```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import ttest_ind
from sklearn.decomposition import PCA
from sklearn.preprocessing import MinMaxScaler

# Load the dataset
data = pd.read_csv('delhivery_data.csv')


# Display the first few rows of the dataset
data.head()
```

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uu
0	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	tr 1537410936476493
1	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	tr 1537410936476493
2	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	tr 1537410936476493
3	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	tr 1537410936476493
4	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	tr 1537410936476493

5 rows × 24 columns

```
# Get basic information about the dataset
data.info()

# Summary statistics
data.describe()

print(data['data'].unique())
```

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

```
# Assuming data is your DataFrame with missing values
print("Missing values before handling:")
print(data.isnull().sum())

# Handle missing values (example: fill with a default value)
data['source_name'].fillna('Unknown', inplace=True)
data['destination_name'].fillna('Unknown', inplace=True)

# Verify missing values after handling
print("Missing values after handling:")
print(data.isnull().sum())
```

```
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
Missing values after handling:
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
/var/folders/2y/9wbng44n0gd0wzly39wrhxzm0000gn/T/ipykernel_53187/209052705.py:6: FutureWarning: A value is trying to be
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[c


  data['source_name'].fillna('Unknown', inplace=True)
/var/folders/2y/9wbng44n0gd0wzly39wrhxzm0000gn/T/ipykernel_53187/209052705.py:7: FutureWarning: A value is trying to be
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[c


  data['destination_name'].fillna('Unknown', inplace=True)
```

```
# Create the segment_key
data['segment_key'] = data['trip_uuid'].astype(str) + '_' + data['source_center'].astype(str) + '_' + data['destination_cent

# Define the aggregation dictionary
create_segment_dict = {
    'trip_uuid': 'first',
    'route_schedule_uuid': 'first',
    'route_type': 'first',
    'source_center': 'first',
    'source_name': 'first',
    'destination_center': 'first',
    'destination_name': 'first',
    'trip_creation_time': 'first',  # Include trip_creation_time in the aggregation
    'od_start_time': 'first',
    'od_end_time': 'last',
    'start_scan_to_end_scan': 'sum',
    'actual_distance_to_destination': 'sum',
    'actual_time': 'sum',
    'osrm_time': 'sum',
    'osrm_distance': 'sum',
    'segment_actual_time': 'sum',
    'segment_osrm_distance': 'sum',
    'segment_osrm_time': 'sum'
}

# Group by segment_key and apply the aggregation functions
aggregated_segment_data = data.groupby('segment_key').agg(create_segment_dict).reset_index()

# Sort the resulting DataFrame
sorted_segment_data = aggregated_segment_data.sort_values(by=['segment_key', 'od_end_time']).reset_index(drop=True)
```

Feature Engineering

```
# Calculate time taken between od_start_time and od_end_time and keep it as a feature named od_time_diff_hour
sorted_segment_data['od_start_time'] = pd.to_datetime(sorted_segment_data['od_start_time'])
sorted_segment_data['od_end_time'] = pd.to_datetime(sorted_segment_data['od_end_time'])
sorted_segment_data['od_time_diff_hour'] = (sorted_segment_data['od_end_time'] - sorted_segment_data['od_start_time']).dt.tc
sorted_segment_data.drop(columns=['od_start_time', 'od_end_time'], inplace=True)

# Extract features from destination_name
destination_split = sorted_segment_data['destination_name'].str.split('_|\\(|\\)', expand=True)
sorted_segment_data = sorted_segment_data.assign(
    destination_city=destination_split[0],
    destination_place=destination_split[1],
    destination_code=destination_split[2],
    destination_state=destination_split[3]
)

# Extract features from source_name
source_split = sorted_segment_data['source_name'].str.split('_|\\(|\\)', expand=True)
sorted_segment_data = sorted_segment_data.assign(
    source_city=source_split[0],
    source_place=source_split[1],
    source_code=source_split[2],
    source_state=source_split[3]
)

# Extract features from trip_creation_time
sorted_segment_data['trip_creation_time'] = pd.to_datetime(sorted_segment_data['trip_creation_time'])
sorted_segment_data['trip_creation_year'] = sorted_segment_data['trip_creation_time'].dt.year
sorted_segment_data['trip_creation_month'] = sorted_segment_data['trip_creation_time'].dt.month
sorted_segment_data['trip_creation_day'] = sorted_segment_data['trip_creation_time'].dt.day
sorted_segment_data['trip_creation_hour'] = sorted_segment_data['trip_creation_time'].dt.hour

# Ensure all values are positive
sorted_segment_data['actual_distance_to_destination'] = sorted_segment_data['actual_distance_to_destination'].abs()
sorted_segment_data['actual_time'] = sorted_segment_data['actual_time'].abs()
```

