

In [ ]: *# Problem Statement*

The central objective **is** to develop a regression model to accurately predict food delivery times **for** Porter. The model will use various factors such **as** order details, restaurant location, **and** the availability of delivery partners to generate precise estimates **for** customers.

```
In [11]: import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from datetime import datetime
import warnings
warnings.filterwarnings('ignore')
```

```
In [12]: # load the dataset
df = pd.read_csv('Porter_data.csv')
```

```
In [13]: # Preview first few rows
df.head()
```

```
Out[13]:
```

	market_id	created_at	actual_delivery_time	store_primary_category	order_protocol	total_items	subtotal	num_distinct_items	min_item_price	ma
0	1.0	2015-02-06 22:24:17	2015-02-06 23:11:17	4	1.0	4	3441	4	557	
1	2.0	2015-02-10 21:49:25	2015-02-10 22:33:25	46	2.0	1	1900	1	1400	
2	2.0	2015-02-16 00:11:35	2015-02-16 01:06:35	36	3.0	4	4771	3	820	
3	1.0	2015-02-12 03:36:46	2015-02-12 04:35:46	38	1.0	1	1525	1	1525	
4	1.0	2015-01-27 02:12:36	2015-01-27 02:58:36	38	1.0	2	3620	2	1425	

```
In [14]: # Check shape (rows, columns)
df.shape
```

```
Out[14]: (175777, 14)
```

```
In [15]: # Get column info, datatypes, nulls
df.columns
```

```
Out[15]: Index(['market_id', 'created_at', 'actual_delivery_time',
               'store_primary_category', 'order_protocol', 'total_items', 'subtotal',
               'num_distinct_items', 'min_item_price', 'max_item_price',
               'total_onshift_dashers', 'total_busy_dashers',
               'total_outstanding_orders',
               'estimated_store_to_consumer_driving_duration'],
              dtype='object')
```

```
In [16]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 175777 entries, 0 to 175776
Data columns (total 14 columns):
#   Column                                     Non-Null Count  Dtype
---  -
0   market_id                                175777 non-null  float64
1   created_at                               175777 non-null  object
2   actual_delivery_time                     175777 non-null  object
3   store_primary_category                   175777 non-null  int64
4   order_protocol                           175777 non-null  float64
5   total_items                              175777 non-null  int64
6   subtotal                                 175777 non-null  int64
7   num_distinct_items                       175777 non-null  int64
8   min_item_price                           175777 non-null  int64
9   max_item_price                           175777 non-null  int64
10  total_onshift_dashers                     175777 non-null  float64
11  total_busy_dashers                       175777 non-null  float64
12  total_outstanding_orders                 175777 non-null  float64
13  estimated_store_to_consumer_driving_duration 175777 non-null  float64
dtypes: float64(6), int64(6), object(2)
memory usage: 18.8+ MB
```

```
In [17]: # Quick stats for numerical features
df.describe()
```

```
Out[17]:
```

	market_id	store_primary_category	order_protocol	total_items	subtotal	num_distinct_items	min_item_price	max_item_price	to
<b>count</b>	175777.000000	175777.000000	175777.000000	175777.000000	175777.000000	175777.000000	175777.000000	175777.000000	
<b>mean</b>	2.743726	35.887949	2.911752	3.204976	2697.111147	2.675060	684.965433	1160.158616	
<b>std</b>	1.330963	20.728254	1.513128	2.674055	1828.554893	1.625681	519.882924	560.828571	
<b>min</b>	1.000000	0.000000	1.000000	1.000000	0.000000	1.000000	-86.000000	0.000000	
<b>25%</b>	2.000000	18.000000	1.000000	2.000000	1412.000000	1.000000	299.000000	799.000000	
<b>50%</b>	2.000000	38.000000	3.000000	3.000000	2224.000000	2.000000	595.000000	1095.000000	
<b>75%</b>	4.000000	55.000000	4.000000	4.000000	3410.000000	3.000000	942.000000	1395.000000	
<b>max</b>	6.000000	72.000000	7.000000	411.000000	26800.000000	20.000000	14700.000000	14700.000000	

```
In [ ]: # Explore Columns

# Categorical variables:

market_id, store_primary_category, order_protocol

# Numerical variables:

total_items, subtotal, num_distinct_items, min_item_price, max_item_price,
total_onshift_partners, total_busy_partners, total_outstanding_orders,
estimated_store_to_consumer_driving_duration
```

In [19]: *# Separate numerical and categorical columns*

```
numerical_cols = ['total_items', 'subtotal', 'num_distinct_items', 'min_item_price', 'max_item_price', 'total_onshift_partners', 'total_busy_partners', 'total_outstanding_orders', 'estimated_store_to_consumer_driving_duration']
categorical_cols = ['market_id', 'store_primary_category', 'order_protocol']
time_cols = ['created_at', 'actual_delivery_time']

print("Numerical variables:")
print(numerical_cols)

print("\nCategorical variables:")
print(categorical_cols)

print("\nTime variables:")
print(time_cols)
```

Numerical variables:

['total\_items', 'subtotal', 'num\_distinct\_items', 'min\_item\_price', 'max\_item\_price', 'total\_onshift\_partners', 'total\_busy\_partners', 'total\_outstanding\_orders', 'estimated\_store\_to\_consumer\_driving\_duration']

Categorical variables:

['market\_id', 'store\_primary\_category', 'order\_protocol']

Time variables:

['created\_at', 'actual\_delivery\_time']

In [20]: *# Convert timestamps to datetime*

```
df['created_at'] = pd.to_datetime(df['created_at'], errors='coerce')
df['actual_delivery_time'] = pd.to_datetime(df['actual_delivery_time'], errors='coerce')
```

