porter

March 20, 2025

0.0.1 About Porter

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.

0.0.2 Business Problem

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.

0.0.3 Dataset

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

Feature	Description
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 i.e., through porter, call to restaurant, pre-booked, third party, 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 the 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

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Importing Required Libraries

[34]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.metrics import mean_squared_error, mean_absolute_error
from sklearn.compose import ColumnTransformer
from category_encoders import TargetEncoder

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.optimizers import Adam, SGD
from tensorflow.keras.callbacks import EarlyStopping


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

[35]:
```
sns.set(style="darkgrid")
bi_palette = ["#4878ff", "#ffde01"]
three_set_palette = ["#4878ff", "#072a98", "#ffde01"]
four_set_palette = ["#4878ff", "#fdfef0", "#ffde01", "#072a98"]
```

Read Dataset

[36]:
```
df = pd.read_csv('../data/dataset.csv')
df.sample(5)
```

[36]:
```
        market_id           created_at actual_delivery_time  \
113769        4.0  2015-01-27 20:07:15  2015-01-27 20:40:34
163235        4.0  2015-02-11 00:47:27  2015-02-11 01:23:41
68335         2.0  2015-02-02 01:43:56  2015-02-02 02:53:03
108477        1.0  2015-02-16 02:03:10  2015-02-16 04:28:33
150242        3.0  2015-02-04 03:31:19  2015-02-04 04:04:02

                                store_id store_primary_category  \
113769  a3f390d88e4c41f2747bfa2f1b5f87db                  other
163235  a86c450b76fb8c371afead6410d55534                mexican
68335   4734ba6f3de83d861c3176a6273cac6d                  greek
108477  8d317bdcf4aafcfc22149d77babee96d                chinese
150242  882735cbdfd9f810814d17892ae50023                dessert

        order_protocol  total_items  subtotal  num_distinct_items  \
113769             3.0            1      1300                   1
163235             5.0            3      1725                   3
```

```
68335              5.0            2     2597                  2
108477             4.0            9    10555                  8
150242             1.0            3     4385                  3

        min_item_price  max_item_price  total_onshift_partners  \
113769             975             975                    71.0
163235             195             685                    25.0
68335             1199            1299                    75.0
108477             595            1495                     0.0
150242            1095            1695                    30.0

        total_busy_partners  total_outstanding_orders
113769                 69.0                     123.0
163235                 23.0                      23.0
68335                  76.0                     120.0
108477                  0.0                       0.0
150242                 27.0                      27.0
```

[37]:

```python
print("Shape of the data: ", df.shape)
print("The Given Dataset has {} rows and {} columns".format(df.shape[0], df.
 ↪shape[1]))
print("Columns: ", df.columns.to_list())
print("Order date ranges from {} to {}".format(df['created_at'].min(),␣
 ↪df['created_at'].max()))
```

```
Shape of the data:  (197428, 14)
The Given Dataset has 197428 rows and 14 columns
Columns:  ['market_id', 'created_at', 'actual_delivery_time', 'store_id',
'store_primary_category', 'order_protocol', 'total_items', 'subtotal',
'num_distinct_items', 'min_item_price', 'max_item_price',
'total_onshift_partners', 'total_busy_partners', 'total_outstanding_orders']
Order date ranges from 2014-10-19 05:24:15 to 2015-02-18 06:00:44
```

0.0.4 Shape and Structure:

- The dataset comprises 197,428 rows and 14 columns, representing a substantial volume of delivery data.
- Each row in this file corresponds to one unique delivery.
- Data is provided for the time period of 2014-10-19 05:24:15 and 2015-02-18 06:00:44

[38]:

```python
df.duplicated().sum()
```

[38]: 0

[39]:

```python
df.info()
```

```
<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
```

[40]:
```
df.isnull().sum()
```

[40]:
```
market_id                    987
created_at                     0
actual_delivery_time           7
store_id                       0
store_primary_category      4760
order_protocol               995
total_items                    0
subtotal                       0
num_distinct_items             0
min_item_price                 0
max_item_price                 0
total_onshift_partners     16262
total_busy_partners        16262
total_outstanding_orders   16262
dtype: int64
```

0.0.5 Dataset Information:

- **Duplicates**: They is no duplicate row present in the given dataset
- **Data Consistency**: All columns have the different non-null count, indicating missing values in the dataset.
- **Data Types**: Columns are classified into integer, float and object types.

0.0.6 Data Preprocessing

[41]:
```
# Data Cleaning
print(f"No. of record missing actual delivery time: {df['actual_delivery_time'].
↪isna().sum()}")
df = df.dropna(subset=['actual_delivery_time'])
```

```
No. of record missing actual delivery time: 7
```

[42]:
```
# Handling Missing Values
df['market_id'] = df['market_id'].fillna(df['market_id'].mode()[0])
df['market_id'] = df['market_id'].astype(int)

df['order_protocol'] = df['order_protocol'].fillna(df['order_protocol'].
↪mode()[0])
df['order_protocol'] = df['order_protocol'].astype(int)

df['store_primary_category'] = df['store_primary_category'].fillna('other')

df['total_onshift_partners'] = df['total_onshift_partners'].fillna(0)
df['total_busy_partners'] = df['total_busy_partners'].fillna(0)
df['total_outstanding_orders'] = df['total_outstanding_orders'].fillna(0)

df['total_onshift_partners'] = df['total_onshift_partners'].astype(int)
df['total_busy_partners'] = df['total_busy_partners'].astype(int)
df['total_outstanding_orders'] = df['total_outstanding_orders'].astype(int)
```

[43]:
```
# Feature Engineering

df['created_at'] = pd.to_datetime(df['created_at'])
df['actual_delivery_time'] = pd.to_datetime(df['actual_delivery_time'])

# Extract the delivery time from the created_at and actual_delivery_time
df['delivery_time'] = df['actual_delivery_time'] - df['created_at']
df['delivery_time'] = df['delivery_time'].dt.total_seconds() / 60

# Extract the day of the week and hour of the day
df['order_hour'] = df['created_at'].dt.hour
df['order_day'] = df['created_at'].dt.dayofweek

# Calculate available partners
df['available_partners'] = df['total_onshift_partners'] -␣
↪df['total_busy_partners']
```

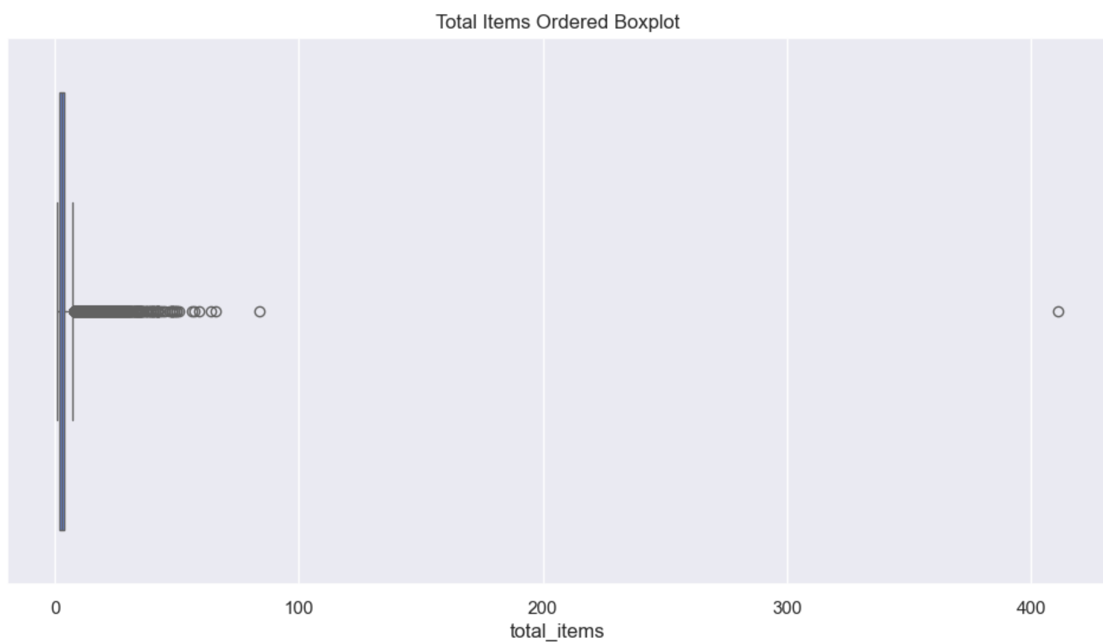
0.0.7 Handling Missing Value:

- **actual_delivery_time**: Actual delivery time is missing in 7 records, hence dropping those records.