In-depth Analysis

```
# Detect outliers using IQR with a higher multiplier
continuous_columns = ['start_scan_to_end_scan', 'actual_distance_to_destination',
                       'osrm_time', 'osrm_distance',
                      'segment_actual_time', 'segment_osrm_time', 'segment_osrm_distance']
Q1 = sorted_segment_data[continuous_columns].quantile(0.25)
Q3 = sorted_segment_data[continuous_columns].quantile(0.75)
IQR = Q3 - Q1

# Calculate lower and upper bounds for outlier detection
lower_bound = Q1 - 3.0 * IQR
upper_bound = Q3 + 3.0 * IQR

# Filter out the outliers
filtered_data = sorted_segment_data[~((sorted_segment_data[continuous_columns] < lower_bound) | (sorted_segment_data[continu
filtered_data.head()
```

	segment_key	trip_uuid	route_schedu
2	trip-153671042288605164_IND561203AAB_IND562101AAA	trip-153671042288605164	thanos::sroute:3 bb0b-4(e
3	trip-153671042288605164_IND572101AAA_IND561203AAB	trip-153671042288605164	thanos::sroute:3 bb0b-4(e
6	trip-153671046011330457_IND400072AAB_IND401104AAA	trip-153671046011330457	thanos::sroute:f a679-45 I
7	trip-153671052974046625_IND583101AAA_IND583201AAA	trip-153671052974046625	thanos::sroute:(65e0-4 (
8	trip-153671052974046625_IND583119AAA_IND583101AAA	trip-153671052974046625	thanos::sroute:(65e0-4 (

