Report: Order Delivery Time Prediction

Objectives

The objective of this assignment is to build a regression model that predicts the delivery time for orders placed through Porter. The model will use various features such as the items ordered, the restaurant location, the order protocol, and the availability of delivery partners.

The key goals are:

- Predict the delivery time for an order based on multiple input features
- Improve delivery time predictions to optimise operational efficiency
- Understand the key factors influencing delivery time to enhance the model's accuracy

Data Pipeline

The data pipeline for this assignment will involve the following steps:

1. **Data Loading**
2. **Data Preprocessing and Feature Engineering**
3. **Exploratory Data Analysis**
4. **Model Building**
5. **Model Inference**

Importing Necessary Libraries

[1]:
```
# Import essential libraries for data manipulation and analysis
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
#data preprocessing
from sklearn.model_selection import train_test_split
import warnings
warnings.filterwarnings(action="ignore")
```

1. Loading the data

```
[3]: # Importing the file porter_data_1.csv
#Load the data set
df=pd.read_csv(r"C:/Users/Thara/Downloads/Delivery_Starter/porter_data_1.csv")
df.head()
```

[3]:

	market_id	created_at	actual_delivery_time	store_primary_category	order_protocol	total_items	subtotal	num_distinct_items	min_item_price	max_iten
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	

2.

```
[65]: # Importing the file porter_data_1.csv
#Load the data set
df=pd.read_csv(r"C:/Users\AMALDAS/Downloads/Delivery_Starter/porter_data_1.csv")
df.head()
```

[65]:

	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_
0	1.0	2015-02-06 22:24:17	2015-02-06 23:11:17	4	1.0	4	3441	4	557	1239	
1	2.0	2015-02-10 21:49:25	2015-02-10 22:33:25	46	2.0	1	1900	1	1400	1400	
2	2.0	2015-02-16 00:11:35	2015-02-16 01:06:35	36	3.0	4	4771	3	820	1604	
3	1.0	2015-02-12 03:36:46	2015-02-12 04:35:46	38	1.0	1	1525	1	1525	1525	
4	1.0	2015-01-27 02:12:36	2015-01-27 02:58:36	38	1.0	2	3620	2	1425	2195	

```
[3]: df.shape
```

```
[3]: (175777, 14)
```

```
[4]: df.describe()
```

	market_id	store_primary_category	order_protocol	total_items	subtotal	num_distinct_items	min_item_price	max_item_price	total_onshift_dashers
count	175777.000000	175777.000000	175777.000000	175777.000000	175777.000000	175777.000000	175777.000000	175777.000000	175777.000000
mean	2.743726	35.887949	2.911752	3.204976	2697.111147	2.675060	684.965433	1160.158616	44.918664
std	1.330963	20.728254	1.513128	2.674055	1828.554893	1.625681	519.882924	560.828571	34.544724
min	1.000000	0.000000	1.000000	1.000000	0.000000	1.000000	-86.000000	0.000000	-4.000000
25%	2.000000	18.000000	1.000000	2.000000	1412.000000	1.000000	299.000000	799.000000	17.000000
50%	2.000000	38.000000	3.000000	3.000000	2224.000000	2.000000	595.000000	1095.000000	37.000000
75%	4.000000	55.000000	4.000000	4.000000	3410.000000	3.000000	942.000000	1395.000000	66.000000
max	6.000000	72.000000	7.000000	411.000000	26800.000000	20.000000	14700.000000	14700.000000	171.000000

```
[5]: #checking null values
df.isnull().sum()
```

```
[5]: 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
distance                    0
dtype: int64
```

3. Data Preprocessing and Feature Engineering

2.1 Fixing the Datatypes

[6]:
```python
# Convert 'created_at' and 'actual_delivery_time' columns to datetime format
datetime_columns = ['created_at','actual_delivery_time']
for col in datetime_columns:
    df[col] = pd.to_datetime(df[col], errors='coerce')  # coerce to handle invalid formats

# Check result
print(df[datetime_columns].dtypes)
```

```
created_at              datetime64[ns]
actual_delivery_time    datetime64[ns]
dtype: object
```

[7]:
```python
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  datetime64[ns]
 2   actual_delivery_time      175777 non-null  datetime64[ns]
 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  distance                  175777 non-null  float64
dtypes: datetime64[ns](2), float64(6), int64(6)
memory usage: 18.8 MB
```

Convert categorical fields to appropriate data type

[9]:
```python
# Convert categorical features to category type
categorical_columns = ['market_id','store_primary_category','order_protocol']

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


[9]:
```python
# Convert categorical features to category type
categorical_columns = ['market_id','store_primary_category','order_protocol']

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


Feature Engineering

```python
# Calculate time taken in minutes
df['delivery_time_minutes'] = (df['actual_delivery_time'] - df['created_at']).dt.seconds/60
```

```
[13]: df.select_dtypes(include=['object', 'bool', 'category']).describe().T
```

[13]:

	count	unique	top	freq
market_id	175777.0	6.0	2.0	53469.0
store_primary_category	175777.0	73.0	4.0	18183.0
order_protocol	175777.0	7.0	1.0	48404.0

```
[14]: df.select_dtypes(include=['number']).describe(percentiles=[0.01, 0.05, .25, .5, .75, 0.9, 0.95, 0.99]).T
```

[14]:

	count	mean	std	min	1%	5%	25%	50%	75%	90%	95%	99%	max
total_items	175777.0	3.204976	2.674055	1.0	1.00	1.00	2.00	3.00	4.00	6.00	7.00	12.00	411.00
subtotal	175777.0	2697.111147	1828.554893	0.0	537.00	805.00	1412.00	2224.00	3410.00	4970.00	6250.00	9460.00	26800.00
num_distinct_items	175777.0	2.675060	1.625681	1.0	1.00	1.00	1.00	2.00	3.00	5.00	6.00	8.00	20.00
min_item_price	175777.0	684.965433	519.882924	-86.0	0.00	125.00	299.00	595.00	942.00	1295.00	1580.00	2500.00	14700.00
max_item_price	175777.0	1160.158616	560.828571	0.0	259.00	440.00	799.00	1095.00	1395.00	1795.00	2100.00	3100.00	14700.00
total_onshift_dashers	175777.0	44.918664	34.544724	-4.0	0.00	4.00	17.00	37.00	66.00	98.00	115.00	136.00	171.00
total_busy_dashers	175777.0	41.861381	32.168505	-5.0	0.00	3.00	15.00	35.00	63.00	90.00	105.00	126.00	154.00
total_outstanding_orders	175777.0	58.230115	52.731043	-6.0	0.00	3.00	17.00	41.00	85.00	140.00	169.00	213.00	285.00
distance	175777.0	21.843090	8.748712	0.0	4.44	7.72	15.36	21.76	28.12	33.32	36.32	41.84	83.52
delivery_time_minutes	175777.0	46.203013	9.327424	32.0	32.00	33.00	39.00	45.00	52.00	59.00	63.00	71.00	110.00

```
[15]: for column in df.select_dtypes(include=['object', 'bool', 'category']).columns:
          print(df[column].value_counts(normalize=True, dropna=False) * 100)
          print("*" * 70, '\n')
```

```
market_id
2.0    30.418655
4.0    26.295818
1.0    21.114822
3.0    11.989623
5.0     9.818122
6.0     0.362960
Name: proportion, dtype: float64
**********************************************************************

store_primary_category
4     10.344357
55     8.957372
46     8.866917
13     5.640670
58     5.117279
         ...
1      0.005689
43     0.005120
8      0.001138
3      0.000569
21     0.000569
Name: proportion, Length: 73, dtype: float64
**********************************************************************

order_protocol
1.0    27.537164
3.0    26.809537
5.0    23.561103
2.0    11.884376
4.0     9.811295
6.0     0.385716
7.0     0.010809
Name: proportion, dtype: float64
**********************************************************************
```

[16]:
```python
# Negative values
numeric_cols = df.select_dtypes(include=[np.number]).columns
columns_with_negatives = df[numeric_cols].columns[(df[numeric_cols] < 0).any()]
neg_sum = (df[columns_with_negatives] < 0).sum()
neg_pct = (df[columns_with_negatives] < 0).mean() * 100

pd.DataFrame({'Count': neg_sum,'Percentage (%)': neg_pct})
```

[16]:

	Count	Percentage (%)
min_item_price	12	0.006827
total_onshift_dashers	21	0.011947
total_busy_dashers	21	0.011947
total_outstanding_orders	41	0.023325

[17]:
```python
# Dropping the negative values as it's might impact the study
neg_rw = (df[numeric_cols]< 0).any(axis=1)
porter_data = df.loc[~neg_rw]

df.shape
```

[17]: (175777, 15)

[18]:
```python
df.describe().round(3).T
```

[19]:
```python
# Extract the hour and day of week from the 'created_at' timestamp
df['created_hour'] = df['created_at'].dt.hour
df['is_weekend'] = df['created_at'].dt.dayofweek.apply(lambda x: 0 if x < 5 else 1)
df['day_of_week'] = df['created_at'].dt.dayofweek
# Create a categorical feature 'isWeekend'

df['is_weekend'] = df['is_weekend'].astype('category')
df.head()
```

[19]:

