_name                    object
od_start_time                       object
od_end_time                         object
start_scan_to_end_scan             float64
is_cutoff                             bool
cutoff_factor                        int64
cutoff_timestamp                    object
actual_distance_to_destination     float64
actual_time                        float64
osrm_time                          float64
osrm_distance                      float64
factor                             float64
segment_actual_time                float64
segment_osrm_time                  float64
segment_osrm_distance              float64
segment_factor                     float64
dtype: object
```

```python
# Check for missing values in the dataset
missing_values = delhivery_data.isnull().sum()
print("Missing values in each column:\n", missing_values)
```

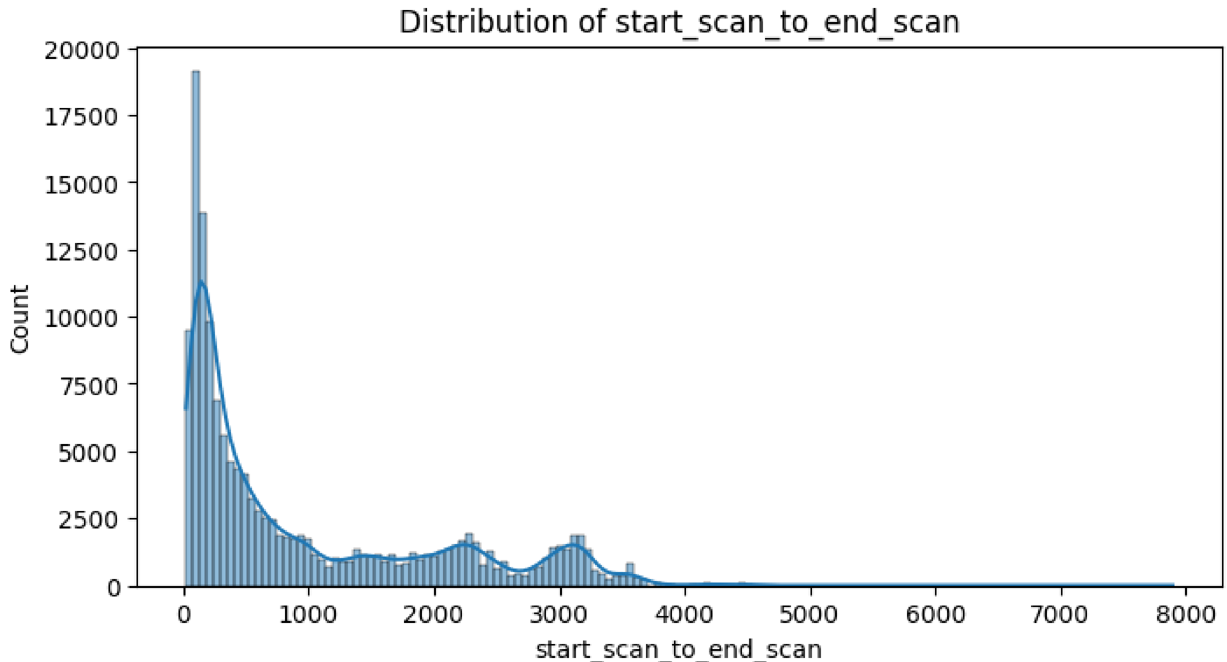
```
Missing values in each column:
 data                                0
trip_creation_time                  0
```

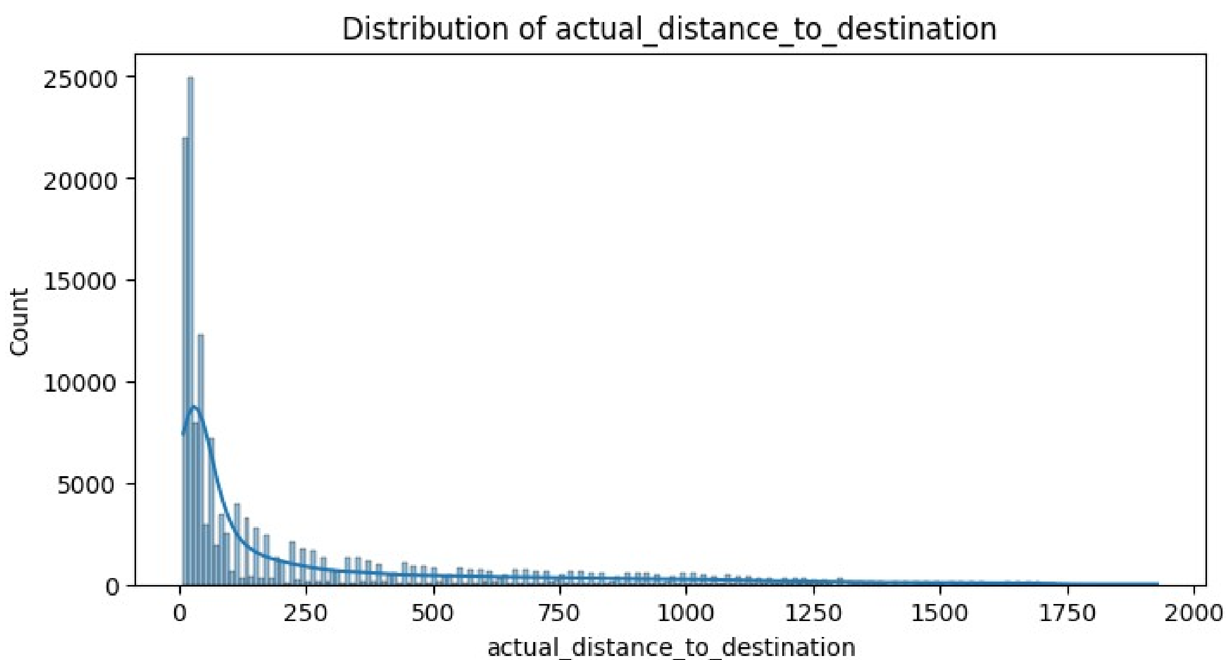
```
route_schedule_uuid                 0
route_type                          0
trip_uuid                           0
source_center                       0
source_name                       293
destination_center                  0
destination_name                  261
od_start_time                       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
```

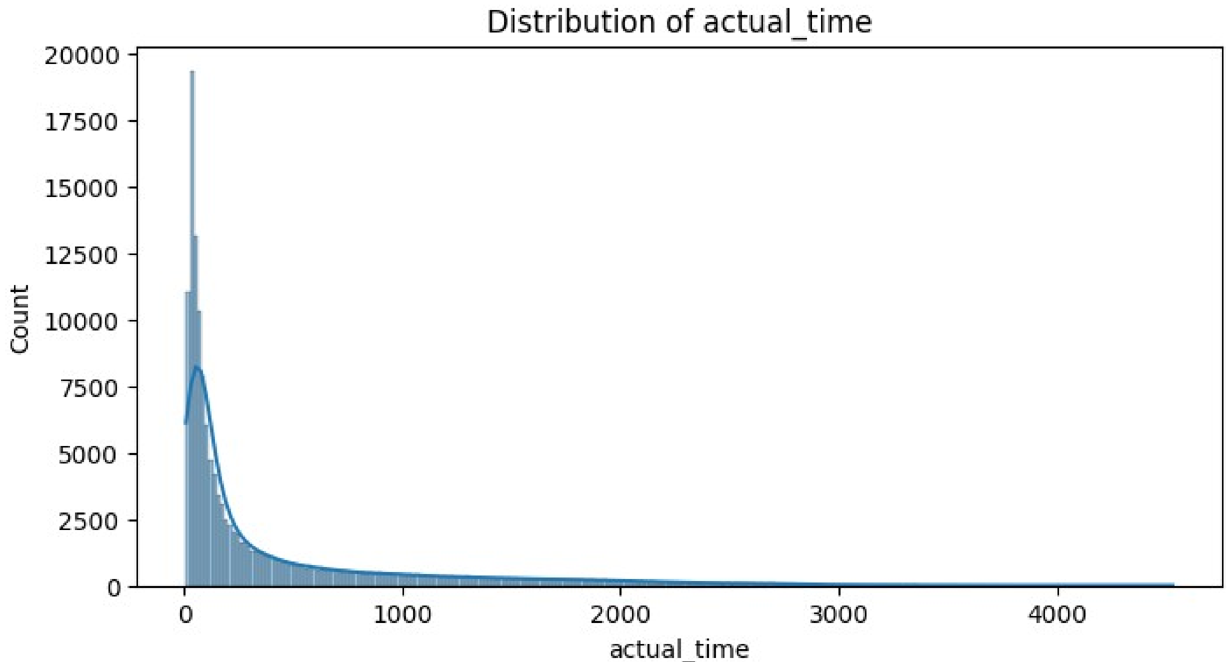
```
# Display statistical summary of the dataset
print("Statistical Summary of the dataset:\n",
delhivery_data.describe())
```

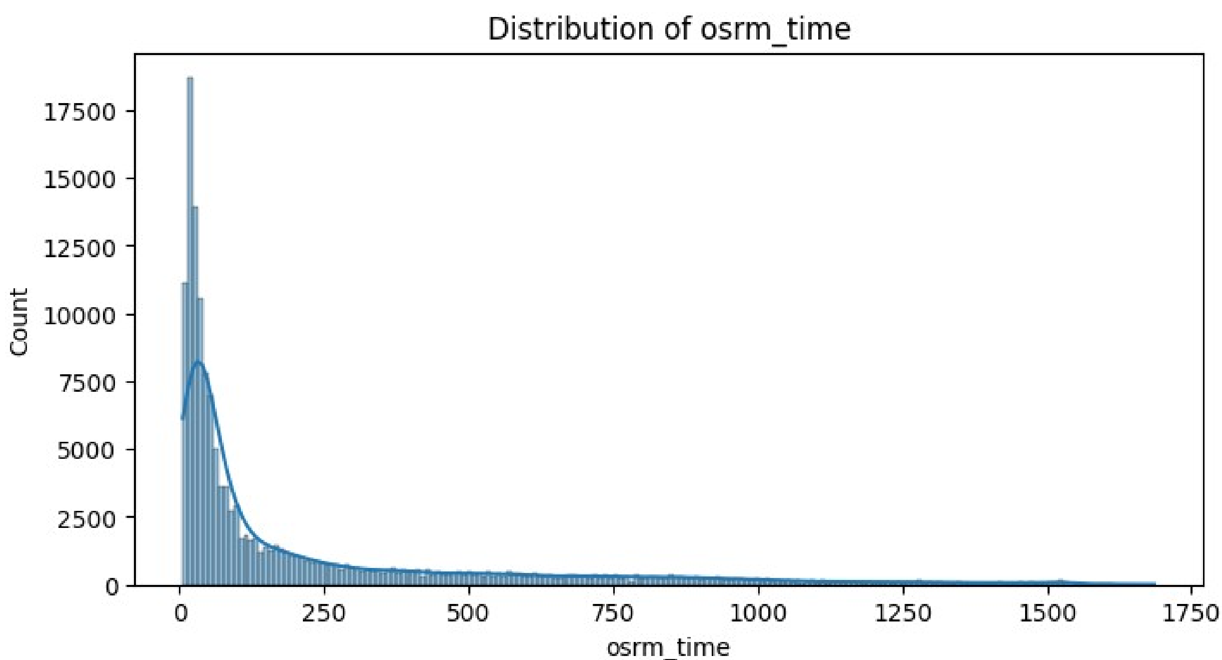
```
Statistical Summary of the dataset:
        start_scan_to_end_scan  cutoff_factor
actual_distance_to_destination  \
count           144867.000000  144867.000000
144867.000000
mean               961.262986     232.926567
234.073372
std               1037.012769     344.755577
344.990009
min                 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
```

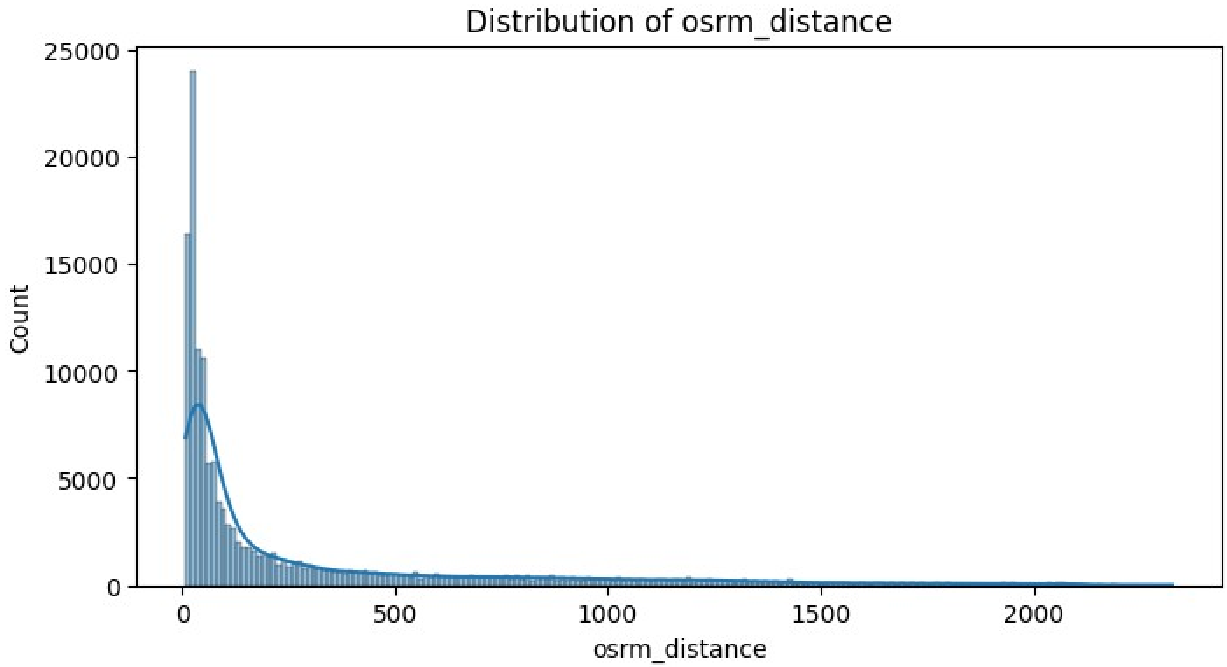
```
mean       416.927527      213.868272      284.771297        2.120107
std        598.103621      308.011085      421.119294        1.715421
min          9.000000        6.000000        9.008200        0.144000
25%         51.000000       27.000000       29.914700        1.604264
50%        132.000000       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