- **market_id / order_protocol**: Missing values in these columns are imputed with the most frequent value.
- **store_primary_category**: Filled with 'Other'.
- **total_onshift_partners / total_busy_partners / total_outstanding_orders**: Imputed with zeros.

0.0.8 Data Visualization and Cleaning

[45]:
```
plt.figure(figsize=(12, 6))
sns.boxplot(x='total_items', data=df, color=bi_palette[0])
plt.title('Total Items Ordered Boxplot')
plt.show()

df['total_items'].describe()
```



[45]:
```
count    197421.000000
mean          3.196367
std           2.666552
min           1.000000
25%           2.000000
50%           3.000000
75%           4.000000
max         411.000000
Name: total_items, dtype: float64
```

[46]:
```python
# Remove outliers - Z-Score
mean = np.mean(df['total_items'])
std_dev = np.std(df['total_items'])

print(f"Mean: {mean}")
print(f"Standard Deviation: {std_dev}")

# Compute the Z-scores
df['z_score'] = (df['total_items'] - mean) / std_dev

# Define the threshold
threshold = 3

# Identify outliers
outliers = df[np.abs(df['z_score']) > threshold]

print(outliers['total_items'].min(), outliers['total_items'].max())

df.drop(['z_score'], axis=1, inplace=True)
```

```
Mean: 3.1963671544567194
Standard Deviation: 2.666544875793508
12 411
```

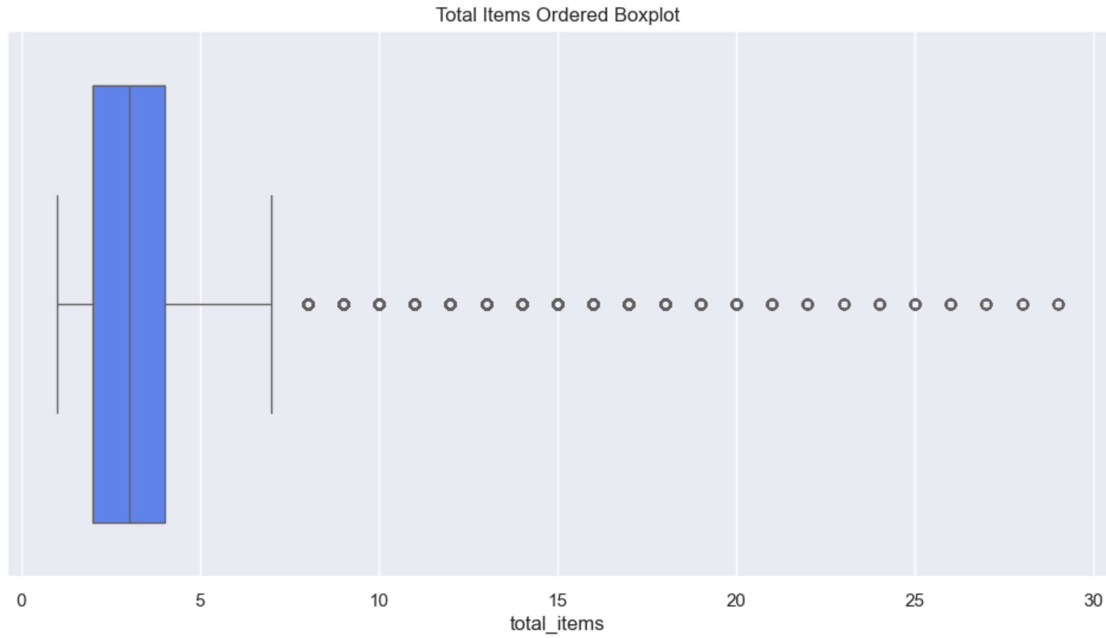
[47]:
```python
# Remove the outliers based on IQR
Q1 = df['total_items'].quantile(0.25)
Q3 = df['total_items'].quantile(0.75)
IQR = Q3 - Q1

print("Lower Bound: ", Q1 - 1.5 * IQR)
print("Upper Bound: ", Q3 + 1.5 * IQR)
```

```
Lower Bound:  -1.0
Upper Bound:  7.0
```

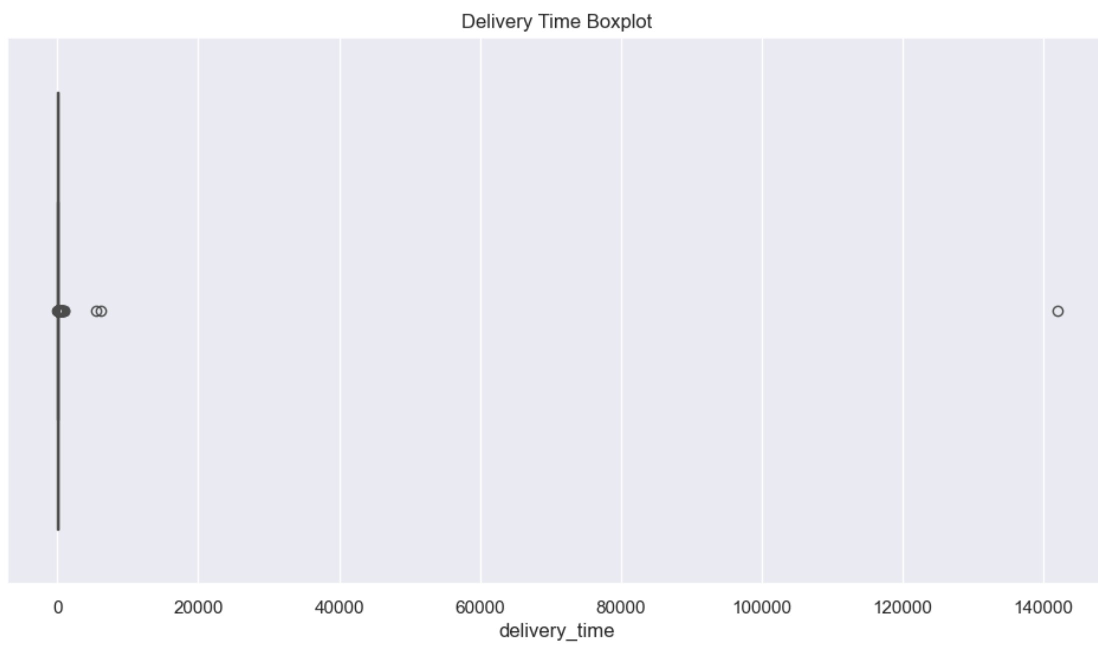
[48]:
```python
t_df = df['total_items'].value_counts().sort_index().reset_index()
t_df.columns = ['total_items', 'count']
t_df[t_df['total_items'] > 30]['count'].sum()
```

[48]: 75

[49]:
```python
df = df[df['total_items'] < 30]
plt.figure(figsize=(12, 6))
sns.boxplot(x='total_items', data=df, color=bi_palette[0])
plt.title('Total Items Ordered Boxplot')
plt.show()
```