In [21]: *# Target variable: time taken for delivery*

```
df['delivery_duration'] = (df['actual_delivery_time'] - df['created_at']).dt.total_seconds() / 60
```

```
In [22]: # Feature Engineering (Time-based)

# Order hour

df['Order hour'] = df['created_at'].dt.hour

# Day of week (0 = Monday, 6 = Sunday)
df['order_dayofweek'] = df['created_at'].dt.dayofweek

# # Weekend flag
df['is_weekend'] = df['order_dayofweek'].isin([5,6]).astype(int)
```

```
In [23]: # Null Value Handling
```

```
df.isnull().sum()
```

```
Out[23]: market_id          0
created_at          0
actual_delivery_time  0
store_primary_category  0
order_protocol      0
total_items         0
subtotal            0
num_distinct_items  0
min_item_price      0
max_item_price      0
total_onshift_dashers  0
total_busy_dashers  0
total_outstanding_orders  0
estimated_store_to_consumer_driving_duration  0
delivery_duration    0
Order hour          0
order_dayofweek      0
is_weekend           0
dtype: int64
```

```
In [24]: # Drop rows  
df = df.dropna(subset=['created_at', 'actual_delivery_time', 'delivery_duration'])
```

```
In [25]: # Fill missing numerical values  
nums_col = df.select_dtypes(['float64', 'int64']).columns  
  
df[nums_col] = df[nums_col].fillna(df[nums_col].median())
```

```
In [26]: # Fill missing categorical values  
  
cat_col = df.select_dtypes(include=['object']).columns  
df[cat_col] = df[cat_col].fillna('Unknown')
```

```
In [27]: # Encode Categorical Variables  
  
# One-hot encoding for small categories  
df = pd.get_dummies(df, columns=['store_primary_category', 'order_protocol'], drop_first=True)
```

```
In [ ]:
```

```
In [28]: df.columns.tolist()
```

```
Out[28]: ['market_id',
          'created_at',
          'actual_delivery_time',
          'total_items',
          'subtotal',
          'num_distinct_items',
          'min_item_price',
          'max_item_price',
          'total_onshift_dashers',
          'total_busy_dashers',
          'total_outstanding_orders',
          'estimated_store_to_consumer_driving_duration',
          'delivery_duration',
          'Order hour',
          'order_dayofweek',
          'is_weekend',
          'store_primary_category_1',
          'store_primary_category_2',
          'store_primary_category_3',
          'store_primary_category_4',
          'store_primary_category_5',
          'store_primary_category_6',
          'store_primary_category_7',
          'store_primary_category_8',
          'store_primary_category_9',
          'store_primary_category_10',
          'store_primary_category_11',
          'store_primary_category_12',
          'store_primary_category_13',
          'store_primary_category_14',
          'store_primary_category_15',
          'store_primary_category_16',
          'store_primary_category_17',
          'store_primary_category_18',
          'store_primary_category_19',
          'store_primary_category_20',
          'store_primary_category_21',
          'store_primary_category_22',
          'store_primary_category_23',
          'store_primary_category_24',
          'store_primary_category_25',
```



```
'store_primary_category_26',  
'store_primary_category_27',  
'store_primary_category_28',  
'store_primary_category_29',  
'store_primary_category_30',  
'store_primary_category_31',  
'store_primary_category_32',  
'store_primary_category_33',  
'store_primary_category_34',  
'store_primary_category_35',  
'store_primary_category_36',  
'store_primary_category_37',  
'store_primary_category_38',  
'store_primary_category_39',  
'store_primary_category_40',  
'store_primary_category_41',  
'store_primary_category_42',  
'store_primary_category_43',  
'store_primary_category_44',  
'store_primary_category_45',  
'store_primary_category_46',  
'store_primary_category_47',  
'store_primary_category_48',  
'store_primary_category_49',  
'store_primary_category_50',  
'store_primary_category_51',  
'store_primary_category_52',  
'store_primary_category_53',  
'store_primary_category_54',  
'store_primary_category_55',  
'store_primary_category_56',  
'store_primary_category_57',  
'store_primary_category_58',  
'store_primary_category_59',  
'store_primary_category_60',  
'store_primary_category_61',  
'store_primary_category_62',  
'store_primary_category_63',  
'store_primary_category_64',  
'store_primary_category_65',  
'store_primary_category_66',  
'store_primary_category_67',
```

```
'store_primary_category_68',  
'store_primary_category_69',  
'store_primary_category_70',  
'store_primary_category_71',  
'store_primary_category_72',  
'order_protocol_2.0',  
'order_protocol_3.0',  
'order_protocol_4.0',  
'order_protocol_5.0',  
'order_protocol_6.0',  
'order_protocol_7.0']
```

```
In [29]: df.head()
```

Out[29]:

	market_id	created_at	actual_delivery_time	total_items	subtotal	num_distinct_items	min_item_price	max_item_price	total_onshift_dashers	total
0	1.0	2015-02-06 22:24:17	2015-02-06 23:11:17	4	3441	4	557	1239	33.0	
1	2.0	2015-02-10 21:49:25	2015-02-10 22:33:25	1	1900	1	1400	1400	1.0	
2	2.0	2015-02-16 00:11:35	2015-02-16 01:06:35	4	4771	3	820	1604	8.0	
3	1.0	2015-02-12 03:36:46	2015-02-12 04:35:46	1	1525	1	1525	1525	5.0	
4	1.0	2015-01-27 02:12:36	2015-01-27 02:58:36	2	3620	2	1425	2195	5.0	