	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_
0	1.0	2015-02-06 22:24:17	2015-02-06 23:11:17	4	1.0	4	3441	4	557	1239	
1	2.0	2015-02-10 21:49:25	2015-02-10 22:33:25	46	2.0	1	1900	1	1400	1400	
2	2.0	2015-02-16 00:11:35	2015-02-16 01:06:35	36	3.0	4	4771	3	820	1604	
3	1.0	2015-02-12 03:36:46	2015-02-12 04:35:46	38	1.0	1	1525	1	1525	1525	
4	1.0	2015-01-27 02:12:36	2015-01-27 02:58:36	38	1.0	2	3620	2	1425	2195	

[20]:
```python
# Drop unnecessary columns
df = df.drop(columns=['created_at', 'actual_delivery_time', 'store_primary_category'])
df.head()
```

Creating training and validation sets

Define target and input features

```
# Define target variable (y) and features (X)
X = df.drop(columns=['delivery_time_minutes'])
y = df['delivery_time_minutes']

X.head()
```

	market_id	order_protocol	total_items	subtotal	num_distinct_items	min_item_price	max_item_price	total_onshift_dashers	total_busy_dashers	total_outstanding_ord
0	1.0	1.0	4	3441	4	557	1239	33.0	14.0	2
1	2.0	2.0	1	1900	1	1400	1400	1.0	2.0	
2	2.0	3.0	4	4771	3	820	1604	8.0	6.0	1
3	1.0	1.0	1	1525	1	1525	1525	5.0	6.0	
4	1.0	1.0	2	3620	2	1425	2195	5.0	5.0	

```
y.head()
```

```
0    47.0
1    44.0
2    55.0
3    59.0
4    46.0
Name: delivery_time_minutes, dtype: float64
```

4. Exploratory Data Analysis on Training Data

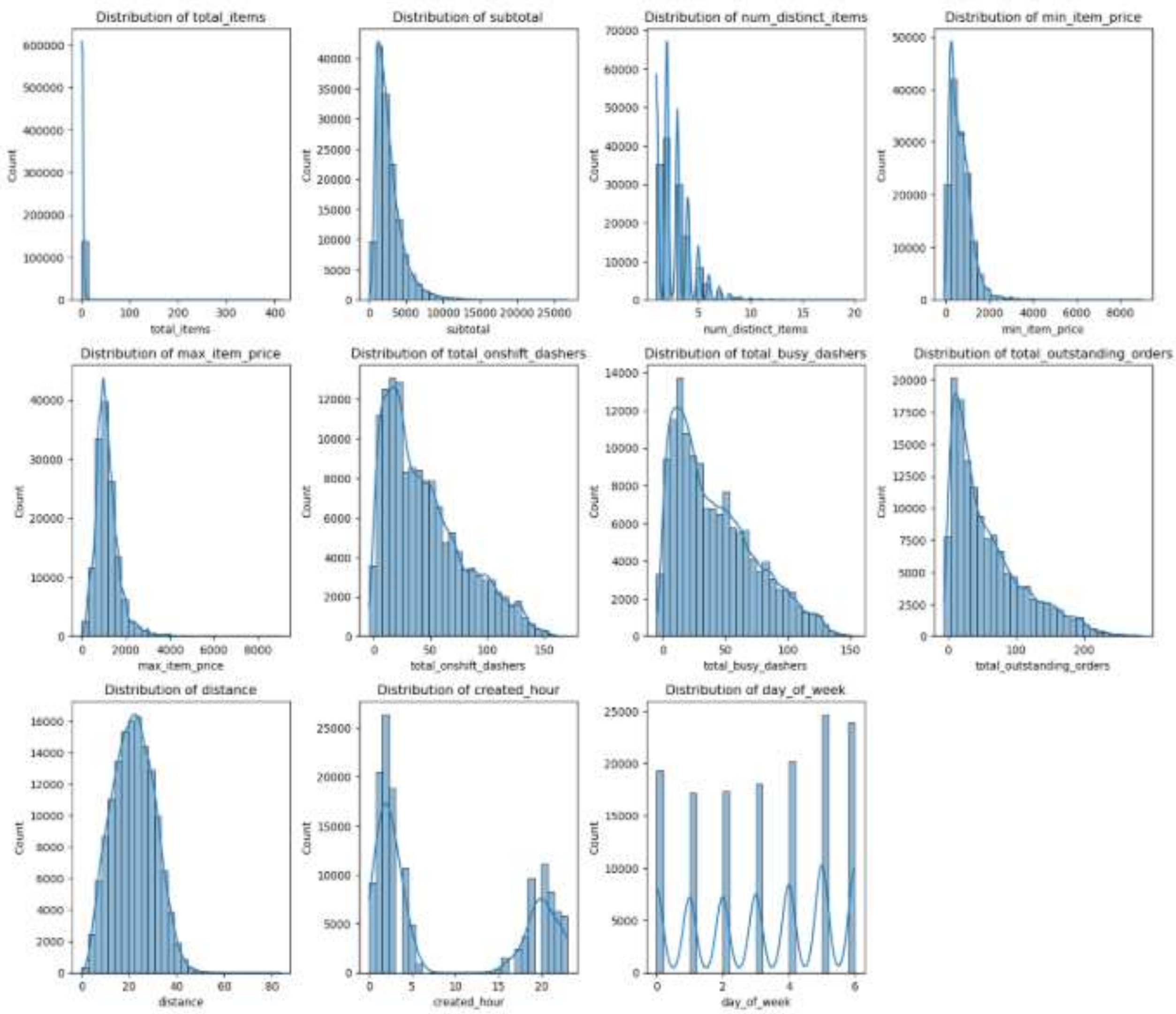
1. Analysing the correlation between variables to identify patterns and relationships
2. Identifying and addressing outliers to ensure the integrity of the analysis
3. Exploring the relationships between variables and examining the distribution of the data for better insights

```
[93]: # Define numerical and categorical columns for easy EDA and data manipulation
numerical_columns = X_train.select_dtypes(include=['number']).columns.tolist()
categorical_columns = X_train.select_dtypes(include=['object', 'bool', 'category']).columns.tolist()

# Printing outputs
print("Numerical Variables:")
print(numerical_columns)

print("\nCategorical Variables:")
print(categorical_columns)
```

```
Numerical Variables:
['total_items', 'subtotal', 'num_distinct_items', 'min_item_price', 'max_item_price', 'total_onshift_dashers', 'total_busy_dashers', 'total_outstanding_orders', 'distance', 'created_hour', 'day_of_week']

Categorical Variables:
['market_id', 'order_protocol', 'is_weekend']
```

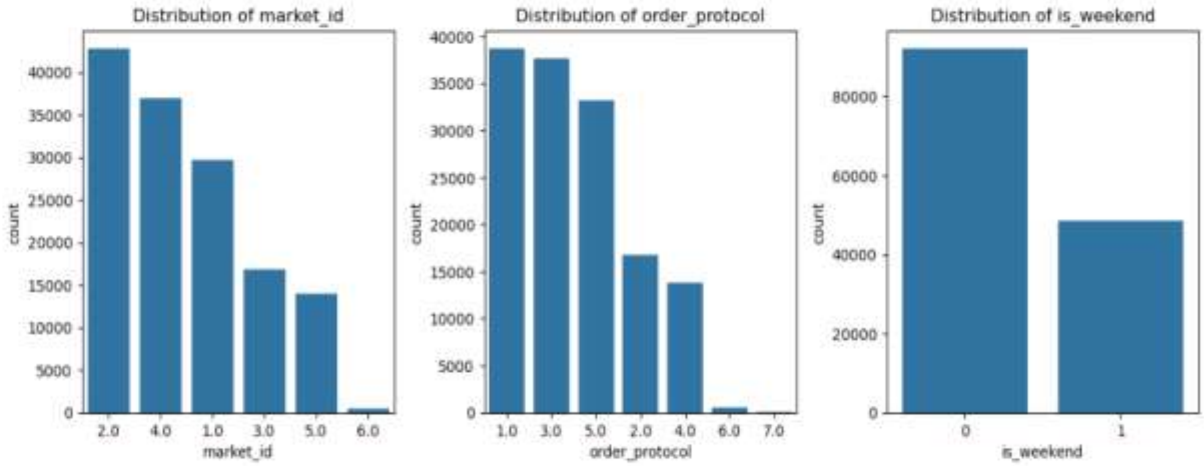
Plot distributions for numerical columns in the training set to understand their spread and any skewness

[94]:
```
# Plot distributions for all numerical columns
plt.figure(figsize=(15, 16))
for i, col in enumerate(numerical_columns, 1):
    plt.subplot(4, 4, i)
    sns.histplot(X_train[col], kde=True, bins=30)
    plt.title(f"Distribution of {col}")
plt.tight_layout()
plt.show()
```



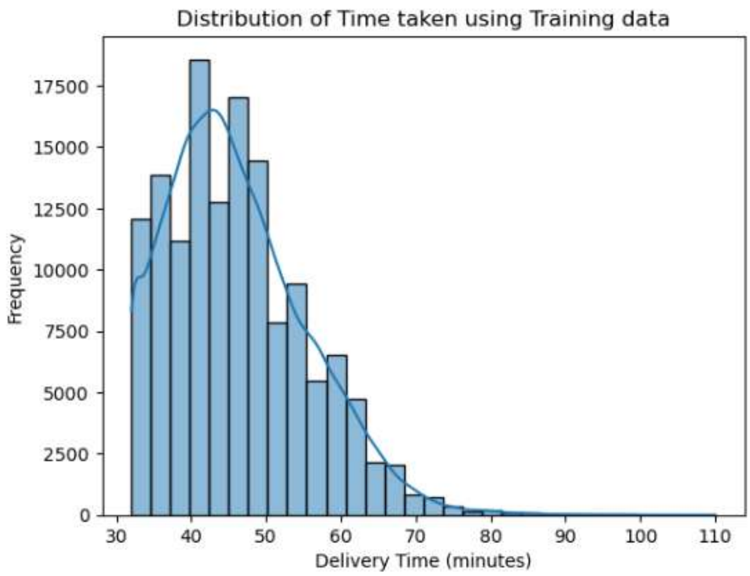
Check the distribution of categorical features

