Business Case: Porter: Neural Networks Regression

Defining Problem Statement & Data Import

Problem Statement:

Porter is India's Largest Marketplace for Intra-City Logistics. Leader in the country's $40 billion intra-city logistics market, Porter strives to improve the lives of 1,50,000+ driver-partners by providing them with consistent earning & independence. Currently, the company has serviced 5+ million customers

Porter works with a wide range of restaurants for delivering their items directly to the people.

Porter has a number of delivery partners available for delivering the food, from various restaurants and wants to get an estimated delivery time that it can provide the customers on the basis of what they are ordering, from where and also the delivery partners.

This dataset has the required data to train a regression model that will do the delivery time estimation, based on all those features.

Dataset:

https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/015/039/original/dataset.csv
1663710760

Data Dictionary:

Each row in this file corresponds to one unique delivery. Each column corresponds to a feature as explained below.

- market_id : integer id for the market where the restaurant lies
- created_at : the timestamp at which the order was placed
- actual_delivery_time : the timestamp when the order was delivered
- store_primary_category : category for the restaurant
- order_protocol : integer code value for order protocol(how the order was placed ie: through porter, call to restaurant, pre booked, third part etc)
- total_items subtotal : final price of the order
- num_distinct_items : the number of distinct items in the order
- min_item_price : price of the cheapest item in the order
- max_item_price : price of the costliest item in order

- total_onshift_partners : number of delivery partners on duty at the time order was placed
- total_busy_partners : number of delivery partners attending to other tasks
- total_outstanding_orders : total number of orders to be fulfilled at the moment

Analysing basic metrics

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
#Loading of dataset
df = pd.read_csv("../Hemangi/dataset.csv")
df.head()
```

Out[2]:

	market_id	created_at	actual_delivery_time	store_id	stor
0	1.0	2015-02-06 22:24:17	2015-02-06 23:27:16	df263d996281d984952c07998dc54358	
1	2.0	2015-02-10 21:49:25	2015-02-10 22:56:29	f0ade77b43923b38237db569b016ba25	
2	3.0	2015-01-22 20:39:28	2015-01-22 21:09:09	f0ade77b43923b38237db569b016ba25	
3	3.0	2015-02-03 21:21:45	2015-02-03 22:13:00	f0ade77b43923b38237db569b016ba25	
4	3.0	2015-02-15 02:40:36	2015-02-15 03:20:26	f0ade77b43923b38237db569b016ba25	

In [3]:
```
df.shape #to observe shape of data
```

Out[3]:
```
(197428, 14)
```

- Dataset is of 205843 rows and 7 attributes.

In [4]:
```
df.info() #to observe the data type
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 197428 entries, 0 to 197427
Data columns (total 14 columns):
 #   Column                    Non-Null Count   Dtype  
---  ------                    --------------   -----  
 0   market_id                 196441 non-null  float64
 1   created_at                197428 non-null  object 
 2   actual_delivery_time      197421 non-null  object 
 3   store_id                  197428 non-null  object 
 4   store_primary_category    192668 non-null  object 
 5   order_protocol            196433 non-null  float64
 6   total_items               197428 non-null  int64  
 7   subtotal                  197428 non-null  int64  
 8   num_distinct_items        197428 non-null  int64  
 9   min_item_price            197428 non-null  int64  
 10  max_item_price            197428 non-null  int64  
 11  total_onshift_partners    181166 non-null  float64
 12  total_busy_partners       181166 non-null  float64
 13  total_outstanding_orders  181166 non-null  float64
dtypes: float64(5), int64(5), object(4)
memory usage: 21.1+ MB
```

Check for Duplicate Values

In [5]:
```
df.duplicated().sum()
```

Out[5]:
```
0
```

- There are no duplicate instances in the data

In [6]:
```
df.dropna(inplace=True)
df.shape
```

Out[6]:
```
(176248, 14)
```

Check for Missing Values

In [7]:
```
# Check Missing Values
df.isna().sum()
```

Out[7]:
```
market_id                   0
created_at                  0
actual_delivery_time        0
store_id                    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_partners      0
total_busy_partners         0
total_outstanding_orders    0
dtype: int64
```

Preprocessing & Feature Creation

In [8]:
```
#Setting datetime format for respective columns
df['created_at']= pd.to_datetime(df['created_at'], dayfirst=True)
df['actual_delivery_time']= pd.to_datetime(df['actual_delivery_time'], dayfirst=
```

In [9]:
```
#Creating new features from Date Time
df['order_hour']=df['created_at'].dt.hour
df['order_day']=df['created_at'].dt.dayofweek
```

In [10]:
```
#Creating Target Variable & converting it to number of minutes
df['time_taken']=df['actual_delivery_time']-df['created_at']
df['delivery_time_taken']=pd.to_timedelta(df['time_taken'])/pd.Timedelta('60s')
```

In [11]:
```
#Dropping the columns that are no longer required
df.drop(['time_taken','created_at','actual_delivery_time','store_id'],axis=1,inp
```

In [12]:
```
df['store_primary_category']=df['store_primary_category'].astype('category').cat
```

In [13]:
```
#Converting required float columns to int datatype
float_cols = ['total_onshift_partners','total_busy_partners','total_outstanding_
df[float_cols] = df[float_cols].astype('int64')
```

In [14]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 176248 entries, 0 to 197427
Data columns (total 14 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   market_id                176248 non-null  int64
 1   store_primary_category   176248 non-null  int8
 2   order_protocol           176248 non-null  int64
 3   total_items              176248 non-null  int64
 4   subtotal                 176248 non-null  int64
 5   num_distinct_items       176248 non-null  int64
 6   min_item_price           176248 non-null  int64
 7   max_item_price           176248 non-null  int64
 8   total_onshift_partners   176248 non-null  int64
 9   total_busy_partners      176248 non-null  int64
 10  total_outstanding_orders 176248 non-null  int64
 11  order_hour               176248 non-null  int64
 12  order_day                176248 non-null  int64
 13  delivery_time_taken      176248 non-null  int64
dtypes: int64(13), int8(1)
memory usage: 19.0 MB
```

In [15]:
```
df.describe().T
```

Out[15]:

	count	mean	std	min	25%	50%	75
market_id	176248.0	2.743747	1.330911	1.0	2.0	2.0	4
store_primary_category	176248.0	35.891482	20.728572	0.0	18.0	38.0	5
order_protocol	176248.0	2.911687	1.512920	1.0	1.0	3.0	4
total_items	176248.0	3.204592	2.673899	1.0	2.0	3.0	4
subtotal	176248.0	2696.498939	1828.922584	0.0	1408.0	2221.0	340
num_distinct_items	176248.0	2.674589	1.625558	1.0	1.0	2.0	3
min_item_price	176248.0	684.937730	519.911425	-86.0	299.0	595.0	94
max_item_price	176248.0	1159.886994	560.784510	0.0	799.0	1095.0	139
total_onshift_partners	176248.0	44.905276	34.529394	-4.0	17.0	37.0	6
total_busy_partners	176248.0	41.845434	32.154573	-5.0	15.0	35.0	6
total_outstanding_orders	176248.0	58.206800	52.708344	-6.0	17.0	41.0	8
order_hour	176248.0	8.493872	8.681474	0.0	2.0	3.0	1
order_day	176248.0	3.221563	2.041332	0.0	1.0	3.0	5
delivery_time_taken	176248.0	47.271992	27.656174	1.0	35.0	44.0	5

In [16]:
```
df.describe(include = np.number, percentiles=[.25,.5,.75,.90,.95, .99, .999]).rc
```