5 rows × 94 columns

In [30]: `df.info()`

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 175777 entries, 0 to 175776
Data columns (total 94 columns):
```

#	Column	Non-Null Count	Dtype
0	market_id	175777 non-null	float64
1	created_at	175777 non-null	datetime64[ns]
2	actual_delivery_time	175777 non-null	datetime64[ns]
3	total_items	175777 non-null	int64
4	subtotal	175777 non-null	int64
5	num_distinct_items	175777 non-null	int64
6	min_item_price	175777 non-null	int64
7	max_item_price	175777 non-null	int64
8	total_onshift_dashers	175777 non-null	float64
9	total_busy_dashers	175777 non-null	float64
10	total_outstanding_orders	175777 non-null	float64
11	estimated_store_to_consumer_driving_duration	175777 non-null	float64
12	delivery_duration	175777 non-null	float64
13	Order hour	175777 non-null	int32
14	order_dayofweek	175777 non-null	int32
15	is_weekend	175777 non-null	int64
16	store_primary_category_1	175777 non-null	bool
17	store_primary_category_2	175777 non-null	bool
18	store_primary_category_3	175777 non-null	bool
19	store_primary_category_4	175777 non-null	bool
20	store_primary_category_5	175777 non-null	bool
21	store_primary_category_6	175777 non-null	bool
22	store_primary_category_7	175777 non-null	bool
23	store_primary_category_8	175777 non-null	bool
24	store_primary_category_9	175777 non-null	bool
25	store_primary_category_10	175777 non-null	bool
26	store_primary_category_11	175777 non-null	bool
27	store_primary_category_12	175777 non-null	bool
28	store_primary_category_13	175777 non-null	bool
29	store_primary_category_14	175777 non-null	bool
30	store_primary_category_15	175777 non-null	bool
31	store_primary_category_16	175777 non-null	bool
32	store_primary_category_17	175777 non-null	bool
33	store_primary_category_18	175777 non-null	bool
34	store_primary_category_19	175777 non-null	bool
35	store_primary_category_20	175777 non-null	bool

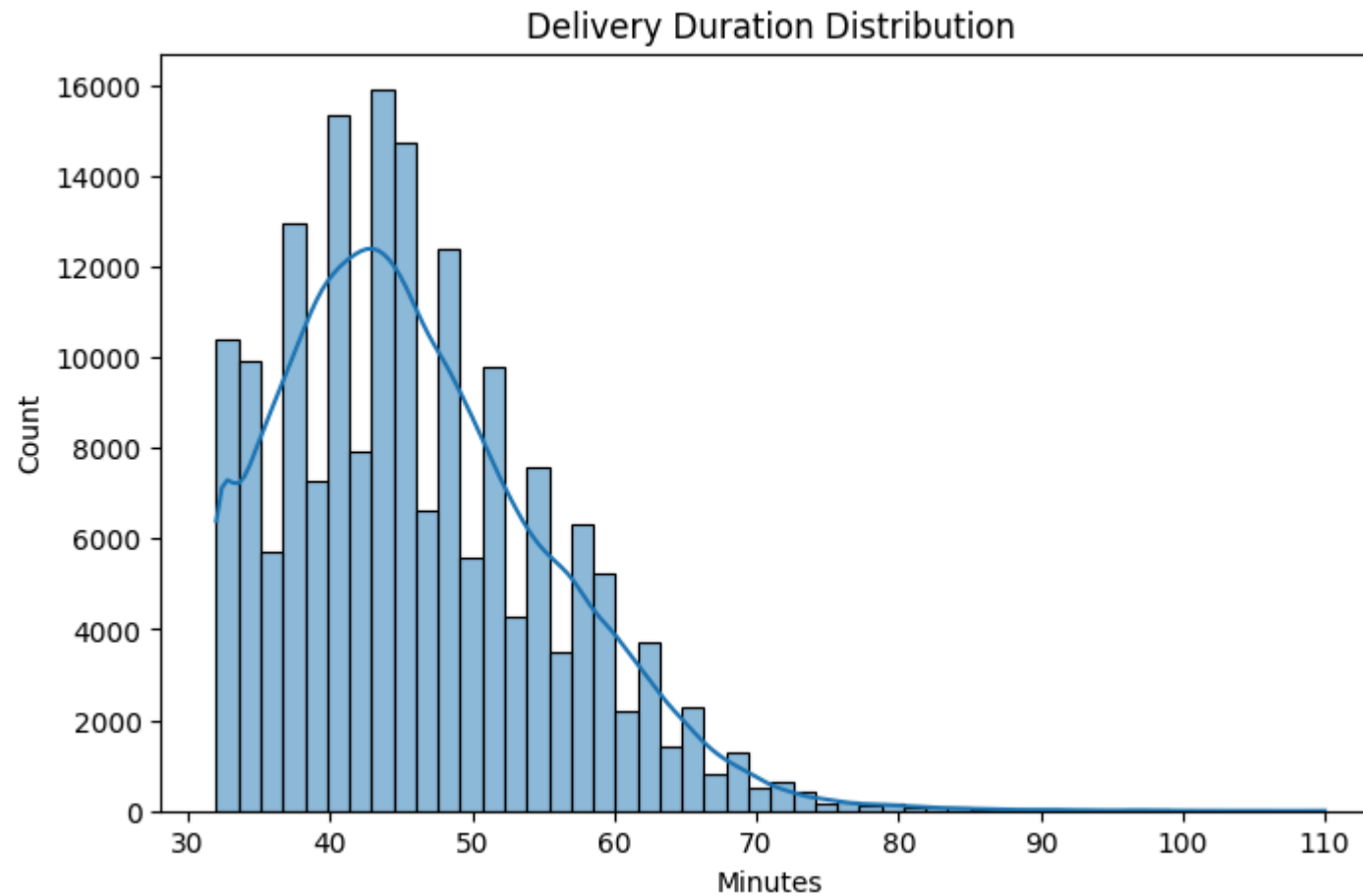
36	store_primary_category_21	175777	non-null	bool
37	store_primary_category_22	175777	non-null	bool
38	store_primary_category_23	175777	non-null	bool
39	store_primary_category_24	175777	non-null	bool
40	store_primary_category_25	175777	non-null	bool
41	store_primary_category_26	175777	non-null	bool
42	store_primary_category_27	175777	non-null	bool
43	store_primary_category_28	175777	non-null	bool
44	store_primary_category_29	175777	non-null	bool
45	store_primary_category_30	175777	non-null	bool
46	store_primary_category_31	175777	non-null	bool
47	store_primary_category_32	175777	non-null	bool
48	store_primary_category_33	175777	non-null	bool
49	store_primary_category_34	175777	non-null	bool
50	store_primary_category_35	175777	non-null	bool
51	store_primary_category_36	175777	non-null	bool
52	store_primary_category_37	175777	non-null	bool
53	store_primary_category_38	175777	non-null	bool
54	store_primary_category_39	175777	non-null	bool
55	store_primary_category_40	175777	non-null	bool
56	store_primary_category_41	175777	non-null	bool
57	store_primary_category_42	175777	non-null	bool
58	store_primary_category_43	175777	non-null	bool
59	store_primary_category_44	175777	non-null	bool
60	store_primary_category_45	175777	non-null	bool
61	store_primary_category_46	175777	non-null	bool
62	store_primary_category_47	175777	non-null	bool
63	store_primary_category_48	175777	non-null	bool
64	store_primary_category_49	175777	non-null	bool
65	store_primary_category_50	175777	non-null	bool
66	store_primary_category_51	175777	non-null	bool
67	store_primary_category_52	175777	non-null	bool
68	store_primary_category_53	175777	non-null	bool
69	store_primary_category_54	175777	non-null	bool
70	store_primary_category_55	175777	non-null	bool
71	store_primary_category_56	175777	non-null	bool
72	store_primary_category_57	175777	non-null	bool
73	store_primary_category_58	175777	non-null	bool
74	store_primary_category_59	175777	non-null	bool
75	store_primary_category_60	175777	non-null	bool
76	store_primary_category_61	175777	non-null	bool
77	store_primary_category_62	175777	non-null	bool