[50]:
```
plt.figure(figsize=(12, 6))
sns.boxplot(x='delivery_time', data=df)
plt.title('Delivery Time Boxplot')
plt.show()
df['delivery_time'].describe()
```

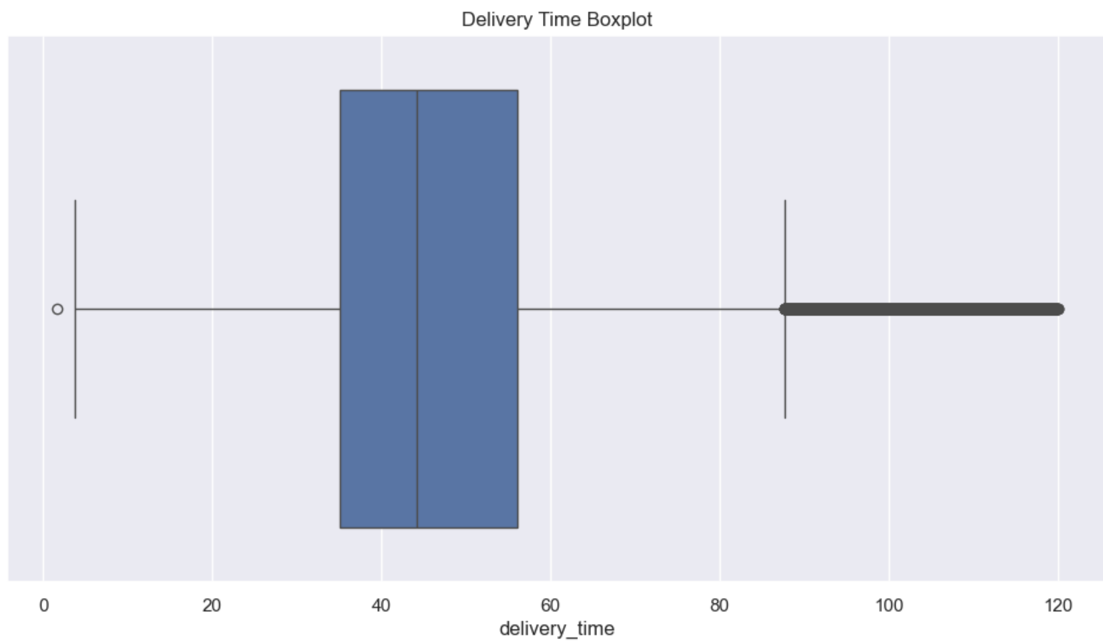


[50]:
```
count    197331.000000
mean         48.469600
std         320.566264
min           1.683333
25%          35.066667
50%          44.333333
75%          56.350000
max      141947.650000
Name: delivery_time, dtype: float64
```

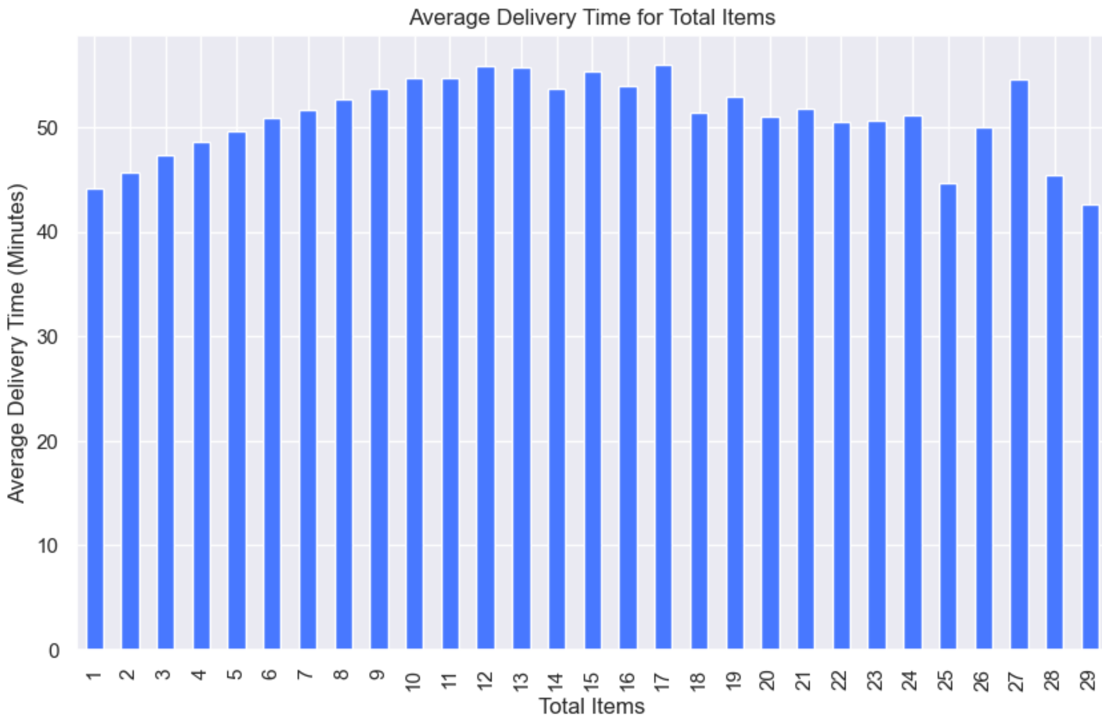
[51]:
```
print("Orders with delivery time more than 60 minutes: ",␣
 ↪df[df['delivery_time'] >= 60].shape[0])
print("Percentage of Orders with delivery time more than 60 minutes: ",␣
 ↪df[df['delivery_time'] >= 60].shape[0] / df.shape[0] * 100)
print("-" * 50)

print("Orders with delivery time more than 90 minutes: ",␣
 ↪df[df['delivery_time'] >= 90].shape[0])
print("Percentage of Orders with delivery time more than 90 minutes: ",␣
 ↪df[df['delivery_time'] >= 90].shape[0] / df.shape[0] * 100)
print("-" * 50)

print("Orders with delivery time more than 120 minutes: ",␣
 ↪df[df['delivery_time'] >= 120].shape[0])
print("Percentage of Orders with delivery time more than 120 minutes: ",␣
 ↪df[df['delivery_time'] >= 120].shape[0] / df.shape[0] * 100)
print("-" * 50)

print("Orders with delivery time more than 180 minutes: ",␣
 ↪df[df['delivery_time'] >= 180].shape[0])
print("Percentage of Orders with delivery time more than 180 minutes: ",␣
 ↪df[df['delivery_time'] >= 180].shape[0] / df.shape[0] * 100)

df = df[df['delivery_time'] < 120]

plt.figure(figsize=(12, 6))
sns.boxplot(x='delivery_time', data=df)
plt.title('Delivery Time Boxplot')
plt.show()
```

```
Orders with delivery time more than 60 minutes:  39235
Percentage of Orders with delivery time more than 60 minutes:  19.88283645245805
--------------------------------------------------
Orders with delivery time more than 90 minutes:  5643
Percentage of Orders with delivery time more than 90 minutes:
2.8596621919515943
--------------------------------------------------
```