[95]:
```
# Distribution of categorical columns
plt.figure(figsize=(12, 8))
for i, col in enumerate(categorical_columns, 1):
    plt.subplot(2, 3, i)
    sns.countplot(x=X_train[col], order=X_train[col].value_counts().index,)
    plt.title(f"Distribution of {col}")

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



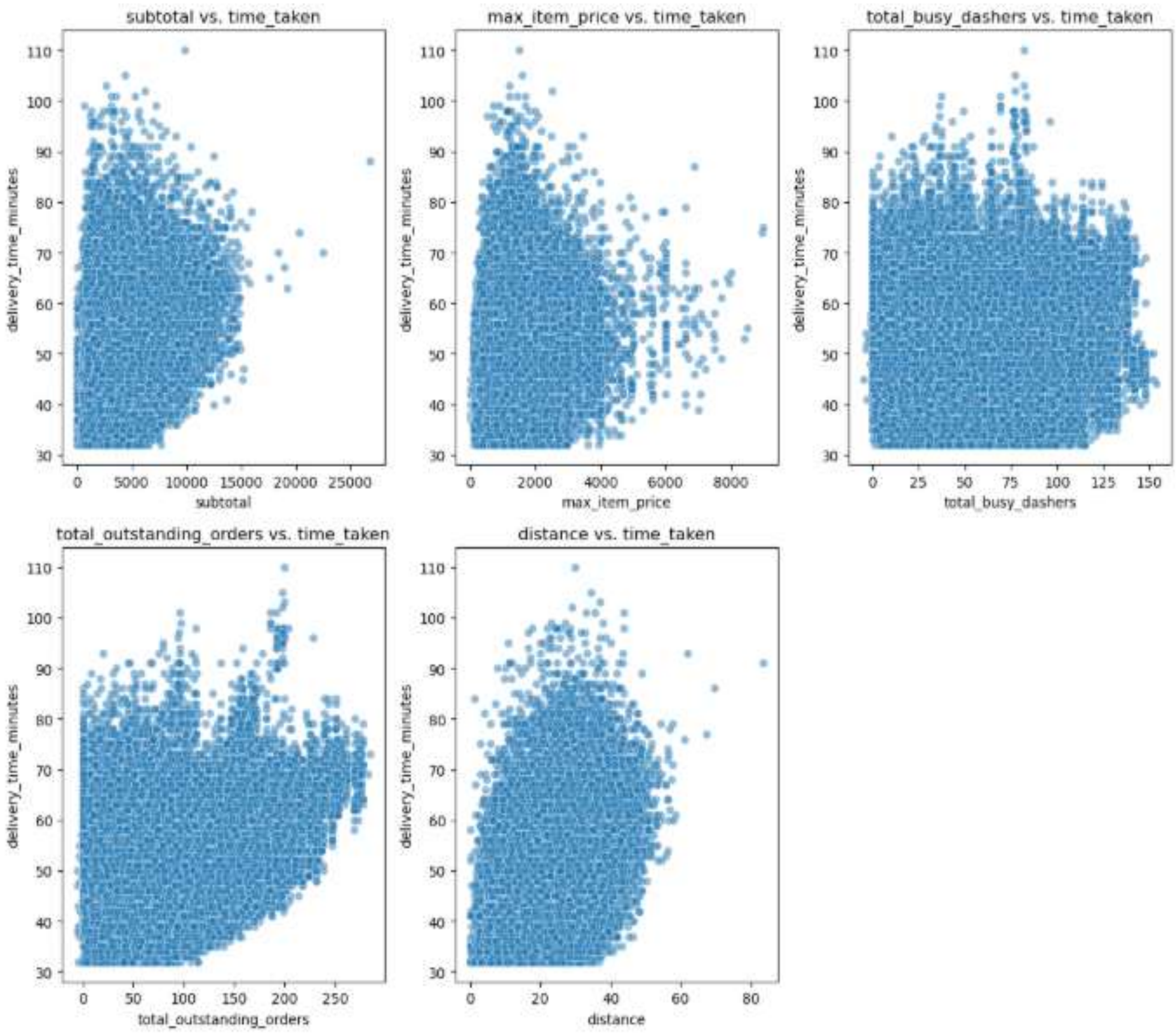
Visualise the distribution of the target variable to understand its spread and any skewness

[96]:
```
# Distribution of time_taken
sns.histplot(y_train, bins=30, kde=True)

plt.xlabel("Delivery Time (minutes)")
plt.ylabel("Frequency")
plt.title("Distribution of Time taken using Training data")

plt.show()
```

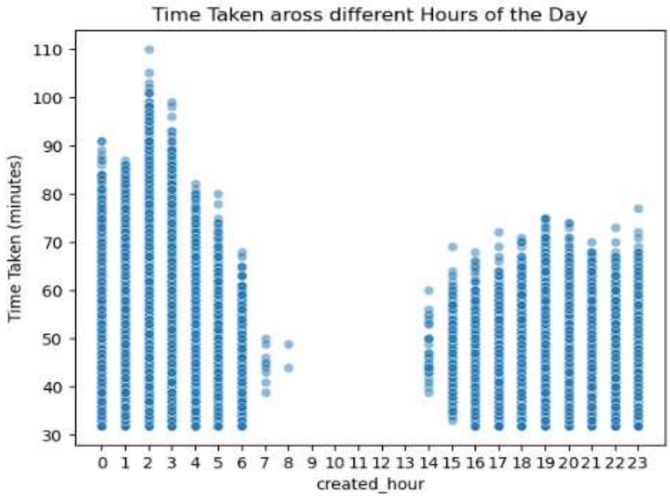


Relationships Between Features

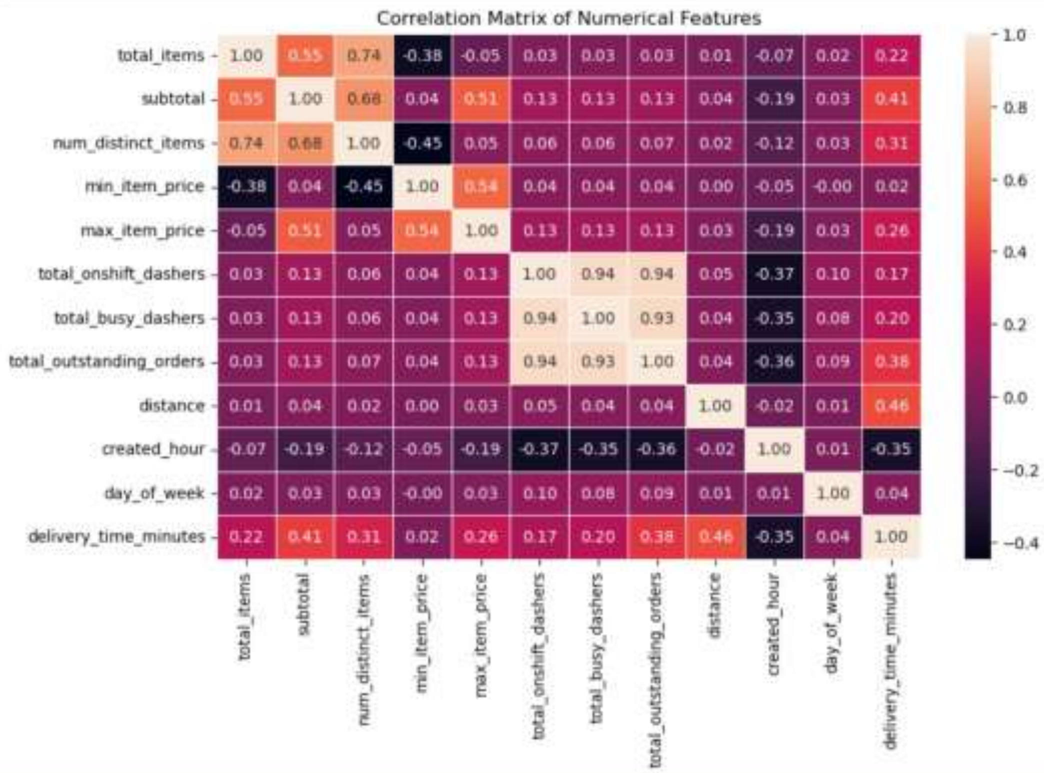
```python
# Scatter plot to visualise the relationship between time_taken and other features
important_features = ['subtotal', 'max_item_price', 'total_busy_dashers', 'total_outstanding_orders', 'distance']

fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(12, 10))
axes = axes.flatten()

for i, col in enumerate(important_features):
    sns.scatterplot(x=X_train[col], y=y_train, alpha=0.5, ax=axes[i])
    axes[i].set_title(f'{col} vs. time_taken')