# Plot distribution of continuous variables
continuous_columns = ['start_scan_to_end_scan',
'actual_distance_to_destination',
                      'actual_time', 'osrm_time', 'osrm_distance',
                      'segment_actual_time', 'segment_osrm_time',
'segment_osrm_distance']

for col in continuous_columns:
    plt.figure(figsize=(8, 4))
    sns.histplot(delhivery_data[col], kde=True)
    plt.title(f'Distribution of {col}')
    plt.show()
```

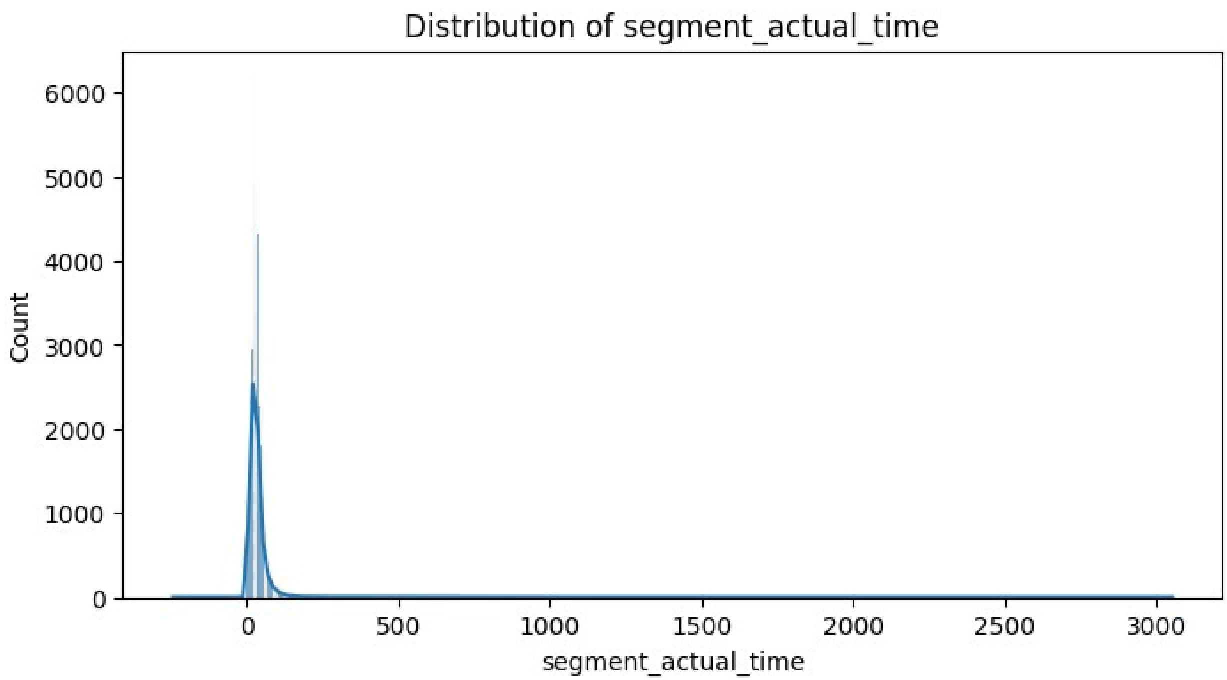

Distribution of start_scan_to_end_scan
Count
20000
17500
15000
12500
10000
7500
5000
2500
0
0
1000
2000
3000
4000
5000
6000
7000
8000
start_scan_to_end_scan

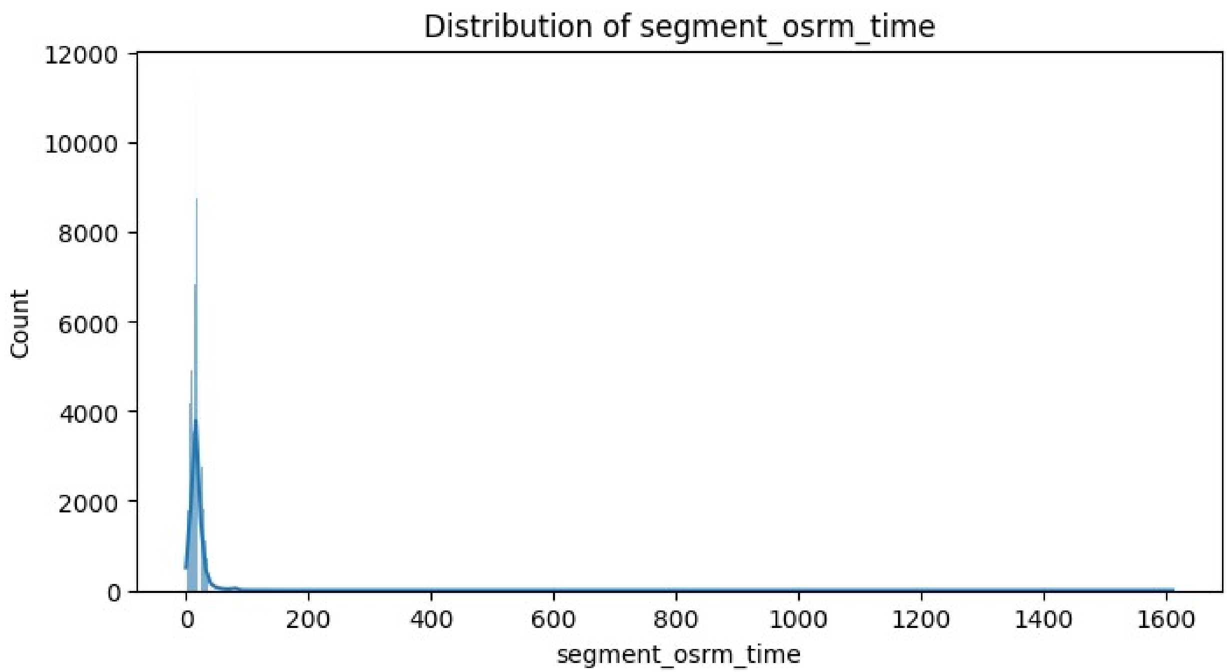

Distribution of actual_distance_to_destination
Count
25000
20000
15000
10000
5000
0
0
250
500
750
1000
1250
1500
1750
2000
actual_distance_to_destination

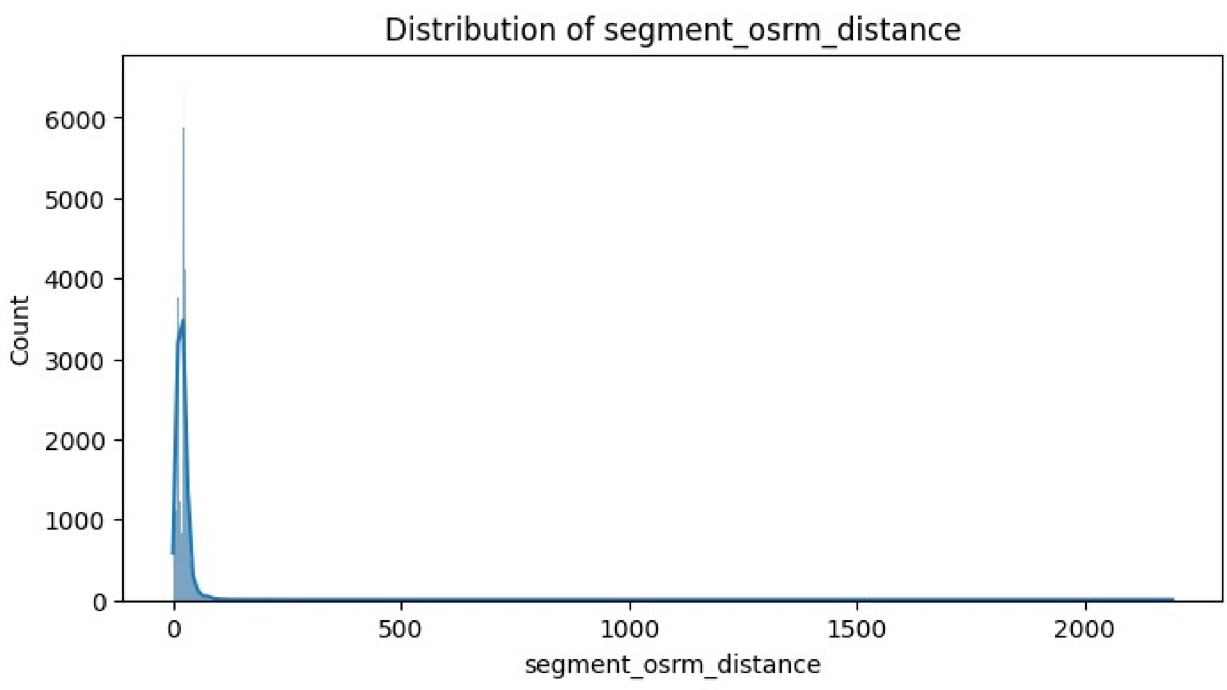

Distribution of actual_time
Count
actual_time
0
2500
5000
7500
10000
12500
15000
17500
20000
1000
2000
3000
4000


Distribution of osrm_time
Count
osrm_time
0
2500
5000
7500
10000
12500
15000
17500
250
500
750
1000
1250
1500
1750


Distribution of osrm_distance
25000
20000
15000
10000
5000
0
Count
0
500
1000
1500
2000
osrm_distance

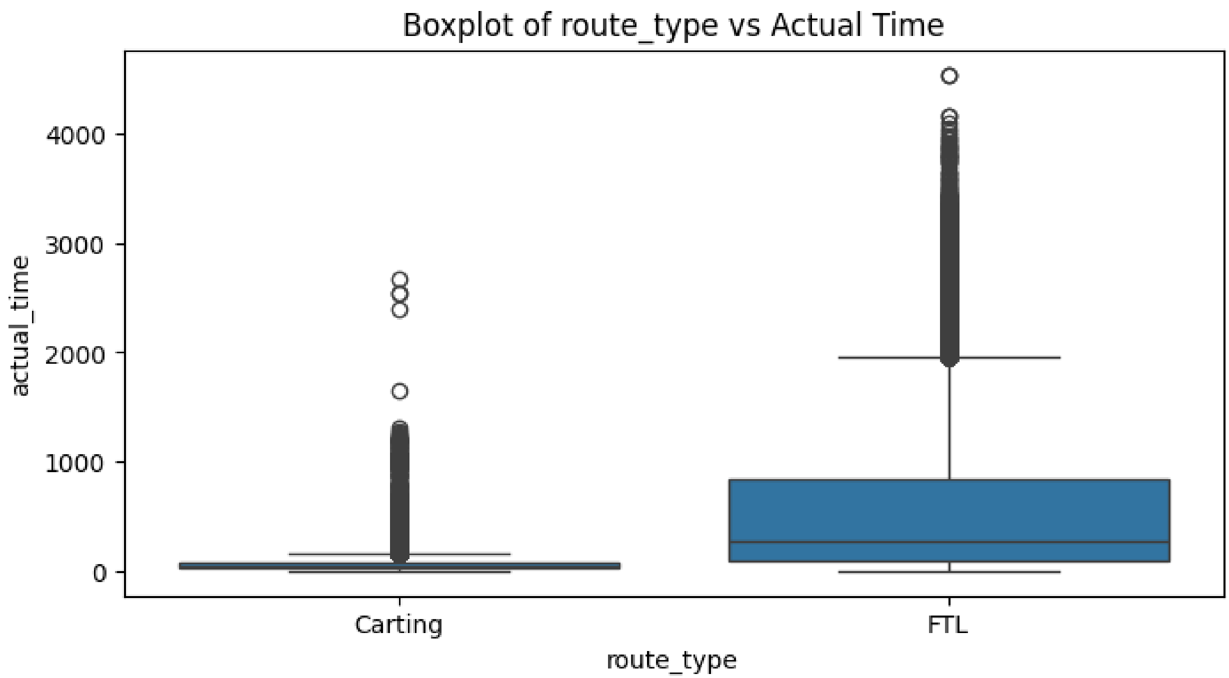

Distribution of segment_actual_time
6000
5000
4000
3000
2000
1000
0
Count
0
500
1000
1500
2000
2500
3000
segment_actual_time

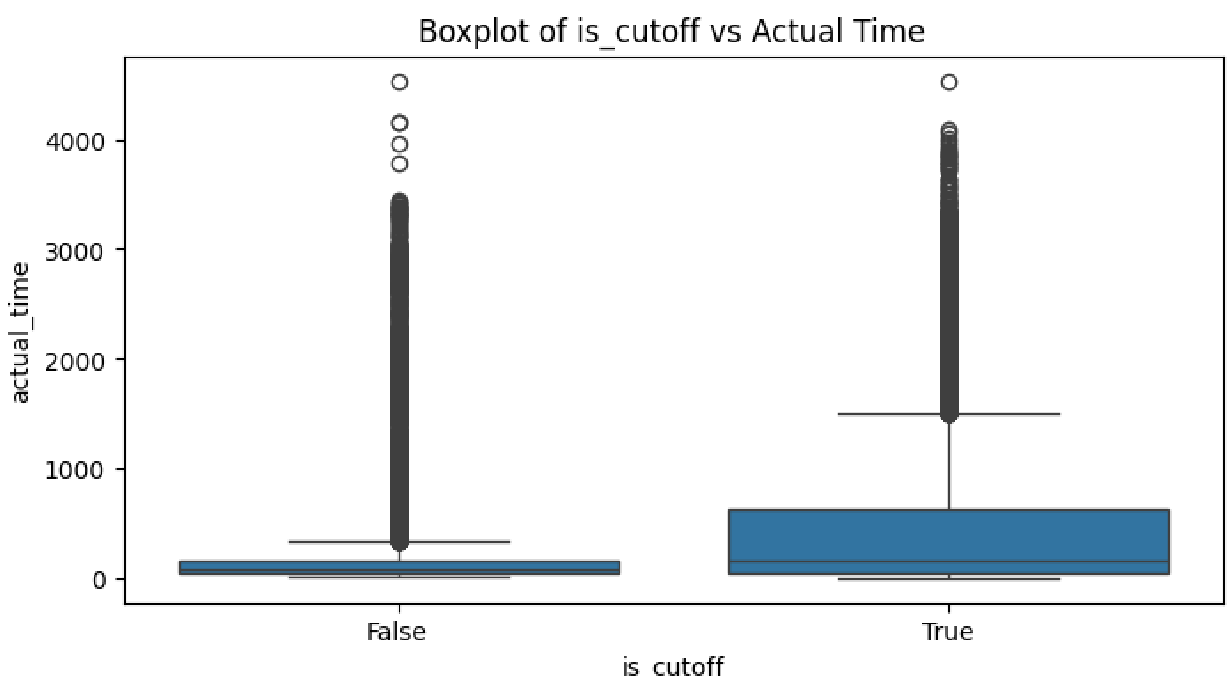





```
# Plot boxplots for categorical variables against a continuous
variable (example with 'actual_time')
categorical_columns_for_boxplot = ['route_type', 'is_cutoff']

for col in categorical_columns_for_boxplot:
    plt.figure(figsize=(8, 4))
    sns.boxplot(x=col, y='actual_time', data=delhivery_data)
```

```
    plt.title(f'Boxplot of {col} vs Actual Time')
    plt.show()
```





Observations and Insights based on EDA

Range of Attributes and Outliers

start_scan_to_end_scan, actual_time, osrm_time, and osrm_distance exhibit significant variation across deliveries.

Some deliveries show start_scan_to_end_scan times as long as 7898 units, with a majority clustering below 2000 units.

actual_time ranges from 9 to 4532 units, which also reveals substantial variation.

There are clear outliers in almost all continuous variables, especially in the upper ranges (e.g., in actual_time, osrm_time, and osrm_distance).

segment_actual_time, segment_osrm_time, and segment_osrm_distance reflect smaller delivery segments, where the majority of values are clustered toward the lower end, with rare but extreme outliers.

Distribution of Variables

Most continuous variables are right-skewed, meaning there is a higher concentration of shorter trips or deliveries (in terms of time or distance), with a small number of long trips or deliveries. This skewness indicates that the majority of deliveries occur over short distances and short durations, with a few longer deliveries that take significantly more time or cover more distance.

Boxplots and Relationship Insights

Route Type vs Actual Time:

The FTL (Full Truck Load) deliveries take longer on average compared to Carting deliveries, with more variability and more significant outliers. Carting shows a tightly clustered distribution with fewer extreme outliers, indicating more consistency in delivery times.

Is Cutoff vs Actual Time:

Trips marked as cutoff show more considerable variability in actual_time, with more extreme outliers. This suggests that cutoff trips may be experiencing delays or other operational challenges that affect delivery time.

Univariate Analysis:

Continuous variables, such as start_scan_to_end_scan, actual_distance_to_destination, and actual_time, show heavy right-skewed distributions. This implies that most deliveries are short, with few long-duration or long-distance deliveries. Segment-related variables (e.g., segment_actual_time) exhibit a similar pattern but with smaller ranges, which is expected since they represent shorter delivery segments.

Bivariate Analysis:

Route Type vs Actual Time shows clear differences in delivery time depending on the transportation type, with FTL deliveries taking more time on average.

Is Cutoff vs Actual Time suggests cutoff deliveries experience delays or variability in actual delivery time, indicating that special handling or exceptions may be required for such deliveries.

Outlier Treatment Recommendation

Due to the presence of extreme outliers, especially in the actual_time, osrm_time, and osrm_distance variables, it would be advisable to treat these outliers using the IQR method. This would help mitigate the influence of extreme values on model building and analysis, ensuring that the majority distribution is better represented in any forecasting models.

Feature Creation

1. Handle Missing Values

We'll handle the missing values in source_name and destination_name. For simplicity, we'll fill the missing values with "Unknown."