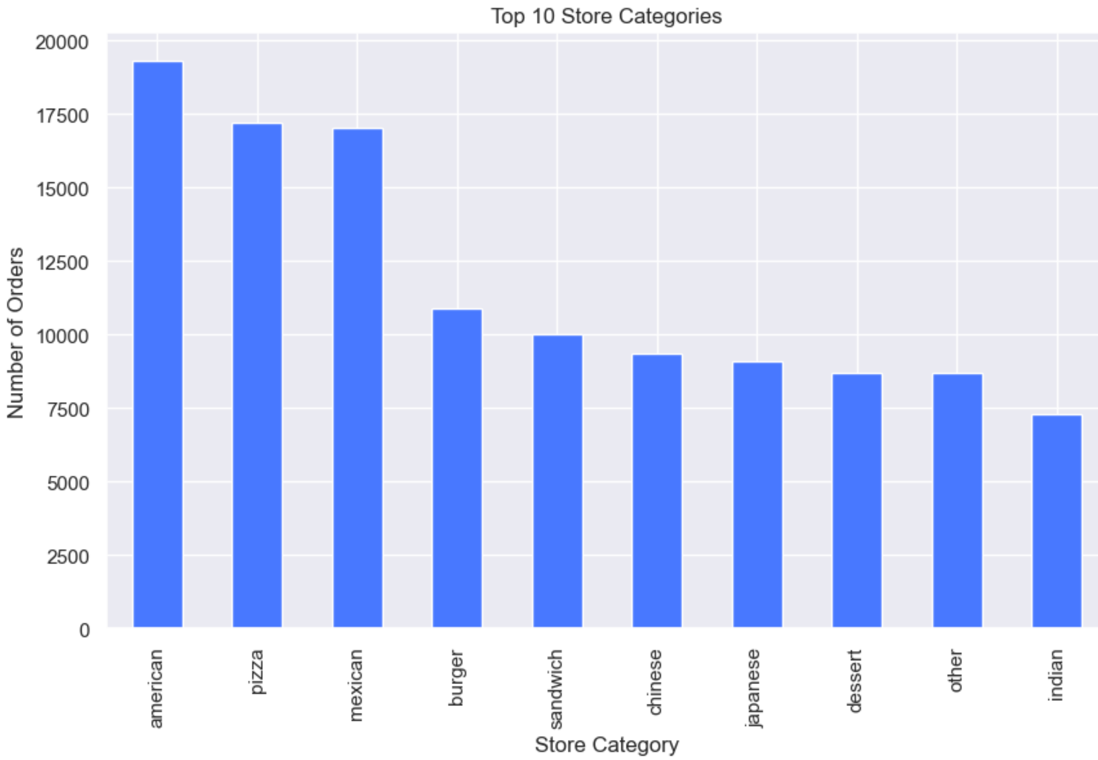
```
Orders with delivery time more than 120 minutes:  1090
Percentage of Orders with delivery time more than 120 minutes:
0.552371396283402
--------------------------------------------------
Orders with delivery time more than 180 minutes:  138
Percentage of Orders with delivery time more than 180 minutes:
0.069933259345972
```



[52]:
```
df.groupby(['total_items'])['delivery_time'].mean().plot(kind='bar',␣
↪figsize=(10, 6), color=bi_palette[0])
plt.title('Average Delivery Time for Total Items')
plt.xlabel('Total Items')
plt.ylabel('Average Delivery Time (Minutes)')
plt.show()
```

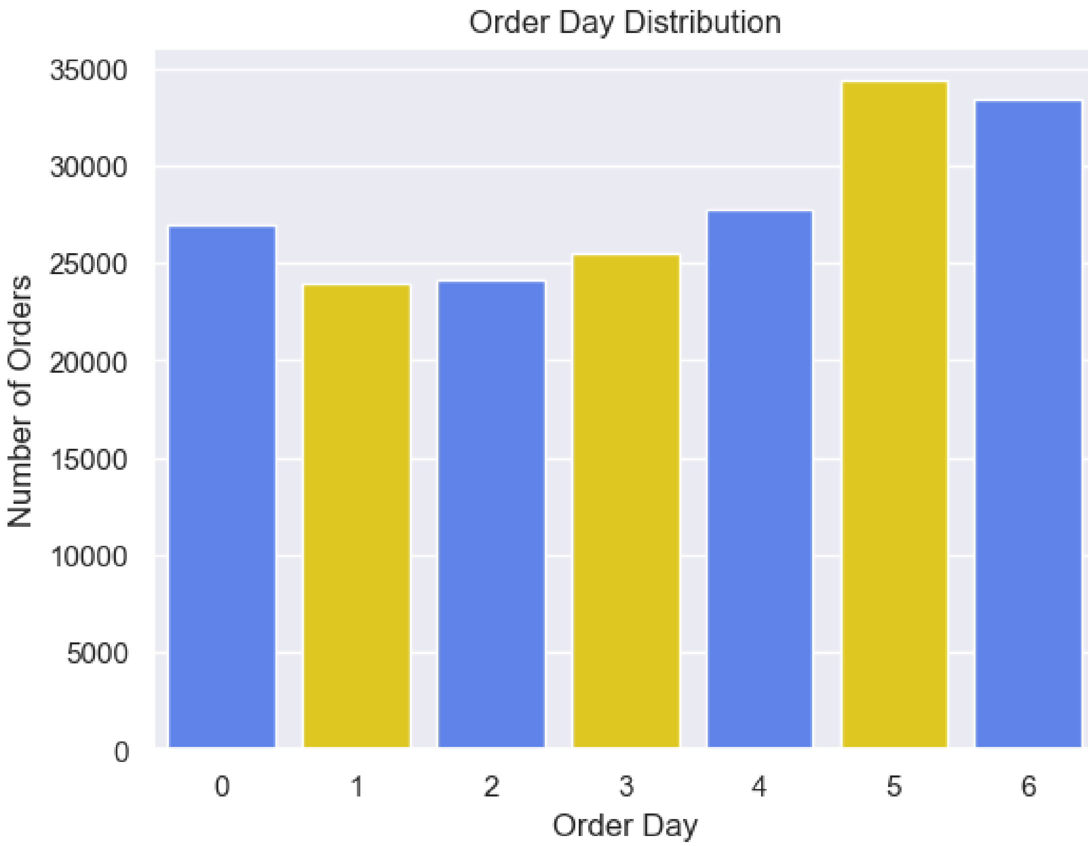


[53]:
```
df['store_primary_category'].value_counts().head(10).plot(kind='bar',␣
↪figsize=(10, 6), color=bi_palette[0])
plt.title('Top 10 Store Categories')
plt.xlabel('Store Category')
plt.ylabel('Number of Orders')
plt.show()
```