5 rows × 30 columns

```
# One-hot encoding for categorical variables
categorical_columns = ['route_schedule_uuid', 'source_center', 'destination_center']
encoded_data = pd.get_dummies(filtered_data, columns=categorical_columns)

# Exclude datetime column from PCA
datetime_columns = ['trip_creation_time']
pca_columns = [col for col in encoded_data.columns if col not in datetime_columns]

# Filter out non-numeric columns if any remain
numeric_columns = encoded_data.select_dtypes(include=['number']).columns
pca_columns = list(set(pca_columns).intersection(numeric_columns))

# Apply PCA for dimensionality reduction
pca = PCA(n_components=0.95)  # Retain 95% of variance
pca_features = pca.fit_transform(encoded_data[pca_columns])

# Initialize the scaler
scaler = MinMaxScaler()

# Apply MinMaxScaler to continuous variables
scaler = MinMaxScaler()
scaled_features = scaler.fit_transform(encoded_data[continuous_columns])
scaled_data = pd.DataFrame(scaled_features, columns=continuous_columns)

# Update the scaled data back to the encoded data
encoded_data[continuous_columns] = scaled_data

# Verify the data after transformation
print(encoded_data.head())
```

```
8              0.017063                         0.000156        182.0

   osrm_time  ...  destination_center_IND852131AAA  \
2   0.025000  ...                            False
3   0.126389  ...                            False
6   0.018056  ...                            False
7   0.006944  ...                            False
8   0.009722  ...                            False

   destination_center_IND852139AAB  destination_center_IND852201AAA  \
2                            False                            False
3                            False                            False
6                            False                            False
7                            False                            False
8                            False                            False

   destination_center_IND853204AAA  destination_center_IND854105AAA  \
2                            False                            False
3                            False                            False
6                            False                            False
7                            False                            False
8                            False                            False

  destination_center_IND854105AAB destination_center_IND854311AAA  \
2                           False                           False
3                           False                           False
6                           False                           False
7                           False                           False
8                           False                           False

  destination_center_IND854326AAB destination_center_IND854334AAA  \
2                           False                           False
3                           False                           False
6                           False                           False
7                           False                           False
8                           False                           False

  destination_center_IND854335AAA
2                           False
3                           False
6                           False
7                           False
8                           False

[5 rows x 4264 columns]
```

```
# Check column names and presence of specific columns
print(encoded_data.columns)

# Sample exploration
print(encoded_data.head())

# Statistical summary
print(encoded_data.describe())

# Ensure specific columns exist before operations
if 'actual_time' in encoded_data.columns:
    # Perform operations involving 'actual_time'
    pass
else:
    print("'actual_time' column is missing.")

# Repeat similar checks for other necessary columns like 'osrm_time', 'segment_actual_time', etc.
```

```
Index(['segment_key', 'trip_uuid', 'route_type', 'source_name',
       'destination_name', 'trip_creation_time', 'start_scan_to_end_scan',
       'actual_distance_to_destination', 'actual_time', 'osrm_time',
       ...
       'destination_center_IND852131AAA', 'destination_center_IND852139AAB',
       'destination_center_IND852201AAA', 'destination_center_IND853204AAA',
       'destination_center_IND854105AAA', 'destination_center_IND854105AAB',
       'destination_center_IND854311AAA', 'destination_center_IND854326AAB',
       'destination_center_IND854334AAA', 'destination_center_IND854335AAA'],
      dtype='object', length=4264)
                                          segment_key                 trip_uuid  \
2  trip-153671042288605164_IND561203AAB_IND562101AAA  trip-153671042288605164
3  trip-153671042288605164_IND572101AAA_IND561203AAB  trip-153671042288605164
6  trip-153671046011330457_IND400072AAB_IND401104AAA  trip-153671046011330457
7  trip-153671052974046625_IND583101AAA_IND583201AAA  trip-153671052974046625
8  trip-153671052974046625_IND583119AAA_IND583101AAA  trip-153671052974046625

  route_type                        source_name  \
2    Carting  Doddablpur_ChikaDPP_D (Karnataka)
3    Carting      Tumkur_Veersagr_I (Karnataka)
6    Carting           Mumbai Hub (Maharashtra)
7        FTL             Bellary_Dc (Karnataka)
8        FTL      Sandur_WrdN1DPP_D (Karnataka)

                    destination_name         trip_creation_time  \
```

```
2  Chikblapur_ShntiSgr_D (Karnataka) 2018-09-12 00:00:22.886430
3  Doddablpur_ChikaDPP_D (Karnataka) 2018-09-12 00:00:22.886430
6     Mumbai_MiraRd_IP (Maharashtra) 2018-09-12 00:01:00.113710
7                 Hospet (Karnataka) 2018-09-12 00:02:09.740725
8             Bellary_Dc (Karnataka) 2018-09-12 00:02:09.740725

   start_scan_to_end_scan  actual_distance_to_destination  actual_time  \
2                0.039964                        0.030805         96.0
3                0.097441                        0.185006        303.0
6                0.022003                        0.025452         82.0
7                0.024023                        0.000426        277.0
8                0.017063                        0.000156        182.0

   osrm_time  ...  destination_center_IND852131AAA  \
2   0.025000  ...                            False
3   0.126389  ...                            False
6   0.018056  ...                            False
7   0.006944  ...                            False
8   0.009722  ...                            False

   destination_center_IND852139AAB  destination_center_IND852201AAA  \
2                            False                            False
3                            False                            False
6                            False                            False
7                            False                            False
8                            False                            False

   destination_center_IND853204AAA  destination_center_IND854105AAA  \
2                            False                            False
3                            False                            False
6                            False                            False
7                            False                            False
8                            False                            False
```