```
78 store_primary_category_63 175777 non-null bool
79 store_primary_category_64 175777 non-null bool
80 store_primary_category_65 175777 non-null bool
81 store_primary_category_66 175777 non-null bool
82 store_primary_category_67 175777 non-null bool
83 store_primary_category_68 175777 non-null bool
84 store_primary_category_69 175777 non-null bool
85 store_primary_category_70 175777 non-null bool
86 store_primary_category_71 175777 non-null bool
87 store_primary_category_72 175777 non-null bool
88 order_protocol_2.0 175777 non-null bool
89 order_protocol_3.0 175777 non-null bool
90 order_protocol_4.0 175777 non-null bool
91 order_protocol_5.0 175777 non-null bool
92 order_protocol_6.0 175777 non-null bool
93 order_protocol_7.0 175777 non-null bool
dtypes: bool(78), datetime64[ns](2), float64(6), int32(2), int64(6)
memory usage: 33.2 MB
```

In [31]: *# Data Visualization*

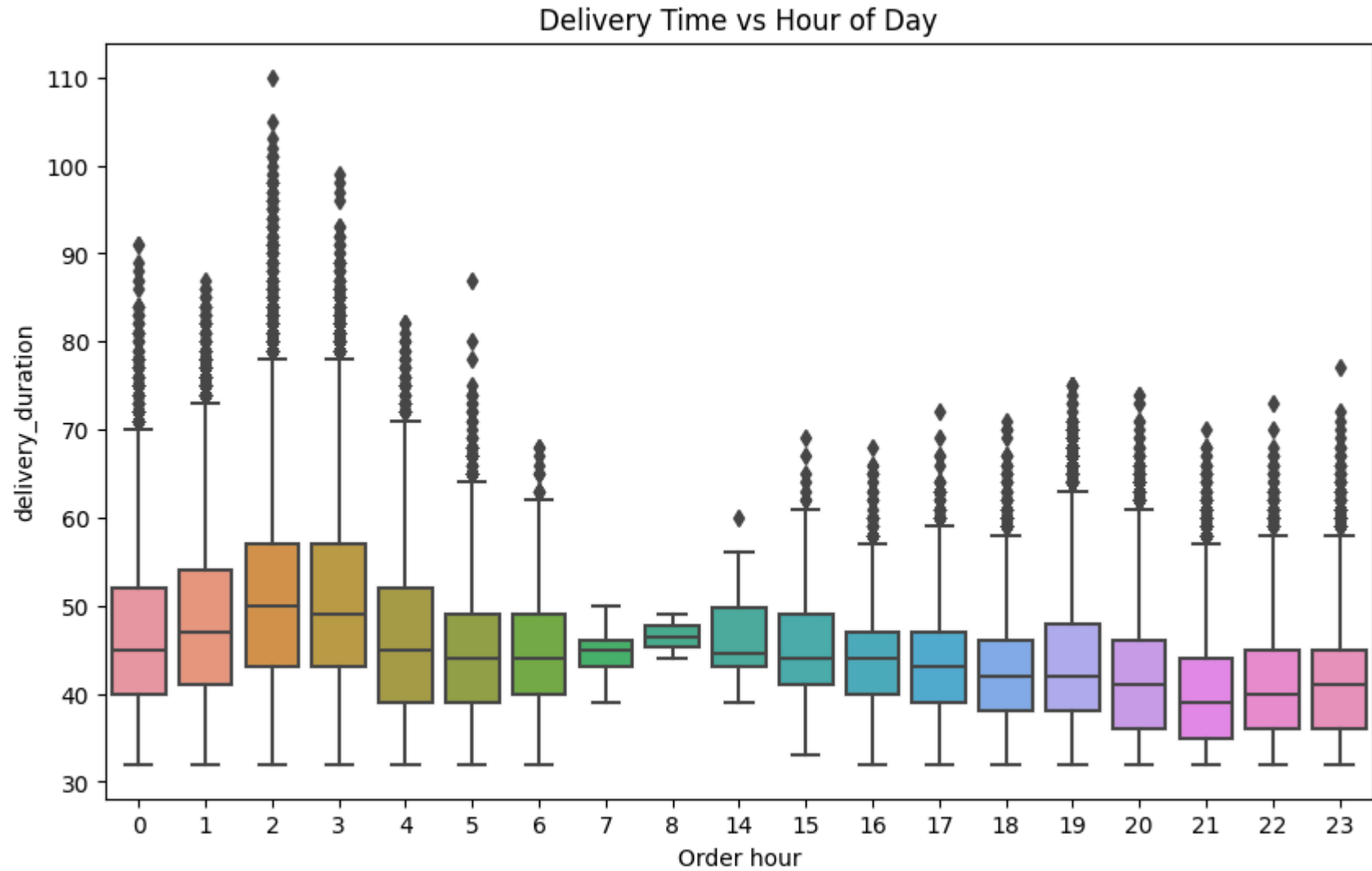
*# Target variable distribution*

```
plt.figure(figsize=(8, 5))  
sns.histplot(df['delivery_duration'], bins=50, kde=True)  
plt.title('Delivery Duration Distribution')  
plt.xlabel('Minutes')  
plt.show()
```