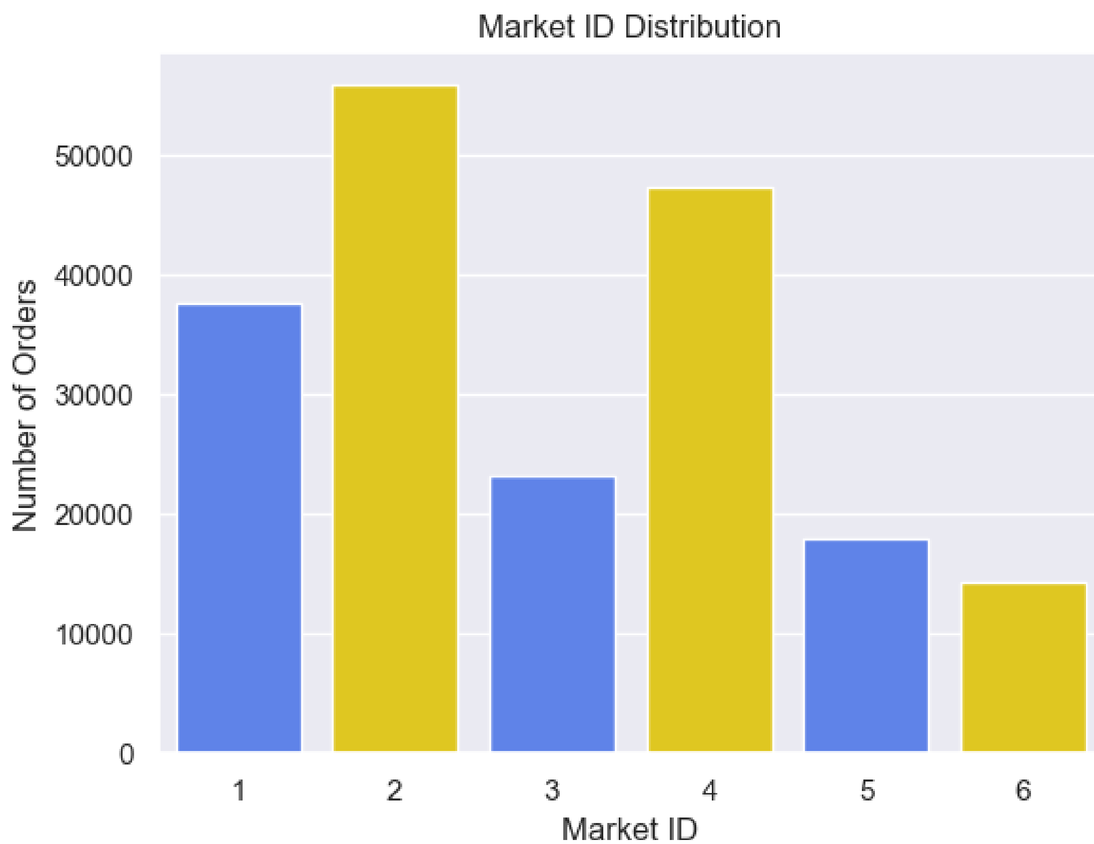


[54]:

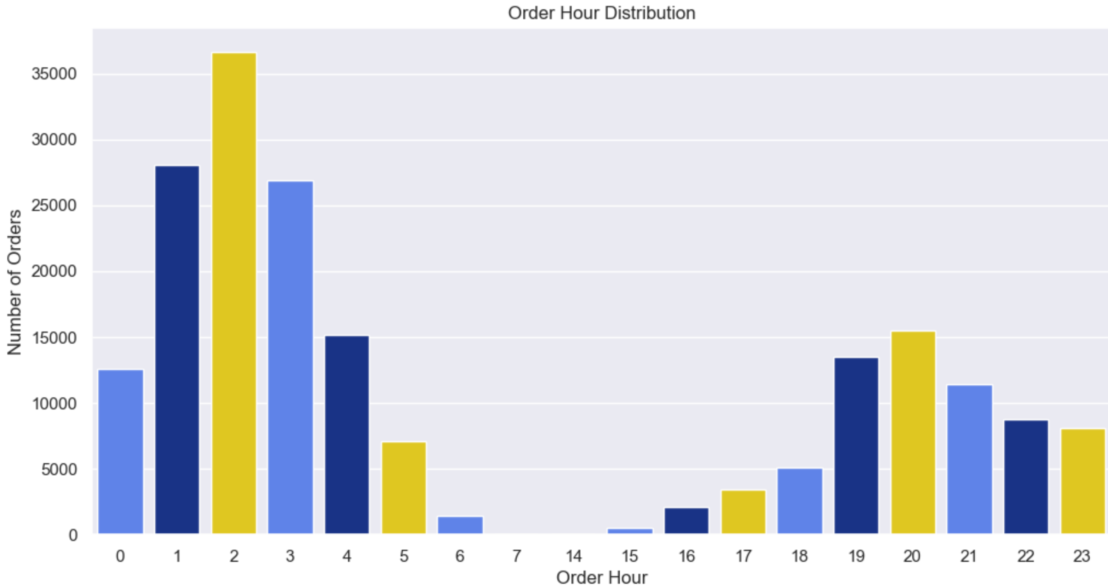
```
sns.countplot(x='order_day', data=df, palette=bi_palette)
plt.title('Order Day Distribution')
plt.xlabel('Order Day')
plt.ylabel('Number of Orders')
plt.show()
```



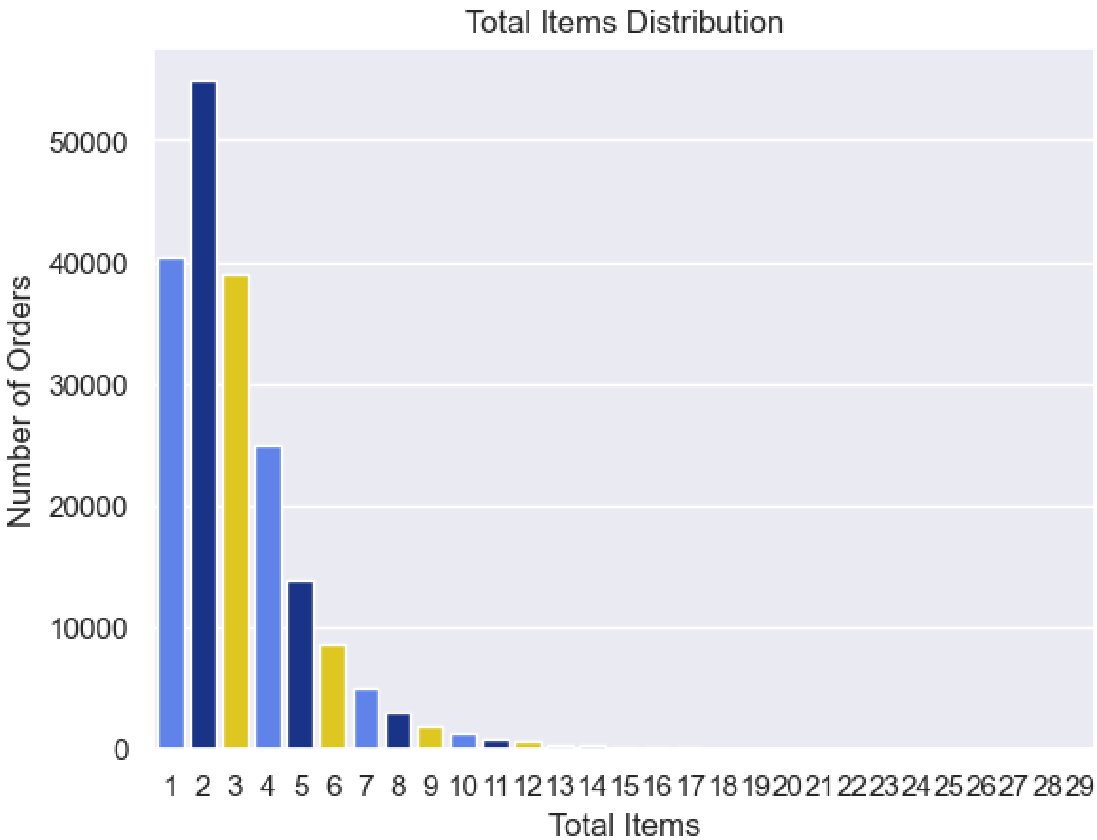
[20]:
```
sns.countplot(x='market_id', data=df, palette=bi_palette)
plt.title('Market ID Distribution')
plt.xlabel('Market ID')
plt.ylabel('Number of Orders')
plt.show()
```



[55]:
```
plt.figure(figsize=(12, 6))
sns.countplot(x='order_hour', data=df, palette=three_set_palette)
plt.title('Order Hour Distribution')
plt.xlabel('Order Hour')
plt.ylabel('Number of Orders')
plt.show()
```