Hypothesis Testing

```
# a. actual_time vs OSRM time
ttest_result_a = ttest_ind(encoded_data['actual_time'], encoded_data['osrm_time'], nan_policy='omit')
print('Hypothesis Test: actual_time vs OSRM time')
print('T-statistic:', ttest_result_a.statistic)
print('P-value:', ttest_result_a.pvalue)

# b. actual_time vs segment actual time
ttest_result_b = ttest_ind(encoded_data['actual_time'], encoded_data['segment_actual_time'], nan_policy='omit')
print('\nHypothesis Test: actual_time vs segment actual time')
print('T-statistic:', ttest_result_b.statistic)
print('P-value:', ttest_result_b.pvalue)

# c. OSRM distance vs segment OSRM distance
ttest_result_c = ttest_ind(encoded_data['osrm_distance'], encoded_data['segment_osrm_distance'], nan_policy='omit')
print('\nHypothesis Test: OSRM distance vs segment OSRM distance')
print('T-statistic:', ttest_result_c.statistic)
print('P-value:', ttest_result_c.pvalue)

# d. OSRM time vs segment OSRM time
ttest_result_d = ttest_ind(encoded_data['osrm_time'], encoded_data['segment_osrm_time'], nan_policy='omit')
print('\nHypothesis Test: OSRM time vs segment OSRM time')
print('T-statistic:', ttest_result_d.statistic)
print('P-value:', ttest_result_d.pvalue)
```

```
Hypothesis Test: actual_time vs OSRM time
T-statistic: 133.00074549661076
P-value: 0.0

Hypothesis Test: actual_time vs segment actual time
T-statistic: 132.9926364224402
P-value: 0.0

Hypothesis Test: OSRM distance vs segment OSRM distance
T-statistic: -7.90108231034694
P-value: 2.836122240253282e-15

Hypothesis Test: OSRM time vs segment OSRM time
T-statistic: -20.383843247404133
P-value: 6.922436195593747e-92
```

```
# Drop rows with any NaN values
encoded_data_clean = encoded_data.dropna()

# Verify missing values after handling
print("Missing values after removing null values:")
print(encoded_data_clean.isnull().sum())
```