```
In [32]: # Hour of order vs delivery duration
```

```
plt.figure(figsize=(10, 6))  
sns.boxplot(x='Order hour', y='delivery_duration', data=df)  
plt.title('Delivery Time vs Hour of Day')  
plt.show()
```





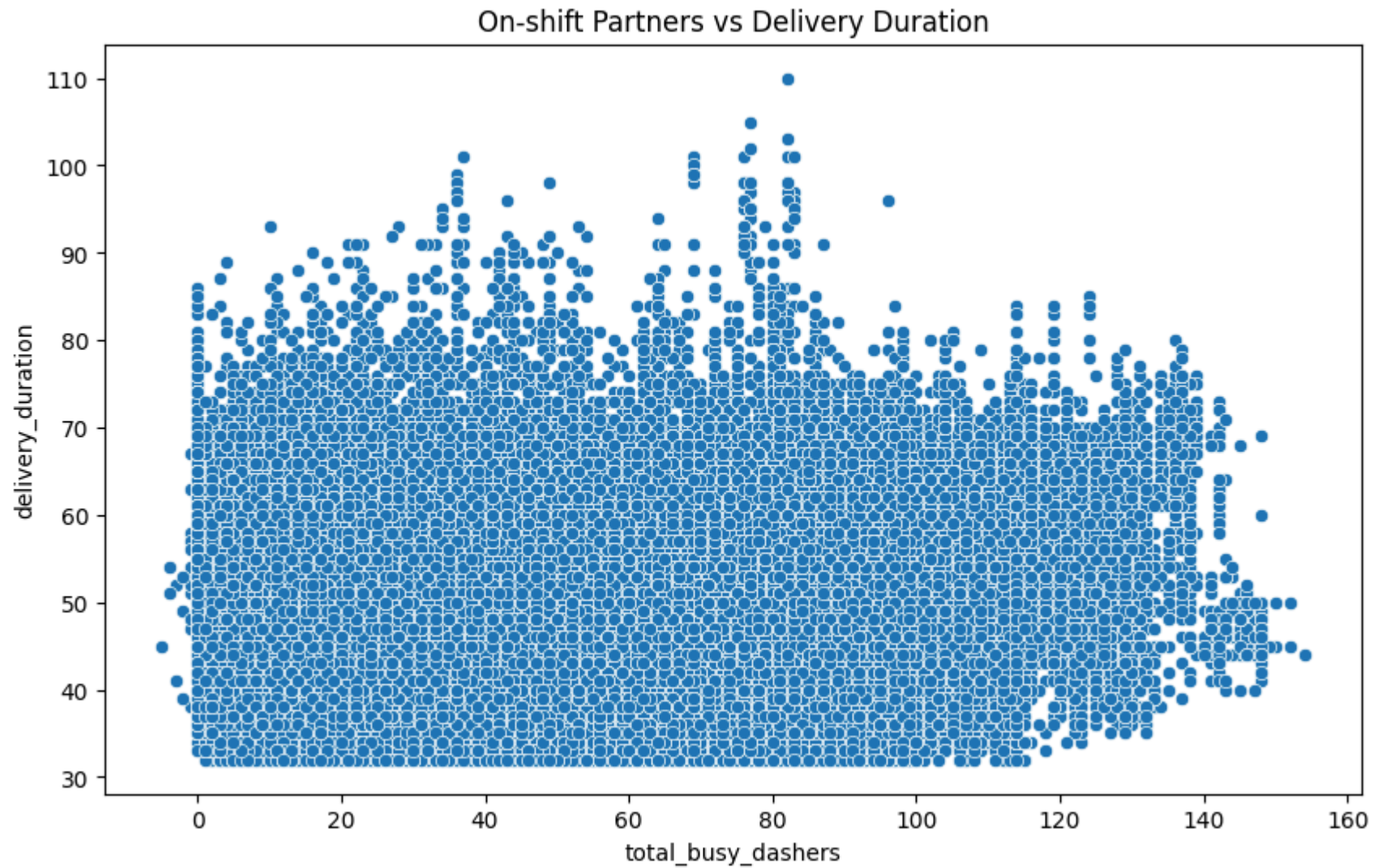
```
In [33]: # Day of week vs delivery duration
```

```
plt.figure(figsize=(10, 6))  
sns.boxplot(x = 'order_dayofweek', y = 'delivery_duration', data = df)  
plt.title('Delivery Time vs Day of Week')  
plt.show()
```



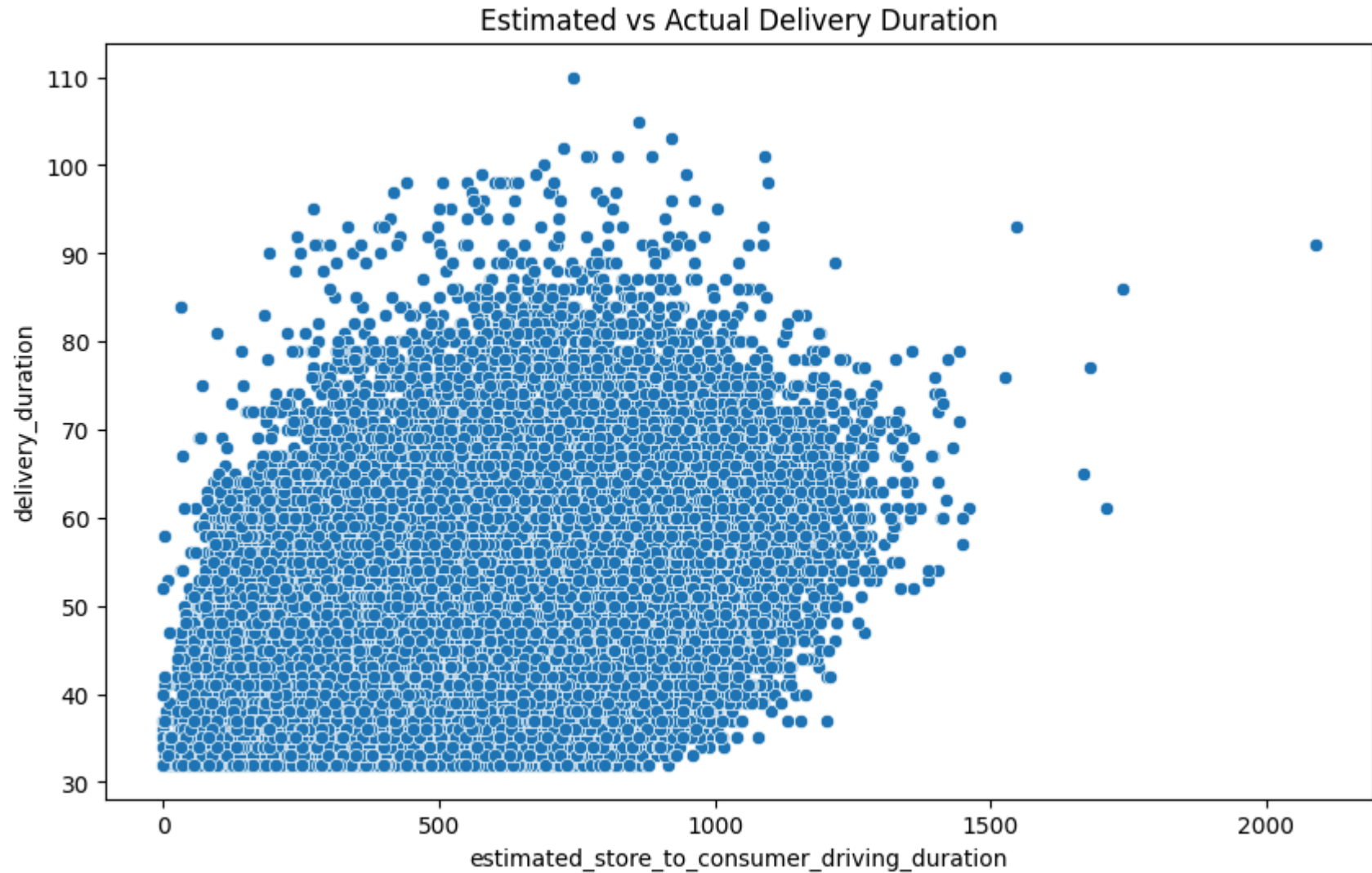
```
In [34]: # Delivery partners vs delivery duration
```

```
plt.figure(figsize=(10, 6))  
sns.scatterplot(x = 'total_busy_dashers', y = 'delivery_duration', data = df)  
plt.title('On-shift Partners vs Delivery Duration')  
plt.show()
```