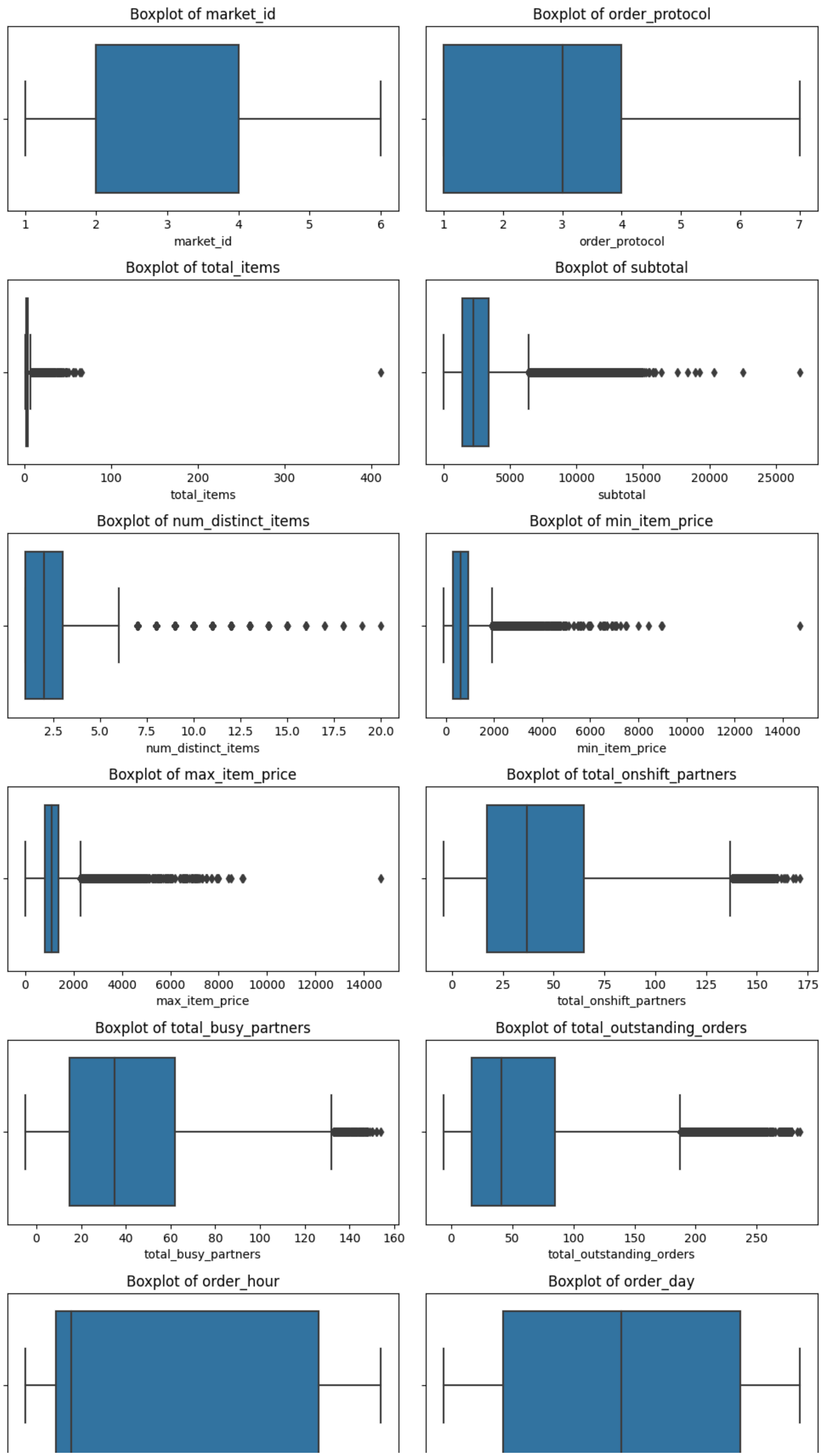
Out[16]:

	count	mean	std	min	25%	50%	75%	90
market_id	176248.0	2.74	1.33	1.0	2.0	2.0	4.0	5
store_primary_category	176248.0	35.89	20.73	0.0	18.0	38.0	55.0	61
order_protocol	176248.0	2.91	1.51	1.0	1.0	3.0	4.0	5
total_items	176248.0	3.20	2.67	1.0	2.0	3.0	4.0	6
subtotal	176248.0	2696.50	1828.92	0.0	1408.0	2221.0	3407.0	4970
num_distinct_items	176248.0	2.67	1.63	1.0	1.0	2.0	3.0	5
min_item_price	176248.0	684.94	519.91	-86.0	299.0	595.0	942.0	1295
max_item_price	176248.0	1159.89	560.78	0.0	799.0	1095.0	1395.0	1795
total_onshift_partners	176248.0	44.91	34.53	-4.0	17.0	37.0	65.0	98
total_busy_partners	176248.0	41.85	32.15	-5.0	15.0	35.0	62.0	90
total_outstanding_orders	176248.0	58.21	52.71	-6.0	17.0	41.0	85.0	140
order_hour	176248.0	8.49	8.68	0.0	2.0	3.0	19.0	21
order_day	176248.0	3.22	2.04	0.0	1.0	3.0	5.0	6
delivery_time_taken	176248.0	47.27	27.66	1.0	35.0	44.0	56.0	70

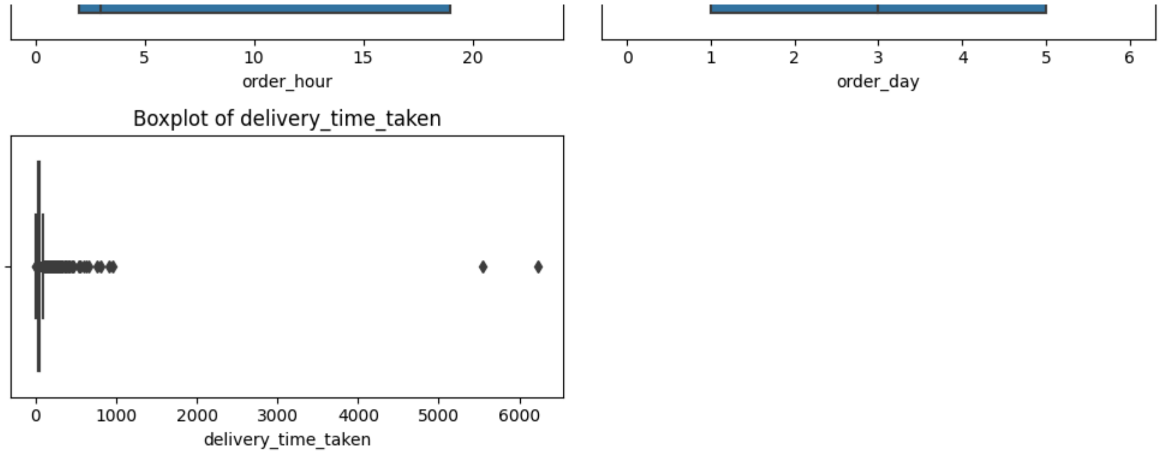
Outlier Detection

In [17]:
```
#Distribution of numerical variables
num_vars = df.select_dtypes('int').columns.tolist()
fig = plt.figure(figsize=(10,21))
i=1
for col in num_vars:
  ax = plt.subplot(7,2,i)
  sns.boxplot(x=df[col])
  plt.title(f'Boxplot of {col}')
  i += 1

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



Boxplot of market_id
1 2 3 4 5 6
market_id
Boxplot of order_protocol
1 2 3 4 5 6 7
order_protocol
Boxplot of total_items
0 100 200 300 400
total_items
Boxplot of subtotal
0 5000 10000 15000 20000 25000
subtotal
Boxplot of num_distinct_items
2.5 5.0 7.5 10.0 12.5 15.0 17.5 20.0
num_distinct_items
Boxplot of min_item_price
0 2000 4000 6000 8000 10000 12000 14000
min_item_price
Boxplot of max_item_price
0 2000 4000 6000 8000 10000 12000 14000
max_item_price
Boxplot of total_onshift_partners
0 25 50 75 100 125 150 175
total_onshift_partners
Boxplot of total_busy_partners
0 20 40 60 80 100 120 140 160
total_busy_partners
Boxplot of total_outstanding_orders
0 50 100 150 200 250
total_outstanding_orders
Boxplot of order_hour
Boxplot of order_day



- Here we can see that many columns have outliers. Lets remove the outliers using IQR method.

In [18]:

```
# Remove outliers through IQR method
num_vars = df.select_dtypes('int').columns.tolist()

for col in num_vars:
  # Calculate Q1 and Q3
  q1 = np.percentile(df[col], 25)
  q3 = np.percentile(df[col], 75)