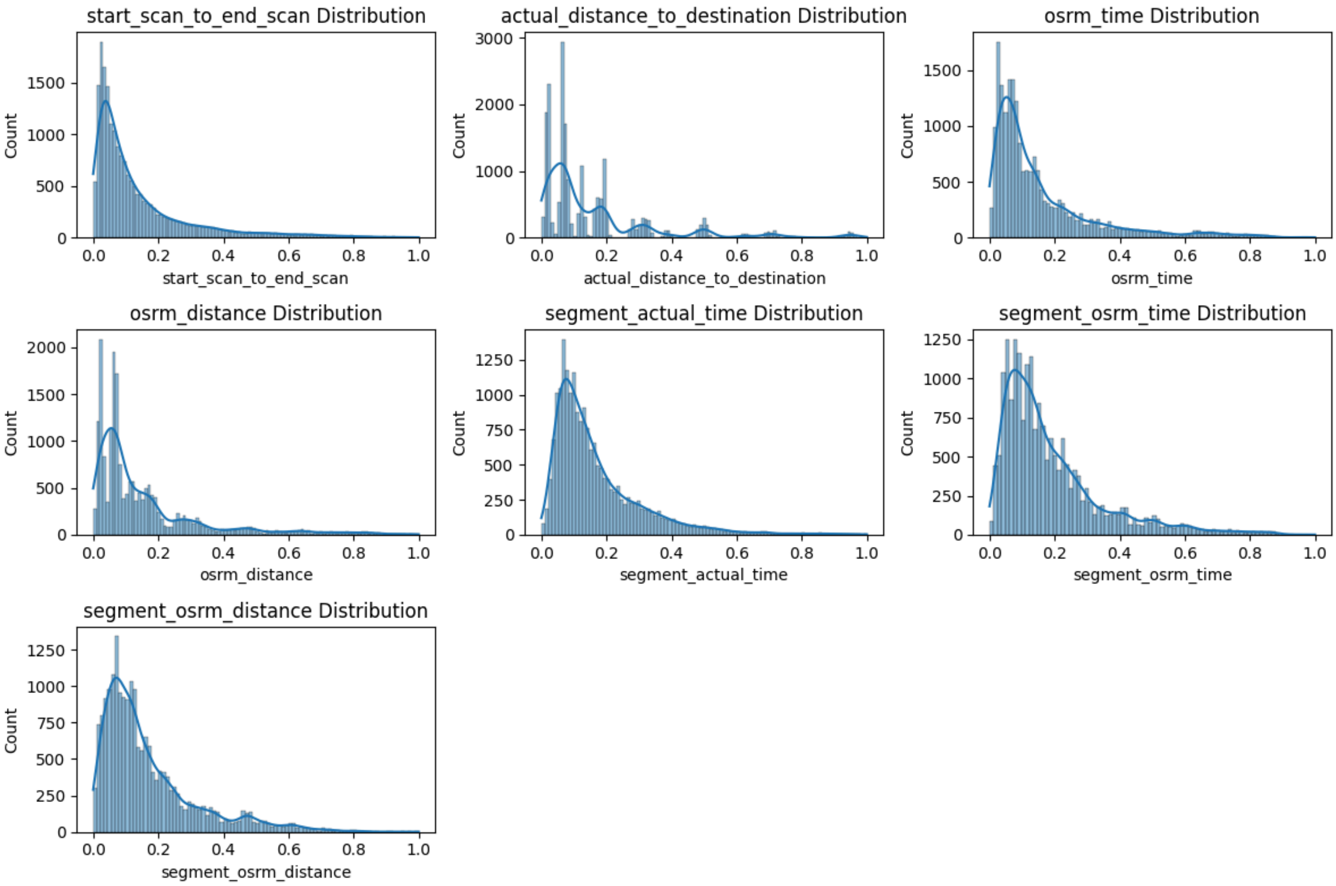
```
Missing values after removing null values:
segment_key                        0
trip_uuid                          0
route_type                         0
source_name                        0
destination_name                   0
                                  ..
destination_center_IND854105AAB    0
destination_center_IND854311AAA    0
destination_center_IND854326AAB    0
destination_center_IND854334AAA    0
destination_center_IND854335AAA    0
Length: 4264, dtype: int64
```

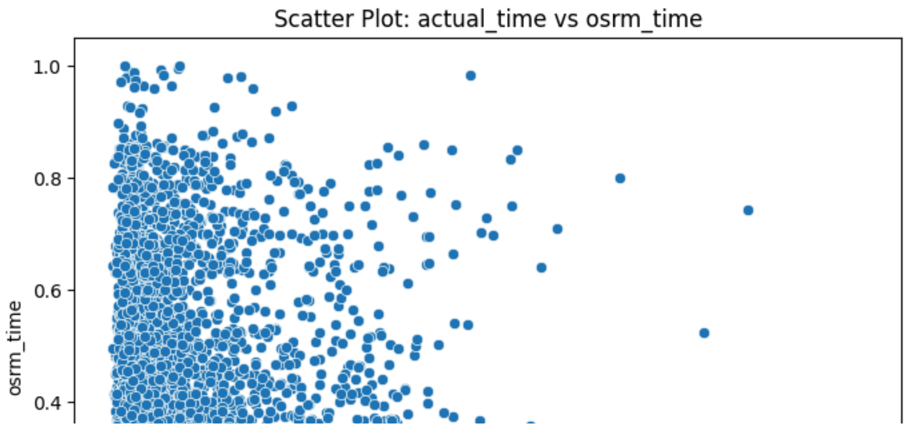
Plotting required visualizations

```
# Histogram or KDE plot for continuous variables
plt.figure(figsize=(12, 8))
for i, col in enumerate(continuous_columns, start=1):
    plt.subplot(3, 3, i)
    sns.histplot(data=encoded_data, x=col, kde=True)
    plt.title(f'{col} Distribution')
plt.tight_layout()
plt.show()

# Scatter plot of actual_time vs osrm_time
plt.figure(figsize=(8, 6))
sns.scatterplot(data=encoded_data, x='actual_time', y='osrm_time')
plt.title('Scatter Plot: actual_time vs osrm_time')
plt.xlabel('actual_time')
plt.ylabel('osrm_time')
plt.show()

# Box plot for continuous variables
plt.figure(figsize=(12, 8))
sns.boxplot(data=encoded_data[continuous_columns])
plt.title('Box Plot of Continuous Variables')
plt.xlabel('Variable')
plt.ylabel('Value')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```


start_scan_to_end_scan Distribution
Count
start_scan_to_end_scan
actual_distance_to_destination Distribution
Count
actual_distance_to_destination
osrm_time Distribution
Count
osrm_time
osrm_distance Distribution
Count
osrm_distance
segment_actual_time Distribution
Count
segment_actual_time
segment_osrm_time Distribution
Count
segment_osrm_time
segment_osrm_distance Distribution
Count
segment_osrm_distance


Scatter Plot: actual_time vs osrm_time
osrm_time