fig.delaxes(axes[-1])
plt.tight_layout()
plt.show()
```



```
[98]: # Show the distribution of time_taken for different hours
sns.scatterplot(x=X_train['created_hour'], y=y_train, alpha=0.5)
plt.xlabel("created_hour")
plt.ylabel("Time Taken (minutes)")
plt.title("Time Taken aross different Hours of the Day")
plt.xticks(range(0, 24))
plt.show()
```



Correlation Analysis



Drop the columns with weak correlations with the target variable

[100]:
```python
# Drop 3-5 weakly correlated columns from training dataset
correlations = X_train[numerical_columns].corrwith(y_train)
threshold = 0.1
weak_features = correlations[abs(correlations) < threshold].index.tolist()
weak_features
```

[100]: ['min_item_price', 'day_of_week']

[101]:
```python
# Drop weakly correlated features from X_train and X_test
X_train = X_train.drop(columns=weak_features)
X_train
```

[101]:

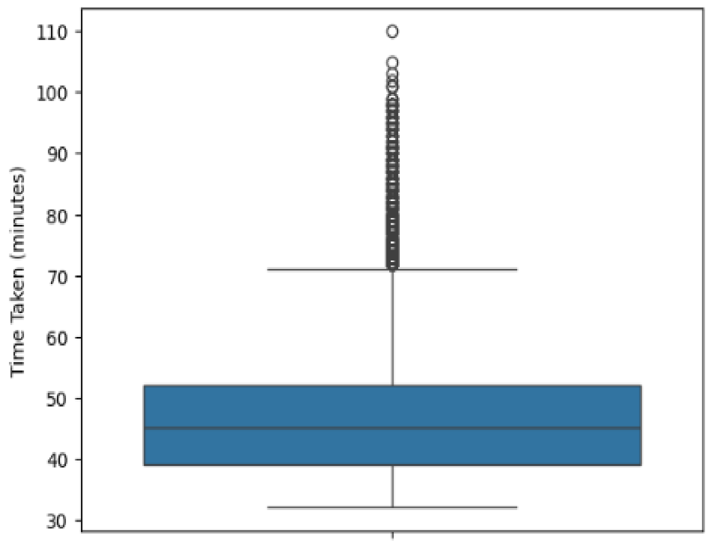
	market_id	order_protocol	total_items	subtotal	num_distinct_items	max_item_price	total_onshift_dashers	total_busy_dashers	total_outstanding_orders	distan
29429	4.0	2.0	4	3590	3	1195	96.0	94.0	152.0	20.
141821	1.0	5.0	3	3184	3	968	21.0	16.0	13.0	17.
32757	4.0	1.0	5	6545	5	1499	50.0	42.0	78.0	18.
46717	1.0	1.0	4	4700	4	1600	5.0	5.0	7.0	13.
42092	3.0	2.0	6	5925	2	1095	46.0	46.0	46.0	10.
...	...	...	...	...	...	...	...	...	...	
119887	2.0	5.0	2	1149	2	999	29.0	39.0	42.0	23.
103702	2.0	1.0	1	1095	1	1095	89.0	111.0	112.0	18.
131941	3.0	5.0	1	590	1	590	6.0	4.0	4.0	7.
146878	2.0	5.0	1	895	1	895	64.0	60.0	64.0	30.
121967	1.0	3.0	2	2687	2	1999	28.0	28.0	36.0	35.

140609 rows × 12 columns

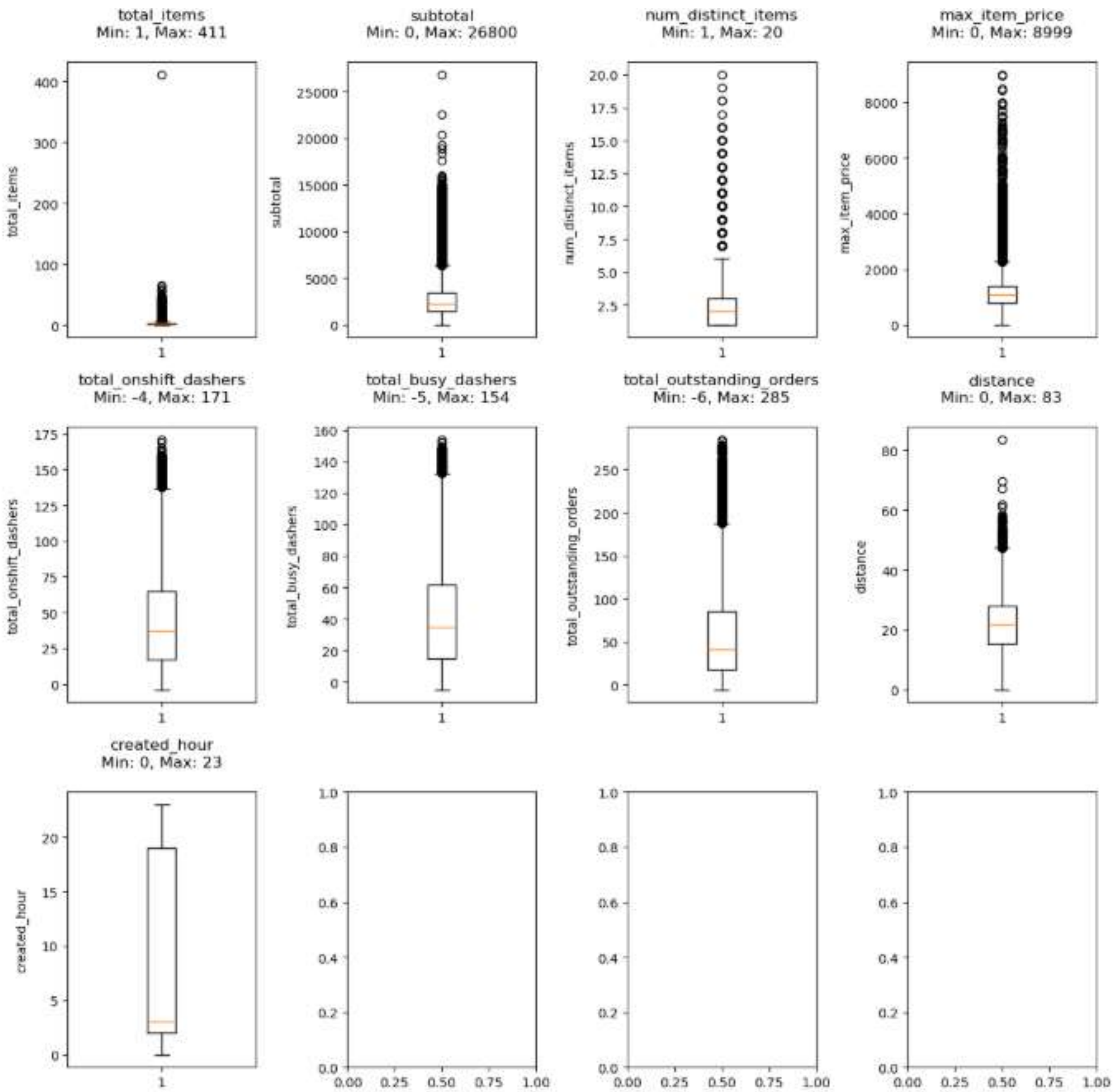
Handling the Outliers

Visualise potential outliers for the target variable and other numerical features using boxplots

[102]:
```python
# Boxplot for time_taken
sns.boxplot(y=y_train)
plt.ylabel("Time Taken (minutes)")

plt.show()
```



```
# Boxplots for numerical features
numerical_columns = X_train.select_dtypes(include=['number']).columns

fig, axes = plt.subplots(nrows=3, ncols=4, figsize=(12, 12))
axes = axes.flatten()

for i, column in enumerate(numerical_columns):

    min_val = int(X_train[column].min())
    max_val = int(X_train[column].max())

    axes[i].boxplot(X_train[column])

    axes[i].set_title(f'{column}\nMin: {min_val}, Max: {max_val}', pad=20)
    axes[i].set_ylabel(column, labelpad=10)