```python
# Fill missing values in source_name and destination_name
delhivery_data['source_name'].fillna('Unknown', inplace=True)
delhivery_data['destination_name'].fillna('Unknown', inplace=True)

# Verify that there are no more missing values
print(delhivery_data.isnull().sum())
```

```
data                              0
trip_creation_time                0
route_schedule_uuid               0
route_type                        0
trip_uuid                         0
source_center                     0
source_name                       0
destination_center                0
destination_name                  0
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
```

2. Convert Categorical Variables

We will convert object columns that represent categories to the 'category' data type for better performance.

```
# Convert categorical columns to 'category' type
categorical_columns = ['data', 'route_type', 'trip_uuid',
'source_center', 'destination_center']

for col in categorical_columns:
    delhivery_data[col] = delhivery_data[col].astype('category')

print("Updated Data Types:\n", delhivery_data.dtypes)

Updated Data Types:
 data                              category
trip_creation_time                  object
route_schedule_uuid                 object
route_type                        category
trip_uuid                         category
source_center                     category
source_name                         object
destination_center                category
destination_name                    object
od_start_time                       object
od_end_time                         object
start_scan_to_end_scan             float64
is_cutoff                             bool
cutoff_factor                        int64
cutoff_timestamp                    object
actual_distance_to_destination     float64
actual_time                        float64
osrm_time                          float64
osrm_distance                      float64
factor                             float64
segment_actual_time                float64
segment_osrm_time                  float64
segment_osrm_distance              float64
segment_factor                     float64
dtype: object
```

3. Feature Creation

3.1 Time Features from trip_creation_time

We will extract temporal features such as year, month, day, etc., from the trip_creation_time column.

```
# Convert 'trip_creation_time' to datetime type and extract features
delhivery_data['trip_creation_time'] =
pd.to_datetime(delhivery_data['trip_creation_time'])

delhivery_data['year'] = delhivery_data['trip_creation_time'].dt.year
delhivery_data['month'] =
delhivery_data['trip_creation_time'].dt.month
```

```python
delhivery_data['day'] = delhivery_data['trip_creation_time'].dt.day
delhivery_data['day_of_week'] =
delhivery_data['trip_creation_time'].dt.dayofweek
delhivery_data['hour'] = delhivery_data['trip_creation_time'].dt.hour
delhivery_data['minute'] =
delhivery_data['trip_creation_time'].dt.minute
```

3.2 Create Total Trip Time from od_start_time and od_end_time

```python
# Convert 'od_start_time' and 'od_end_time' to datetime type and
create total_trip_time
delhivery_data['od_start_time'] =
pd.to_datetime(delhivery_data['od_start_time'])
delhivery_data['od_end_time'] =
pd.to_datetime(delhivery_data['od_end_time'])

# Create a new feature for total trip time (in minutes)
delhivery_data['total_trip_time'] = (delhivery_data['od_end_time'] -
delhivery_data['od_start_time']).dt.total_seconds() / 60
```

3.3 Extract Features from source_name and destination_name

```python
# Split source and destination names to extract city and state
delhivery_data['source_city'] =
delhivery_data['source_name'].str.split('_').str[0]
delhivery_data['source_state'] =
delhivery_data['source_name'].str.extract(r'\((.*?)\)')

delhivery_data['destination_city'] =
delhivery_data['destination_name'].str.split('_').str[0]
delhivery_data['destination_state'] =
delhivery_data['destination_name'].str.extract(r'\((.*?)\)')
```

3.4 Aggregated Features for Trips

```python
trip_features = delhivery_data.groupby('trip_uuid').agg({
    'actual_time': ['sum', 'mean', 'max'],
    'osrm_time': ['sum', 'mean', 'max'],
    'osrm_distance': ['sum', 'mean', 'max'],
    'segment_actual_time': ['sum', 'mean', 'max'],
    'segment_osrm_time': ['sum', 'mean', 'max'],
    'segment_osrm_distance': ['sum', 'mean', 'max']
})

# Flatten the multi-level index but keep the 'trip_uuid' intact
trip_features.columns = ['_'.join(col).strip() for col in
trip_features.columns.values]
trip_features = trip_features.reset_index()  # Reset index to bring
back 'trip_uuid'
```

```
<ipython-input-16-ade8d2aba560>:1: FutureWarning: The default of
observed=False is deprecated and will be changed to True in a future
version of pandas. Pass observed=False to retain current behavior or
observed=True to adopt the future default and silence this warning.
  trip_features = delhivery_data.groupby('trip_uuid').agg({
```

3.5 Create Ratio Features

We can create ratio features between actual and predicted values.

```
# Create ratio features
delhivery_data['actual_osrm_time_ratio'] =
delhivery_data['actual_time'] / delhivery_data['osrm_time']
delhivery_data['segment_time_ratio'] =
delhivery_data['segment_actual_time'] /
delhivery_data['segment_osrm_time']
```

3.6 Boolean Feature for Cutoff

We'll convert the is_cutoff column to a binary feature.

```
# Binary feature for cutoff
delhivery_data['cutoff'] = delhivery_data['is_cutoff'].astype(int)
```

4. Outlier Detection and Treatment

We will use the Interquartile Range (IQR) method to detect and handle outliers.

```
# Function to remove outliers using IQR method
def remove_outliers(df, column):
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    return df[(df[column] >= lower_bound) & (df[column] <=
upper_bound)]

# Apply outlier treatment on key columns
columns_to_treat = ['actual_time', 'osrm_time',
'actual_distance_to_destination', 'start_scan_to_end_scan']
for col in columns_to_treat:
    delhivery_data = remove_outliers(delhivery_data, col)
```

5. One-Hot Encoding for Categorical Variables

We will one-hot encode the necessary categorical columns such as route_type, source_state, and destination_state.

```
# One-hot encode categorical variables
delhivery_data = pd.get_dummies(delhivery_data, columns=['route_type',
'source_state', 'destination_state'], drop_first=True)
```

6. Standardization of Numerical Features

We will standardize or normalize the continuous features (like distances and times) using MinMaxScaler or StandardScaler from sklearn.

```
from sklearn.preprocessing import StandardScaler, MinMaxScaler

# Using MinMaxScaler for scaling
scaler = MinMaxScaler()

# List of continuous columns to scale
continuous_columns = ['actual_time', 'osrm_time',
'actual_distance_to_destination', 'start_scan_to_end_scan']

# Apply scaling
delhivery_data[continuous_columns] =
scaler.fit_transform(delhivery_data[continuous_columns])

print(delhivery_data[continuous_columns].head())
```

```
   actual_time  osrm_time  actual_distance_to_destination  \
0     0.004456   0.015974                        0.006169
1     0.013369   0.044728                        0.042700
2     0.027629   0.070288                        0.080088
3     0.047237   0.108626                        0.116531
4     0.052585   0.121406                        0.130574

   start_scan_to_end_scan
0                0.057946
1                0.057946
2                0.057946
3                0.057946
4                0.057946
```

7. Final Dataset Check

Finally, we can check the dataset after all preprocessing steps.

```
# Check the final dataset
print(delhivery_data.head())
print(delhivery_data.info())
```

```
       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
trip_uuid  \
0  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...  trip-
153741093647649320
1  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...  trip-
153741093647649320
2  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...  trip-
153741093647649320
3  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...  trip-
153741093647649320
4  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...  trip-
153741093647649320

  source_center                 source_name destination_center  \
0  IND388121AAA  Anand_VUNagar_DC (Gujarat)       IND388620AAB
1  IND388121AAA  Anand_VUNagar_DC (Gujarat)       IND388620AAB
2  IND388121AAA  Anand_VUNagar_DC (Gujarat)       IND388620AAB
3  IND388121AAA  Anand_VUNagar_DC (Gujarat)       IND388620AAB
4  IND388121AAA  Anand_VUNagar_DC (Gujarat)       IND388620AAB

                destination_name              od_start_time  \
0  Khambhat_MotvdDPP_D (Gujarat) 2018-09-20 03:21:32.418600
1  Khambhat_MotvdDPP_D (Gujarat) 2018-09-20 03:21:32.418600
2  Khambhat_MotvdDPP_D (Gujarat) 2018-09-20 03:21:32.418600
3  Khambhat_MotvdDPP_D (Gujarat) 2018-09-20 03:21:32.418600
4  Khambhat_MotvdDPP_D (Gujarat) 2018-09-20 03:21:32.418600

                 od_end_time  ...  destination_state_Orissa  \
0 2018-09-20 04:47:45.236797  ...                     False
1 2018-09-20 04:47:45.236797  ...                     False
2 2018-09-20 04:47:45.236797  ...                     False
3 2018-09-20 04:47:45.236797  ...                     False
4 2018-09-20 04:47:45.236797  ...                     False

   destination_state_Pondicherry  destination_state_Punjab  \
0                          False                     False
1                          False                     False
2                          False                     False
3                          False                     False
4                          False                     False

  destination_state_Rajasthan  destination_state_Tamil Nadu  \
0                       False                         False
1                       False                         False
2                       False                         False
3                       False                         False
4                       False                         False
```

```
   destination_state_Telangana  destination_state_Tripura  \
0                        False                      False
1                        False                      False
2                        False                      False
3                        False                      False
4                        False                      False

   destination_state_Uttar Pradesh  destination_state_Uttarakhand  \
0                            False                          False
1                            False                          False
2                            False                          False
3                            False                          False
4                            False                          False

   destination_state_West Bengal
0                          False
1                          False
2                          False
3                          False
4                          False

[5 rows x 97 columns]
<class 'pandas.core.frame.DataFrame'>
Index: 94755 entries, 0 to 144866
Data columns (total 97 columns):
 #   Column                                    Non-Null Count  Dtype

---  ------                                    --------------  -----

 0   data                                      94755 non-null
category
 1   trip_creation_time                        94755 non-null
datetime64[ns]
 2   route_schedule_uuid                       94755 non-null  object

 3   trip_uuid                                 94755 non-null
category
 4   source_center                             94755 non-null
category
 5   source_name                               94755 non-null  object

 6   destination_center                        94755 non-null
category
 7   destination_name                          94755 non-null  object

 8   od_start_time                             94755 non-null
datetime64[ns]
 9   od_end_time                               94755 non-null
datetime64[ns]
```

```
 10  start_scan_to_end_scan          94755 non-null  float64
 11  is_cutoff                       94755 non-null  bool
 12  cutoff_factor                   94755 non-null  int64
 13  cutoff_timestamp                94755 non-null  object
 14  actual_distance_to_destination  94755 non-null  float64
 15  actual_time                     94755 non-null  float64
 16  osrm_time                       94755 non-null  float64
 17  osrm_distance                   94755 non-null  float64
 18  factor                          94755 non-null  float64
 19  segment_actual_time             94755 non-null  float64
 20  segment_osrm_time               94755 non-null  float64
 21  segment_osrm_distance           94755 non-null  float64
 22  segment_factor                  94755 non-null  float64
 23  year                            94755 non-null  int32
 24  month                           94755 non-null  int32
 25  day                             94755 non-null  int32
 26  day_of_week                     94755 non-null  int32
 27  hour                            94755 non-null  int32
 28  minute                          94755 non-null  int32
 29  total_trip_time                 94755 non-null  float64
 30  source_city                     94755 non-null  object
 31  destination_city                94755 non-null  object
 32  actual_osrm_time_ratio          94755 non-null  float64
 33  segment_time_ratio              93101 non-null  float64
 34  cutoff                          94755 non-null  int64
 35  route_type_FTL                  94755 non-null  bool
```

```
 36  source_state_Arunachal Pradesh       94755 non-null  bool
 37  source_state_Assam                   94755 non-null  bool
 38  source_state_Bihar                   94755 non-null  bool
 39  source_state_Chandigarh              94755 non-null  bool
 40  source_state_Chhattisgarh            94755 non-null  bool
 41  source_state_Dadra and Nagar Haveli  94755 non-null  bool
 42  source_state_Delhi                   94755 non-null  bool
 43  source_state_Goa                     94755 non-null  bool
 44  source_state_Gujarat                 94755 non-null  bool
 45  source_state_Haryana                 94755 non-null  bool
 46  source_state_Himachal Pradesh        94755 non-null  bool
 47  source_state_Jammu & Kashmir         94755 non-null  bool
 48  source_state_Jharkhand               94755 non-null  bool
 49  source_state_Karnataka               94755 non-null  bool
 50  source_state_Kerala                  94755 non-null  bool
 51  source_state_Madhya Pradesh          94755 non-null  bool
 52  source_state_Maharashtra             94755 non-null  bool
 53  source_state_Meghalaya               94755 non-null  bool
 54  source_state_Mizoram                 94755 non-null  bool
 55  source_state_Nagaland                94755 non-null  bool
 56  source_state_Orissa                  94755 non-null  bool
 57  source_state_Pondicherry             94755 non-null  bool
 58  source_state_Punjab                  94755 non-null  bool
 59  source_state_Rajasthan               94755 non-null  bool
 60  source_state_Tamil Nadu              94755 non-null  bool
 61  source_state_Telangana               94755 non-null  bool
```

```
 62  source_state_Tripura                      94755 non-null  bool
 63  source_state_Uttar Pradesh                94755 non-null  bool
 64  source_state_Uttarakhand                  94755 non-null  bool
 65  source_state_West Bengal                  94755 non-null  bool
 66  destination_state_Arunachal Pradesh       94755 non-null  bool
 67  destination_state_Assam                   94755 non-null  bool
 68  destination_state_Bihar                   94755 non-null  bool
 69  destination_state_Chandigarh              94755 non-null  bool
 70  destination_state_Chhattisgarh            94755 non-null  bool
 71  destination_state_Dadra and Nagar Haveli  94755 non-null  bool
 72  destination_state_Daman & Diu             94755 non-null  bool
 73  destination_state_Delhi                   94755 non-null  bool
 74  destination_state_Goa                     94755 non-null  bool
 75  destination_state_Gujarat                 94755 non-null  bool
 76  destination_state_Haryana                 94755 non-null  bool
 77  destination_state_Himachal Pradesh        94755 non-null  bool
 78  destination_state_Jammu & Kashmir         94755 non-null  bool
 79  destination_state_Jharkhand               94755 non-null  bool
 80  destination_state_Karnataka               94755 non-null  bool
 81  destination_state_Kerala                  94755 non-null  bool
 82  destination_state_Madhya Pradesh          94755 non-null  bool
 83  destination_state_Maharashtra             94755 non-null  bool
 84  destination_state_Meghalaya               94755 non-null  bool
 85  destination_state_Mizoram                 94755 non-null  bool
 86  destination_state_Nagaland                94755 non-null  bool
 87  destination_state_Orissa                  94755 non-null  bool
```

```
 88  destination_state_Pondicherry                 94755 non-null  bool
 89  destination_state_Punjab                      94755 non-null  bool
 90  destination_state_Rajasthan                   94755 non-null  bool
 91  destination_state_Tamil Nadu                  94755 non-null  bool
 92  destination_state_Telangana                   94755 non-null  bool
 93  destination_state_Tripura                     94755 non-null  bool
 94  destination_state_Uttar Pradesh               94755 non-null  bool
 95  destination_state_Uttarakhand                 94755 non-null  bool
 96  destination_state_West Bengal                 94755 non-null  bool
dtypes: bool(63), category(4), datetime64[ns](3), float64(13), 
int32(6), int64(2), object(6)
memory usage: 27.3+ MB
None
```

Merging of rows and aggregation of fields