```
In [35]: # Driving duration estimate vs actual duration
```

```
plt.figure(figsize=(10, 6))  
sns.scatterplot(x = 'estimated_store_to_consumer_driving_duration', y = 'delivery_duration', data = df)  
plt.title('Estimated vs Actual Delivery Duration')  
plt.show()
```

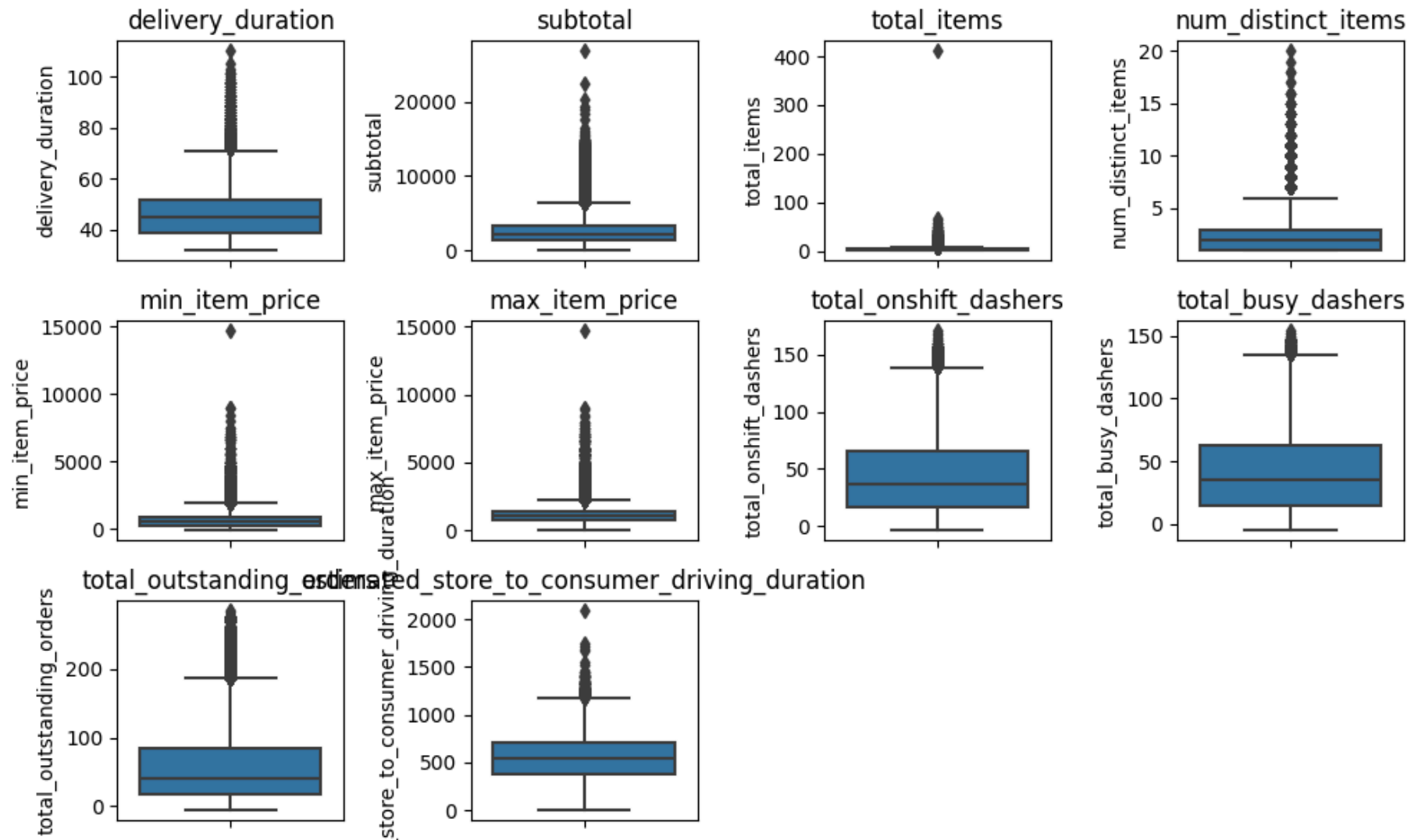


In [36]: *# Outlier Detection*

*# boxplots & IQR method for numerical columns*

```
num_cols = ['delivery_duration', 'subtotal', 'total_items', 'num_distinct_items',  
            'min_item_price', 'max_item_price',  
            'total_onshift_dashers', 'total_busy_dashers',  
            'total_outstanding_orders', 'estimated_store_to_consumer_driving_duration']
```

```
In [37]: # Boxplots for numerical features
plt.figure(figsize=(10, 6))
for i, j in enumerate(num_cols, 1):
    plt.subplot(3, 4, i)
    sns.boxplot(y = df[j])
    plt.title(j)
plt.tight_layout()
plt.show()
```



```
In [38]: # Removing Outliers (IQR method)
```

```
def remove_Outliers(data, col):  
    Q1 = data[col].quantile(0.25)  
    Q2 = data[col].quantile(0.75)  
    IQR = Q2 - Q1  
    lower = Q1 - 1.5 * IQR  
    upper = Q2 + 1.5 * IQR  
  
    return data[(data[col] >= lower) & (data[col] <= upper)]
```

```
In [39]: df_clean = remove_Outliers(df, 'delivery_duration')  
df_clean.shape
```

```
Out[39]: (174028, 94)
```

```
In [40]: df.shape
```

```
Out[40]: (175777, 94)
```

```
In [41]: num_cols = df.select_dtypes(include=['int64', 'float64']).columns  
  
df_clean = df.copy()  
for col in num_cols:  
    df_clean = remove_Outliers(df_clean, col)  
  
print("Before:", df.shape)  
print("After removing outliers from all num cols:", df_clean.shape)
```

```
Before: (175777, 94)
```

```
After removing outliers from all num cols: (144990, 94)
```

```
In [42]: # Data Splitting
```

```
from sklearn.model_selection import train_test_split
```

```
In [43]: X = df_clean.drop(columns=['delivery_duration', 'created_at', 'actual_delivery_time'])
y = df_clean['delivery_duration']
```

```
In [44]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state= 42)
```

```
In [45]: # Data Scaling (for Neural Networks)
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
```

```
In [46]: X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```
In [47]: X_train_scaled
```