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



4. Exploratory Data Analysis on Validation Data

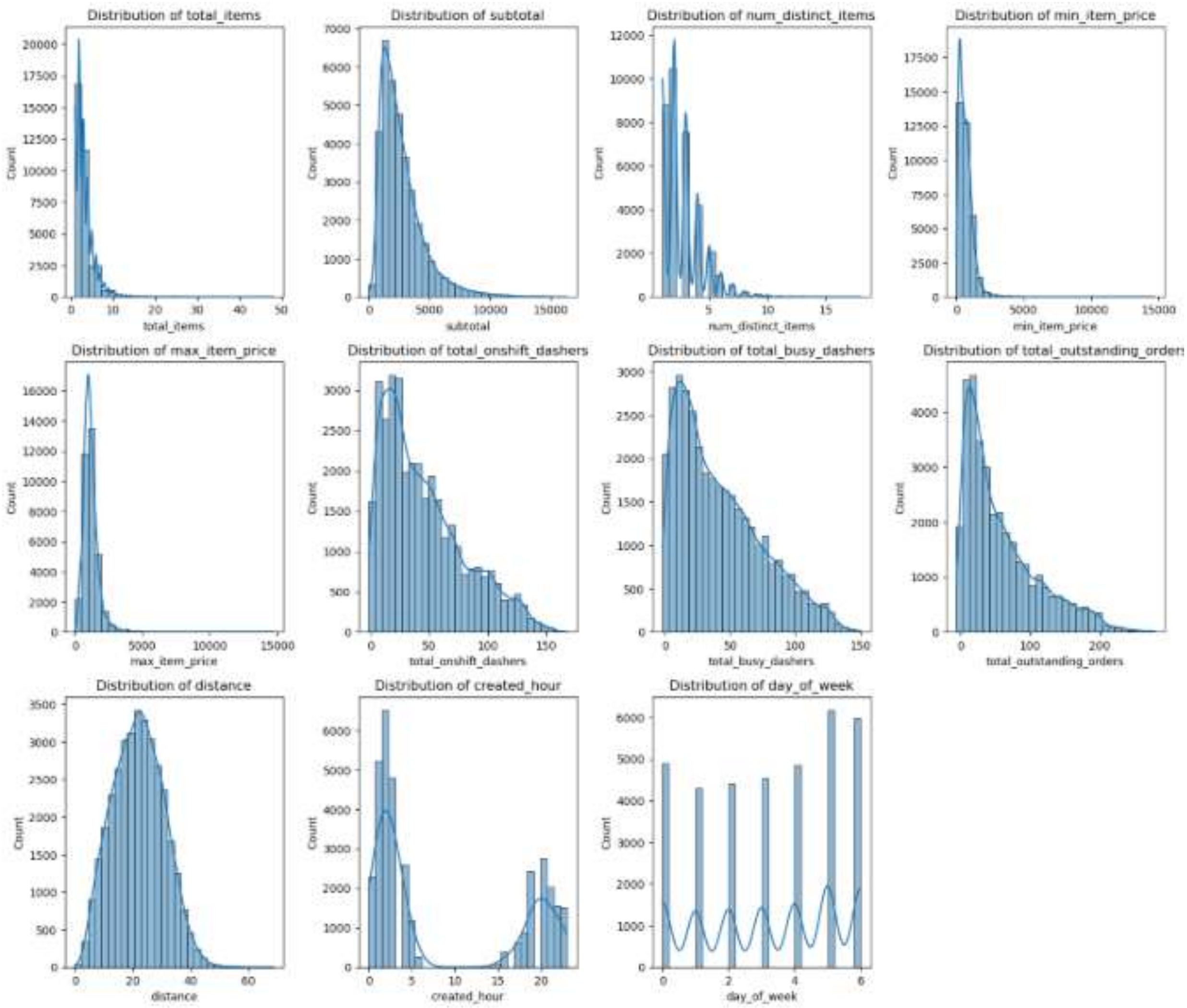
[41]:
```
# Define numerical and categorical columns for easy EDA and data manipulation
numerical_columns = X_test.select_dtypes(include=['number']).columns.tolist()
categorical_columns = X_test.select_dtypes(include=['object', 'bool', 'category']).columns.tolist()

# Printing outputs
print("Numerical Variables:")
print(numerical_columns)

print("\nCategorical Variables:")
print(categorical_columns)
```

```
Numerical Variables:
['total_items', 'subtotal', 'num_distinct_items', 'min_item_price', 'max_item_price', 'total_onshift_dashers', 'total_busy_dashers', 'total_outstanding_orders', 'distance', 'created_hour', 'day_of_week']

Categorical Variables:
['market_id', 'order_protocol', 'is_weekend']
```

4.1.1

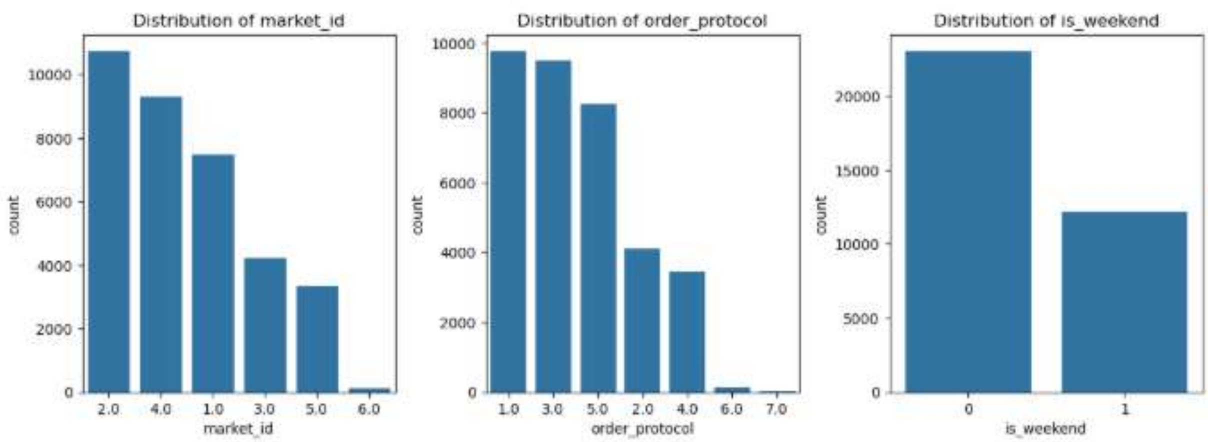
Plot distributions for numerical columns in the validation set to understand their spread and any skewness

[42]:
```
# Plot distributions for all numerical columns
plt.figure(figsize=(15, 16))
for i, col in enumerate(numerical_columns, 1):
    plt.subplot(4, 4, i)
    sns.histplot(X_test[col], kde=True, bins=30)
    plt.title(f"Distribution of {col}")
plt.tight_layout()
plt.show()
```

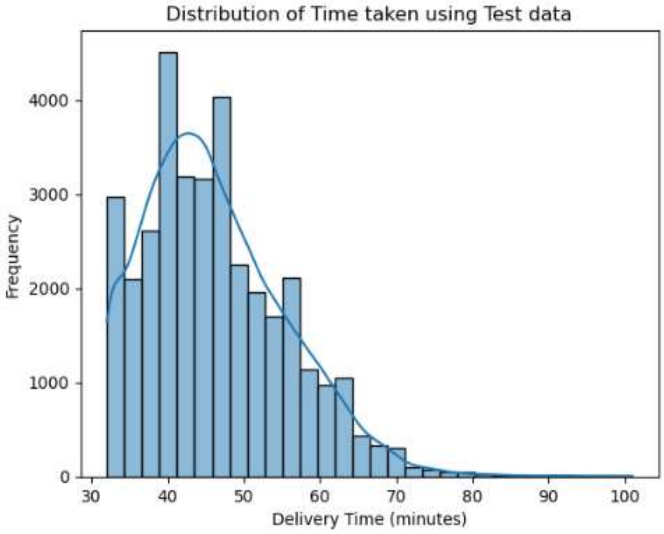


Check the distribution of categorical features

[43]:
```
# Distribution of categorical columns
plt.figure(figsize=(12, 8))
for i, col in enumerate(categorical_columns, 1):
    plt.subplot(2, 3, i)
    sns.countplot(x=X_test[col], order=X_test[col].value_counts().index,)
    plt.title(f"Distribution of {col}")

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

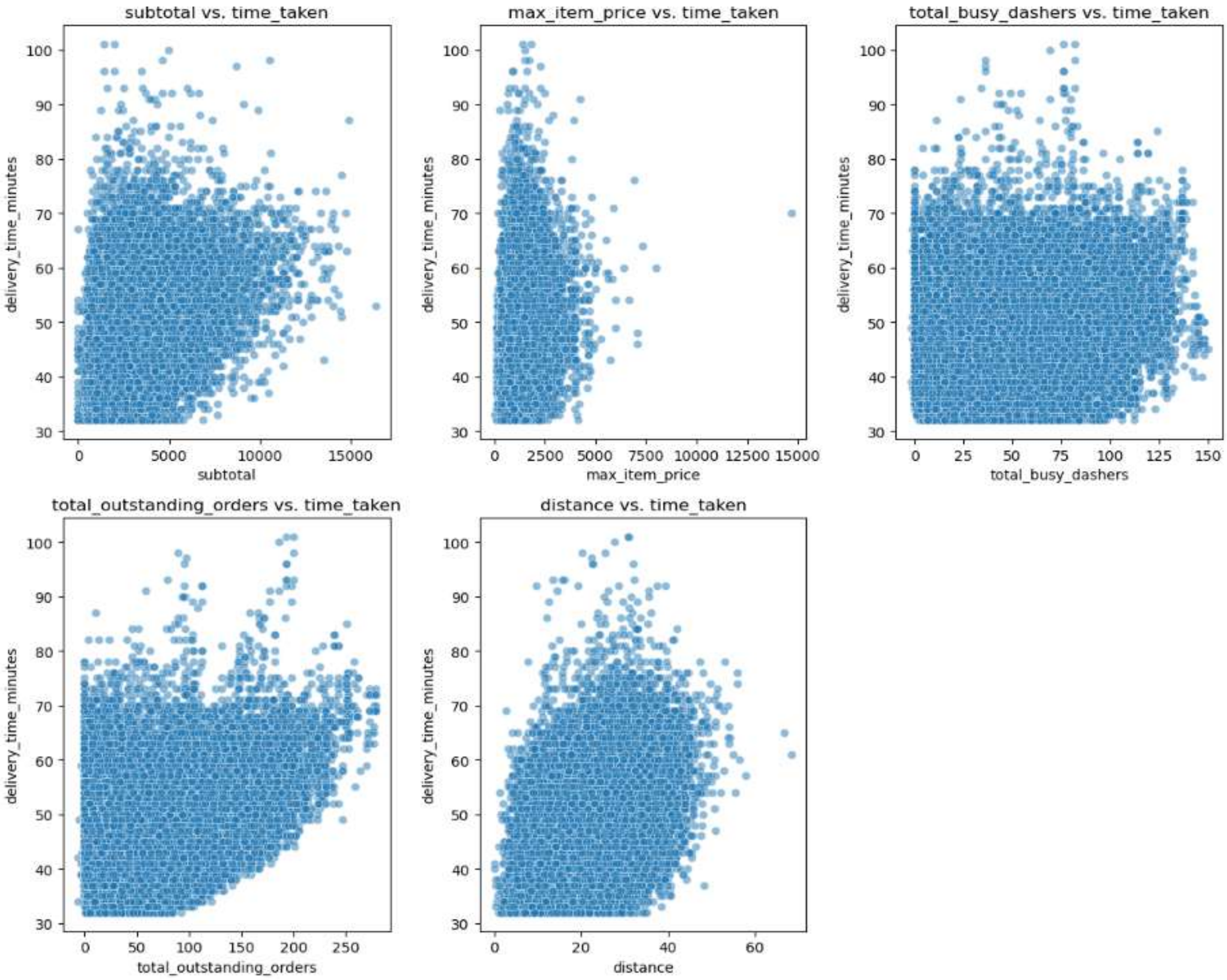