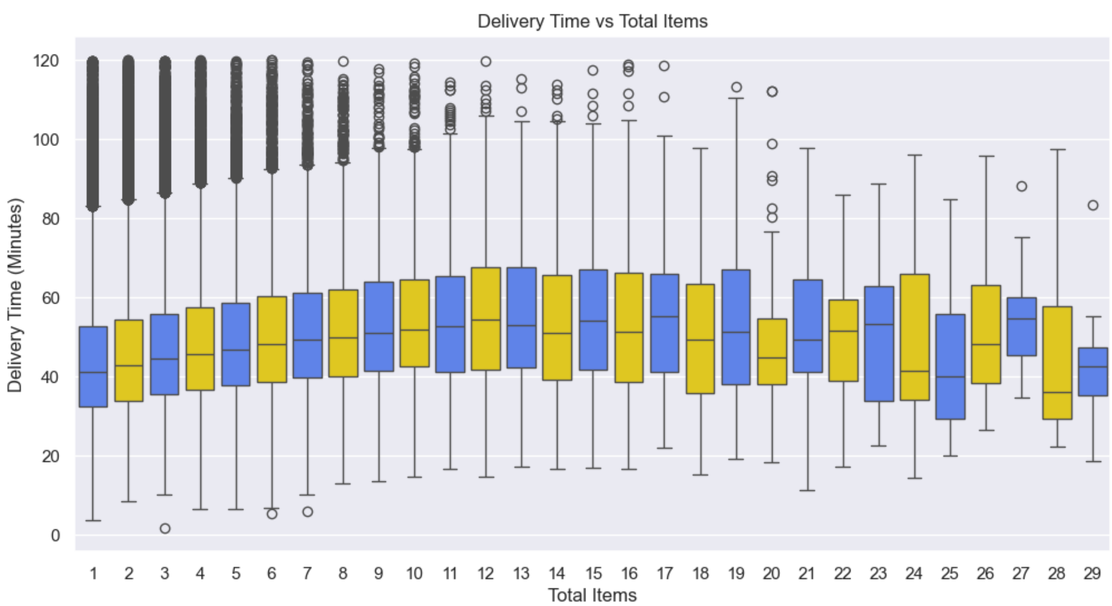


[23]:
```
sns.countplot(x='total_items', data=df, palette=three_set_palette)
plt.title('Total Items Distribution')
plt.xlabel('Total Items')
plt.ylabel('Number of Orders')
plt.show()
```



[24]:
```
plt.figure(figsize=(12, 6))
sns.boxplot(x='order_protocol', y='delivery_time', data=df, palette=bi_palette)
plt.title('Delivery Time vs Order Protocol')
plt.xlabel('Order Protocol')
plt.ylabel('Delivery Time (Minutes)')
plt.show()
```

[25]:
```
plt.figure(figsize=(12, 6))
sns.boxplot(x='total_items', y='delivery_time', data=df, palette=bi_palette)
plt.title('Delivery Time vs Total Items')
plt.xlabel('Total Items')
plt.ylabel('Delivery Time (Minutes)')
plt.show()
```



0.0.9 EDA Analysis

- **total_items**: Total items fields has more outlier ranges from 1 to 400+. Based on the manual filtering condition eliminating the records having more than 30 items.
- **delivery_time**: 1090 orders having more than 2 hours delivery time, indicating potential outlier.
- **store_primary_category**: Most of orders are placed in American category followed by Pizza, mexican dishes. Indicating preferred choices of customer.
- Most number of orders are generally placed during weekend
- Orders placed generally place during 0hr to 6hr and 16hr to 23hr
- Number of items: Most of the orders has 2 items, generally range from 1 items to 12 items

0.0.10 MRDS Preparation

[26]:
```
# Drop columns that are not needed or are timestamps
df = df.drop(columns=['created_at', 'actual_delivery_time', 'store_id'])
```

[27]:
```
# Separate features and target variable
X = df.drop(columns=['delivery_time'])
y = df['delivery_time']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

[ ]:
```
# Define the column transformer for preprocessing
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), ['total_items', 'subtotal',␣
↪'num_distinct_items', 'min_item_price', 'max_item_price',␣
↪'total_onshift_partners', 'total_busy_partners', 'total_outstanding_orders',␣
↪'order_hour', 'order_day']),
        ('cat_ord', OneHotEncoder(), ['market_id', 'order_protocol']),
        ('cat_high_card', TargetEncoder(), ['store_primary_category'])
    ])

# Apply the transformations
X_train_transformed = preprocessor.fit_transform(X_train, y_train)
X_test_transformed = preprocessor.transform(X_test)
```

[29]:
```
def create_model(learning_rate=0.01, activation='relu', optimizer='adam'):
    model = Sequential()
    model.add(Dense(64, input_dim=X_train_transformed.shape[1],␣
↪activation=activation))
    model.add(Dense(32, activation=activation))
    model.add(Dense(1))  # Output layer for regression
    if optimizer == 'adam':
        opt = Adam(learning_rate=learning_rate)
```

```
    elif optimizer == 'sgd':
        opt = SGD(learning_rate=learning_rate)
    model.compile(optimizer=opt, loss='mean_squared_error')
    return model
```

[30]:
```
# Trying different configurations
learning_rates = [0.01, 0.001]
activations = ['relu', 'tanh']
optimizers = ['adam', 'sgd']
epochs = 100
batch_size = 32
```

[31]:
```
best_model = None
best_loss = float('inf')

for lr in learning_rates:
    for activation in activations:
        for optimizer in optimizers:
            model = create_model(learning_rate=lr, activation=activation,␣
 ↪optimizer=optimizer)
            early_stopping = EarlyStopping(monitor='val_loss', patience=10,␣
 ↪restore_best_weights=True)
            history = model.fit(X_train_transformed, y_train,␣
 ↪validation_split=0.2, epochs=epochs, batch_size=batch_size,␣
 ↪callbacks=[early_stopping], verbose=0)
            val_loss = min(history.history['val_loss'])
            if val_loss < best_loss:
                best_loss = val_loss
                best_model = model
                best_history = history
```

[32]:
```
# Model Training
final_model = best_model
history = final_model.fit(X_train_transformed, y_train, validation_split=0.2,␣
 ↪epochs=epochs, batch_size=batch_size, verbose=1)

# Plotting the losses
plt.plot(history.history['loss'], label='train_loss')
plt.plot(history.history['val_loss'], label='val_loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

```
Epoch 1/100
3925/3925             10s 2ms/step -
loss: 206.6773 - val_loss: 214.3726
```

```
Epoch 2/100
3925/3925            10s 2ms/step -
loss: 207.0781 - val_loss: 213.6046
Epoch 3/100
3925/3925            8s 2ms/step -
loss: 208.6119 - val_loss: 216.0162
Epoch 4/100
3925/3925            10s 2ms/step -
loss: 206.1639 - val_loss: 214.2502
Epoch 5/100
3925/3925            9s 2ms/step -
loss: 206.2784 - val_loss: 217.8281
Epoch 6/100
3925/3925            8s 2ms/step -
loss: 207.3243 - val_loss: 214.8597
Epoch 7/100
3925/3925            7s 2ms/step -
loss: 207.0352 - val_loss: 215.5517
Epoch 8/100
3925/3925            8s 2ms/step -
loss: 207.6759 - val_loss: 213.1503
Epoch 9/100
3925/3925            7s 2ms/step -
loss: 206.5524 - val_loss: 213.0868
Epoch 10/100
3925/3925            6s 2ms/step -
loss: 206.3566 - val_loss: 213.0260
Epoch 11/100
3925/3925            10s 2ms/step -
loss: 205.8700 - val_loss: 212.8530
Epoch 12/100
3925/3925            8s 2ms/step -
loss: 206.8431 - val_loss: 218.2813
Epoch 13/100
3925/3925            7s 2ms/step -
loss: 206.6624 - val_loss: 215.4286
Epoch 14/100
3925/3925            7s 2ms/step -
loss: 208.5483 - val_loss: 213.2323
Epoch 15/100
3925/3925            9s 2ms/step -
loss: 204.4367 - val_loss: 215.0871
Epoch 16/100
3925/3925            7s 2ms/step -
loss: 206.0930 - val_loss: 215.7175
Epoch 17/100
3925/3925            7s 2ms/step -
loss: 208.1123 - val_loss: 213.7063
```

```
Epoch 18/100
3925/3925             7s 2ms/step -
loss: 205.2066 - val_loss: 214.6739
Epoch 19/100
3925/3925             7s 2ms/step -
loss: 208.5617 - val_loss: 222.0289
Epoch 20/100
3925/3925             7s 2ms/step -
loss: 206.4415 - val_loss: 213.3595
Epoch 21/100
3925/3925             8s 2ms/step -
loss: 206.3785 - val_loss: 213.6547
Epoch 22/100
3925/3925             9s 2ms/step -
loss: 205.0640 - val_loss: 212.4607
Epoch 23/100
3925/3925             22s 6ms/step -
loss: 206.1658 - val_loss: 214.7889
Epoch 24/100
3925/3925             20s 5ms/step -
loss: 205.4271 - val_loss: 214.2533
Epoch 25/100
3925/3925             19s 5ms/step -
loss: 204.0929 - val_loss: 213.5503
Epoch 26/100
3925/3925             12s 3ms/step -
loss: 204.5480 - val_loss: 214.1476
Epoch 27/100
3925/3925             8s 2ms/step -
loss: 204.7964 - val_loss: 213.1775
Epoch 28/100
3925/3925             8s 2ms/step -
loss: 204.9360 - val_loss: 212.8515
Epoch 29/100
3925/3925             9s 2ms/step -
loss: 205.1582 - val_loss: 215.5527
Epoch 30/100
3925/3925             8s 2ms/step -
loss: 205.8482 - val_loss: 212.6363
Epoch 31/100
3925/3925             8s 2ms/step -
loss: 203.9615 - val_loss: 213.4459
Epoch 32/100
3925/3925             7s 2ms/step -
loss: 204.5116 - val_loss: 213.2271
Epoch 33/100
3925/3925             8s 2ms/step -
loss: 202.7076 - val_loss: 214.5251
```