```
Out[47]: array([[ -0.55842349, -0.49823908, -0.42800158, ..., -0.55829776,
        -0.06612705, -0.01098693],
       [ 0.92978203,  0.18706564,  0.04700813, ..., -0.55829776,
        -0.06612705, -0.01098693],
       [-1.30252624,  2.24297982,  2.93456719, ..., -0.55829776,
        -0.06612705, -0.01098693],
       ...,
       [ 0.92978203,  0.18706564,  0.13034317, ...,  1.7911589 ,
        -0.06612705, -0.01098693],
       [ 1.67388479,  0.87237037,  0.62201989, ..., -0.55829776,
        -0.06612705, -0.01098693],
       [ 0.92978203,  2.24297982,  2.06704945, ...,  1.7911589 ,
        -0.06612705, -0.01098693]])
```

```
In [48]: X_test_scaled
```

```
Out[48]: array([[ 0.92978203,  0.18706564, -0.15549601, ...,  1.7911589 ,
                -0.06612705, -0.01098693],
                [-0.55842349,  0.18706564, -0.03216015, ..., -0.55829776,
                -0.06612705, -0.01098693],
                [-1.30252624, -0.49823908, -0.53800383, ..., -0.55829776,
                -0.06612705, -0.01098693],
                ...,
                [-0.55842349,  0.18706564,  0.18451095, ..., -0.55829776,
                -0.06612705, -0.01098693],
                [-1.30252624, -1.18354381, -1.0121802 , ..., -0.55829776,
                -0.06612705, -0.01098693],
                [ 0.92978203, -0.49823908, -1.01301355, ...,  1.7911589 ,
                -0.06612705, -0.01098693]])
```

```
In [49]: # Training a Random Forest Model
from sklearn.ensemble import RandomForestRegressor
import numpy as pd
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

```
In [50]: rf = RandomForestRegressor(n_estimators= 200, max_depth=15, random_state=42)
rf.fit(X_train, y_train)
```

```
Out[50]: RandomForestRegressor(max_depth=15, n_estimators=200, random_state=42)
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.
```

```
In [51]: y_pred = rf.predict(X_test)
```



In [52]:

```
print("Random Forest Results:")
print("MAE:", mean_absolute_error(y_test, y_pred))
print("RMSE:", np.sqrt(mean_squared_error(y_test, y_pred)))
print("R²:", r2_score(y_test, y_pred))
```

Random Forest Results:  
MAE: 1.4961055591369534  
RMSE: 1.9876598310213827  
R²: 0.9382126362735221

In [ ]:

```
from sklearn.model_selection import GridSearchCV

params = {
    'n_estimators': [100, 200, 300],
    'max_depth': [10, 15, 20]
}
```

In [54]: *# Neural Network Architecture (Keras / TensorFlow)*

```
import tensorflow as tf
from tensorflow.keras import layers, models
```

In [55]: *# Define architecture*

```
nn = models.Sequential([
    layers.Dense(128, activation='relu', input_shape=(X_train_scaled.shape[1],)),
    layers.Dense(64, activation='relu'),
    layers.Dense(32, activation='relu'),
    layers.Dense(1) # Regression → 1 output
])
```