```python
# Distribution of time_taken
sns.histplot(y_test, bins=30, kde=True)

plt.xlabel("Delivery Time (minutes)")
plt.ylabel("Frequency")
plt.title("Distribution of Time taken using Test data")

plt.show()
```



Relationships Between Features

```python
# Scatter plot to visualise the relationship between time_taken and other features
important_features = ['subtotal', 'max_item_price', 'total_busy_dashers', 'total_outstanding_orders', 'distance']

fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(12, 10))
axes = axes.flatten()

for i, col in enumerate(important_features):
    sns.scatterplot(x=X_test[col], y=y_test, alpha=0.5, ax=axes[i])
    axes[i].set_title(f'{col} vs. time_taken')

fig.delaxes(axes[-1])
plt.tight_layout()
plt.show()
```



Drop the columns with weak correlations with the target variable

[46]:
```python
# Drop the weakly correlated columns from training dataset
X_test = X_test.drop(columns=weak_features)
```

[47]:
```python
# capping the X_test to maintain the cosistency with training data;
numerical_columns = X_test.select_dtypes(include=['number']).columns
capping_columns = [col for col in numerical_columns if col != "num_distinct_items"]
X_test = capping_outliers(X_test, capping_columns)
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(140609, 12)
(35153, 12)
(140609,)
(35153,)
```

5. Model Building

Import Necessary Libraries

[48]:
```
# Import libraries
import statsmodels.api as sm
import scipy.stats as stats
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

from sklearn.preprocessing import StandardScaler, LabelEncoder

from sklearn.feature_selection import RFE
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

5.1 Feature Scaling [3 marks]

[49]:
```
# Apply scaling to the numerical columns
# Use standard scaler as it ensures all features have mean = 0 and standard deviation = 1. This support better for Linear Regression
test_num_cols = X_train.select_dtypes(include=['number']).columns.tolist()

scaler = StandardScaler()

# keeping the original data (unscaled data) to compare later
X_train_scaled = X_train.copy()
X_test_scaled = X_test.copy()

# scaling the data
X_train_scaled[test_num_cols] = scaler.fit_transform(X_train[test_num_cols])
X_test_scaled[test_num_cols] = scaler.transform(X_test[test_num_cols])

X_train_scaled.head()
```

[49]:

	market_id	order_protocol	total_items	subtotal	num_distinct_items	max_item_price	total_onshift_dashers	total_busy_dashers	total_outstanding_orders	dista
29429	4.0	2.0	0.559973	0.642631	0.199152	0.130916	1.492231	1.627877	1.864033	-0.131
141821	1.0	5.0	-0.009127	0.377376	0.199152	-0.358700	-0.694441	-0.805047	-0.877504	-0.471
32757	4.0	1.0	1.129072	2.473936	1.427499	0.786614	0.151072	0.005928	0.404510	-0.406
46717	1.0	1.0	0.559973	1.367836	0.813326	1.004461	-1.160931	-1.148151	-0.995843	-0.975
42092	3.0	2.0	1.698172	2.168174	-0.415021	-0.084774	0.034450	0.130693	-0.226635	-1.287

[50]:
```python
X_train_scaled.describe().round(3)
```

[50]:

	total_items	subtotal	num_distinct_items	max_item_price	total_onshift_dashers	total_busy_dashers	total_outstanding_orders	distance	created_hour
count	140609.000	140609.000	140609.000	140609.000	140609.000	140609.000	140609.000	140609.000	140609.000
mean	-0.000	-0.000	-0.000	-0.000	0.000	0.000	-0.000	0.000	0.000
std	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
min	-1.147	-1.703	-1.029	-2.447	-1.423	-1.460	-1.252	-2.503	-0.977
25%	-0.578	-0.780	-1.029	-0.723	-0.811	-0.836	-0.799	-0.746	-0.746
50%	-0.009	-0.251	-0.415	-0.085	-0.228	-0.212	-0.325	-0.008	-0.631
75%	0.560	0.522	0.199	0.562	0.588	0.630	0.543	0.721	1.213
max	2.267	2.474	10.640	2.491	2.688	2.829	2.554	2.923	1.674

Note that linear regression is agnostic to feature scaling. However, with feature scaling, we get the coefficients to be somewhat on the same scale so that it becomes easier to compare them.

[51]:
```python
# label encoding for the categorical features
test_cat_cols = X_train.select_dtypes(include=['object', 'bool', 'category']).columns.tolist()

label_encoder = LabelEncoder()

for col in test_cat_cols:
    X_train_scaled[col] = label_encoder.fit_transform(X_train_scaled[col])
    X_test_scaled[col] = label_encoder.transform(X_test_scaled[col])

X_train_scaled.head()
```

[51]:

	market_id	order_protocol	total_items	subtotal	num_distinct_items	max_item_price	total_onshift_dashers	total_busy_dashers	total_outstanding_orders	dista
29429	3	1	0.559973	0.642631	0.199152	0.130916	1.492231	1.627877	1.864033	-0.131
141821	0	4	-0.009127	0.377376	0.199152	-0.358700	-0.694441	-0.805047	-0.877504	-0.471
32757	3	0	1.129072	2.473936	1.427499	0.786614	0.151072	0.005928	0.404510	-0.406
46717	0	0	0.559973	1.367836	0.813326	1.004461	-1.160931	-1.148151	-0.995843	-0.975
42092	2	1	1.698172	2.168174	-0.415021	-0.084774	0.034450	0.130693	-0.226635	-1.287

[52]:
```
X_train_scaled.describe().round(3)
```

[52]:

	market_id	order_protocol	total_items	subtotal	num_distinct_items	max_item_price	total_onshift_dashers	total_busy_dashers	total_outstanding_orders	di
count	140609.000	140609.000	140609.000	140609.000	140609.000	140609.000	140609.000	140609.000	140609.000	1406
mean	1.746	1.913	-0.000	-0.000	-0.000	-0.000	0.000	0.000	-0.000	
std	1.332	1.513	1.000	1.000	1.000	1.000	1.000	1.000	1.000	
min	0.000	0.000	-1.147	-1.703	-1.029	-2.447	-1.423	-1.460	-1.252	
25%	1.000	0.000	-0.578	-0.780	-1.029	-0.723	-0.811	-0.836	-0.799	
50%	1.000	2.000	-0.009	-0.251	-0.415	-0.085	-0.228	-0.212	-0.325	
75%	3.000	3.000	0.560	0.522	0.199	0.562	0.588	0.630	0.543	
max	5.000	6.000	2.267	2.474	10.640	2.491	2.688	2.829	2.554	

[53]:
```
X_train.dtypes
```

[53]:
```
market_id                   category
order_protocol              category
total_items                    int64
subtotal                       int64
num_distinct_items             int64
max_item_price                 int64
total_onshift_dashers        float64
total_busy_dashers           float64
total_outstanding_orders     float64
distance                     float64
created_hour                   int32
is_weekend                  category
dtype: object
```

[54]:
```
X_train.head()
```

[54]:

	market_id	order_protocol	total_items	subtotal	num_distinct_items	max_item_price	total_onshift_dashers	total_busy_dashers	total_outstanding_orders	distan
29429	4.0	2.0	4	3590	3	1195	96.0	94.0	152.0	20.
141821	1.0	5.0	3	3184	3	968	21.0	16.0	13.0	17.
32757	4.0	1.0	5	6393	5	1499	50.0	42.0	78.0	18.
46717	1.0	1.0	4	4700	4	1600	5.0	5.0	7.0	13.
42092	3.0	2.0	6	5925	2	1095	46.0	46.0	46.0	10.