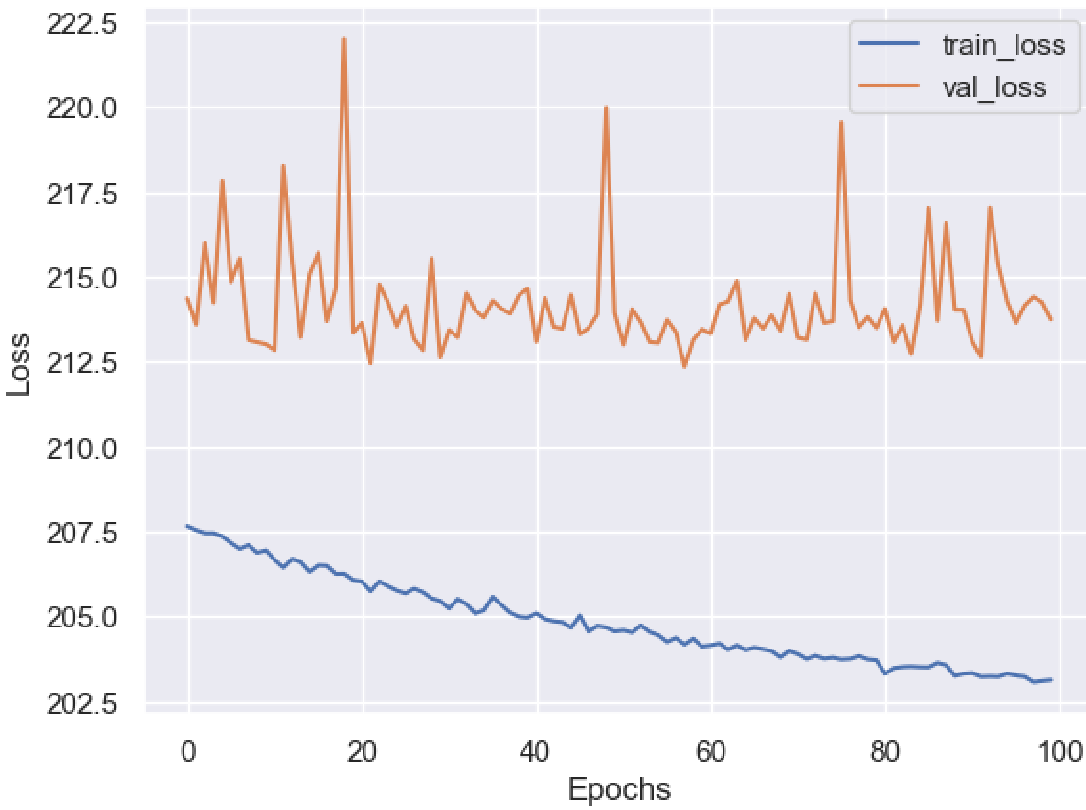
```
Epoch 34/100
3925/3925             7s 2ms/step -
loss: 205.2308 - val_loss: 214.0200
Epoch 35/100
3925/3925             8s 2ms/step -
loss: 205.8709 - val_loss: 213.8134
Epoch 36/100
3925/3925             8s 2ms/step -
loss: 205.9865 - val_loss: 214.3049
Epoch 37/100
3925/3925             7s 2ms/step -
loss: 204.8238 - val_loss: 214.0727
Epoch 38/100
3925/3925             8s 2ms/step -
loss: 203.6641 - val_loss: 213.9259
Epoch 39/100
3925/3925             8s 2ms/step -
loss: 205.6735 - val_loss: 214.4646
Epoch 40/100
3925/3925             7s 2ms/step -
loss: 204.6816 - val_loss: 214.6617
Epoch 41/100
3925/3925             7s 2ms/step -
loss: 204.4052 - val_loss: 213.0989
Epoch 42/100
3925/3925             8s 2ms/step -
loss: 207.3675 - val_loss: 214.3844
Epoch 43/100
3925/3925             7s 2ms/step -
loss: 205.8183 - val_loss: 213.5381
Epoch 44/100
3925/3925             8s 2ms/step -
loss: 205.1947 - val_loss: 213.4796
Epoch 45/100
3925/3925             7s 2ms/step -
loss: 206.3185 - val_loss: 214.4799
Epoch 46/100
3925/3925             7s 2ms/step -
loss: 204.1744 - val_loss: 213.3234
Epoch 47/100
3925/3925             7s 2ms/step -
loss: 205.0696 - val_loss: 213.5021
Epoch 48/100
3925/3925             9s 2ms/step -
loss: 203.2759 - val_loss: 213.9038
Epoch 49/100
3925/3925             8s 2ms/step -
loss: 203.6615 - val_loss: 219.9989
```

```
Epoch 50/100
3925/3925             7s 2ms/step -
loss: 203.2464 - val_loss: 213.9451
Epoch 51/100
3925/3925             7s 2ms/step -
loss: 205.4455 - val_loss: 213.0095
Epoch 52/100
3925/3925             7s 2ms/step -
loss: 206.2806 - val_loss: 214.0591
Epoch 53/100
3925/3925             7s 2ms/step -
loss: 205.8570 - val_loss: 213.6727
Epoch 54/100
3925/3925             6s 2ms/step -
loss: 204.2038 - val_loss: 213.0919
Epoch 55/100
3925/3925             7s 2ms/step -
loss: 205.5063 - val_loss: 213.0663
Epoch 56/100
3925/3925             7s 2ms/step -
loss: 205.7423 - val_loss: 213.7416
Epoch 57/100
3925/3925             7s 2ms/step -
loss: 203.7598 - val_loss: 213.3840
Epoch 58/100
3925/3925             7s 2ms/step -
loss: 203.4575 - val_loss: 212.3636
Epoch 59/100
3925/3925             7s 2ms/step -
loss: 204.6786 - val_loss: 213.1560
Epoch 60/100
3925/3925             7s 2ms/step -
loss: 204.7653 - val_loss: 213.4647
Epoch 61/100
3925/3925             7s 2ms/step -
loss: 204.2737 - val_loss: 213.3400
Epoch 62/100
3925/3925             7s 2ms/step -
loss: 204.1850 - val_loss: 214.1963
Epoch 63/100
3925/3925             7s 2ms/step -
loss: 206.6922 - val_loss: 214.2777
Epoch 64/100
3925/3925             8s 2ms/step -
loss: 204.2055 - val_loss: 214.8876
Epoch 65/100
3925/3925             7s 2ms/step -
loss: 206.0215 - val_loss: 213.1461
```

```
Epoch 66/100
3925/3925              8s 2ms/step -
loss: 204.3620 - val_loss: 213.7937
Epoch 67/100
3925/3925              10s 2ms/step -
loss: 204.0092 - val_loss: 213.4852
Epoch 68/100
3925/3925              8s 2ms/step -
loss: 202.9279 - val_loss: 213.8748
Epoch 69/100
3925/3925              9s 2ms/step -
loss: 203.2410 - val_loss: 213.4243
Epoch 70/100
3925/3925              8s 2ms/step -
loss: 206.0589 - val_loss: 214.5114
Epoch 71/100
3925/3925              10s 3ms/step -
loss: 204.3565 - val_loss: 213.2217
Epoch 72/100
3925/3925              9s 2ms/step -
loss: 203.5523 - val_loss: 213.1599
Epoch 73/100
3925/3925              8s 2ms/step -
loss: 202.2342 - val_loss: 214.5226
Epoch 74/100
3925/3925              7s 2ms/step -
loss: 203.1801 - val_loss: 213.6558
Epoch 75/100
3925/3925              8s 2ms/step -
loss: 202.0834 - val_loss: 213.7077
Epoch 76/100
3925/3925              7s 2ms/step -
loss: 204.1942 - val_loss: 219.5652
Epoch 77/100
3925/3925              7s 2ms/step -
loss: 203.2649 - val_loss: 214.3134
Epoch 78/100
3925/3925              8s 2ms/step -
loss: 205.4943 - val_loss: 213.5216
Epoch 79/100
3925/3925              8s 2ms/step -
loss: 201.7213 - val_loss: 213.8305
Epoch 80/100
3925/3925              8s 2ms/step -
loss: 201.1774 - val_loss: 213.5087
Epoch 81/100
3925/3925              7s 2ms/step -
loss: 203.1357 - val_loss: 214.0703
```

```
Epoch 82/100
3925/3925             7s 2ms/step -
loss: 201.6516 - val_loss: 213.0932
Epoch 83/100
3925/3925             7s 2ms/step -
loss: 204.9221 - val_loss: 213.5905
Epoch 84/100
3925/3925             7s 2ms/step -
loss: 202.2008 - val_loss: 212.7328
Epoch 85/100
3925/3925             7s 2ms/step -
loss: 203.9614 - val_loss: 214.1850
Epoch 86/100
3925/3925             8s 2ms/step -
loss: 203.6924 - val_loss: 217.0360
Epoch 87/100
3925/3925             9s 2ms/step -
loss: 203.1732 - val_loss: 213.7243
Epoch 88/100
3925/3925             7s 2ms/step -
loss: 204.0556 - val_loss: 216.5861
Epoch 89/100
3925/3925             8s 2ms/step -
loss: 202.2836 - val_loss: 214.0379
Epoch 90/100
3925/3925             8s 2ms/step -
loss: 203.0763 - val_loss: 214.0354
Epoch 91/100
3925/3925             8s 2ms/step -
loss: 204.1295 - val_loss: 213.1016
Epoch 92/100
3925/3925             8s 2ms/step -
loss: 201.8574 - val_loss: 212.6522
Epoch 93/100
3925/3925             8s 2ms/step -
loss: 205.2000 - val_loss: 217.0442
Epoch 94/100
3925/3925             8s 2ms/step -
loss: 203.4324 - val_loss: 215.3376
Epoch 95/100
3925/3925             8s 2ms/step -
loss: 203.8365 - val_loss: 214.2798
Epoch 96/100
3925/3925             8s 2ms/step -
loss: 203.8459 - val_loss: 213.6494
Epoch 97/100
3925/3925             7s 2ms/step -
loss: 201.5459 - val_loss: 214.1638
```

```
Epoch 98/100
3925/3925          7s 2ms/step -
loss: 203.0029 - val_loss: 214.4167
Epoch 99/100
3925/3925          8s 2ms/step -
loss: 201.4917 - val_loss: 214.2625
Epoch 100/100
3925/3925          8s 2ms/step -
loss: 200.4692 - val_loss: 213.7560
```