```
# 1. Group by 'trip_uuid' to aggregate time and distance features for 
each trip
trip_features = delhivery_data.groupby('trip_uuid').agg({
    'actual_time': ['sum', 'mean', 'max'],
    'osrm_time': ['sum', 'mean', 'max'],
    'osrm_distance': ['sum', 'mean', 'max'],
    'segment_actual_time': ['sum', 'mean', 'max'],
    'segment_osrm_time': ['sum', 'mean', 'max'],
    'segment_osrm_distance': ['sum', 'mean', 'max']
}).reset_index()

# 2. Flatten the multi-level column names
trip_features.columns = ['_'.join(col).strip() if col[1] else col[0] 
for col in trip_features.columns.values]

# Fix the renaming of 'trip_uuid_'
trip_features.rename(columns={'trip_uuid_': 'trip_uuid'}, 
inplace=True)

# Check the structure of aggregated features
print("Aggregated Trip Features:")
print(trip_features.head())

# 3. Merge the aggregated features back into the original dataset
```

```
delhivery_data = pd.merge(delhivery_data, trip_features,
on='trip_uuid', how='left')

# 4. Calculate additional derived features (e.g., time difference
between actual and osrm time)
delhivery_data['time_diff'] = delhivery_data['actual_time_sum'] -
delhivery_data['osrm_time_sum']

# 5. Optionally, drop columns related to individual segments if no
longer needed
columns_to_drop = [
    'actual_time', 'osrm_time', 'segment_actual_time',
'segment_osrm_time', 'segment_osrm_distance'
]
delhivery_data.drop(columns=columns_to_drop, axis=1, inplace=True)

# Check the final structure of the dataset
print("Final Dataset after Aggregation and Merging:")
print(delhivery_data.head())

# 6. Additional check: Display dataset info to ensure everything is in
place
print(delhivery_data.info())

# 7. Save the processed dataset to a new CSV file (optional)
delhivery_data.to_csv("processed_delhivery_data.csv", index=False)
```

```
Aggregated Trip Features:
                 trip_uuid  actual_time_sum  actual_time_mean  \
0  trip-153671041653548748         1.789661          0.178966
1  trip-153671042288605164         0.283422          0.031491
2  trip-153671043369099517         1.930481          0.175498
3  trip-153671046011330457         0.057041          0.028520
4  trip-153671052974046625         0.439394          0.062771

   actual_time_max  osrm_time_sum  osrm_time_mean  osrm_time_max  \
0         0.312834       2.840256        0.284026       0.536741
1         0.077540       0.498403        0.055378       0.115016
2         0.536542       3.715655        0.337787       0.658147
3         0.044563       0.038339        0.019169       0.028754
4         0.122995       0.527157        0.075308       0.127796

   osrm_distance_sum  osrm_distance_mean  osrm_distance_max  \
0          1344.6487          134.464870           243.0267
1           269.4308           29.936756            56.9116
2          1700.2867          154.571518           281.2109
3            31.6475           15.823750            19.6800
4           266.2914           38.041629            63.6461

   segment_actual_time_sum  segment_actual_time_mean
```

```
segment_actual_time_max  \
0                    354.0                       35.400000
76.0
1                    141.0                       15.666667
22.0
2                    584.0                       53.090909
275.0
3                     59.0                       29.500000
36.0
4                    340.0                       48.571429
79.0

   segment_osrm_time_sum  segment_osrm_time_mean
segment_osrm_time_max  \
0                  242.0               24.200000
52.0
1                   65.0                7.222222
10.0
2                  216.0               19.636364
28.0
3                   16.0                8.000000
9.0
4                  115.0               16.428571
26.0

   segment_osrm_distance_sum  segment_osrm_distance_mean  \
0                   342.1519                   34.215190
1                    84.1894                    9.354378
2                   295.8973                   26.899755
3                    19.8766                    9.938300
4                   146.7919                   20.970271

   segment_osrm_distance_max
0                    73.8647
1                    12.2746
2                    36.1317
3                    11.9675
4                    29.0538

<ipython-input-23-0cb16b16e65b>:2: FutureWarning: The default of
observed=False is deprecated and will be changed to True in a future
version of pandas. Pass observed=False to retain current behavior or
observed=True to adopt the future default and silence this warning.
  trip_features = delhivery_data.groupby('trip_uuid').agg({

Final Dataset after Aggregation and Merging:
       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
trip_uuid  \
0  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...  trip-
153741093647649320
1  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...  trip-
153741093647649320
2  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...  trip-
153741093647649320
3  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...  trip-
153741093647649320
4  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...  trip-
153741093647649320

  source_center                 source_name destination_center  \
0  IND388121AAA  Anand_VUNagar_DC (Gujarat)       IND388620AAB
1  IND388121AAA  Anand_VUNagar_DC (Gujarat)       IND388620AAB
2  IND388121AAA  Anand_VUNagar_DC (Gujarat)       IND388620AAB
3  IND388121AAA  Anand_VUNagar_DC (Gujarat)       IND388620AAB
4  IND388121AAA  Anand_VUNagar_DC (Gujarat)       IND388620AAB

                destination_name              od_start_time  \
0  Khambhat_MotvdDPP_D (Gujarat) 2018-09-20 03:21:32.418600
1  Khambhat_MotvdDPP_D (Gujarat) 2018-09-20 03:21:32.418600
2  Khambhat_MotvdDPP_D (Gujarat) 2018-09-20 03:21:32.418600
3  Khambhat_MotvdDPP_D (Gujarat) 2018-09-20 03:21:32.418600
4  Khambhat_MotvdDPP_D (Gujarat) 2018-09-20 03:21:32.418600

                 od_end_time  ...  segment_actual_time_sum  \
0 2018-09-20 04:47:45.236797  ...                    167.0
1 2018-09-20 04:47:45.236797  ...                    167.0
2 2018-09-20 04:47:45.236797  ...                    167.0
3 2018-09-20 04:47:45.236797  ...                    167.0
4 2018-09-20 04:47:45.236797  ...                    167.0

   segment_actual_time_mean  segment_actual_time_max
segment_osrm_time_sum  \
0                      16.7                     28.0
88.0
1                      16.7                     28.0
88.0
2                      16.7                     28.0
88.0
3                      16.7                     28.0
88.0
4                      16.7                     28.0
88.0
```

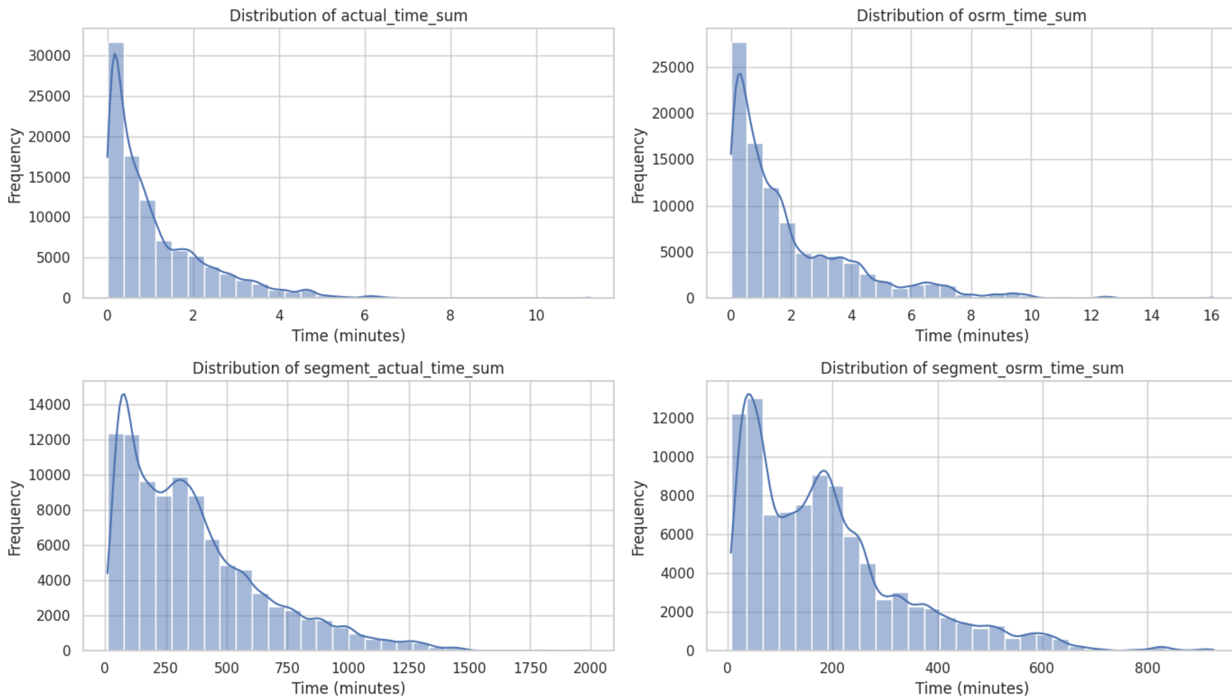
```
   segment_osrm_time_mean  segment_osrm_time_max
segment_osrm_distance_sum  \
0                     8.8                   12.0
102.7106
1                     8.8                   12.0
102.7106
2                     8.8                   12.0
102.7106
3                     8.8                   12.0
102.7106
4                     8.8                   12.0
102.7106

   segment_osrm_distance_mean  segment_osrm_distance_max  time_diff
0                    10.27106                    14.5362  -0.341323
1                    10.27106                    14.5362  -0.341323
2                    10.27106                    14.5362  -0.341323
3                    10.27106                    14.5362  -0.341323
4                    10.27106                    14.5362  -0.341323

[5 rows x 111 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 94755 entries, 0 to 94754
Columns: 111 entries, data to time_diff
dtypes: bool(63), category(4), datetime64[ns](3), float64(27),
int32(6), int64(2), object(6)
memory usage: 36.7+ MB
None
```

Comparison & Visualization of time and distance fields

1. Visualizing the Distribution of Time and Distance Fields

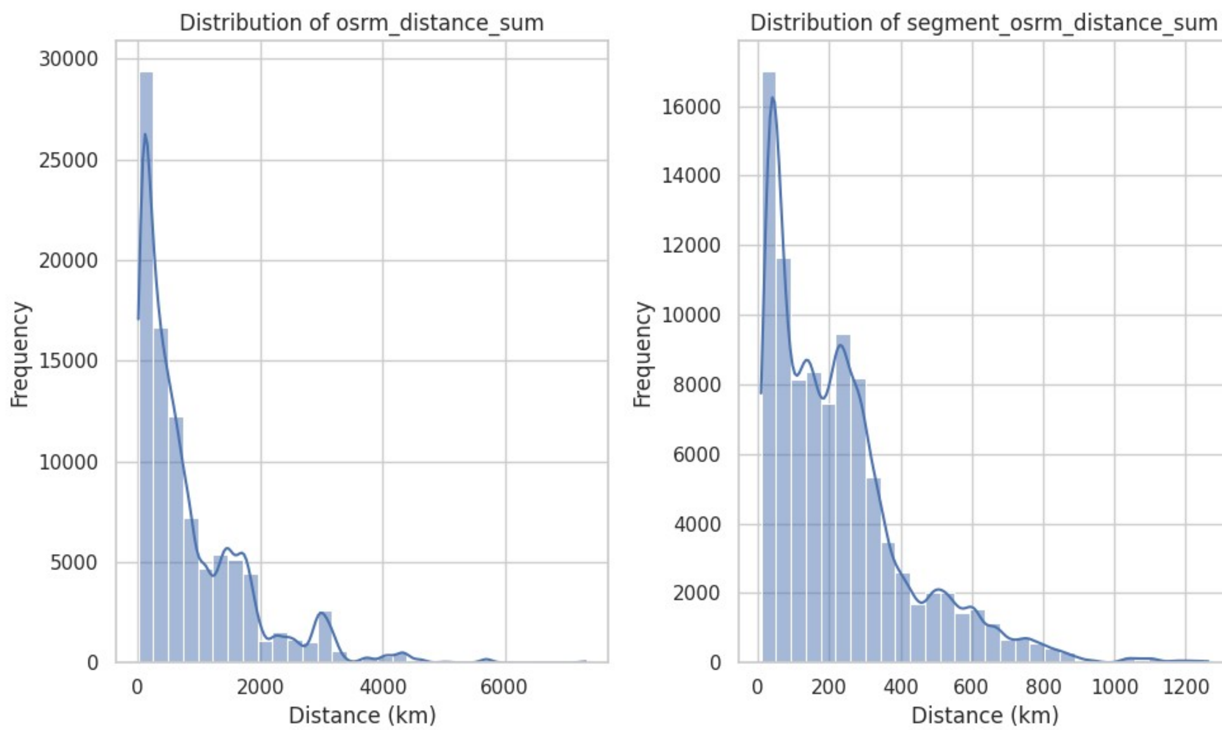
```
import matplotlib.pyplot as plt
import seaborn as sns

# Set the plot style
sns.set(style="whitegrid")

# 1. Visualize the distribution of time fields
time_columns = ['actual_time_sum', 'osrm_time_sum',
'segment_actual_time_sum', 'segment_osrm_time_sum']
plt.figure(figsize=(14, 8))

for i, col in enumerate(time_columns, 1):
    plt.subplot(2, 2, i)
    sns.histplot(delhivery_data[col], kde=True, bins=30)
```

```
    plt.title(f'Distribution of {col}')
    plt.xlabel('Time (minutes)')
    plt.ylabel('Frequency')