  # Calculate IQR
  iqr = q3 - q1

  # Define lower and upper bounds
  lower_bound = q1 - (1.5 * iqr)
  upper_bound = q3 + (1.5 * iqr)

  # Remove outliers
  df = df.loc[~((df[col] < lower_bound) | (df[col] > upper_bound))]

df.shape
```

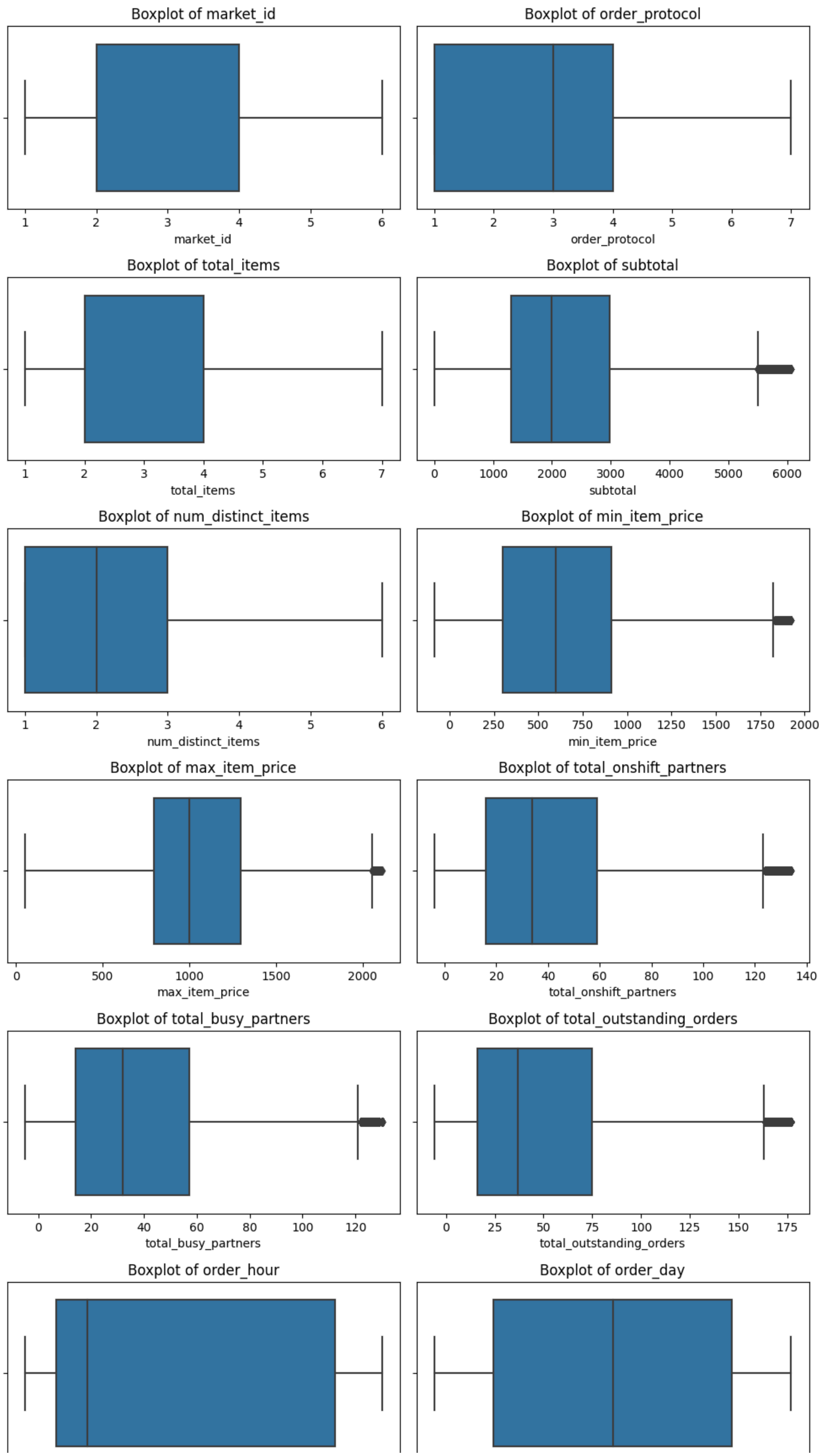
Out[18]:

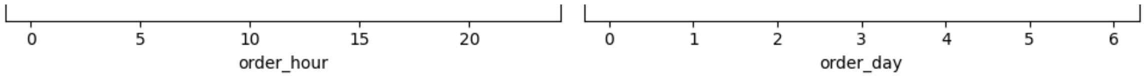
```
(142029, 14)
```

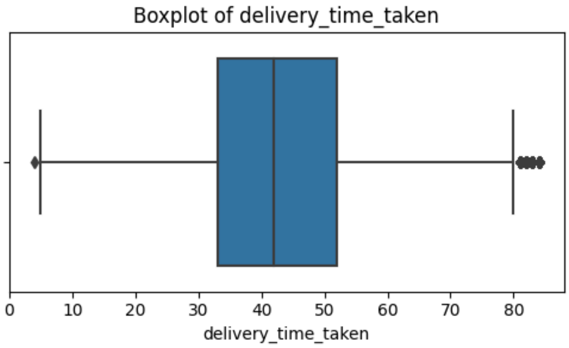
In [19]:

```
#Distribution of numerical variables
num_vars = df.select_dtypes('int').columns.tolist()
fig = plt.figure(figsize=(10,21))
i=1
for col in num_vars:
  ax = plt.subplot(7,2,i)
  sns.boxplot(x=df[col])
  plt.title(f'Boxplot of {col}')
  i += 1

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


Boxplot of market_id
1 2 3 4 5 6
market_id
Boxplot of order_protocol
1 2 3 4 5 6 7
order_protocol
Boxplot of total_items
1 2 3 4 5 6 7
total_items
Boxplot of subtotal
0 1000 2000 3000 4000 5000 6000
subtotal
Boxplot of num_distinct_items
1 2 3 4 5 6
num_distinct_items
Boxplot of min_item_price
0 250 500 750 1000 1250 1500 1750 2000
min_item_price
Boxplot of max_item_price
0 500 1000 1500 2000
max_item_price
Boxplot of total_onshift_partners
0 20 40 60 80 100 120 140
total_onshift_partners
Boxplot of total_busy_partners
0 20 40 60 80 100 120
total_busy_partners
Boxplot of total_outstanding_orders
0 25 50 75 100 125 150 175
total_outstanding_orders
Boxplot of order_hour
Boxplot of order_day





Non-Graphical Analysis

In [20]:
```
# Replace min & max item price with average price
df['avg_item_price'] = (df['min_item_price']+df['max_item_price'])/2
df.drop(columns=['min_item_price','max_item_price'], inplace=True)
```

In [21]:
```
# Number of unique values in all columns
unique_num = df.columns.tolist()
for col in unique_num:
  print(f"No. of unique values in {col}: {df[col].nunique()}")
```

```
No. of unique values in market_id: 6
No. of unique values in store_primary_category: 72
No. of unique values in order_protocol: 7
No. of unique values in total_items: 7
No. of unique values in subtotal: 5195
No. of unique values in num_distinct_items: 6
No. of unique values in total_onshift_partners: 139
No. of unique values in total_busy_partners: 136
No. of unique values in total_outstanding_orders: 184
No. of unique values in order_hour: 18
No. of unique values in order_day: 7
No. of unique values in delivery_time_taken: 81
No. of unique values in avg_item_price: 3057
```

In [22]:
```
# unique value market_id column(listed in %)
market_id = df['market_id'].value_counts(normalize=True).map(lambda calc: round(
market_id.columns = ['market_id', 'Count']
market_id
```

Out[22]:

	market_id	Count
0	2	29.60
1	4	25.55
2	1	21.22
3	3	12.67
4	5	10.59
5	6	0.37

In [23]:
```
# unique value order_protocol column(listed in %)
order_protocol = df['order_protocol'].value_counts(normalize=True).map(lambda ca
order_protocol.columns = ['order_protocol', 'Count']
order_protocol
```

Out[23]:

	order_protocol	Count
0	1	27.68
1	3	26.46
2	5	23.89
3	2	11.98
4	4	9.60
5	6	0.38
6	7	0.01

In [24]:
```
# unique value total_items column(listed in %)
total_items = df['total_items'].value_counts(normalize=True).map(lambda calc: rc
total_items.columns = ['total_items', 'Count']
total_items
```