Build a linear regression model

[55]:
```
# Create/Initialise the model
lr = LinearRegression()
```

[56]:
```
# Train the model using the training data
lr.fit(X_train_scaled, y_train)
```

[56]:
```
LinearRegression
LinearRegression()
```

[57]:
```
# Make predictions
y_pred = lr.predict(X_test_scaled)
y_pred[:10]
```

[57]:
```
array([41.03050261, 53.28653302, 45.87134092, 45.32638664, 39.89369811,
       50.66911581, 51.86625462, 46.91006002, 41.08148574, 30.7006665 ])
```

[58]:
```python
# Find results for evaluation metrics
mae = mean_absolute_error(y_test, y_pred)
print(f"Mean Absolute Error (MAE): {mae:.2f}")

mse = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error (MSE): {mse:.2f}")

rmse = mse ** 0.5  # Square root of MSE
print(f"Root Mean Squared Error (RMSE): {rmse:.2f}")

r2 = r2_score(y_test, y_pred)
print(f"R² Score: {r2:.4f}")
```

```
Mean Absolute Error (MAE): 2.46
Mean Squared Error (MSE): 11.59
Root Mean Squared Error (RMSE): 3.40
R² Score: 0.8665
```

[59]:
```python
X_train_scaled.columns
```

[59]:
```
Index(['market_id', 'order_protocol', 'total_items', 'subtotal',
       'num_distinct_items', 'max_item_price', 'total_onshift_dashers',
       'total_busy_dashers', 'total_outstanding_orders', 'distance',
       'created_hour', 'is_weekend'],
      dtype='object')
```

Build the model and fit RFE to select the most important features

[60]:
```python
# Loop through the number of features and test the model
def compute_vif(X):
    vif_data = pd.DataFrame()
    vif_data["Feature"] = X.columns
    vif_data["VIF"] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
    return vif_data

# Initialize variables
X_selected = X_train_scaled.copy()
num_features = len(X_selected.columns)
lr = LinearRegression()

while num_features > 8:   # Stop when we have the top 8 features
    # Perform RFE to rank features
    rfe = RFE(estimator=lr, n_features_to_select=num_features - 1)
    rfe.fit(X_selected, y_train)

    selected_features = X_selected.columns[rfe.support_]

    X_train_selected = X_selected[selected_features]
    X_test_selected = X_test_scaled[selected_features]

    # Train model
    lr.fit(X_train_selected, y_train)

    # Predictions
    y_pred = lr.predict(X_test_selected)

    # Evaluation
    r2 = r2_score(y_test, y_pred)
    rmse = mean_squared_error(y_test, y_pred, squared=False)

    # Compute VIF
    vif_scores = compute_vif(X_train_selected)

    # Identify feature to drop
    high_vif_features = vif_scores[vif_scores["VIF"] > 10].sort_values(by="VIF", ascending=False)

    if not high_vif_features.empty:
        drop_feature = high_vif_features.iloc[0]["Feature"]  # Drop the feature with highest VIF
        reason = f"High VIF ({high_vif_features.iloc[0]['VIF']:.2f})"
    # else:
    #     # If no high-VIF features, drop the least important feature according to RFE ranking
    #     drop_feature = X_selected.columns[~rfe.support_][0]  # Feature eliminated by RFE
    #     reason = "Removed by RFE"
    else:
        # If no high-VIF features, drop the least important feature based on R² contribution
        feature_contributions = abs(lr.coef_)
        drop_feature = X_train_selected.columns[np.argmin(feature_contributions)]
        reason = "Lowest contribution to R²"

    # Print results
    print(f"\nIteration {len(selected_features)} Features")
    print(f"R² Score: {r2:.4f}")
    print(f"RMSE Score: {rmse:.2f}")
    print("VIF Scores:")
    print(vif_scores.to_string(index=False))
    print(f"Dropping feature: {drop_feature} ({reason})")

    # Drop feature and update X_selected
    X_selected = X_selected.drop(columns=[drop_feature])
    num_features -= 1

# Final selected features
final_selected_features = list(X_selected.columns)
print("\nFinal 8 Selected Features:", final_selected_features)
```

```
Iteration 11 Features
R² Score: 0.8661
RMSE Score: 3.41
VIF Scores:
                 Feature        VIF
               market_id   1.747405
          order_protocol   1.748656
             total_items   4.581795
                subtotal   2.003884
      num_distinct_items   4.538488
   total_onshift_dashers  12.458629
      total_busy_dashers  11.477510
total_outstanding_orders  10.622670
                distance   1.004046
            created_hour   1.207939
              is_weekend   1.379524
Dropping feature: total_onshift_dashers (High VIF (12.46))

Iteration 10 Features
R² Score: 0.7107
RMSE Score: 5.01
VIF Scores:
                 Feature       VIF
               market_id  1.746092
          order_protocol  1.747837
             total_items  4.581795
                subtotal  2.003786
      num_distinct_items  4.538479
      total_busy_dashers  8.094457
total_outstanding_orders  8.190391
                distance  1.003868
            created_hour  1.196617
              is_weekend  1.374545
Dropping feature: total_items (Lowest contribution to R²)

Iteration 9 Features
R² Score: 0.7105
RMSE Score: 5.01
VIF Scores:
```


```
Iteration 9 Features
R² Score: 0.7105
RMSE Score: 5.01
VIF Scores:
```


```
                 Feature       VIF
               market_id  1.744757
          order_protocol  1.745620
                subtotal  1.885873
      num_distinct_items  1.805487
      total_busy_dashers  8.094261
total_outstanding_orders  8.189963
                distance  1.003718
            created_hour  1.195935
              is_weekend  1.374507
Dropping feature: market_id (Lowest contribution to R²)

Iteration 8 Features
R² Score: 0.6988
RMSE Score: 5.11
VIF Scores:
                 Feature       VIF
          order_protocol  1.282530
                subtotal  1.885859
      num_distinct_items  1.805405
      total_busy_dashers  8.080537
total_outstanding_orders  8.184946
                distance  1.003366
            created_hour  1.195317
              is_weekend  1.279654
Dropping feature: num_distinct_items (Lowest contribution to R²)

Final 8 Selected Features: ['order_protocol', 'subtotal', 'max_item_price', 'total_busy_dashers', 'total_outstanding_orders', 'distance', 'created_hou
r', 'is_weekend']
```

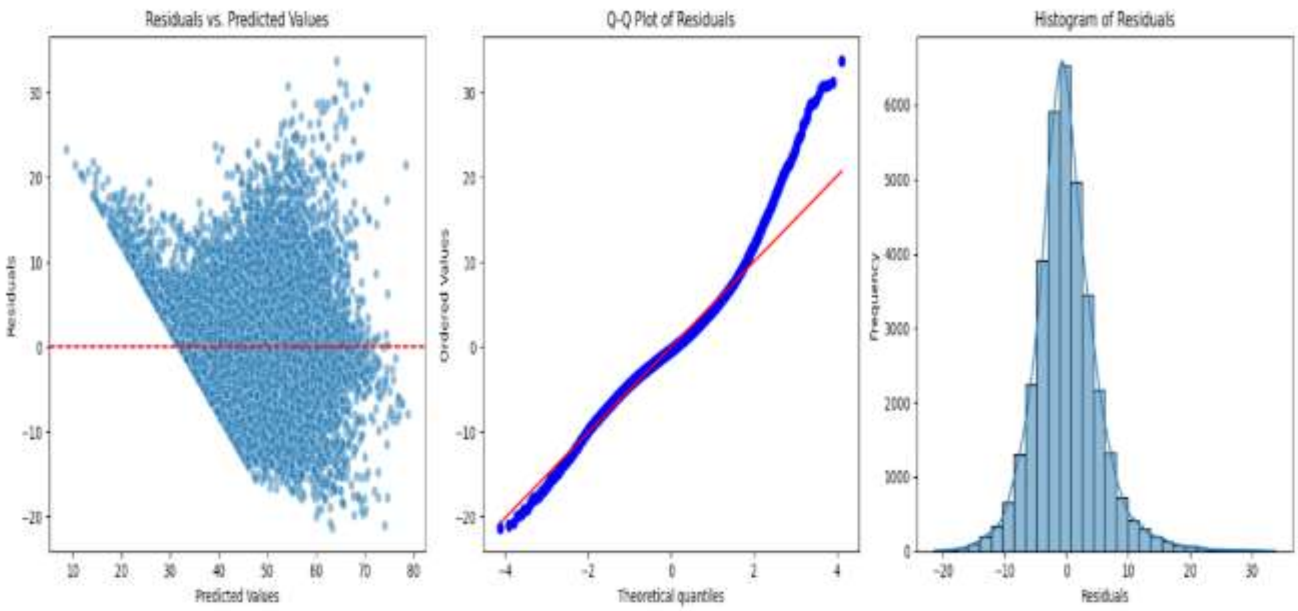
[61]:
```python
# Build the final model with selected number of features
X_train_final = X_train_scaled[final_selected_features]
X_test_final = X_test_scaled[final_selected_features]

# Initialize and train the final Linear Regression model
lr_1 = LinearRegression()
lr_1.fit(X_train_final, y_train)

# Make predictions
y_pred_final = lr_1.predict(X_test_final)

# Evaluate the final model
final_r2 = r2_score(y_test, y_pred_final)
final_rmse = mean_squared_error(y_test, y_pred_final, squared=False)

# Print final model performance
print(f"Final Model Performance:")
print(f"R² Score: {final_r2:.4f}")
print(f"RMSE Score: {final_rmse:.2f}")
```

```
Final Model Performance:
R² Score: 0.6956
RMSE Score: 5.14
```

6. Results and Inference

6.1 Perform Residual Analysis [3 marks]

[62]:
```python
# Perform residual analysis using plots like residuals vs predicted values, Q-Q plot and residual histogram
residuals = y_test - y_pred_final

fig, axes = plt.subplots(1, 3, figsize=(18, 5))

# residuals vs predicted values
sns.scatterplot(x=y_pred_final, y=residuals, alpha=0.5, ax=axes[0])
axes[0].axhline(y=0, color='red', linestyle='--')
axes[0].set_xlabel("Predicted Values")
axes[0].set_ylabel("Residuals")
axes[0].set_title("Residuals vs. Predicted Values")

# Q-Q Plot
stats.probplot(residuals, dist="norm", plot=axes[1])
axes[1].set_title("Q-Q Plot of Residuals")

# residual histogram
sns.histplot(residuals, bins=30, kde=True, ax=axes[2])
axes[2].set_xlabel("Residuals")
axes[2].set_ylabel("Frequency")
axes[2].set_title("Histogram of Residuals")

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



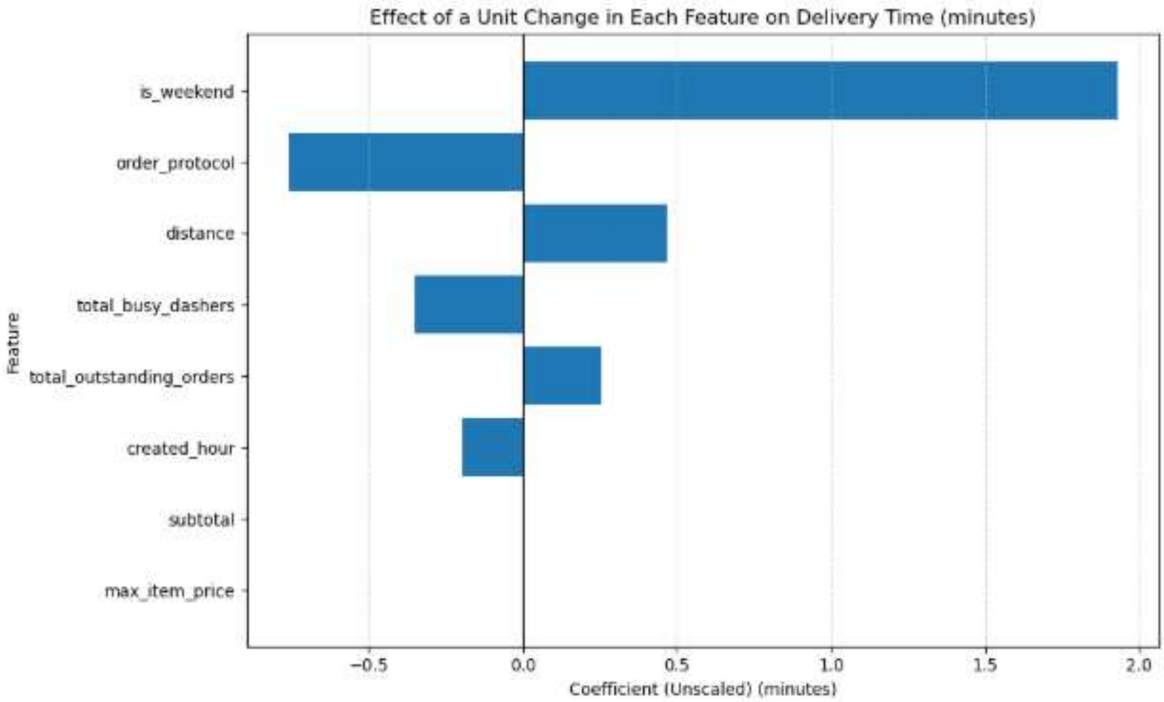
[Your inferences here:]

Perform Coefficient Analysis

```
[63]: # Compare the scaled vs unscaled features used in the final model
# coefficients on scaled data
coef_scaled = lr_1.coef_

# train a new model on unscaled data
lr_2 = LinearRegression()
lr_2.fit(X_train[final_selected_features], y_train)
coef_unscaled = lr_2.coef_

coef_comparison = pd.DataFrame({
                                "Feature": final_selected_features,
                                "Coefficient (Scaled)": coef_scaled,
                                "Coefficient (Unscaled)": coef_unscaled
                              })

# Sort by absolute impact
coef_comparison = coef_comparison.sort_values(by="Coefficient (Unscaled)", ascending=False)

# Display coefficients
print("\nScaled vs. Unscaled Coefficients:")
print(coef_comparison)
```

```
Scaled vs. Unscaled Coefficients:
                  Feature  Coefficient (Scaled)  Coefficient (Unscaled)
7              is_weekend              1.929578                1.929578
5                distance              4.081253                0.467994
4  total_outstanding_orders           12.837319                0.253194
1                subtotal              2.930545                0.001915
2          max_item_price             -0.073089               -0.000158
6            created_hour             -1.705933               -0.196644
3       total_busy_dashers            -11.204927              -0.349497
0          order_protocol             -0.761149               -0.761149
```

[64]:
```
# Analyze the effect of a unit change in a feature, say 'total_items'
coef_comparison["abs_coef"] = coef_comparison["Coefficient (Unscaled)"].abs()
df_sorted = coef_comparison.sort_values("abs_coef", ascending=True)

# Plot horizontal bar chart
plt.figure(figsize=(10, 6))
plt.barh(df_sorted["Feature"], df_sorted["Coefficient (Unscaled)"])
plt.axvline(0, color='black', linewidth=0.8)
plt.title("Effect of a Unit Change in Each Feature on Delivery Time (minutes)")
plt.xlabel("Coefficient (Unscaled) (minutes)")
plt.ylabel("Feature")
plt.grid(axis='x', linestyle='--', alpha=0.6)
plt.tight_layout()
plt.show()
```



Subjective Questions

1. Are there any categorical variables in the data? From your analysis of the categorical variables from the dataset, what could you infer about their effect on the dependent variable?

Answer:

Yes, the dataset had 6 numerical categorical variables. market_id, store_primary_category, order_protocol, order_day, order_hour, isWeekend. To train the model I have used isweekend and order hour. Orders placed on weekends increase delivery time by ~1.92 minutes. For every 1-hour increase, delivery time decreases by ~0.20 minutes. This could be because of lower traffic at night, making deliveries faster.

2. What does test_size = 0.2 refer to during splitting the data into training and test sets?

Answer:

Yes, 20% of the dataset is assigned to the test set. This will help us to evaluate model performance on unseen data

3. Looking at the heatmap, which one has the highest correlation with the target variable?

Answer:

distance has the highest positive correlation (0.47) and order hour has the highest negative correlation This make sense as Longer distances lead to longer delivery times and Later in the day (especially at night), delivery times tend to be shorter.

4. What was your approach to detect the outliers? How did you address them?

Answer: Approach to detect the outliers -

I have used boxplots to visualize the data distribution and identifying extreme values. Calculate the IQR, lower bound and upper bound. Any value outside these bounds is an outlier

Handle outliers -

Capping for Most Features using lower bound and upper bounds. Havn't capped 'num_distinct_items' as represents unique item counts in an order, so high values are valid

5. Based on the final model, which are the top 3 features significantly affecting the delivery time?

Answer:

- isWeekend (+1.9295) - Weekends increase delivery time significantly.
- distance (+0.4679) - Longer distances increase delivery time.
- total_outstanding_orders (+0.2531) - More pending orders increase delivery time.

6. Explain the linear regression algorithm in detail

Answer:

Linear regression is a statistical method used to model the relationship between a dependent variable and one or more independent variables by fitting a linear equation to the observed data. Linear regression assumes a linear relationship between the input variables (X) and a single output variable (y). Equation - y= B0 + BiXi + e; y - dependent variable, Xi - independent variable, B0 - intercept, Bi - slope, e - represent error terms.

There are two types of linear regression - 1) Simple linear regression - involve single independent variable 2) Multiple linear regression - involves multiple independent variable.

7. Explain the difference between simple linear regression and multiple linear regression

Answer:

Simple linear regression Uses a single independent variable to predict a dependent variable. Usually represents a straight line relationship. Advantage - less complex can be visualize easily on a 2D diagram. Disadvantage - limited predictive power

Eq - y = A0 + A1X + e

Multiple linear regression Uses two or more independent variables to predict a dependent variable. Wokrs very well with complex, multi-factor relationships. Advantage - help us on more accurate predictions. Disadvantage - Multicollinearity can cause instability in the regression coefficients, making it difficult to interpret the results of the analysis.

Eq - y = A0 + A1X1 + A2X2 + …… +

8. What is the role of the cost function in linear regression, and how is it minimized?

Answer:

The cost function in linear regression plays a central role in guiding the learning process. Here's a breakdown of its role and how it's minimized:

In linear regression, the goal is to find the best-fitting line through the data points. The cost function quantifies how well (or poorly) a particular line fits the data. Specifically, it measures the error between the predicted values and the actual values. Techniques like gradient descent are used to find the values of the parameters that result in the lowest possible cost, meaning the best fit to the data.

9. Explain the difference between overfitting and underfitting.

Answer:

Underfitting happens when a model is too simple to capture the underlying patterns in the data. Symptoms: Poor performance on training data Even worse performance on validation/test data

Overfitting happens when a model is too complex and starts to "memorize" the training data, including noise. Symptoms: Very good performance on training data Poor performance on validation/test data A high-degree polynomial model that fits every training point exactly, but fails to predict new data accurately.

10. How do residual plots help in diagnosing a linear regression model?

Answer:

Residual plots are a powerful diagnostic tool in linear regression. They help you understand how well your model fits the data by visualizing the errors (residuals)—the differences between actual and predicted values.

Detecting Non-Linearity Good Sign: Residuals are randomly scattered around zero. Problem: Curved pattern in the residuals suggests that the relationship is nonlinear, and a linear model is a poor fit.

Identifying Heteroscedasticity (Non-constant Variance) Good Sign: Spread of residuals is roughly constant across all levels of x. Problem: "Funnel" shape (narrow then wide or vice versa) indicates heteroscedasticity, which violates linear regression assumptions.

Spotting Outliers and Influential Points Large residuals far from the rest may indicate outliers or leverage points that could distort the model.

Checking for Independence (Autocorrelation) If residuals show a clear pattern (like a wave), they may be autocorrelated, especially in time series data.