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



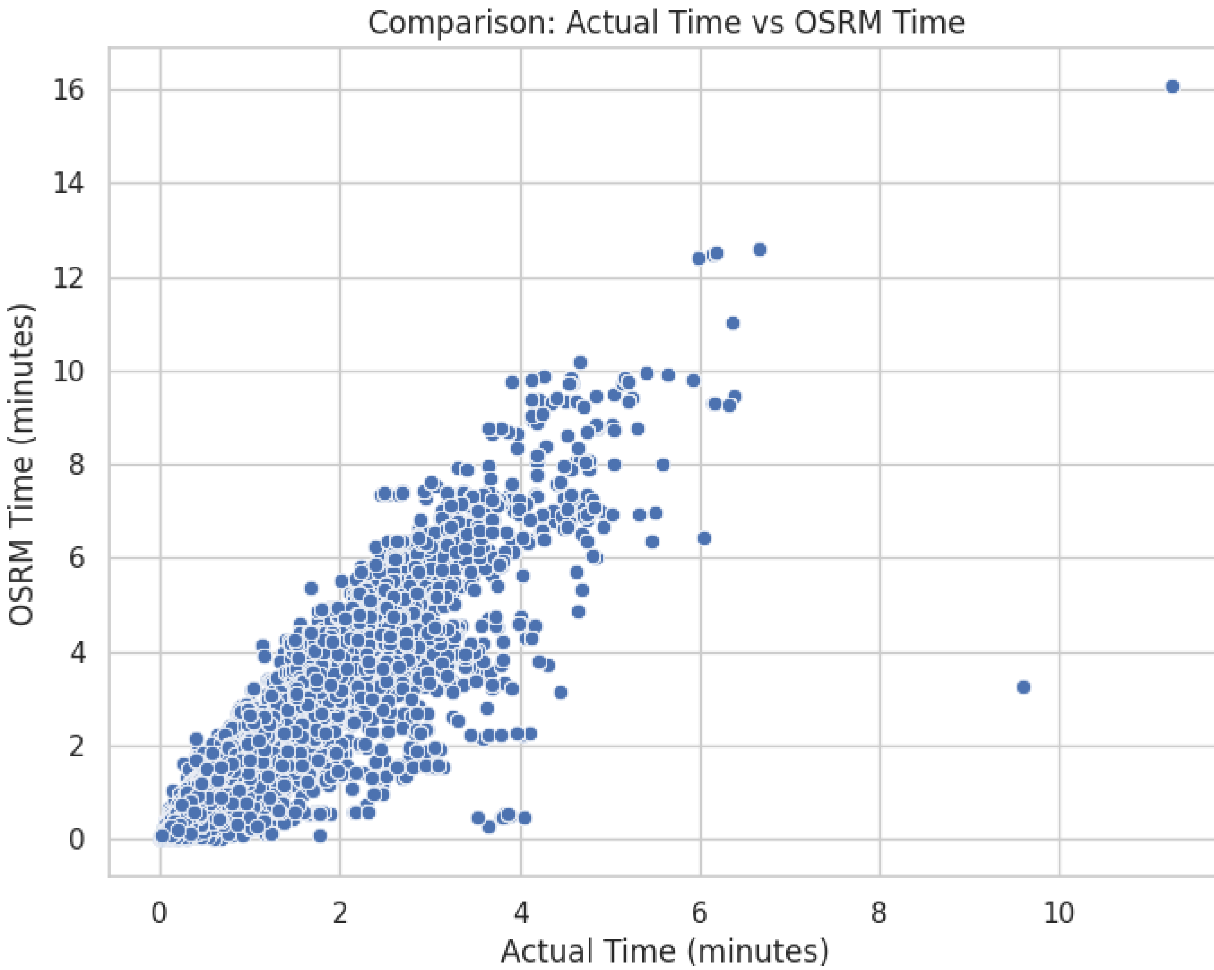
1. Visualize the Distribution of Distance Fields

```
# 2. Visualize the distribution of distance fields
distance_columns = ['osrm_distance_sum', 'segment_osrm_distance_sum']
plt.figure(figsize=(10, 6))

for i, col in enumerate(distance_columns, 1):
    plt.subplot(1, 2, i)
    sns.histplot(delhivery_data[col], kde=True, bins=30)
    plt.title(f'Distribution of {col}')
    plt.xlabel('Distance (km)')
    plt.ylabel('Frequency')

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



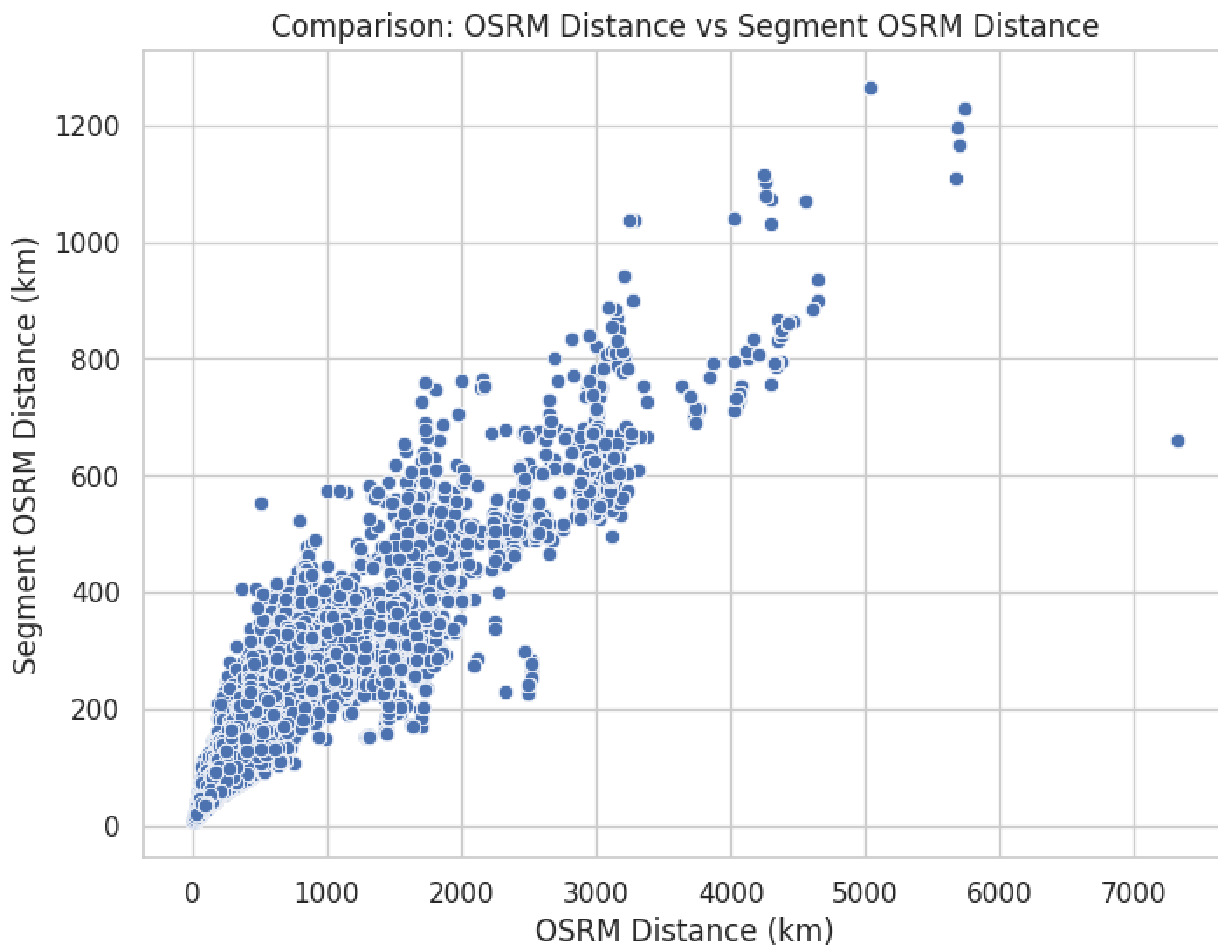
1. Compare Aggregated Time Fields

```
# 3. Compare actual_time_sum vs osrm_time_sum
plt.figure(figsize=(8, 6))
sns.scatterplot(x='actual_time_sum', y='osrm_time_sum',
data=delhivery_data)
plt.title('Comparison: Actual Time vs OSRM Time')
plt.xlabel('Actual Time (minutes)')
plt.ylabel('OSRM Time (minutes)')
plt.show()
```



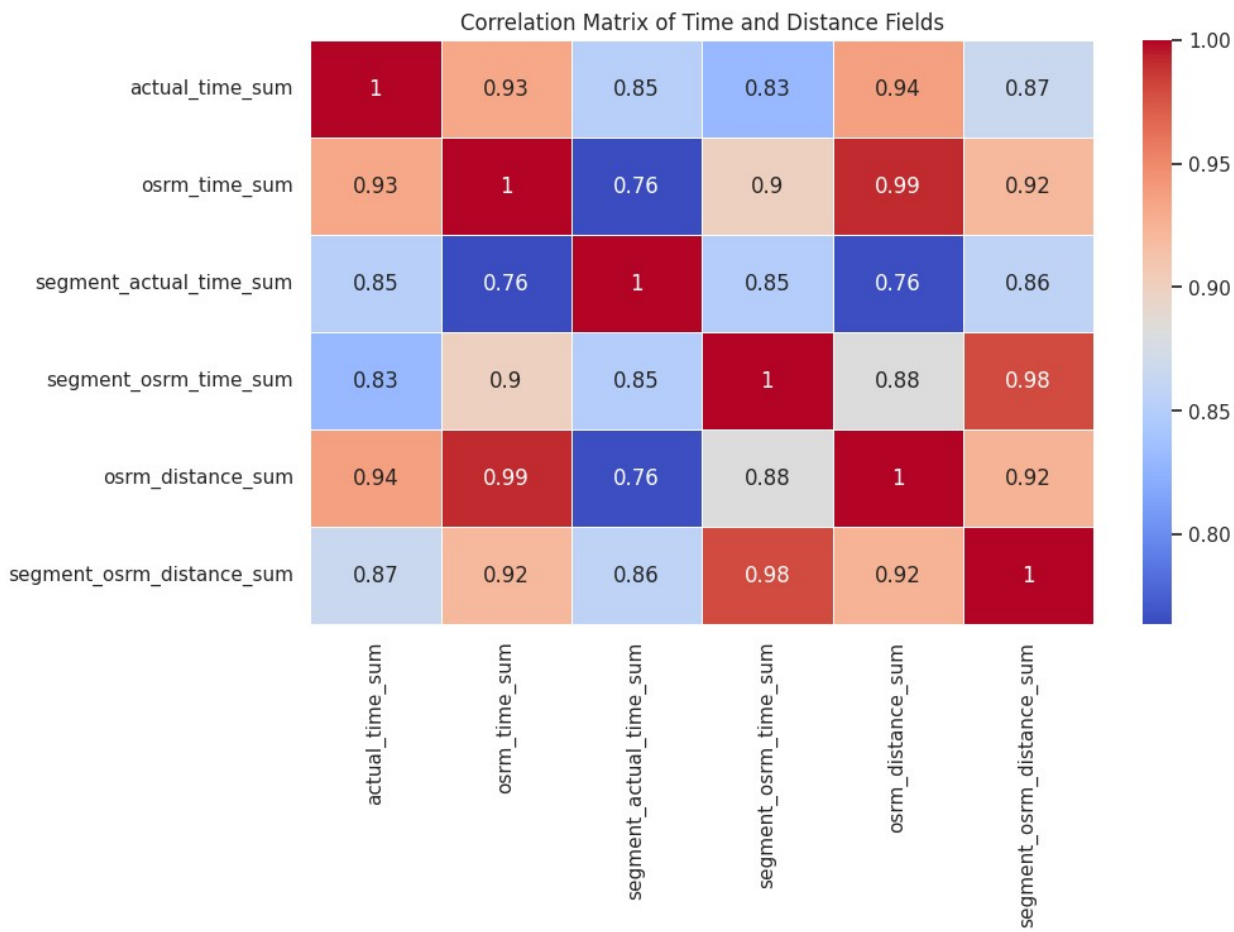
1. Compare Aggregated Distance Fields

```
# 4. Compare osrm_distance_sum vs segment_osrm_distance_sum
plt.figure(figsize=(8, 6))
sns.scatterplot(x='osrm_distance_sum', y='segment_osrm_distance_sum',
data=delhivery_data)
plt.title('Comparison: OSRM Distance vs Segment OSRM Distance')
plt.xlabel('OSRM Distance (km)')
plt.ylabel('Segment OSRM Distance (km)')
plt.show()
```



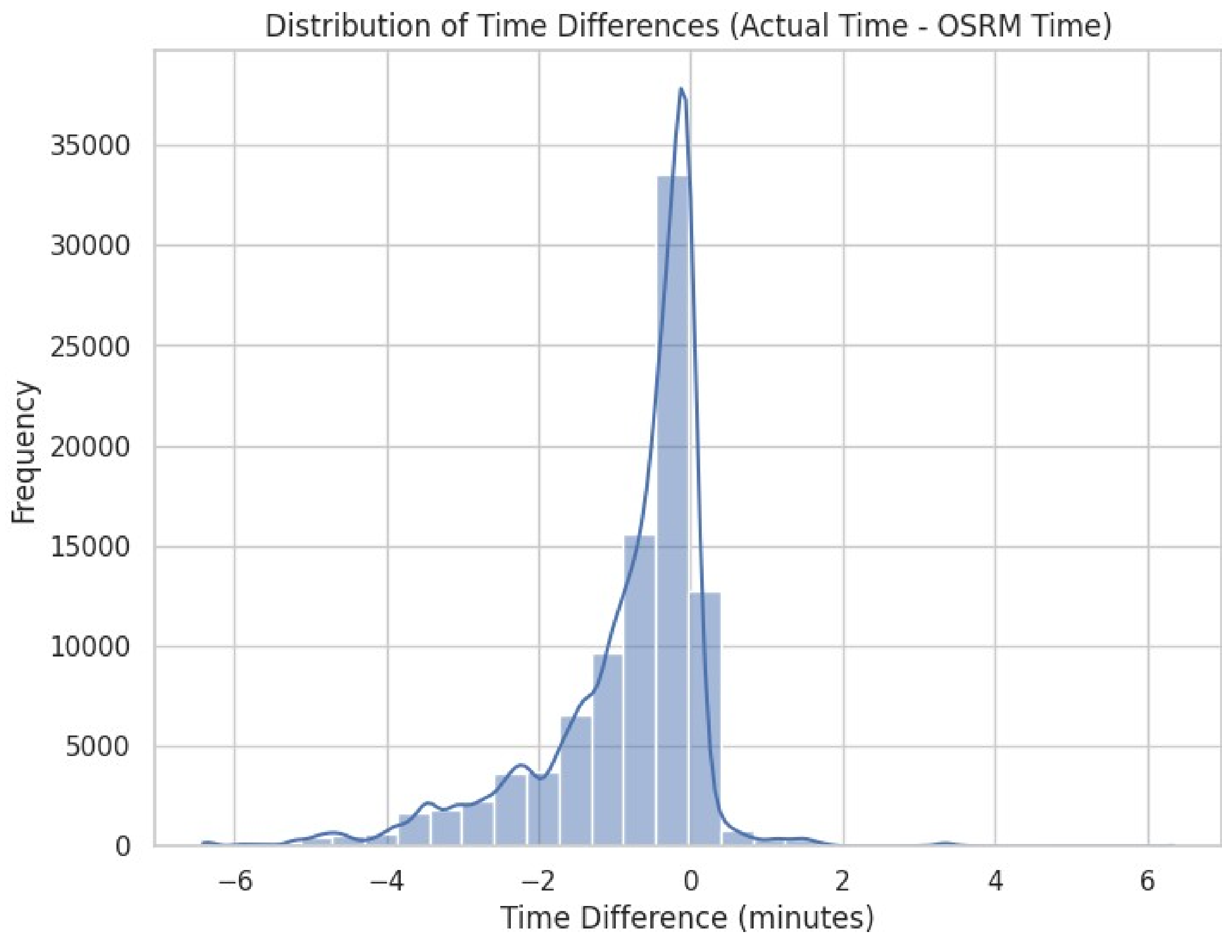
1. Bivariate Relationships: Heatmap for Correlation

```
# 5. Correlation heatmap of time and distance fields
corr_columns = ['actual_time_sum', 'osrm_time_sum',
'segment_actual_time_sum',
                'segment_osrm_time_sum', 'osrm_distance_sum',
'segment_osrm_distance_sum']

corr_matrix = delhivery_data[corr_columns].corr()

plt.figure(figsize=(10, 6))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', linewidths=0.5)
plt.title('Correlation Matrix of Time and Distance Fields')
plt.show()
```



1. Time Differences

```
# 6. Plot the distribution of time differences (actual - osrm)
plt.figure(figsize=(8, 6))
sns.histplot(delhivery_data['time_diff'], kde=True, bins=30)
plt.title('Distribution of Time Differences (Actual Time - OSRM
Time)')
plt.xlabel('Time Difference (minutes)')
plt.ylabel('Frequency')
plt.show()
```



Missing values Treatment & Outlier treatment

1. Missing Values Treatment

1.1. Identify Missing Values

```
# Check for missing values
missing_values = delhivery_data.isnull().sum()

# Show columns with missing values
print("Missing Values per Column:")
print(missing_values[missing_values > 0])
```

```
Missing Values per Column:
segment_time_ratio    1654
dtype: int64
```

1.2. Impute Missing Values

```
# Fill missing values in categorical columns with the mode
delhivery_data['source_name'].fillna(delhivery_data['source_name'].mod
e()[0], inplace=True)
delhivery_data['destination_name'].fillna(delhivery_data['destination_
name'].mode()[0], inplace=True)

# Fill missing values in numerical columns with the median
numerical_columns = ['actual_time_sum', 'osrm_time_sum',
'osrm_distance_sum']  # Add relevant columns with missing values
for col in numerical_columns:
    delhivery_data[col].fillna(delhivery_data[col].median(),
inplace=True)
```

2. Outlier Treatment

```
# Function to remove outliers using IQR
def remove_outliers(df, column):
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    # Filter out rows with outliers
    return df[(df[column] >= lower_bound) & (df[column] <=
upper_bound)]