[ ]:
```
# Evaluate the model
y_pred = final_model.predict(X_test_transformed)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
mae = mean_absolute_error(y_test, y_pred)

print(f'Test MSE: {mse}')
print(f'Test RMSE: {rmse}')
print(f'Test MAE: {mae}')
```

```
1227/1227          1s 940us/step
Test MSE: 210.24183364843694
```

```
Test RMSE: 14.499718398935785
Test MAE: 11.006912906960366
```

An RMSE of approximately 14.50 means that on average, the model's predictions are off by about 14.50 minutes. This can be considered high or low depending on the context of the delivery times.

Questions:

1. Defining the Problem Statements and Use Cases

- **Problem Statement**: The primary problem is to estimate the delivery time for orders placed through Porter, considering various factors such as order details, restaurant location, and delivery partner availability.
- **Use Cases**:
  - *Real-time Delivery Time Estimation*: Provide customers with accurate delivery time estimates when they place an order.
  - *Resource Allocation*: Optimize the allocation of delivery partners based on estimated delivery times and current workload.

2. Pandas Datetime Functions

   - *pd.to_datetime()*: Converts a column or series to datetime format.
   - *dt.strftime()*: Formats datetime objects as strings according to a specified format.
   - *dt.total_seconds()*: Returns the total number of seconds in a timedelta object.

3. Short Note on Datetime, Timedelta, Time Span (Period)

   - *Datetime*: Represents a specific point in time, including date and time information (e.g., 2023-10-05 14:30:00).
   - *Timedelta*: Represents the difference between two datetime objects, often used for calculating durations (e.g., 2 days, 3:00:00).
   - *Time Span (Period)*: Represents a span of time, such as a month or a year, and is useful for aggregating data over regular intervals (e.g., 2023-10 for October 2023).

4. Why Check for Outliers in Data?

   - Outliers can significantly skew the results of a model, leading to inaccurate predictions and poor performance. Identifying and handling outliers ensures the model is trained on representative data, improving its robustness and accuracy.

5. Outlier Removal Methods

   - *Z-Score Method*: Removes data points that lie beyond a specified number of standard deviations from the mean.
   - *IQR Method*: Removes data points that lie outside 1.5 times the interquartile range (IQR) above the third quartile or below the first quartile.

6. Classical Machine Learning Methods

   - Linear Regression: Models the relationship between features and the target variable using a linear approach.

- Decision Tree Regression: Uses a tree-like model of decisions to predict the target variable.
- Random Forest Regression: An ensemble method that uses multiple decision trees to improve prediction accuracy.

7. Why Scaling is Required for Neural Networks?
   - Scaling ensures that all input features contribute equally to the model's learning process, preventing features with larger ranges from dominating the learning process. It helps in faster convergence and improves the model's performance.
8. Choice of Optimizer
   - *Adam Optimizer*: Combines the advantages of both the AdaGrad and RMSProp algorithms, providing adaptive learning rates for each parameter. It is efficient, requires less memory, and is well-suited for problems with large datasets and high-dimensional parameter spaces.
9. Activation Function Used and Why
   - *ReLU (Rectified Linear Unit)*: Commonly used in hidden layers of neural networks because it introduces non-linearity, allowing the network to learn complex patterns. It also helps mitigate the vanishing gradient problem, enabling faster training.
10. Why Neural Networks Perform Well on Large Datasets
    - Neural networks can capture complex, non-linear relationships in data due to their deep architecture. With large datasets, they have enough data to learn these intricate patterns effectively, leading to better generalization and performance on unseen data.

[ ]:

```

```