Out[24]:

	total_items	Count
0	2	30.60
1	3	21.74
2	1	21.40
3	4	13.63
4	5	7.02
5	6	3.96
6	7	1.65

In [25]:
```
# unique value num_distinct_items column(listed in %)
num_distinct_items = df['num_distinct_items'].value_counts(normalize=True).map(l
num_distinct_items.columns = ['num_distinct_items', 'Count']
num_distinct_items
```

Out[25]:

	num_distinct_items	Count
0	2	32.72
1	1	26.65
2	3	22.56
3	4	11.58
4	5	4.88
5	6	1.61

In [26]:
```python
# unique value order_day column(listed in %)
order_day = df['order_day'].value_counts(normalize=True).map(lambda calc: round(
order_day.columns = ['order_day', 'Count']
order_day
```

Out[26]:

	order_day	Count
0	6	16.52
1	5	15.65
2	4	14.64
3	3	13.60
4	0	13.31
5	2	13.27
6	1	13.01

In [27]:
```python
df.describe().loc[['min', 'max']]
```

Out[27]:

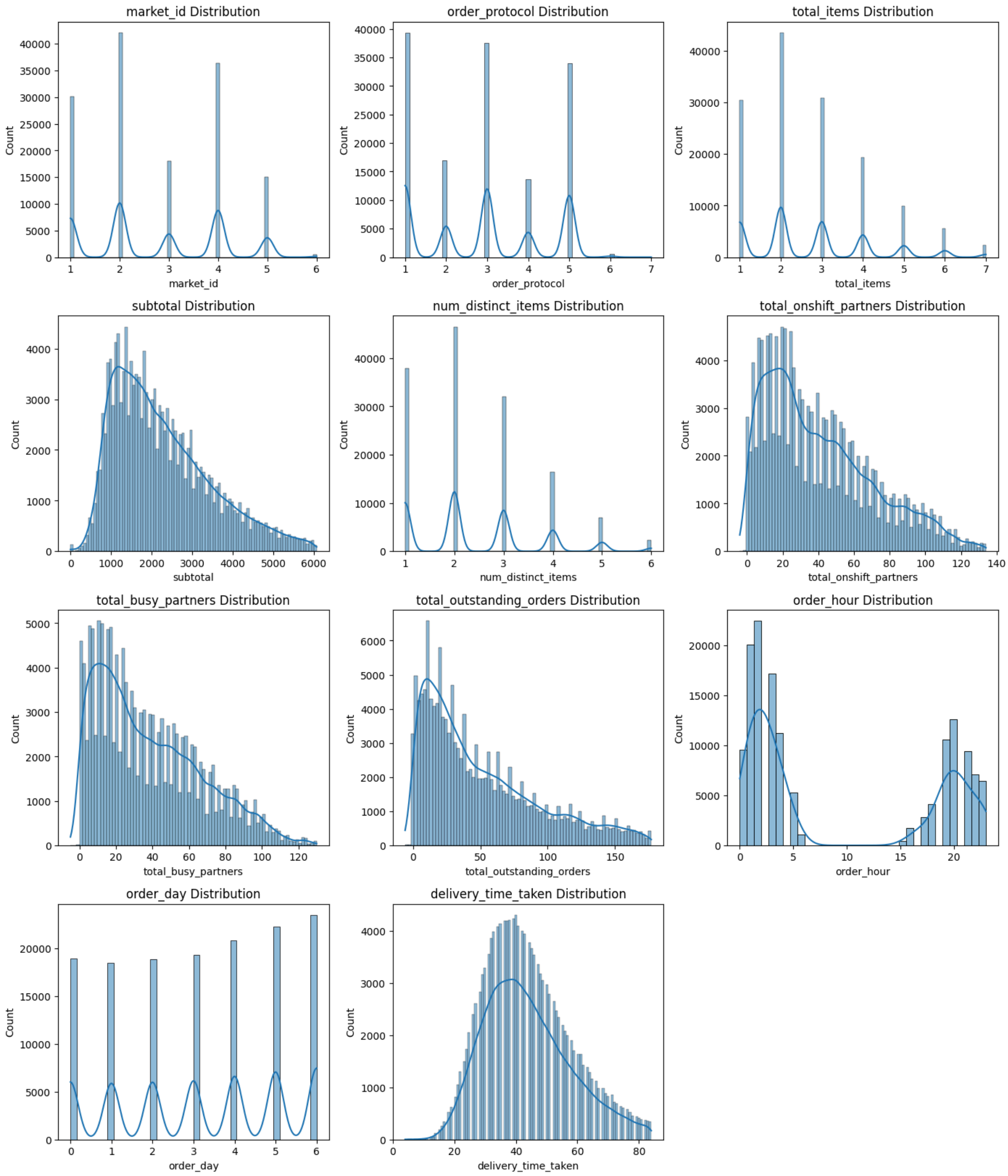
	market_id	store_primary_category	order_protocol	total_items	subtotal	num_dist
min	1.0	0.0	1.0	1.0	0.0	
max	6.0	72.0	7.0	7.0	6065.0	

Univariate Analysis

In [28]:
```python
plot = df.select_dtypes('int').columns.tolist()

plt.figure(figsize=(14, 20))
i = 1
for col in plot:
    ax = plt.subplot(5, 3, i)
    sns.histplot(data=df, x=col, kde=True)
    plt.title(f'{col} Distribution')
    i += 1

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

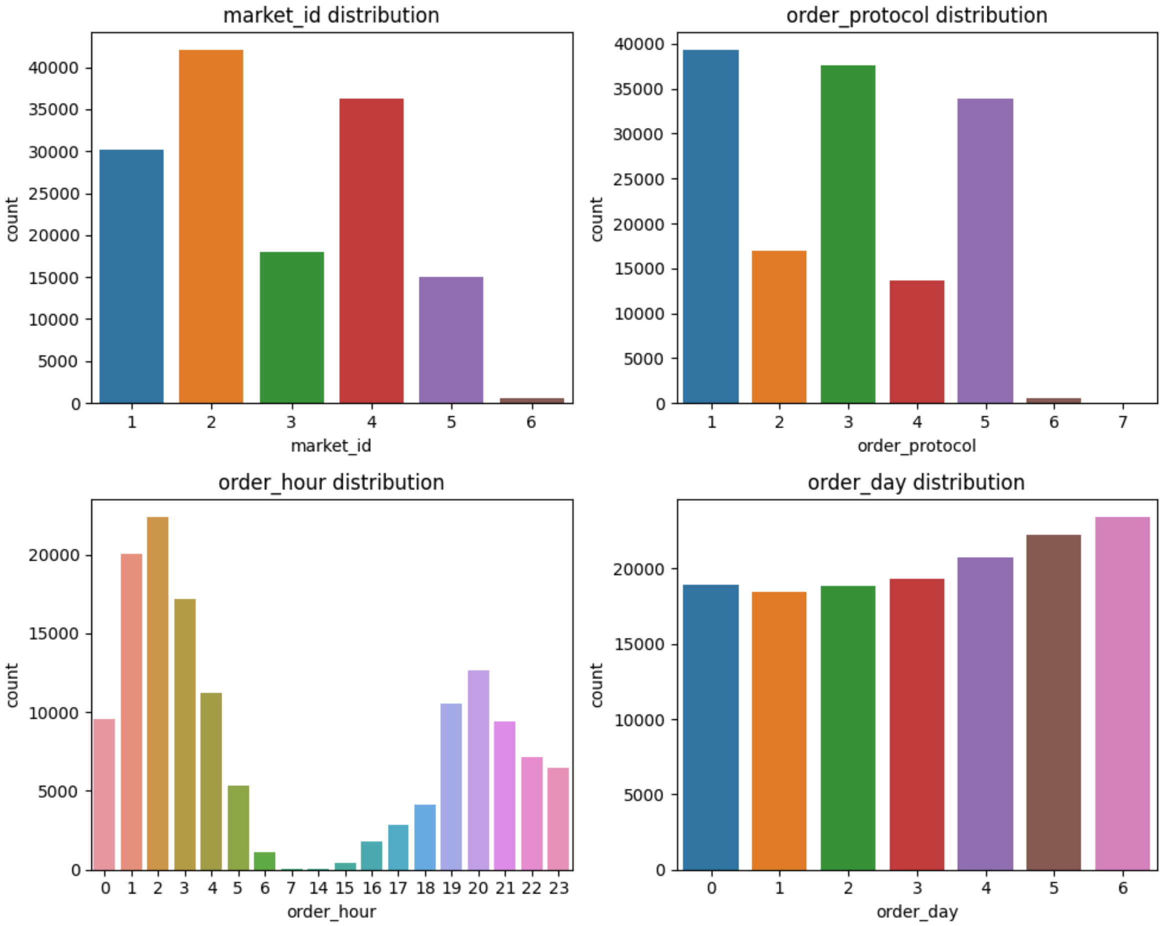


In [29]:

```
plot = ['market_id','order_protocol','order_hour','order_day']

plt.figure(figsize=(10,8))
i=1
for col in plot:
  ax=plt.subplot(2,2,i)
  sns.countplot(x=df[col])
  plt.title(f'{col} distribution')
  i += 1

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

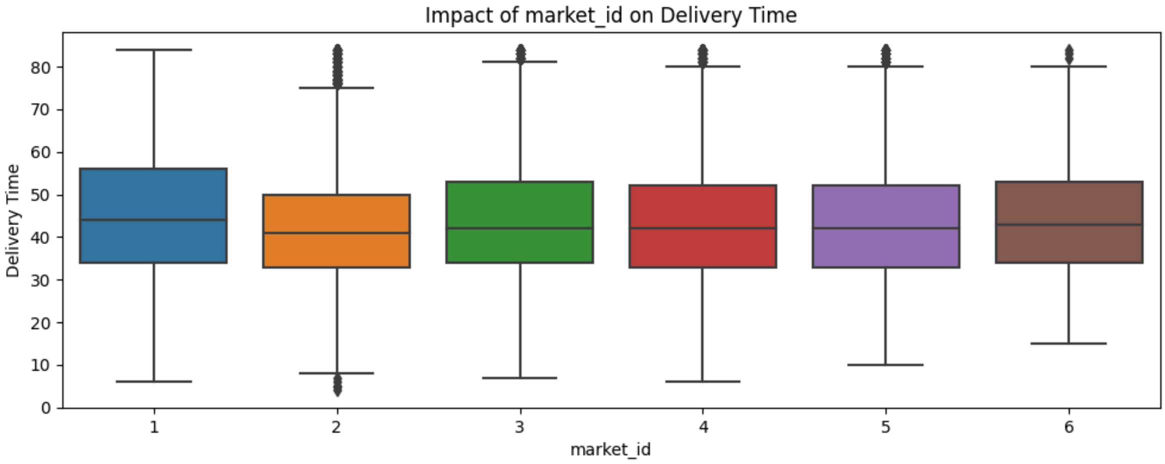


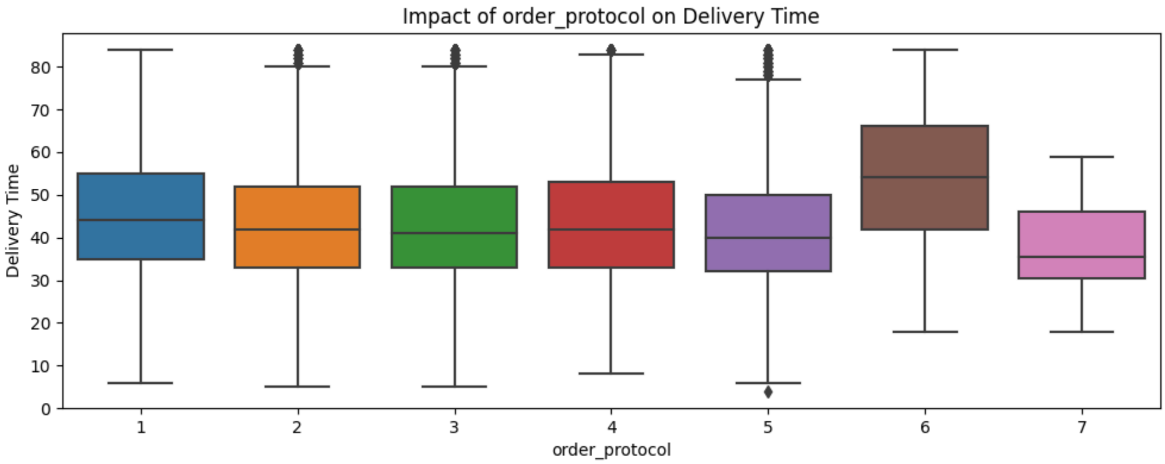
In [30]:
```
# Boxplots to analyse the relationship between categorical variables and deliver

cat_cols = ['market_id','order_protocol','order_hour', 'order_day']

plt.figure(figsize=(10,16))
i=1
for col in cat_cols:
  ax = plt.subplot(4,1,i)
  sns.boxplot(data = df, x=col, y='delivery_time_taken')
  plt.title(f"Impact of {col} on Delivery Time")
  plt.xlabel(col)
  plt.ylabel('Delivery Time')
  i+=1

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

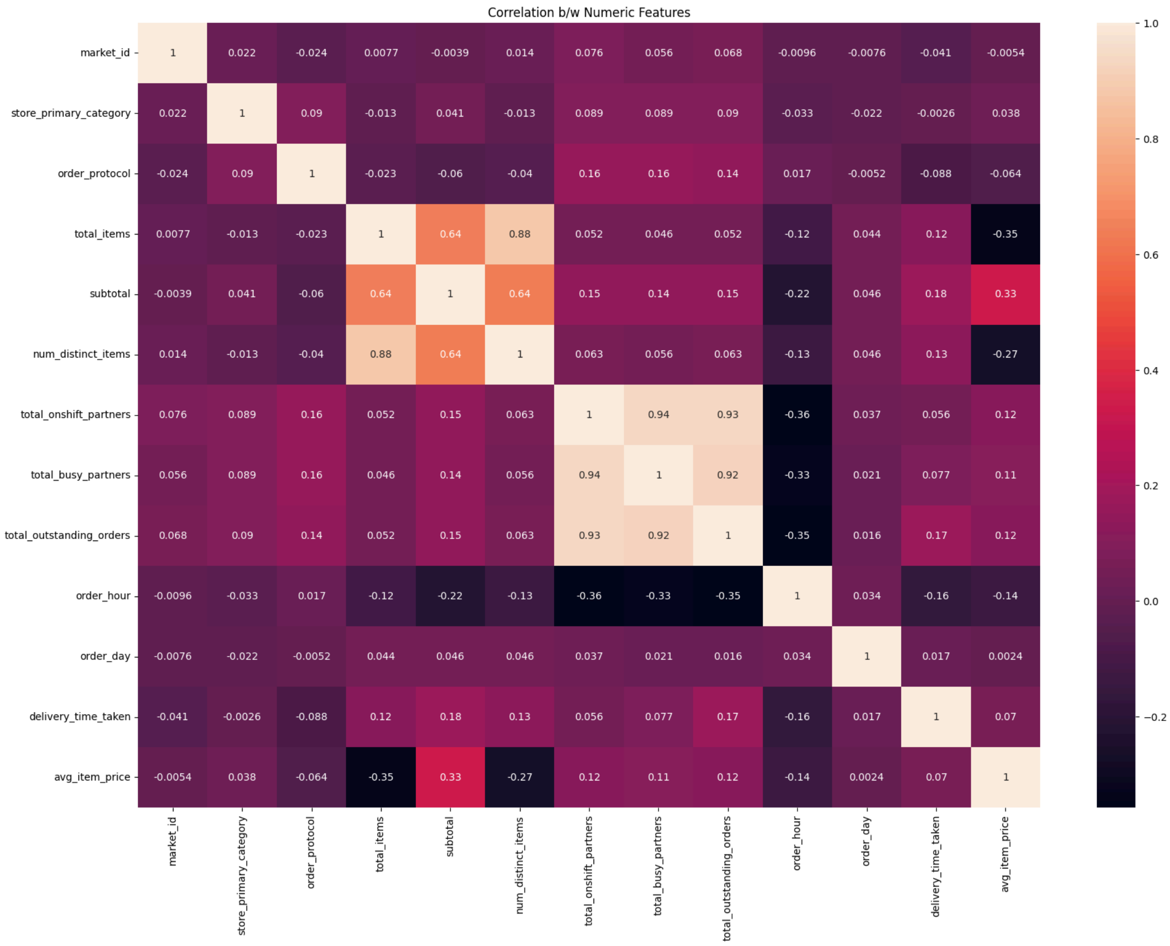




- Market ID shows no notable impact on delivery duration.

- Orders processed through protocol number 6 show relatively extended delivery times.
- Delivery times are significantly higher at 2 pm than at any other hour.
- Delivery times fluctuate more on Mondays, Saturdays, and Sundays, potentially due to increased order numbers.

In [31]:
```
##Correlation Matrix
corr = df.corr()
plt.figure(figsize=(20,14))
sns.heatmap(corr, annot = True)
plt.title('Correlation b/w Numeric Features')
plt.show()
```



Model Building

In [32]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler

from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import (r2_score,mean_squared_error,mean_absolute_error,mea
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import OneHotEncoder
from sklearn.ensemble import RandomForestRegressor
```