# Apply IQR outlier treatment to the relevant numerical columns
columns_to_treat = ['actual_time_sum', 'osrm_time_sum',
'osrm_distance_sum']

for col in columns_to_treat:
    delhivery_data = remove_outliers(delhivery_data, col)

# Check the dataset after outlier removal
print("Dataset after Outlier Treatment:")
print(delhivery_data.describe())

Dataset after Outlier Treatment:
                  trip_creation_time                  od_start_time  \
count                          85649                          85649
mean   2018-09-22 11:39:48.361330432  2018-09-22 15:27:47.617502976
min       2018-09-12 00:00:16.535741     2018-09-12 00:00:16.535741
25%    2018-09-17 01:05:27.833006080  2018-09-17 05:45:39.140850944
50%    2018-09-22 01:34:33.498785024  2018-09-22 05:24:44.491769088
75%    2018-09-27 17:56:30.269254912  2018-09-27 20:42:08.818902016
max       2018-10-03 23:59:42.701692     2018-10-06 00:08:33.866586
std                              NaN                            NaN

                         od_end_time  start_scan_to_end_scan
cutoff_factor  \
```

```
count                            85649            85649.000000
85649.000000
mean   2018-09-22 20:04:41.977695232                  0.225117
44.552242
min       2018-09-12 00:50:10.814399                  0.000000
9.000000
25%    2018-09-17 10:05:02.069167104                  0.079895
18.000000
50%    2018-09-22 09:57:49.596393984                  0.150132
27.000000
75%    2018-09-28 01:14:55.942010112                  0.307287
54.000000
max       2018-10-06 08:34:19.218998                  0.999122
241.000000
std                                NaN                  0.202431
42.763901

       actual_distance_to_destination  osrm_distance        factor  \
count                    85649.000000   85649.000000  85649.000000
mean                         0.156762      56.917650      2.188244
min                          0.000000       9.008200      0.247788
25%                          0.042592      23.636900      1.520000
50%                          0.081569      37.070000      1.859649
75%                          0.196777      71.476400      2.367521
max                          1.000000     342.666700     70.000000
std                          0.184316      53.101496      1.621765

       segment_factor     year  ...  segment_actual_time_sum  \
count    85649.000000  85649.0  ...             85649.000000
mean         2.346236   2018.0  ...               313.763406
min        -23.444444   2018.0  ...                 9.000000
25%          1.333333   2018.0  ...               119.000000
50%          1.750000   2018.0  ...               271.000000
75%          2.375000   2018.0  ...               431.000000
max        493.000000   2018.0  ...              1996.000000
std          4.431141      0.0  ...               240.470440

       segment_actual_time_mean  segment_actual_time_max  \
count              85649.000000             85649.000000
mean                  33.419655                87.250441
min                    6.000000                 9.000000
25%                   18.625000                36.000000
50%                   29.666667                56.000000
75%                   39.400000                87.000000
max                 1061.000000              1131.000000
std                   26.935882               115.880964

       segment_osrm_time_sum  segment_osrm_time_mean
segment_osrm_time_max  \
count           85649.000000            85649.000000
```

```
85649.000000
mean                 157.222851               15.899987
30.522049
min                    6.000000                3.500000
6.000000
25%                   59.000000                9.636364
16.000000
50%                  144.000000               15.105263
26.000000
75%                  221.000000               20.555556
37.000000
max                  675.000000              221.000000
294.000000
std                  114.889962                7.589024
21.382717

       segment_osrm_distance_sum  segment_osrm_distance_mean  \
count               85649.000000                85649.000000
mean                  185.037676                   18.339072
min                     9.072900                    4.568200
25%                    62.942000                   10.477120
50%                   163.020400                   17.193108
75%                   273.575700                   24.788015
max                   766.431800                  281.454800
std                   136.632194                    8.815096

       segment_osrm_distance_max     time_diff
count               85649.000000  85649.000000
mean                   33.654371     -0.583647
min                     9.072900     -3.693835
25%                    15.976400     -0.920253
50%                    29.170600     -0.375382
75%                    40.529000     -0.098797
max                   290.145500      3.390947
std                    24.654107      0.691423

[8 rows x 38 columns]

/usr/local/lib/python3.10/dist-packages/numpy/core/_methods.py:49:
RuntimeWarning: invalid value encountered in reduce
  return umr_sum(a, axis, dtype, out, keepdims, initial, where)
```

```python
# Remove rows with negative or zero values in time-related columns
delhivery_data = delhivery_data[(delhivery_data['actual_time_sum'] >
0) & (delhivery_data['osrm_time_sum'] > 0)]

# Summary of missing values after treatment
print("Missing Values after Imputation:")
print(delhivery_data.isnull().sum())
```

```python
# Save the cleaned dataset to a CSV file
delhivery_data.to_csv("cleaned_delhivery_data.csv", index=False)
```

```
Missing Values after Imputation:
data                           0
trip_creation_time             0
route_schedule_uuid            0
trip_uuid                      0
source_center                  0
                              ..
segment_osrm_time_max          0
segment_osrm_distance_sum      0
segment_osrm_distance_mean     0
segment_osrm_distance_max      0
time_diff                      0
Length: 111, dtype: int64
```

Checking relationship between aggregated fields

1. Calculate Correlation Between Aggregated Fields

```python
# List of relevant aggregated fields
aggregated_fields = [
    'actual_time_sum', 'osrm_time_sum', 'segment_actual_time_sum',
    'osrm_distance_sum', 'segment_osrm_distance_sum'
]

# Calculate the correlation matrix
correlation_matrix = delhivery_data[aggregated_fields].corr()

# Display the correlation matrix
print("Correlation Matrix:")
print(correlation_matrix)
```

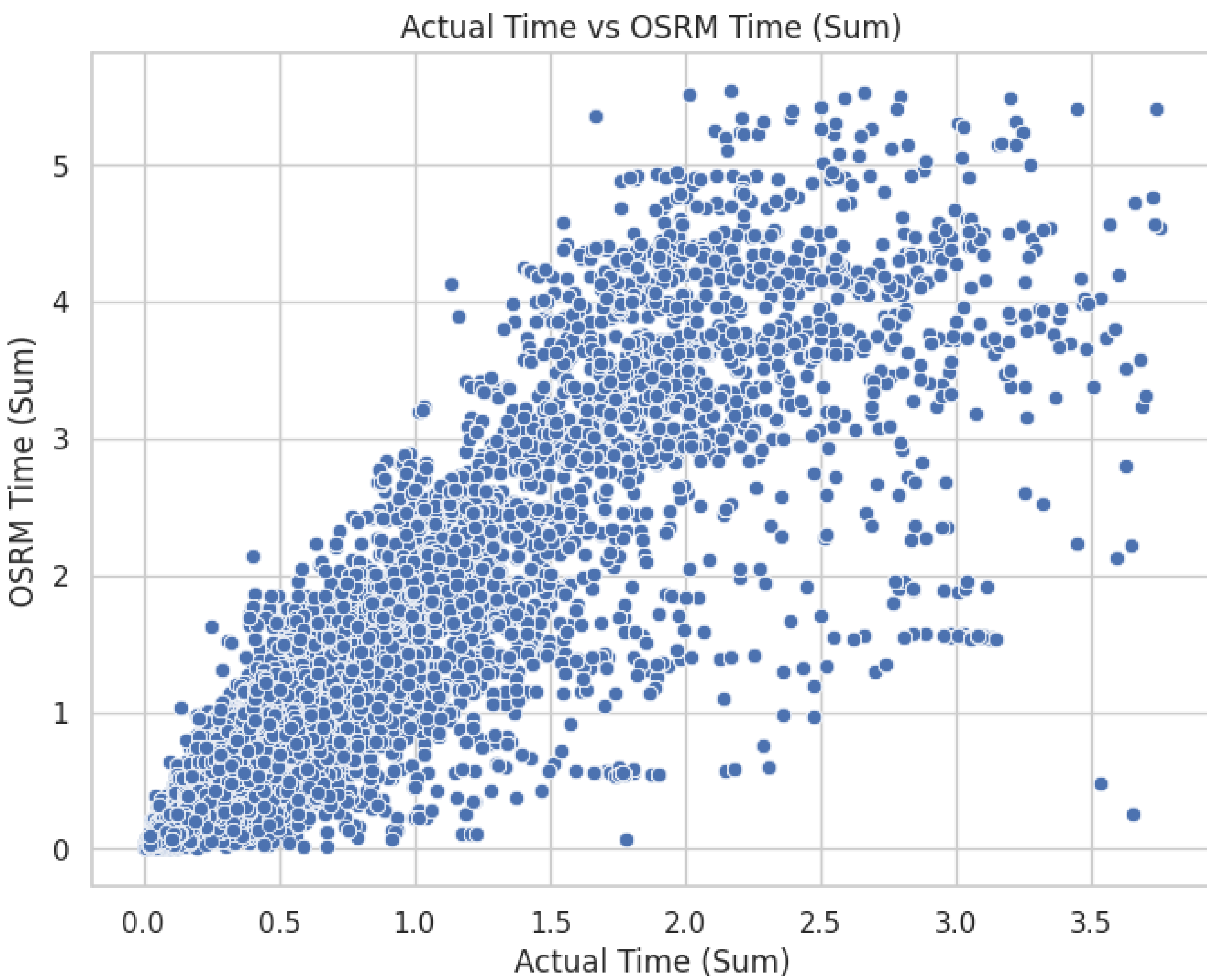
```
Correlation Matrix:
                           actual_time_sum  osrm_time_sum  \
actual_time_sum                   1.000000       0.899645
osrm_time_sum                     0.899645       1.000000
segment_actual_time_sum           0.806401       0.680007
osrm_distance_sum                 0.910920       0.984507
segment_osrm_distance_sum         0.797704       0.865424

                           segment_actual_time_sum  osrm_distance_sum
\
actual_time_sum                           0.806401           0.910920
```

```
osrm_time_sum                                    0.680007            0.984507

segment_actual_time_sum                          1.000000            0.683384

osrm_distance_sum                                0.683384            1.000000

segment_osrm_distance_sum                        0.823881            0.871402


                           segment_osrm_distance_sum
actual_time_sum                             0.797704
osrm_time_sum                               0.865424
segment_actual_time_sum                     0.823881
osrm_distance_sum                           0.871402
segment_osrm_distance_sum                   1.000000
```

2. Visualize Relationships Using Scatter Plots

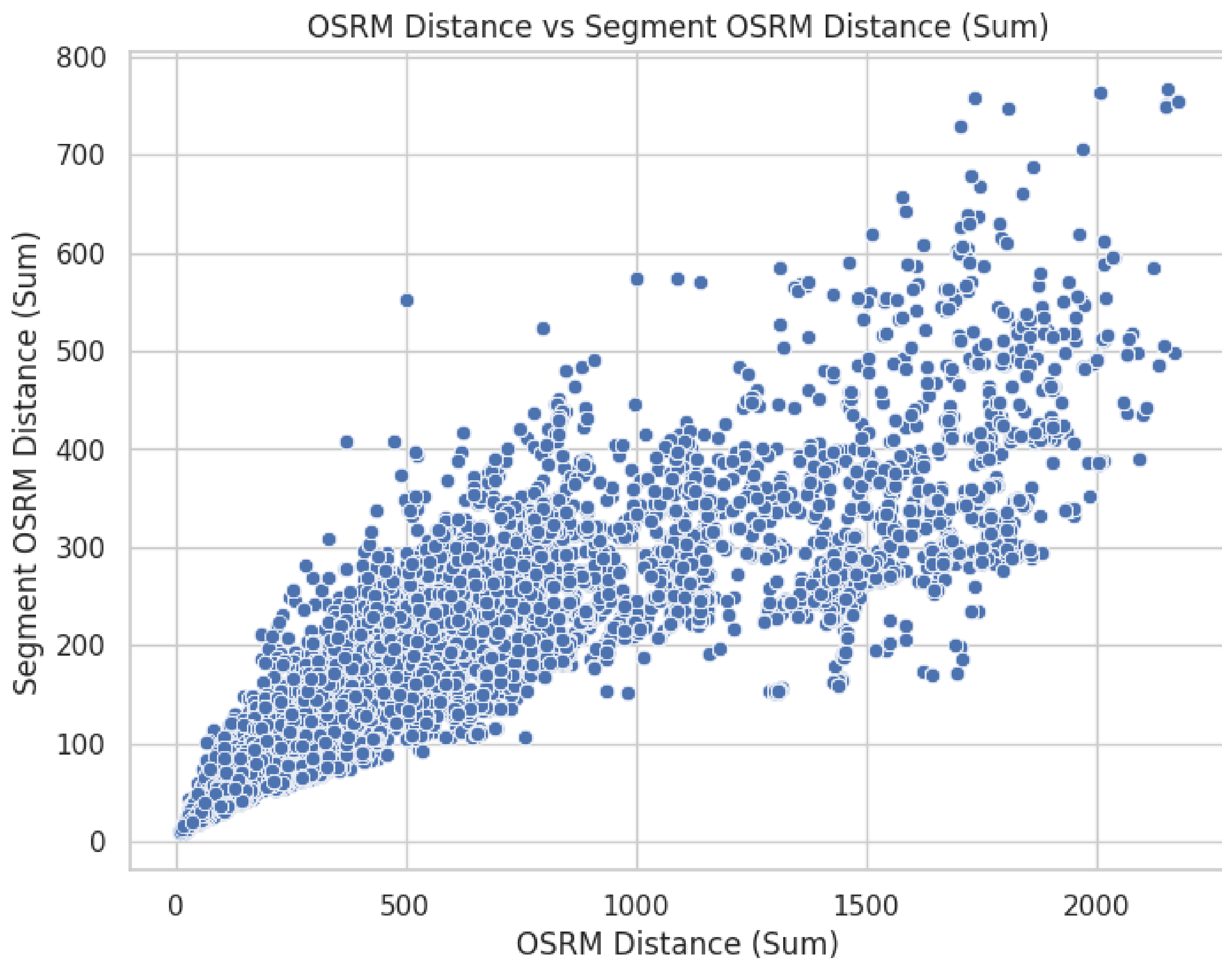
2.1. Scatter Plot Between actual_time_sum and osrm_time_sum

```
import matplotlib.pyplot as plt
import seaborn as sns

# Scatter plot between actual_time_sum and osrm_time_sum
plt.figure(figsize=(8, 6))
sns.scatterplot(x='actual_time_sum', y='osrm_time_sum',
data=delhivery_data)
plt.title('Actual Time vs OSRM Time (Sum)')
plt.xlabel('Actual Time (Sum)')
plt.ylabel('OSRM Time (Sum)')
plt.show()
```



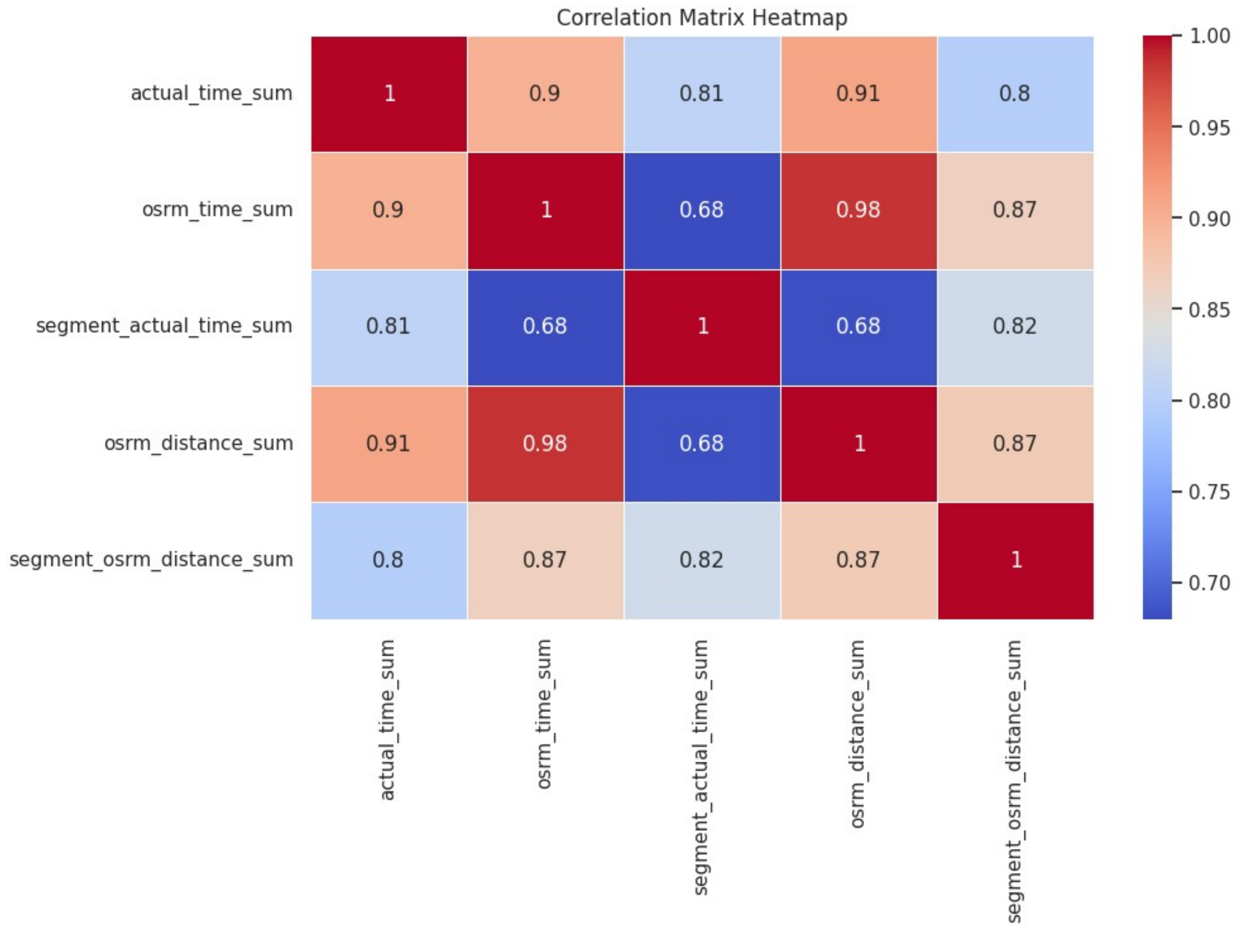
2.2. Scatter Plot Between osrm_distance_sum and segment_osrm_distance_sum

```
# Scatter plot between osrm_distance_sum and segment_osrm_distance_sum
plt.figure(figsize=(8, 6))
sns.scatterplot(x='osrm_distance_sum', y='segment_osrm_distance_sum',
data=delhivery_data)
plt.title('OSRM Distance vs Segment OSRM Distance (Sum)')
plt.xlabel('OSRM Distance (Sum)')
plt.ylabel('Segment OSRM Distance (Sum)')
plt.show()
```



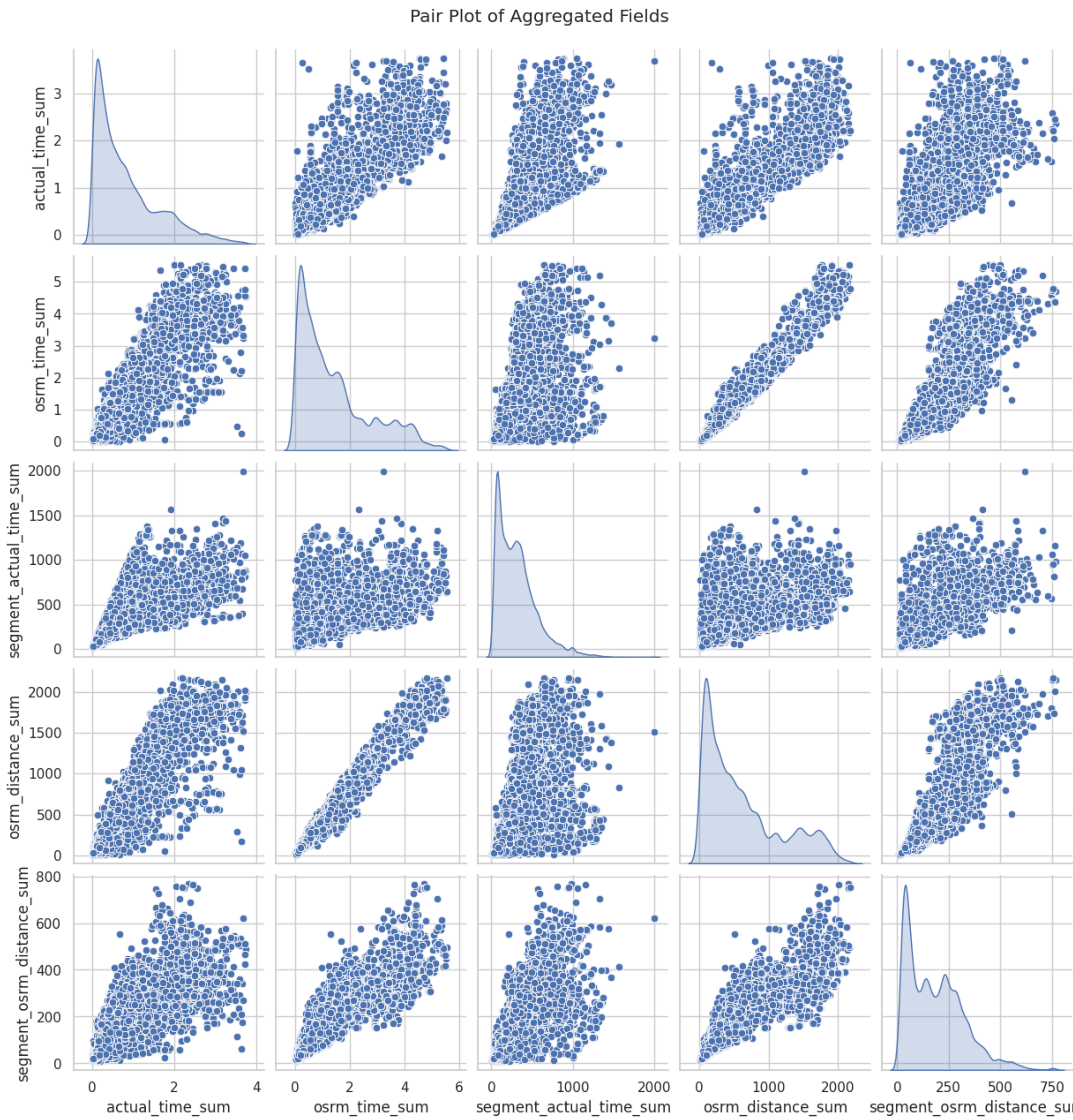
3. Visualizing the Correlation Matrix Using a Heatmap

```
# Heatmap for the correlation matrix
plt.figure(figsize=(10, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
linewidths=0.5)
plt.title('Correlation Matrix Heatmap')
plt.show()
```



4. Pair Plot for Aggregated Fields

```
# Pair plot for aggregated fields
sns.pairplot(delhivery_data[aggregated_fields], diag_kind='kde')
plt.suptitle('Pair Plot of Aggregated Fields', y=1.02)
plt.show()
```



Handling categorical values

```
# Identify categorical columns
categorical_columns = delhivery_data.select_dtypes(include=['object',
'category']).columns

# Show categorical columns
print("Categorical Columns:", categorical_columns)
```

```
Categorical Columns: Index(['data', 'route_schedule_uuid',
'trip_uuid', 'source_center',
       'source_name', 'destination_center', 'destination_name',
       'cutoff_timestamp', 'source_city', 'destination_city'],
      dtype='object')
```

```python
# Extract source_state and destination_state from source_name and
destination_name
delhivery_data['source_state'] =
delhivery_data['source_name'].str.extract(r'\((.*?)\)')
delhivery_data['destination_state'] =
delhivery_data['destination_name'].str.extract(r'\((.*?)\)')

# Apply One-Hot Encoding to available categorical columns
delhivery_data_encoded = pd.get_dummies(delhivery_data,
columns=['source_name', 'destination_name', 'source_state',
'destination_state'], drop_first=True)

# Check the first few rows of the encoded dataset
print(delhivery_data_encoded.head())
```

```
       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
trip_uuid  \
0  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...  trip-
153741093647649320
1  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...  trip-
153741093647649320
2  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...  trip-
153741093647649320
3  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...  trip-
153741093647649320
4  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...  trip-
153741093647649320

  source_center destination_center              od_start_time  \
0  IND388121AAA       IND388620AAB 2018-09-20 03:21:32.418600
1  IND388121AAA       IND388620AAB 2018-09-20 03:21:32.418600
2  IND388121AAA       IND388620AAB 2018-09-20 03:21:32.418600
3  IND388121AAA       IND388620AAB 2018-09-20 03:21:32.418600
4  IND388121AAA       IND388620AAB 2018-09-20 03:21:32.418600

                od_end_time  start_scan_to_end_scan
is_cutoff  ...  \
```

```
0 2018-09-20 04:47:45.236797                0.057946       True  ...

1 2018-09-20 04:47:45.236797                0.057946       True  ...

2 2018-09-20 04:47:45.236797                0.057946       True  ...

3 2018-09-20 04:47:45.236797                0.057946       True  ...

4 2018-09-20 04:47:45.236797                0.057946      False  ...


   destination_state_Orissa destination_state_Pondicherry  \
0                     False                         False
1                     False                         False
2                     False                         False
3                     False                         False
4                     False                         False

   destination_state_Punjab  destination_state_Rajasthan  \
0                     False                        False
1                     False                        False
2                     False                        False
3                     False                        False
4                     False                        False

   destination_state_Tamil Nadu  destination_state_Telangana  \
0                         False                        False
1                         False                        False
2                         False                        False
3                         False                        False
4                         False                        False

   destination_state_Tripura  destination_state_Uttar Pradesh  \
0                      False                            False
1                      False                            False
2                      False                            False
3                      False                            False
4                      False                            False

   destination_state_Uttarakhand  destination_state_West Bengal
0                          False                          False
1                          False                          False
2                          False                          False
3                          False                          False
4                          False                          False

[5 rows x 3111 columns]

# Check the columns after encoding
print("Columns after One-Hot Encoding:",
delhivery_data_encoded.columns)
```

```
Columns after One-Hot Encoding: Index(['data', 'trip_creation_time',
'route_schedule_uuid', 'trip_uuid',
       'source_center', 'destination_center', 'od_start_time',
'od_end_time',
       'start_scan_to_end_scan', 'is_cutoff',
       ...
       'destination_state_Orissa', 'destination_state_Pondicherry',
       'destination_state_Punjab', 'destination_state_Rajasthan',
       'destination_state_Tamil Nadu', 'destination_state_Telangana',
       'destination_state_Tripura', 'destination_state_Uttar Pradesh',
       'destination_state_Uttarakhand', 'destination_state_West
Bengal'],
      dtype='object', length=3111)

# Frequency encoding for high-cardinality categorical variables
frequency_encoding =
delhivery_data['source_name'].value_counts().to_dict()
delhivery_data['source_name_freq'] =
delhivery_data['source_name'].map(frequency_encoding)

# Check the frequency-encoded column
print(delhivery_data[['source_name', 'source_name_freq']].head())

                  source_name  source_name_freq
0  Anand_VUNagar_DC (Gujarat)                54
1  Anand_VUNagar_DC (Gujarat)                54
2  Anand_VUNagar_DC (Gujarat)                54
3  Anand_VUNagar_DC (Gujarat)                54
4  Anand_VUNagar_DC (Gujarat)                54

# Save the encoded dataset to a CSV file
delhivery_data_encoded.to_csv("delhivery_data_encoded.csv",
index=False)
```

Column Normalization /Column Standardization

1. Normalization (Min-Max Scaling)

```
from sklearn.preprocessing import MinMaxScaler

# List of numerical columns to normalize
numerical_columns = ['actual_time_sum', 'osrm_time_sum',
'osrm_distance_sum',
                     'segment_actual_time_sum',
'segment_osrm_time_sum', 'segment_osrm_distance_sum']
```

```
# Initialize the MinMaxScaler
scaler = MinMaxScaler()

# Apply Min-Max scaling
delhivery_data_normalized = delhivery_data.copy()  # Make a copy to
avoid modifying the original dataframe
delhivery_data_normalized[numerical_columns] =
scaler.fit_transform(delhivery_data_normalized[numerical_columns])

# Check the first few rows of the normalized data
print("Normalized Data (Min-Max Scaling):")
print(delhivery_data_normalized[numerical_columns].head())

Normalized Data (Min-Max Scaling):
   actual_time_sum  osrm_time_sum  osrm_distance_sum
segment_actual_time_sum  \
0         0.099549       0.128604           0.150744
0.079053
1         0.099549       0.128604           0.150744
0.079053
2         0.099549       0.128604           0.150744
0.079053
3         0.099549       0.128604           0.150744
0.079053
4         0.099549       0.128604           0.150744
0.079053

   segment_osrm_time_sum  segment_osrm_distance_sum
0               0.121257                   0.123637
1               0.121257                   0.123637
2               0.121257                   0.123637
3               0.121257                   0.123637
4               0.121257                   0.123637
```

2. Standardization (Z-score Scaling)

```
from sklearn.preprocessing import StandardScaler

# Initialize the StandardScaler
scaler = StandardScaler()

# Apply Standard scaling
delhivery_data_standardized = delhivery_data.copy()  # Make a copy to
avoid modifying the original dataframe
delhivery_data_standardized[numerical_columns] =
scaler.fit_transform(delhivery_data_standardized[numerical_columns])

# Check the first few rows of the standardized data
print("Standardized Data (Z-score Scaling):")
print(delhivery_data_standardized[numerical_columns].head())
```

```
Standardized Data (Z-score Scaling):
   actual_time_sum  osrm_time_sum  osrm_distance_sum  
segment_actual_time_sum  \
0        -0.605478      -0.548625          -0.514899                       -
0.610371   
1        -0.605478      -0.548625          -0.514899                       -
0.610371   
2        -0.605478      -0.548625          -0.514899                       -
0.610371   
3        -0.605478      -0.548625          -0.514899                       -
0.610371   
4        -0.605478      -0.548625          -0.514899                       -
0.610371   

   segment_osrm_time_sum  segment_osrm_distance_sum  
0              -0.602571                    -0.6026  
1              -0.602571                    -0.6026  
2              -0.602571                    -0.6026  
3              -0.602571                    -0.6026  
4              -0.602571                    -0.6026  
```

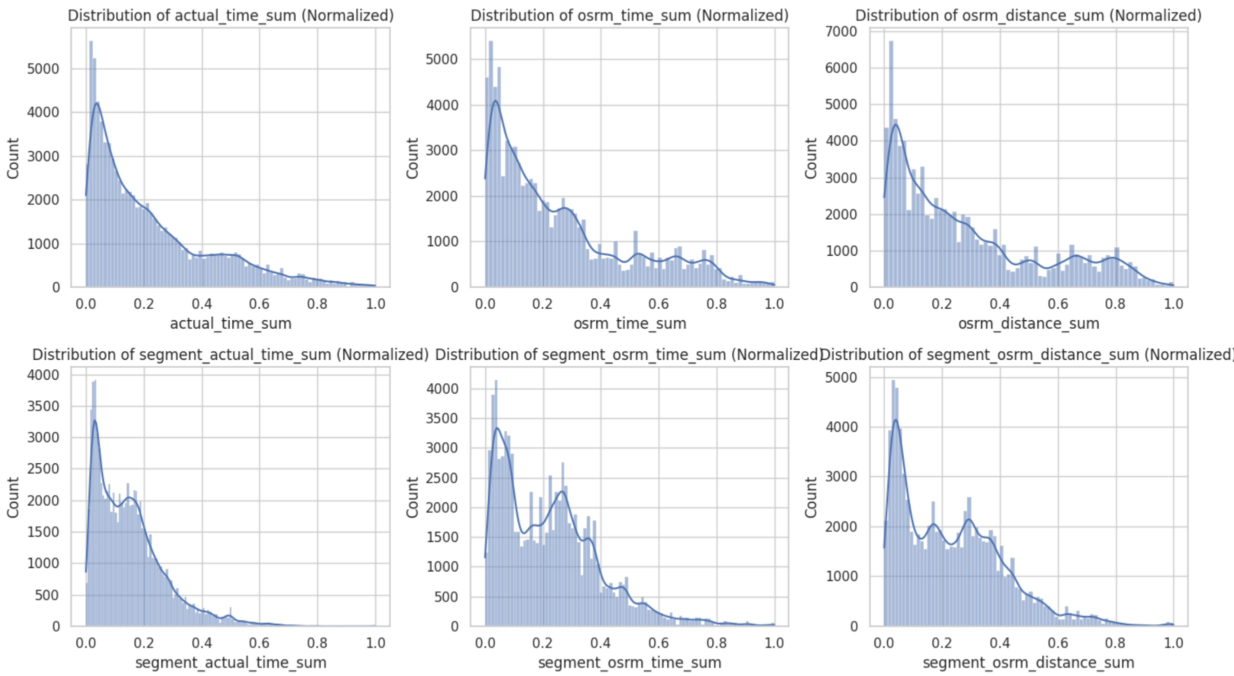
3. Save the Normalized and Standardized Data

```python
# Save the normalized dataset to a CSV file
delhivery_data_normalized.to_csv("delhivery_data_normalized.csv",
index=False)

# Save the standardized dataset to a CSV file
delhivery_data_standardized.to_csv("delhivery_data_standardized.csv",
index=False)
```

4. Visualizing the Effect of Normalization and Standardization

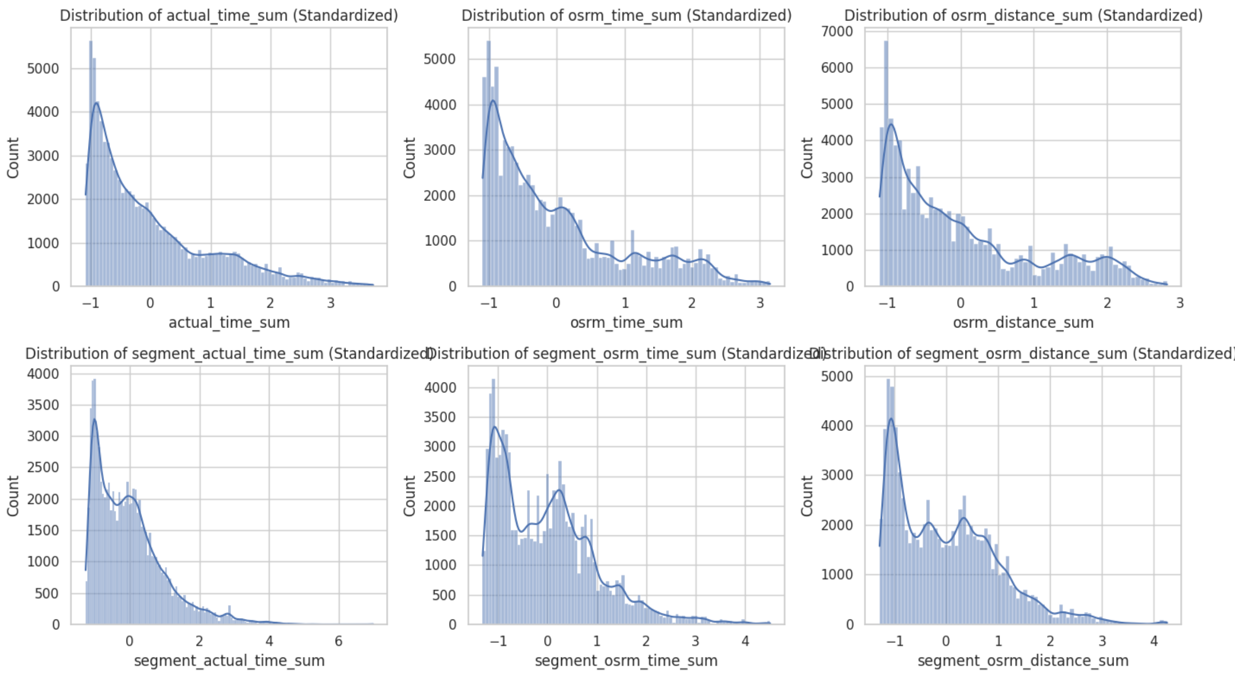
4.1. Visualize Normalized Data

```python
import matplotlib.pyplot as plt
import seaborn as sns

# Visualize the distribution of normalized data
plt.figure(figsize=(14, 8))
for i, col in enumerate(numerical_columns, 1):
    plt.subplot(2, 3, i)
    sns.histplot(delhivery_data_normalized[col], kde=True)
    plt.title(f'Distribution of {col} (Normalized)')

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



4.2. Visualize Standardized Data

```
# Visualize the distribution of standardized data
plt.figure(figsize=(14, 8))
for i, col in enumerate(numerical_columns, 1):
    plt.subplot(2, 3, i)
    sns.histplot(delhivery_data_standardized[col], kde=True)
    plt.title(f'Distribution of {col} (Standardized)')

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



Business Insights

1. Identify Most Frequent Source and Destination States

We will start by finding the states from which most orders are originating and the states where they are delivered.

```
# Check most frequent source states
most_frequent_source_states =
delhivery_data['source_state'].value_counts().head(5)
print("Most Frequent Source States:")
print(most_frequent_source_states)

# Check most frequent destination states
most_frequent_destination_states =
delhivery_data['destination_state'].value_counts().head(5)
print("Most Frequent Destination States:")
print(most_frequent_destination_states)
```

```
Most Frequent Source States:
source_state
Karnataka        11536
Maharashtra      10788
Haryana           8827
Tamil Nadu        7103
Uttar Pradesh     5130
Name: count, dtype: int64
Most Frequent Destination States:
```

```
destination_state
Karnataka          11858
Maharashtra        10677
Haryana             8676
Tamil Nadu          6848
Uttar Pradesh       5322
Name: count, dtype: int64
```

2. Identify the Busiest Corridor

A corridor is defined as a route between a source and destination. We will identify the busiest corridors by counting the most frequent source-destination pairs.

```
# Create a corridor (source to destination) column
delhivery_data['corridor'] = delhivery_data['source_name'] + " to " +
delhivery_data['destination_name']

# Find the busiest corridors
busiest_corridors = delhivery_data['corridor'].value_counts().head(5)
print("Busiest Corridors:")
print(busiest_corridors)

Busiest Corridors:
corridor
Sonipat_Kundli_H (Haryana) to Gurgaon_Bilaspur_HB (Haryana)
760
Gurgaon_Bilaspur_HB (Haryana) to Sonipat_Kundli_H (Haryana)
741
Chandigarh_Mehmdpur_H (Punjab) to Gurgaon_Bilaspur_HB (Haryana)
705
Gurgaon_Bilaspur_HB (Haryana) to Chandigarh_Mehmdpur_H (Punjab)
616
Bengaluru_Bomsndra_HB (Karnataka) to Bengaluru_KGAirprt_HB (Karnataka)
605
Name: count, dtype: int64
```

3. Calculate Average Distance and Average Time for Deliveries

We will calculate the average distance and time for deliveries between the source and destination pairs, which will help us analyze how long deliveries typically take across different corridors.

3.1. Average Distance Between Key Corridors

```
# Calculate the average distance for the top corridors
avg_distance_by_corridor = delhivery_data.groupby('corridor')
['osrm_distance_sum'].mean().sort_values(ascending=False).head(5)
print("Average Distance for Top Corridors (in km):")
print(avg_distance_by_corridor)
```

```
Average Distance for Top Corridors (in km):
corridor
Gwalior_HrihrNgr_I (Madhya Pradesh) to Datia_TownDPP_D (Madhya
Pradesh)    2124.335300
Bangalore_Nelmngla_H (Karnataka) to Davangere_Central_I_1 (Karnataka)
2092.519500
Moradabad_DC (Uttar Pradesh) to Rudrapur_UdhamNgr_H (Uttarakhand)
2056.262300
Choutuppal_Nagaram_D (Telangana) to Miryalguda_Ragvendr_D (Telangana)
2038.038433
Bokakhat_MlnprDPP_D (Assam) to Golaghat_BaruaRd_D (Assam)
2020.807300
Name: osrm_distance_sum, dtype: float64
```

3.2. Average Time Between Key Corridors

```
# Calculate the average actual time for deliveries across the top
corridors
avg_time_by_corridor = delhivery_data.groupby('corridor')
['actual_time_sum'].mean().sort_values(ascending=False).head(5)
print("Average Time Taken for Top Corridors (in minutes):")
print(avg_time_by_corridor)
```

```
Average Time Taken for Top Corridors (in minutes):
corridor
Sagara_Vardhard_D (Karnataka) to Bangalore_Nelmngla_H (Karnataka)
3.725490
Sidhi_Padra_D (Madhya Pradesh) to Allahabad_Central_H_1 (Uttar
Pradesh)        3.682709
Kolkata_Dankuni_HB (West Bengal) to Berhampore_Central_I_2 (West
Bengal)       3.658200
Phulpur_Shekhpur_D (Uttar Pradesh) to Allahabad_Central_H_1 (Uttar
Pradesh)    3.589572
Surat_HUB (Gujarat) to Pune_Tathawde_H (Maharashtra)
3.419786
Name: actual_time_sum, dtype: float64
```

4. Compare Actual and OSRM-Predicted Time

We can analyze how the actual delivery times compare to the OSRM-predicted times. This insight will help us identify routes or corridors where deliveries are faster or slower than expected.

```
# Calculate the time difference between actual and OSRM-predicted
times
delhivery_data['time_diff'] = delhivery_data['actual_time_sum'] -
delhivery_data['osrm_time_sum']

# Check the corridors with the highest and lowest time differences
```

```python
largest_time_differences = delhivery_data.groupby('corridor')
['time_diff'].mean().sort_values(ascending=False).head(5)
print("Corridors with Largest Time Differences (Actual Time - OSRM
Time):")
print(largest_time_differences)

# Corridors where deliveries are faster than expected (negative time
difference)
fastest_corridors = delhivery_data.groupby('corridor')
['time_diff'].mean().sort_values(ascending=True).head(5)
print("Corridors where Deliveries are Faster than Expected (Negative
Time Difference):")
print(fastest_corridors)
```

```
Corridors with Largest Time Differences (Actual Time - OSRM Time):
corridor
Phulpur_Shekhpur_D (Uttar Pradesh) to Allahabad_Central_H_1 (Uttar
Pradesh)    3.222160
Jaynagar_Wardno6_D (Bihar) to Muzaffrpur_Bbganj_I (Bihar)
1.398467
Madhubani_Bardivan_D (Bihar) to Jaynagar_Wardno6_D (Bihar)
1.314350
Muzaffrpur_Bbganj_I (Bihar) to Madhubani_Bardivan_D (Bihar)
1.251774
Peterbar_GagiDPP_D (Jharkhand) to Ranchi_Hub (Jharkhand)
1.145287
Name: time_diff, dtype: float64
Corridors where Deliveries are Faster than Expected (Negative Time
Difference):
corridor
Jaisalmer_Gopa3PL_D (Rajasthan) to Pokhran_SttinDPP_D (Rajasthan)   -
3.102367
Barmer_Nehru3PL_D (Rajasthan) to Jaisalmer_Gopa3PL_D (Rajasthan)    -
3.024463
Jaisalmer_Gopa3PL_D (Rajasthan) to Phalodi_PalikDPP_D (Rajasthan)   -
3.001387
Ahmedabad_East_H_1 (Gujarat) to Gandhidham_Sector1A_IP (Gujarat)    -
2.833945
Pallakad_ChndrNgr_D (Kerala) to Bangalore_Nelmngla_H (Karnataka)    -
2.808555
Name: time_diff, dtype: float64
```

Overall Insights:

Karnataka, Maharashtra, and Haryana are the most significant states in terms of both originating and receiving orders, indicating these regions should be a key focus for optimizing logistics operations.

Haryana has the busiest corridors, especially between Sonipat and Gurgaon, which highlights the importance of managing logistical flow within the state.

There is a significant discrepancy between actual and predicted delivery times on certain corridors, with some corridors taking longer than expected and others being faster. These findings can be used to prioritize route optimization and mitigate delays.

Long-distance corridors present challenges, especially when spanning multiple states. Focus should be placed on improving efficiency for these corridors through better planning and resource allocation.

Recommendations

1. Focus on Optimizing Karnataka and Maharashtra

Why: Karnataka and Maharashtra are the top states for both sending and receiving orders.

Action: Invest in additional resources such as more vehicles, warehouse space, and staff in these states to handle the high volume of deliveries more efficiently.

2. Improve Operations in Haryana's Busiest Corridors

Why: The busiest delivery routes are between Sonipat and Gurgaon in Haryana, handling hundreds of trips daily.

Action: Streamline these corridors by setting up dedicated lanes, increasing delivery slots, and automating processes for faster handoffs. Consider implementing more precise traffic management to avoid congestion.

3. Address Delays on Specific Corridors

Why: Certain corridors, like Phulpur to Allahabad and Jaynagar to Muzaffrpur, are taking much longer than predicted, suggesting logistical issues or delays.

Action: Investigate the causes of delays on these corridors. It could be due to poor road conditions, congestion, or bottlenecks at certain points. After identifying the problem areas, work on solutions like rerouting, improving road access, or adjusting delivery schedules to avoid peak hours.

4. Expand Delivery Capacity in Haryana and Punjab

Why: Routes between Haryana and Punjab are among the busiest in terms of delivery volume.

Action: Consider establishing new delivery centers or expanding existing facilities along these routes to increase capacity and reduce the burden on current resources.

5. Learn from Fast Corridors

Why: Some corridors, such as Jaisalmer to Pokhran and Ahmedabad to Gandhidham, have consistently faster-than-expected deliveries.

Action: Study these routes to identify best practices and replicate them across slower-performing routes. For instance, assess the route planning, traffic patterns, and vehicle usage on these routes to see what can be applied elsewhere.

6. Invest in Long-Distance Route Optimization

Why: Routes like Gwalior to Datia and Bangalore to Davangere cover long distances and involve complex logistics.

Action: Introduce automated route optimization tools to better plan fuel stops, driver shifts, and vehicle usage to maximize efficiency over these long distances. Consider using hub-and-spoke models to reduce travel time.

7. Allocate Additional Resources to Underperforming States

Why: Certain states, such as Bihar and Uttar Pradesh, show higher-than-expected delivery times.

Action: Allocate additional resources like vehicles, staff, or technology upgrades in these underperforming states to bring delivery times in line with predictions. Regularly review performance in these states and adjust resources accordingly.

8. Increase Capacity for Short-Distance High-Volume Routes

Why: Shorter routes within the same state, such as Bengaluru to Bengaluru in Karnataka, have a high volume of trips.

Action: Increase the number of delivery slots and use smaller, faster vehicles for these short-distance, high-volume routes. This will ensure faster and more frequent deliveries within cities.

9. Monitor and Adjust Based on Traffic Patterns

Why: Some routes take longer than expected due to unpredictable traffic conditions.

Action: Implement real-time traffic monitoring and dynamic route adjustments to avoid congested roads. Adjust delivery times or routes based on traffic forecasts to minimize delays.

10. Encourage Collaboration with Local Authorities

Why: Delays on specific routes can be caused by road conditions or infrastructure issues.

Action: Work with local authorities to improve road conditions on key delivery routes, particularly in areas where deliveries take longer than expected. Collaborating with local governments to improve road access can significantly reduce delays.