```
# Display the first few rows of the final processed data
encoded_data.head()
```

	segment_key	trip_uuid	route_type	source_name	destination_name	t
2	trip-153671042288605164_IND561203AAB_IND562101AAA	trip-153671042288605164	Carting	Doddablpur_ChikaDPP_D (Karnataka)	Chikblapur_ShntiSgr_D (Karnataka)	
3	trip-153671042288605164_IND572101AAA_IND561203AAB	trip-153671042288605164	Carting	Tumkur_Veersagr_I (Karnataka)	Doddablpur_ChikaDPP_D (Karnataka)	
6	trip-153671046011330457_IND400072AAB_IND401104AAA	trip-153671046011330457	Carting	Mumbai Hub (Maharashtra)	Mumbai_MiraRd_IP (Maharashtra)	
7	trip-153671052974046625_IND583101AAA_IND583201AAA	trip-153671052974046625	FTL	Bellary_Dc (Karnataka)	Hospet (Karnataka)	
8	trip-153671052974046625_IND583119AAA_IND583101AAA	trip-153671052974046625	FTL	Sandur_WrdN1DPP_D (Karnataka)	Bellary_Dc (Karnataka)	

5 rows × 4264 columns

```
# Find the busiest corridor
busiest_corridor = data.groupby(['source_name', 'destination_name'], observed=False)['route_type'].count().idxmax()
print(f"The busiest corridor is from {busiest_corridor[0]} to {busiest_corridor[1]}")

busiest_corridor_encoded = encoded_data.groupby(['source_name', 'destination_name'], observed=False)['route_type'].count().i
print(f"The busiest corridor (encoded) is from {busiest_corridor_encoded[0]} to {busiest_corridor_encoded[1]}")
```

```
The busiest corridor is from Gurgaon_Bilaspur_HB (Haryana) to Bangalore_Nelmngla_H (Karnataka)
The busiest corridor (encoded) is from Bangalore_Nelmngla_H (Karnataka) to Bengaluru_KGAirprt_HB (Karnataka)
```

```
# Average distance and time between corridors
avg_distance_between_corridor = data.groupby(['source_name', 'destination_name'], observed=False)['actual_distance_to_destir
avg_time_between_corridor = data.groupby(['source_name', 'destination_name'], observed=False)['actual_time'].mean()
print(f"Average distance between corridors: {avg_distance_between_corridor.mean()} Kms")
print(f"Average time taken between corridors: {avg_time_between_corridor.mean()}")

avg_distance_between_corridor_encoded = encoded_data.groupby(['source_name', 'destination_name'], observed=False)['actual_di
avg_time_between_corridor_encoded = encoded_data.groupby(['source_name', 'destination_name'], observed=False)['actual_time']
print(f"Average distance between corridors (encoded): {avg_distance_between_corridor_encoded.mean()} Kms")
print(f"Average time taken between corridors (encoded): {avg_time_between_corridor_encoded.mean()}")
```

```
Average distance between corridors: 51.5385851159853 Kms
Average time taken between corridors: 119.01870587893055
Average distance between corridors (encoded): 0.15525961756531734 Kms
Average time taken between corridors (encoded): 261.8564295738579
```