In [33]:
```
X = df.drop(columns=['delivery_time_taken'])
y = df['delivery_time_taken']
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)
```

In [34]:
```
print(f'Shape of x_train: {X_train.shape}')
print(f'Shape of x_test: {X_test.shape}')
```

```
Shape of x_train: (113623, 12)
Shape of x_test: (28406, 12)
```

In [35]:
```
print(f'Shape of y_train: {y_train.shape}')
print(f'Shape of y_test: {y_test.shape}')
```

```
Shape of y_train: (113623,)
Shape of y_test: (28406,)
```

Linear Regression

In [36]:
```
#Initialising object of Class LinearRegression()
lr_Test = LinearRegression()     # training LinearRegression model
lr_Test.fit(X_train,y_train)
```

Out[36]:
```
▾ LinearRegression
LinearRegression()
```

In [37]:
```
#r2 score on train data
r2_score(y_train,lr_Test.predict(X_train))
```

Out[37]: 0.1674240826950587

In [38]:
```
#r2 score on test data
r2_score(y_test,lr_Test.predict(X_test))
```

Out[38]: 0.16141248202773462

In [39]:
```
def MAPE(Y_actual,Y_Predicted):
    mape = np.mean(np.abs((Y_actual - Y_Predicted)/Y_actual))*100
    return mape
```

In [40]:
```
y_pred = lr_Test.predict(X_test)
print("MSE:",mean_squared_error(y_test,y_pred)) #MSE
print("RMSE:",np.sqrt(mean_squared_error(y_test,y_pred))) #RMSE
print("MAE :",mean_absolute_error(y_test,y_pred) ) #MAE
print("MAPE :",MAPE(y_test,y_pred) ) #MAPE
print("r2_score:",r2_score(y_test,y_pred)) #r2score
```

```
MSE: 166.17941324668996
RMSE: 12.89105943073299
MAE : 10.254421327002385
MAPE : 26.342697198065252
r2_score: 0.16141248202773462
```

Random Forest Regressor

In [41]:
```
regressor=RandomForestRegressor()
regressor.fit(X_train,y_train)
```

Out[41]:

▾ RandomForestRegressor

```
RandomForestRegressor()
```

In [42]:

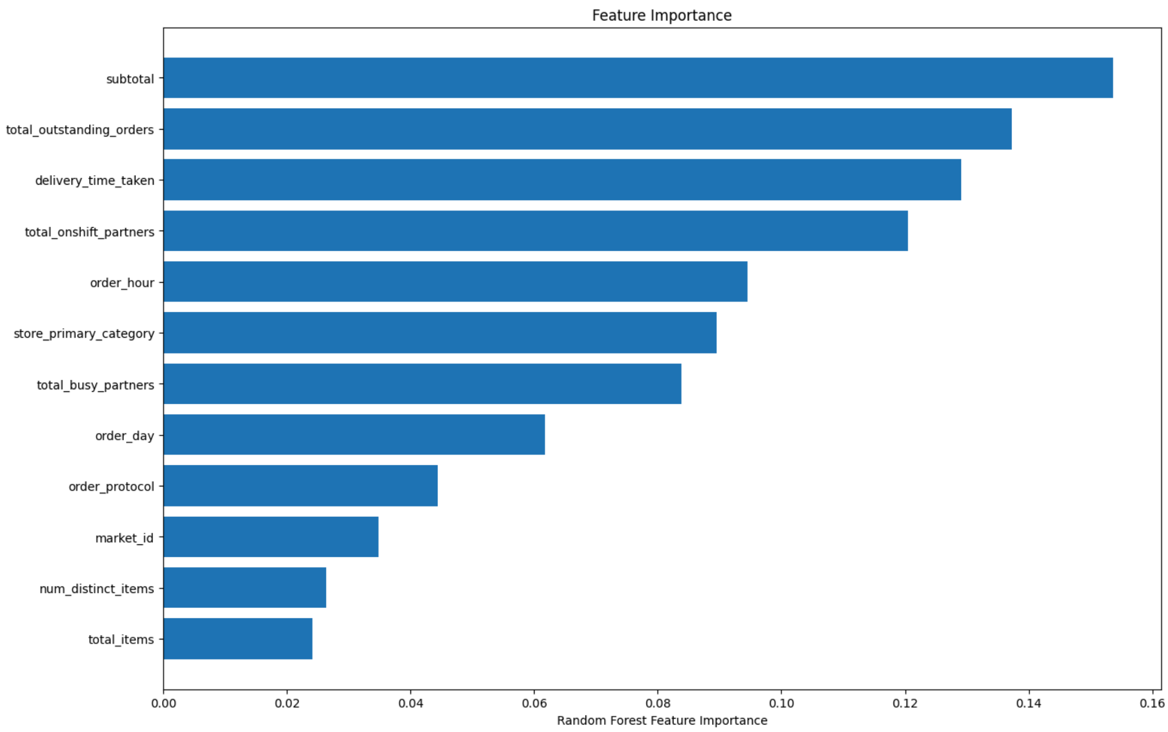
```
y_pred = regressor.predict(X_test)
print("MSE:",mean_squared_error(y_test,y_pred)) #MSE
print("RMSE:",np.sqrt(mean_squared_error(y_test,y_pred))) #RMSE
print("MAE :",mean_absolute_error(y_test,y_pred) ) #MAE
print("MAPE :",MAPE(y_test,y_pred) ) #MAPE
print("r2_score:",r2_score(y_test,y_pred)) #r2score
```

```
MSE: 154.1705630354631
RMSE: 12.416543924758736
MAE : 9.849843166936564
MAPE : 25.2465187704979
r2_score: 0.22201247871555574
```

Feature Importance

In [43]:

```
sorted_idx = regressor.feature_importances_.argsort()
plt.figure(figsize=(15,10))
plt.barh(df.columns[sorted_idx], regressor.feature_importances_[sorted_idx])
plt.title('Feature Importance')
plt.xlabel("Random Forest Feature Importance")
plt.show()
```



In [44]:

```
from sklearn import preprocessing
scaler = preprocessing.MinMaxScaler()
x_scaled = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(x_scaled, y, test_size=0.2,
```

In [45]:

```
import tensorflow as tf
from tensorflow.keras import Model
from tensorflow.keras import Sequential
```

```
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.layers import Dense, Dropout, BatchNormalization, LeakyReL
```

In [46]:
```
model = Sequential([
    Dense(64, activation='relu', input_shape=(X_train.shape[1],)),
    Dense(512, activation='relu'),
    Dropout(0.2),
    Dense(256, activation='relu'),
    Dropout(0.2),
    Dense(1, activation='linear')
])
```

In [47]:
```
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 64)	832
dense_1 (Dense)	(None, 512)	33,280
dropout (Dropout)	(None, 512)	0
dense_2 (Dense)	(None, 256)	131,328
dropout_1 (Dropout)	(None, 256)	0
dense_3 (Dense)	(None, 1)	257

Total params: 165,697 (647.25 KB)

Trainable params: 165,697 (647.25 KB)

Non-trainable params: 0 (0.00 B)

In [48]:
```
checkpoint = tf.keras.callbacks.ModelCheckpoint("CNN_best.keras", save_best_only
early_stop = tf.keras.callbacks.EarlyStopping(monitor='val_loss', patience=10, r

# Compile the model
adam = Adam(learning_rate=0.001)
model.compile(loss='mse', optimizer=adam, metrics=['mae'])

# Train the model with callbacks
history = model.fit(X_train, y_train,
                    epochs=50, verbose=1,
                    batch_size=64, validation_split=0.2,
                    callbacks=[early_stop, checkpoint])
```

```
Epoch 1/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 25s 10ms/step - loss: 309.3676 - mae: 13.2066 - va
l_loss: 164.8390 - val_mae: 10.1866
Epoch 2/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 13s 9ms/step - loss: 170.8811 - mae: 10.3742 - val
_loss: 163.9697 - val_mae: 10.2849
Epoch 3/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 12s 9ms/step - loss: 169.9551 - mae: 10.3621 - val
_loss: 161.5222 - val_mae: 10.1004
Epoch 4/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 13s 9ms/step - loss: 169.4972 - mae: 10.3421 - val
_loss: 160.8855 - val_mae: 10.0460
Epoch 5/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 13s 9ms/step - loss: 166.3934 - mae: 10.2174 - val
_loss: 165.4484 - val_mae: 9.9875
Epoch 6/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 14s 10ms/step - loss: 167.0592 - mae: 10.2488 - va
l_loss: 160.1856 - val_mae: 10.1329
Epoch 7/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 14s 10ms/step - loss: 165.5129 - mae: 10.2045 - va
l_loss: 167.8309 - val_mae: 10.5551
Epoch 8/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 14s 10ms/step - loss: 165.2750 - mae: 10.1992 - va
l_loss: 158.2682 - val_mae: 10.0260
Epoch 9/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 13s 9ms/step - loss: 163.7004 - mae: 10.1437 - val
_loss: 165.3157 - val_mae: 9.9958
Epoch 10/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 14s 10ms/step - loss: 165.2803 - mae: 10.2051 - va
l_loss: 158.6365 - val_mae: 9.9117
Epoch 11/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 15s 11ms/step - loss: 163.3475 - mae: 10.1465 - va
l_loss: 156.7323 - val_mae: 9.8632
Epoch 12/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 13s 9ms/step - loss: 162.2817 - mae: 10.1012 - val
_loss: 155.6695 - val_mae: 9.9116
Epoch 13/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 12s 9ms/step - loss: 162.1728 - mae: 10.0948 - val
_loss: 156.0915 - val_mae: 9.8097
Epoch 14/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 15s 10ms/step - loss: 160.3668 - mae: 10.0241 - va
l_loss: 158.0540 - val_mae: 10.0579
Epoch 15/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 14s 10ms/step - loss: 161.5063 - mae: 10.0671 - va
l_loss: 157.4915 - val_mae: 9.8663
Epoch 16/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 12s 8ms/step - loss: 160.1142 - mae: 10.0001 - val
_loss: 157.5523 - val_mae: 9.8296
Epoch 17/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 13s 9ms/step - loss: 162.1541 - mae: 10.0766 - val
_loss: 155.4148 - val_mae: 9.9064
Epoch 18/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 14s 10ms/step - loss: 160.3498 - mae: 10.0404 - va
l_loss: 156.5645 - val_mae: 9.8258
Epoch 19/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 14s 9ms/step - loss: 161.1077 - mae: 10.0246 - val
_loss: 154.6116 - val_mae: 9.8697
Epoch 20/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 13s 9ms/step - loss: 159.6297 - mae: 10.0076 - val
_loss: 159.6281 - val_mae: 9.8194
```

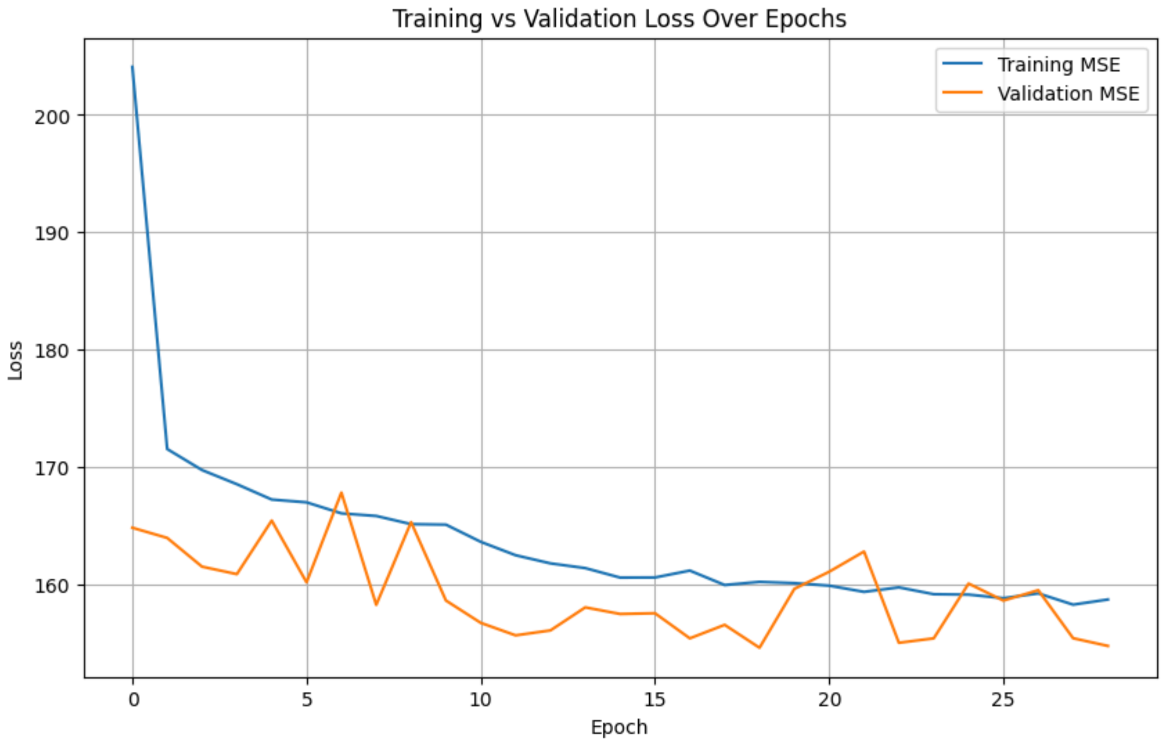
```
Epoch 21/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 13s 9ms/step - loss: 160.2094 - mae: 10.0259 - val
_loss: 161.0898 - val_mae: 9.8277
Epoch 22/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 12s 9ms/step - loss: 159.7376 - mae: 10.0306 - val
_loss: 162.8111 - val_mae: 9.8998
Epoch 23/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 14s 10ms/step - loss: 158.6777 - mae: 9.9571 - val
_loss: 155.0361 - val_mae: 9.9213
Epoch 24/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 15s 11ms/step - loss: 159.2619 - mae: 9.9726 - val
_loss: 155.4119 - val_mae: 9.9142
Epoch 25/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 13s 9ms/step - loss: 158.9671 - mae: 9.9737 - val_
loss: 160.0805 - val_mae: 9.7909
Epoch 26/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 14s 10ms/step - loss: 159.3607 - mae: 9.9716 - val
_loss: 158.6290 - val_mae: 9.7932
Epoch 27/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 14s 10ms/step - loss: 158.5242 - mae: 9.9351 - val
_loss: 159.5169 - val_mae: 9.8321
Epoch 28/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 14s 10ms/step - loss: 157.4952 - mae: 9.9380 - val
_loss: 155.4253 - val_mae: 9.8607
Epoch 29/50
1421/1421 ━━━━━━━━━━━━━━━━━━━━ 13s 9ms/step - loss: 160.1654 - mae: 10.0049 - val
_loss: 154.7669 - val_mae: 9.7804
```

In [49]:

```
fig, ax = plt.subplots(figsize=(10, 6))
ax.plot(history.history['loss'], label='Training MSE')
ax.plot(history.history['val_loss'], label='Validation MSE')

ax.set_title('Training vs Validation Loss Over Epochs')
ax.set_xlabel('Epoch')
ax.set_ylabel('Loss')

ax.legend(loc='best')
plt.grid(True)
plt.show()
```



In [50]:
```
y_pred = model.predict(X_test)
print("MSE:",mean_squared_error(y_test,y_pred)) #MSE
print("RMSE:",np.sqrt(mean_squared_error(y_test,y_pred))) #RMSE
print("MAE :",mean_absolute_error(y_test,y_pred) ) #MAE
print("MAPE :",mean_absolute_percentage_error(y_test,y_pred) ) #MAPE
print("r2_score:",r2_score(y_test,y_pred)) #r2score
```

```
888/888 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step
MSE: 155.6469484899873
RMSE: 12.475854619623751
MAE : 9.926205313844445
MAPE : 0.25493256842432643
r2_score: 0.22020153682583432
```

Conclusion:

- The Logistic Regression model required considerably more time for training compared to the Neural Network model and Random Forest Regressor.
- Prediction time was also longer with the Neural Network model.
- Generally, neural networks are known to deliver higher accuracy than random forest regressors across various problem types, as they are capable of learning more intricate relationships between input features and target variables.

Questions

1. Defining the problem statements and where can this and modifications of this be used?

- Porter, India's largest marketplace for intra-city logistics, partners with restaurants to handle food deliveries.

- The company aims to provide its customers with accurate delivery time estimates based on several influencing factors.
- Key factors include order time, items ordered, delivery partner availability, the number of outstanding orders, and the type of restaurant.
- The objective is to develop a regression model that can predict delivery times with high accuracy using these features.

---

2. List 3 functions the pandas datetime provides with one line explanation.

- **pd.to_datetime():** Converts input data to datetime format.
- **pd.date_range():** Creates a sequence of dates between specified start and end.
- **pd.to_timedelta:** Converts input to a timedelta, representing durations.

---

3. Short note on datetime, timedelta, time span (period)

- **datetime:** Represents a specific point in time, including date and time components. It is used for precise timekeeping and manipulating time-related data.

- **timedelta:** Represents a duration or difference between two dates or times. It is used for arithmetic operations involving dates and times, such as adding or subtracting durations.

- **time Span (Period):** Defines a range or interval of time. It can be represented by a pair of datetime objects (start and end) or by a datetime object combined with a timedelta to specify the extent of the period.

---

4. Why do we need to check for outliers in our data?

- Outliers are data points that deviate significantly from the majority of the dataset. They can arise from various sources, such as data entry errors, and may distort statistical analyses, making it challenging to draw precise conclusions.

- Here’s why identifying outliers is crucial:

  1. Impact on Statistical Analysis: Outliers can disproportionately affect statistical measures like the mean, median, and standard deviation. They may skew these values, leading to misleading results and inaccurate interpretations.

  2. Challenges in Drawing Conclusions: Outliers can obscure the true distribution of data and mask underlying patterns. This distortion makes it harder to derive meaningful insights and understand the data accurately.

  3. Errors in Data Entry: Outliers might be introduced due to mistakes in data recording. For instance, an incorrectly entered value can create an outlier, so it’s essential to detect and address these anomalies before performing data analysis.

---

5. Name 3 outlier removal methods?

- Here are three common methods for removing outliers:

  1. **Z-Score Method:** Identifies outliers by calculating the Z-score, which measures how many standard deviations a data point is from the mean. Data points with a Z-score beyond a certain threshold are considered outliers.
  2. **IQR Method:** Uses the Interquartile Range (IQR), which is the range between the first (25th percentile) and third quartile (75th percentile). Data points that fall below Q1 − 1.5 × IQR or above Q3 + 1.5 × IQR are flagged as outliers.
  3. **Isolation Forest:** A machine learning-based method that isolates observations by randomly selecting features and splitting values. Outliers are identified as observations that are isolated earlier in the process compared to normal data points.

---

6. What classical machine learning methods can we use for this problem?

- For outlier detection, classical machine learning methods include:

  1. **K-Nearest Neighbors (KNN):** Uses distance metrics to find the k-nearest neighbors of a data point. Outliers are identified as points that have a larger average distance to their neighbors compared to the majority of points.
  2. **One-Class SVM (Support Vector Machine):** Trains a model to separate the data from the origin in a high-dimensional space. Data points that fall outside the learned boundary are considered outliers.
  3. **Isolation Forest:** Specifically designed for anomaly detection, it isolates observations by randomly selecting features and splitting values. Points that are isolated quickly are likely outliers.
  4. **Local Outlier Factor (LOF):** Measures the local density deviation of a data point compared to its neighbors. Points with significantly lower density compared to their neighbors are flagged as outliers.
  5. **Robust PCA (Principal Component Analysis):** Decomposes the data into a low-rank matrix and a sparse matrix. Outliers are captured in the sparse matrix, making it possible to detect anomalous data points.

---

7. Why is scaling required for neural networks?

- Scaling is crucial for neural networks due to several reasons:

  1. **Improves Convergence:** Scaling features to a similar range (e.g., [0, 1] or standardizing to zero mean and unit variance) helps the neural network converge faster during training. It ensures that gradients are more stable and prevents some features from disproportionately influencing the weight updates.

2. **Reduces Numerical Instability:** Neural networks often involve operations that can lead to numerical instability, such as large matrix multiplications and activation functions. Scaling inputs helps mitigate issues related to overflow or underflow, ensuring more stable computations.

3. **Facilitates Activation Function Efficiency:** Many activation functions (like sigmoid and tanh) are sensitive to the scale of the inputs. Scaling ensures that inputs to these functions lie within the region where they can effectively learn and provide meaningful gradients.

4. **Balances Feature Importance:** Different features might have different scales (e.g., height in cm vs. weight in kg). Scaling ensures that each feature contributes equally to the model's learning process, preventing features with larger scales from dominating the learning process.

5. **Improves Training Speed:** When features are on a similar scale, the optimization process (e.g., gradient descent) can proceed more smoothly and efficiently, potentially reducing the number of epochs required to train the model.

---

8. Briefly explain your choice of optimizer.

- **Combines Momentum and RMSProp:** Adam integrates the benefits of both Momentum (which uses moving averages of past gradients) and RMSProp (which uses moving averages of squared gradients).
- **Adaptive Learning Rates:** It automatically adjusts learning rates for each parameter, allowing for efficient and reliable convergence.
- **Faster Convergence:** The combination of momentum and adaptive learning rates often leads to faster and more stable convergence compared to traditional optimizers.
- **Robust Performance:** Adam performs well across a wide range of problems and is less sensitive to hyperparameter tuning.
- **Efficient:** It is computationally efficient and has low memory requirements, making it suitable for large-scale machine learning problems.

---

9. Which activation function did you use and why?

1. **ReLU: A Popular Activation Function**

    - ReLU, widely used in neural networks and deep learning, addresses the vanishing gradient problem seen in functions like sigmoid and tanh. By introducing sparsity, ReLU deactivates neurons with negative inputs, improving network efficiency.

2. **Advantages of ReLU in Neural Networks**

    - ReLU is a favored activation function in deep learning for its ability to tackle the vanishing gradient problem. It introduces sparsity by deactivating neurons with negative inputs, enhancing the performance of neural networks.

3. **ReLU's Benefits in Deep Learning**

    - ReLU is commonly used in neural networks because it helps reduce the vanishing gradient problem, unlike sigmoid and tanh. It also creates sparse activation by turning off neurons with negative outputs, making the model more efficient.

---

10. Why does a neural network perform well on a large dataset?

- A neural network performs well on a large dataset because larger datasets provide more diverse and comprehensive information for the model to learn from, leading to better generalization. Here are the key reasons:

    1. Better Learning of Patterns: Large datasets capture a wider range of patterns, relationships, and nuances in the data, allowing the neural network to learn complex features effectively.

    2. Reduced Overfitting: With more data, the model is less likely to memorize specific samples, reducing the risk of overfitting. This leads to a model that performs better on unseen data.

    3. Improved Generalization: Large datasets provide the network with a broader understanding of the underlying distribution of the data, enhancing its ability to make accurate predictions on new inputs.

    4. Balanced Classes: Larger datasets are more likely to provide balanced class distributions, which helps the model learn equally well across different classes, improving overall performance.

    5. Enhanced Training Stability: With more examples, the gradient estimates during training are more accurate, leading to smoother and more stable convergence.

- Overall, a large dataset equips neural networks with the information needed to learn complex decision boundaries and improve their predictive capabilities.

In [ ]:

```

```