*# Compile model*

```
nn.compile(optimizer='adam', loss='mse', metrics=['mae'])
```

```
In [56]: history = nn.fit(
            X_train_scaled, y_train,
            validation_split=0.2,
            epochs=50,
            batch_size=32,
            verbose=1
        )










# Evaluate
y_pred_nn = nn.predict(X_test_scaled).flatten()

print("Neural Network Results:")
print("MAE:", mean_absolute_error(y_test, y_pred_nn))
print("RMSE:", np.sqrt(mean_squared_error(y_test, y_pred_nn)))
print("R²:", r2_score(y_test, y_pred_nn))
```

```
Epoch 1/50
2900/2900 ————— 2s 472us/step - loss: 36.0531 - mae: 2.8030 - val_loss: 4.3845 - val_mae: 1.4796
Epoch 2/50
2900/2900 ————— 1s 448us/step - loss: 3.5551 - mae: 1.3298 - val_loss: 3.0257 - val_mae: 1.1476
Epoch 3/50
2900/2900 ————— 1s 450us/step - loss: 2.2302 - mae: 0.9914 - val_loss: 1.9532 - val_mae: 0.8524
Epoch 4/50
2900/2900 ————— 1s 460us/step - loss: 1.5394 - mae: 0.7937 - val_loss: 1.4698 - val_mae: 0.6903
Epoch 5/50
2900/2900 ————— 1s 452us/step - loss: 1.2327 - mae: 0.6914 - val_loss: 1.1798 - val_mae: 0.7304
Epoch 6/50
2900/2900 ————— 1s 451us/step - loss: 1.0237 - mae: 0.6334 - val_loss: 1.3014 - val_mae: 0.6126
Epoch 7/50
2900/2900 ————— 1s 452us/step - loss: 0.9957 - mae: 0.6017 - val_loss: 0.9908 - val_mae: 0.6360
Epoch 8/50
2900/2900 ————— 1s 463us/step - loss: 0.8670 - mae: 0.5722 - val_loss: 1.0972 - val_mae: 0.6004
Epoch 9/50
2900/2900 ————— 1s 451us/step - loss: 0.8317 - mae: 0.5504 - val_loss: 0.7868 - val_mae: 0.5099
Epoch 10/50
2900/2900 ————— 1s 452us/step - loss: 0.7470 - mae: 0.5303 - val_loss: 0.7365 - val_mae: 0.4896
Epoch 11/50
2900/2900 ————— 1s 452us/step - loss: 0.7141 - mae: 0.5226 - val_loss: 0.9662 - val_mae: 0.5086
Epoch 12/50
2900/2900 ————— 1s 452us/step - loss: 0.6683 - mae: 0.5054 - val_loss: 0.5785 - val_mae: 0.4668
Epoch 13/50
2900/2900 ————— 1s 454us/step - loss: 0.6368 - mae: 0.4881 - val_loss: 0.5725 - val_mae: 0.4549
Epoch 14/50
2900/2900 ————— 1s 456us/step - loss: 0.6075 - mae: 0.4781 - val_loss: 0.5805 - val_mae: 0.4
```

```
400
Epoch 15/50
2900/2900 ————— 1s 453us/step - loss: 0.5814 - mae: 0.4731 - val_loss: 1.0712 - val_mae: 0.7
384
Epoch 16/50
2900/2900 ————— 1s 489us/step - loss: 0.5567 - mae: 0.4591 - val_loss: 0.5209 - val_mae: 0.4
645
Epoch 17/50
2900/2900 ————— 1s 471us/step - loss: 0.5317 - mae: 0.4524 - val_loss: 0.7702 - val_mae: 0.5
344
Epoch 18/50
2900/2900 ————— 1s 460us/step - loss: 0.5232 - mae: 0.4514 - val_loss: 0.4897 - val_mae: 0.4
449
Epoch 19/50
2900/2900 ————— 1s 454us/step - loss: 0.4758 - mae: 0.4379 - val_loss: 0.6724 - val_mae: 0.4
433
Epoch 20/50
2900/2900 ————— 1s 453us/step - loss: 0.4799 - mae: 0.4349 - val_loss: 0.5424 - val_mae: 0.4
191
Epoch 21/50
2900/2900 ————— 1s 454us/step - loss: 0.4329 - mae: 0.4273 - val_loss: 0.4603 - val_mae: 0.4
115
Epoch 22/50
2900/2900 ————— 1s 454us/step - loss: 0.4514 - mae: 0.4261 - val_loss: 0.4249 - val_mae: 0.3
880
Epoch 23/50
2900/2900 ————— 1s 457us/step - loss: 0.4139 - mae: 0.4160 - val_loss: 0.5186 - val_mae: 0.4
048
Epoch 24/50
2900/2900 ————— 1s 458us/step - loss: 0.4364 - mae: 0.4228 - val_loss: 0.4133 - val_mae: 0.4
286
Epoch 25/50
2900/2900 ————— 1s 463us/step - loss: 0.4006 - mae: 0.4124 - val_loss: 0.5175 - val_mae: 0.4
021
Epoch 26/50
2900/2900 ————— 1s 461us/step - loss: 0.3959 - mae: 0.4104 - val_loss: 0.3316 - val_mae: 0.3
808
Epoch 27/50
2900/2900 ————— 1s 460us/step - loss: 0.3911 - mae: 0.4079 - val_loss: 0.4003 - val_mae: 0.3
863
Epoch 28/50
2900/2900 ————— 1s 467us/step - loss: 0.3675 - mae: 0.4026 - val_loss: 0.4804 - val_mae: 0.4
```

```
322
Epoch 29/50
2900/2900 ————— 1s 461us/step - loss: 0.3621 - mae: 0.3993 - val_loss: 0.3770 - val_mae: 0.3
894
Epoch 30/50
2900/2900 ————— 1s 461us/step - loss: 0.3417 - mae: 0.3916 - val_loss: 0.4813 - val_mae: 0.4
080
Epoch 31/50
2900/2900 ————— 1s 460us/step - loss: 0.3919 - mae: 0.4011 - val_loss: 0.4085 - val_mae: 0.3
880
Epoch 32/50
2900/2900 ————— 1s 461us/step - loss: 0.3200 - mae: 0.3867 - val_loss: 0.3905 - val_mae: 0.3
735
Epoch 33/50
2900/2900 ————— 1s 461us/step - loss: 0.3450 - mae: 0.3917 - val_loss: 0.4763 - val_mae: 0.3
864
Epoch 34/50
2900/2900 ————— 1s 474us/step - loss: 0.3315 - mae: 0.3857 - val_loss: 0.3528 - val_mae: 0.3
985
Epoch 35/50
2900/2900 ————— 1s 461us/step - loss: 0.3251 - mae: 0.3817 - val_loss: 0.3343 - val_mae: 0.3
594
Epoch 36/50
2900/2900 ————— 1s 470us/step - loss: 0.3147 - mae: 0.3784 - val_loss: 0.4872 - val_mae: 0.5
155
Epoch 37/50
2900/2900 ————— 1s 462us/step - loss: 0.3138 - mae: 0.3768 - val_loss: 0.3716 - val_mae: 0.3
940
Epoch 38/50
2900/2900 ————— 1s 460us/step - loss: 0.3056 - mae: 0.3738 - val_loss: 0.4307 - val_mae: 0.4
267
Epoch 39/50
2900/2900 ————— 1s 459us/step - loss: 0.2862 - mae: 0.3683 - val_loss: 0.3511 - val_mae: 0.3
631
Epoch 40/50
2900/2900 ————— 1s 468us/step - loss: 0.2966 - mae: 0.3718 - val_loss: 0.3818 - val_mae: 0.3
666
Epoch 41/50
2900/2900 ————— 1s 460us/step - loss: 0.2972 - mae: 0.3667 - val_loss: 0.3703 - val_mae: 0.3
716
Epoch 42/50
2900/2900 ————— 1s 459us/step - loss: 0.3008 - mae: 0.3671 - val_loss: 0.3043 - val_mae: 0.3
```

666  
Epoch 43/50  
**2900/2900**  **1s** 471us/step - loss: 0.2842 - mae: 0.3641 - val\_loss: 0.2913 - val\_mae: 0.3574  
Epoch 44/50  
**2900/2900**  **1s** 466us/step - loss: 0.2829 - mae: 0.3650 - val\_loss: 0.3054 - val\_mae: 0.3562  
Epoch 45/50  
**2900/2900**  **1s** 461us/step - loss: 0.2847 - mae: 0.3608 - val\_loss: 0.3715 - val\_mae: 0.3945  
Epoch 46/50  
**2900/2900**  **1s** 459us/step - loss: 0.2712 - mae: 0.3565 - val\_loss: 0.3526 - val\_mae: 0.3855  
Epoch 47/50  
**2900/2900**  **1s** 459us/step - loss: 0.2702 - mae: 0.3556 - val\_loss: 0.4198 - val\_mae: 0.4538  
Epoch 48/50  
**2900/2900**  **1s** 461us/step - loss: 0.2798 - mae: 0.3586 - val\_loss: 0.3838 - val\_mae: 0.4426  
Epoch 49/50  
**2900/2900**  **1s** 469us/step - loss: 0.2582 - mae: 0.3522 - val\_loss: 0.2821 - val\_mae: 0.3441  
Epoch 50/50  
**2900/2900**  **1s** 465us/step - loss: 0.2721 - mae: 0.3542 - val\_loss: 0.2557 - val\_mae: 0.3410  
**907/907**  **0s** 231us/step  
Neural Network Results:  
MAE: 0.3387588443357506  
RMSE: 0.5009834246474352  
R<sup>2</sup>: 0.9960747957728479

```
In [57]: from sklearn.model_selection import RandomizedSearchCV
from sklearn.ensemble import RandomForestRegressor

params = {
    'n_estimators': [100, 200, 300],
    'max_depth': [10, 15, 20]
}

search = RandomizedSearchCV(
    RandomForestRegressor(random_state=42),
    param_distributions=params,
    n_iter=5,           # try only 5 random combos
    cv=3,
    scoring='r2',
    n_jobs=-1,
    random_state=42
)

search.fit(X_train, y_train)
print("Best RF params:", search.best_params_)
```

Best RF params: {'n\_estimators': 300, 'max\_depth': 20}



In [ ]:

In [ ]:

In [ ]:

In [ ]: