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Context:

- **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**

Problem Statement

- **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**

Data Dictionary

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

1. market_id : integer id for the market where the restaurant lies

2. created_at : the timestamp at which the order was placed

3. actual_delivery_time : the timestamp when the order was delivered

4. store_primary_category : category for the restaurant

5. order_protocol : integer code value for order protocol(how the order was placed ie: through porter, call to restaurant, pre booked, third part etc)

6. total_items subtotal : final price of the order

7. num_distinct_items : the number of distinct items in the order

8. min_item_price : price of the cheapest item in the order

9. max_item_price : price of the costliest item in order

10. total_onshift_partners : number of delivery partners on duty at the time order was placed

11. total_busy_partners : number of delivery partners attending to other tasks

12. total_outstanding_orders : total number of orders to be fulfilled at the moment

13. estimated_store_to_consumer_driving_duration : approximate travel time from restaurant to customer

```
# Downloading the data
! gdown 1kkgBGldeswHBgVKEJiqqG7VZvqZNMc-5
```

```
Downloading...
From: https://drive.google.com/uc?id=1kkgBGldeswHBgVKEJiqqG7VZvqZNMc-5
To: /content/data_2.csv
100% 15.7M/15.7M [00:00<00:00, 152MB/s]
```

```
# Importing the Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

```
# Reading or Loading a CSV file into a pandas DataFrame.
df = pd.read_csv("/content/data_2.csv")
```

```
# Viewing the first few rows of a DataFrame.
df.head()
```

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

```
# Viewing the last few rows of a DataFrame.
df.tail()
```

	market_id	created_at	actual_delivery_time	store_primary_category	order_protocol	total_items	subtotal	num_disti
175772	1.0	2015-02-17 00:19:41	2015-02-17 01:02:41	28	4.0	3	1389	
175773	1.0	2015-02-13 00:01:59	2015-02-13 01:03:59	28	4.0	6	3010	
175774	1.0	2015-01-24 04:46:08	2015-01-24 05:32:08	28	4.0	5	1836	
175775	1.0	2015-02-01 18:18:15	2015-02-01 19:03:15	58	1.0	1	1175	
175776	1.0	2015-02-08 19:24:33	2015-02-08 20:01:33	58	1.0	4	2605	

```
# Retrieving the dimensions of a DataFrame (Rows, Columns).
df.shape
```

```
(175777, 14)
```

```
# Retrieving the column labels (names) of a DataFrame .
df.columns
```

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

```
# Retrive the overview of a DataFrame's structure and content.
df.info()
```

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

- No, duplicate values and no null values.

```
df.describe().T
```

	count	mean	std	min	25%	50%	75%	max
market_id	175777.0	2.743726	1.330963	1.0	2.0	2.0	4.0	6.0
store_primary_category	175777.0	35.887949	20.728254	0.0	18.0	38.0	55.0	72.0
order_protocol	175777.0	2.911752	1.513128	1.0	1.0	3.0	4.0	7.0
total_items	175777.0	3.204976	2.674055	1.0	2.0	3.0	4.0	411.0
subtotal	175777.0	2697.111147	1828.554893	0.0	1412.0	2224.0	3410.0	26800.0
num_distinct_items	175777.0	2.675060	1.625681	1.0	1.0	2.0	3.0	20.0
min_item_price	175777.0	684.965433	519.882924	-86.0	299.0	595.0	942.0	14700.0
max_item_price	175777.0	1160.158616	560.828571	0.0	799.0	1095.0	1395.0	14700.0
total_onshift_dashers	175777.0	44.918664	34.544724	-4.0	17.0	37.0	66.0	171.0
total_busy_dashers	175777.0	41.861381	32.168505	-5.0	15.0	35.0	63.0	154.0
total_outstanding_orders	175777.0	58.230115	52.731043	-6.0	17.0	41.0	85.0	285.0
estimated_store_to_consumer_driving_duration	175777.0	546.077240	218.717798	0.0	384.0	544.0	703.0	2088.0

EDA

```
# Checking for null values
df.isnull().sum()
```

	0
market_id	0
created_at	0
actual_delivery_time	0
store_primary_category	0
order_protocol	0
total_items	0
subtotal	0
num_distinct_items	0
min_item_price	0
max_item_price	0
total_onshift_dashers	0
total_busy_dashers	0
total_outstanding_orders	0
estimated_store_to_consumer_driving_duration	0

dtype: int64

- No, null values.

```
numeric = df.select_dtypes(include='number').columns
numeric
```

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

```
df.columns
```

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

```
df.head()
```

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

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 175777 entries, 0 to 175776
Data columns (total 14 columns):
 #   Column                                        Non-Null Count   Dtype
---  ------                                        --------------   -----
 0   market_id                                     175777 non-null  float64
 1   created_at                                    175777 non-null  object
 2   actual_delivery_time                          175777 non-null  object
 3   store_primary_category                        175777 non-null  int64
 4   order_protocol                                175777 non-null  float64
 5   total_items                                   175777 non-null  int64
```

```
 6   subtotal                                      175777 non-null  int64
 7   num_distinct_items                            175777 non-null  int64
 8   min_item_price                                175777 non-null  int64
 9   max_item_price                                175777 non-null  int64
 10  total_onshift_dashers                         175777 non-null  float64
 11  total_busy_dashers                            175777 non-null  float64
 12  total_outstanding_orders                      175777 non-null  float64
 13  estimated_store_to_consumer_driving_duration  175777 non-null  float64
dtypes: float64(6), int64(6), object(2)
memory usage: 18.8+ MB
```

Data Cleaning and Feature Engineering

```
# Converting necessary columns into datetime format
df["actual_delivery_time"] = pd.to_datetime(df["actual_delivery_time"])
df["created_at"] = pd.to_datetime(df["created_at"])
```

```
# Convert driving duration column in minutes
df["estimated_store_to_consumer_driving_duration_minutes"] = round(df["estimated_store_to_consumer_driving_duration"]/60,2)
```

```
# Creating the target column time taken in each delivery from order timestamp (created_at) and delivery timestamp (actual_d
df["time_taken_to_delivery"] = df["actual_delivery_time"] - df["created_at"]
```

```
# Getting hour and day of the week from order time
df["hour_of_order"] = df["created_at"].dt.hour
df["week_of_order"] = df["created_at"].dt.day_name()
```

```
df["time_taken_to_delivery_minutes"] = df["time_taken_to_delivery"].dt.seconds // 60

df.drop(columns=["time_taken_to_delivery","created_at","actual_delivery_time","estimated_store_to_consumer_driving_duratior
```

```
df.head()
```

	market_id	store_primary_category	order_protocol	total_items	subtotal	num_distinct_items	min_item_price	max_item_pr
0	1.0	4	1.0	4	3441	4	557	1
1	2.0	46	2.0	1	1900	1	1400	1
2	2.0	36	3.0	4	4771	3	820	1
3	1.0	38	1.0	1	1525	1	1525	1
4	1.0	38	1.0	2	3620	2	1425	2

Outliers check reamining

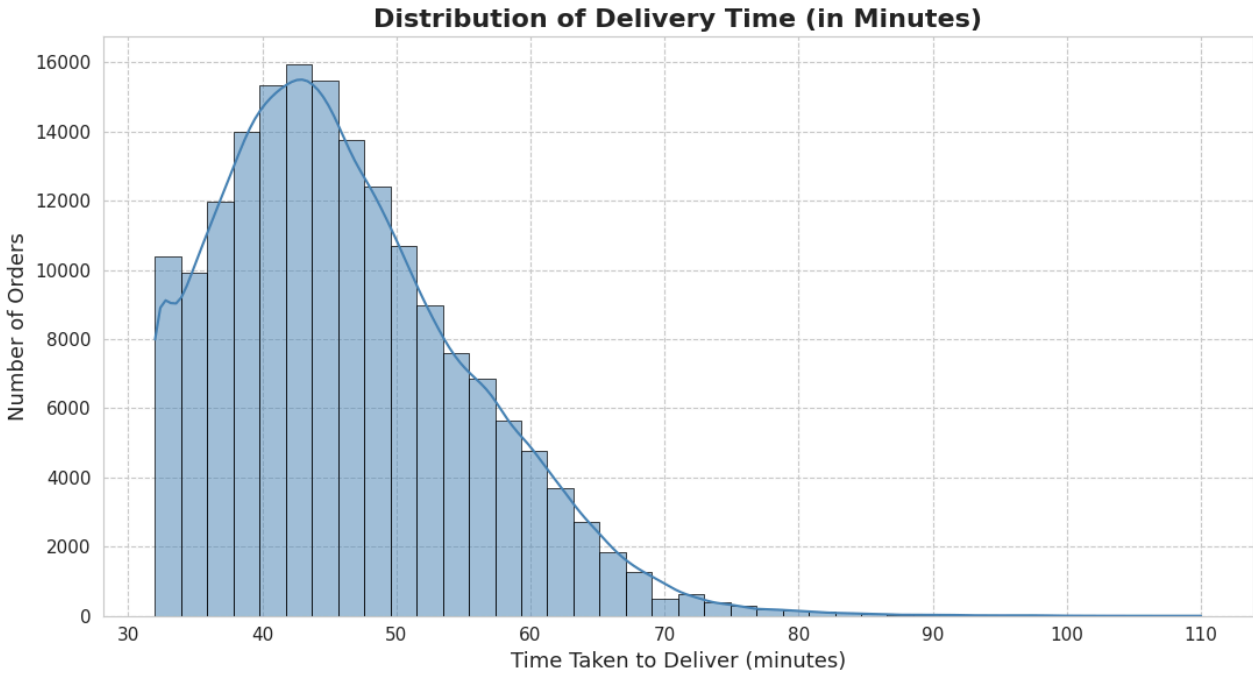
Data visualization

```
plt.figure(figsize=(11, 6))
sns.set_style("whitegrid")  # clean background with grid

sns.histplot(
    df["time_taken_to_delivery_minutes"],
    kde=True,
    bins=40,
    color="steelblue",
    edgecolor="black",
    linewidth=0.5

)

plt.title("Distribution of Delivery Time (in Minutes)", fontsize=16, fontweight="bold")
plt.xlabel("Time Taken to Deliver (minutes)", fontsize=13)
plt.ylabel("Number of Orders", fontsize=13)
plt.xticks(fontsize=11)
plt.yticks(fontsize=11)
plt.grid(True, linestyle="--")
plt.tight_layout()
plt.show()
```



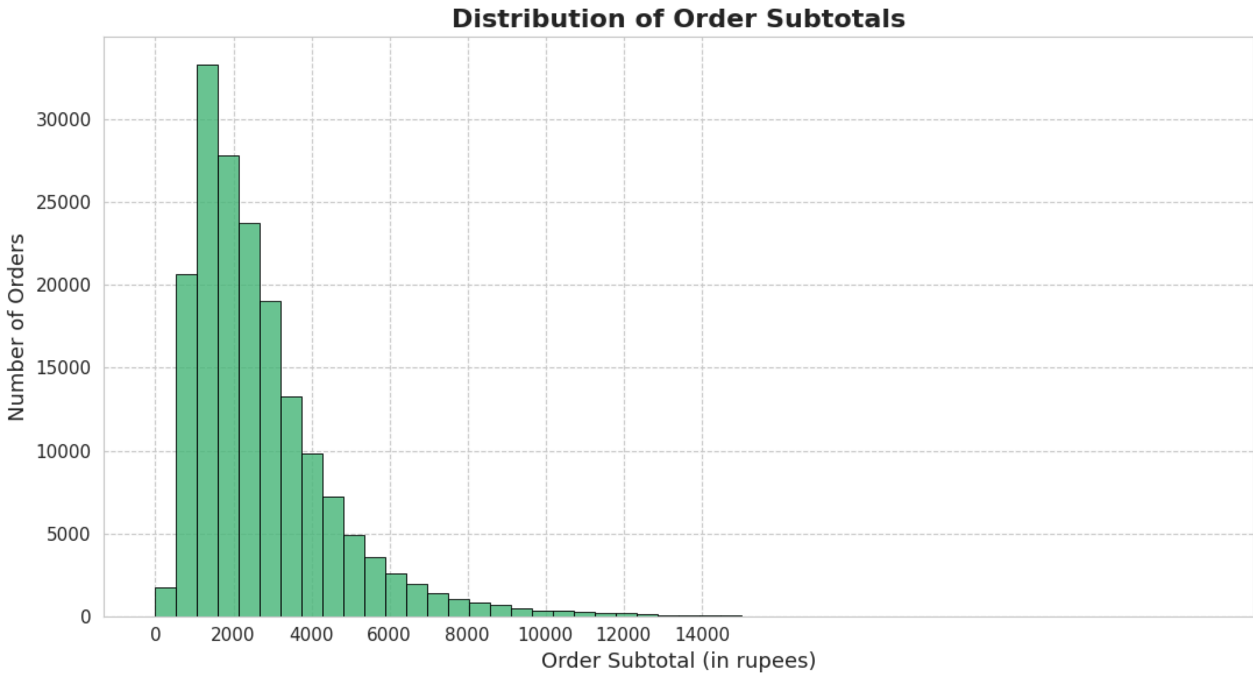
Notes:

- The delivery time follows a right-skewed distribution, with most orders delivered between 38–50 minutes.
- A smaller number of orders take significantly longer, creating a long tail toward higher delivery times.

```
plt.figure(figsize=(11, 6))
sns.set_style("whitegrid")

sns.histplot(
    df["subtotal"],
    bins=50,
    color="mediumseagreen",
    edgecolor="black",
    linewidth=0.6
)

plt.title("Distribution of Order Subtotals", fontsize=16, fontweight="bold")
plt.xlabel("Order Subtotal (in rupees)", fontsize=13)
plt.ylabel("Number of Orders", fontsize=13)
plt.xticks(range(0, 15000, 2000), fontsize=11)
plt.yticks(fontsize=11)
plt.grid(True, linestyle="--")
plt.tight_layout()
plt.show()
```



Notes:

-Order subtotals show a right-skewed distribution, with most orders falling between ₹800–₹2500.

- A long tail toward high values indicates occasional large orders, but they occur far less frequently.

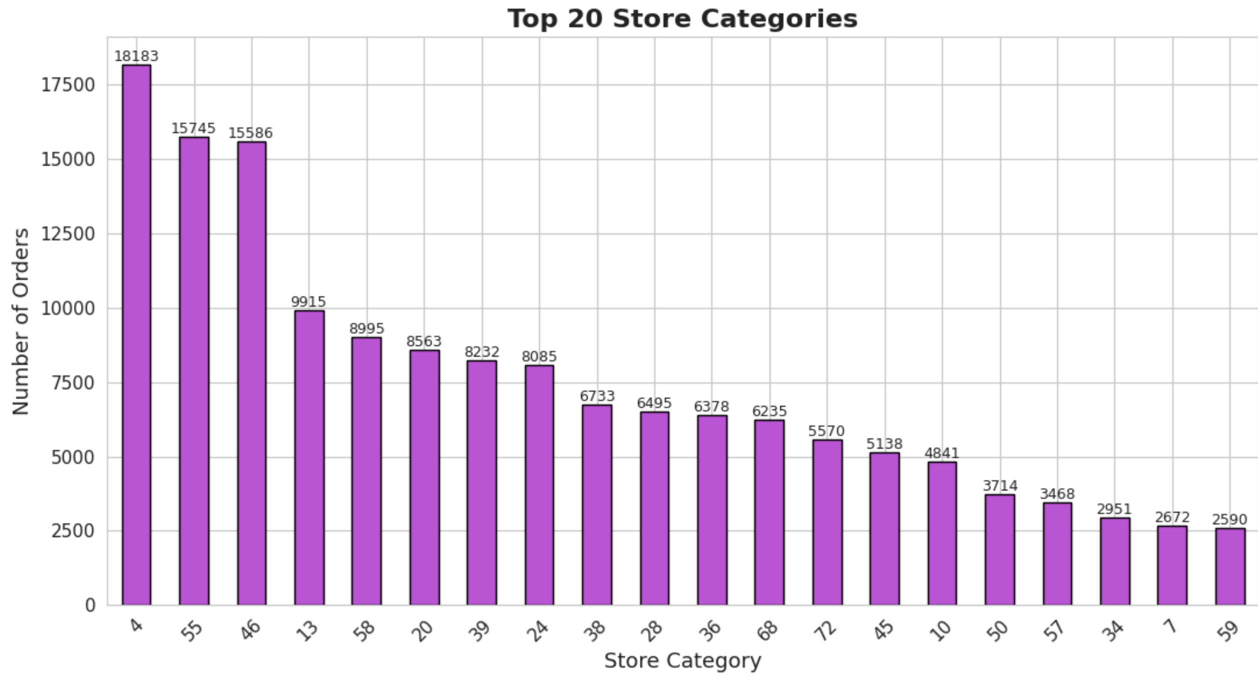
```
plt.figure(figsize=(11, 6))
sns.set_style("whitegrid")

# Get top 20 store categories
top_categories = df["store_primary_category"].value_counts().head(20)

# Plot vertical bar chart
ax = top_categories.plot(
    kind="bar",
    color="mediumorchid",
    edgecolor="black"
)

for i in ax.containers:
    ax.bar_label(i, fontsize=9)

# Title and labels
plt.title("Top 20 Store Categories", fontsize=16, fontweight="bold")
plt.xlabel("Store Category", fontsize=13)
plt.ylabel("Number of Orders", fontsize=13)
plt.xticks(rotation=45, fontsize=11)
plt.yticks(fontsize=11)
plt.tight_layout()
plt.show()
```



Notes:

- Category 4, 55, and 46 receive the highest number of orders, indicating they are the most in-demand store types.
- The distribution drops steadily across other categories, suggesting a concentration of order volume in a few key store categories.

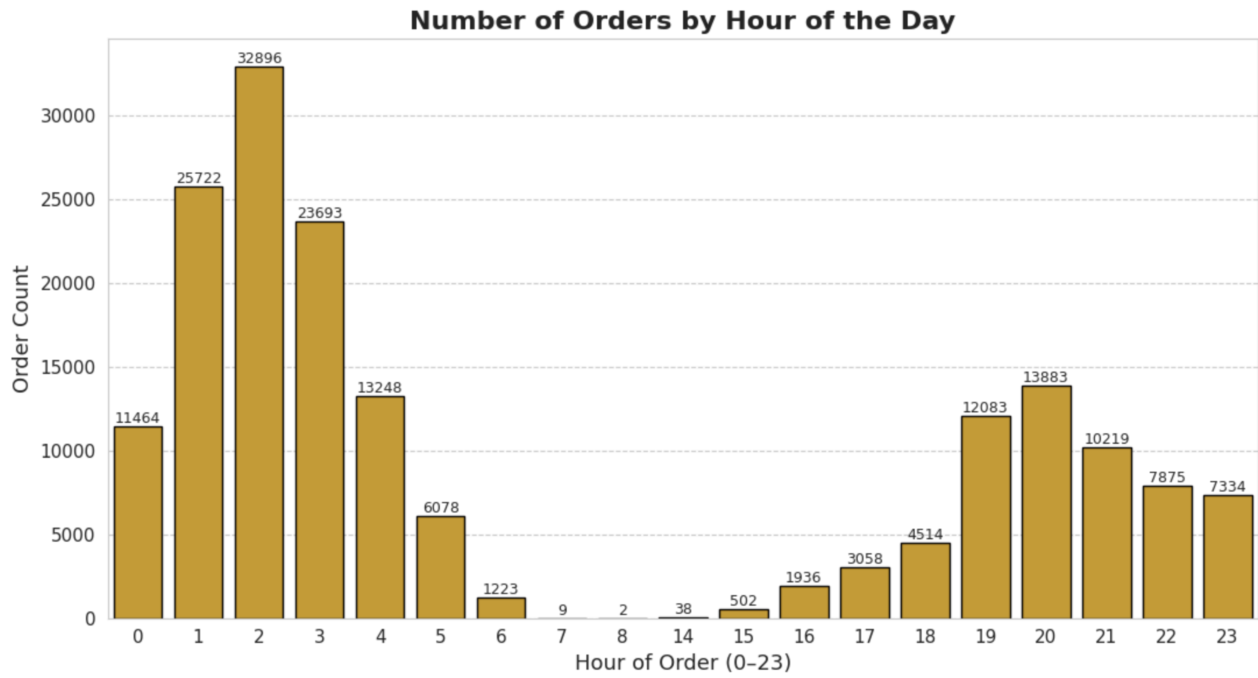
```
plt.figure(figsize=(11, 6))
sns.set_style("whitegrid")

ax = sns.countplot(
    x="hour_of_order",
    data=df,
    color="goldenrod",
    edgecolor="black"
)

for i in ax.containers:
    ax.bar_label(i, fontsize=9)

plt.title("Number of Orders by Hour of the Day", fontsize=16, fontweight="bold")
plt.xlabel("Hour of Order (0-23)", fontsize=13)
plt.ylabel("Order Count", fontsize=13)
plt.xticks(fontsize=11)
plt.yticks(fontsize=11)
plt.grid(axis="y", linestyle="--")

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



Notes:

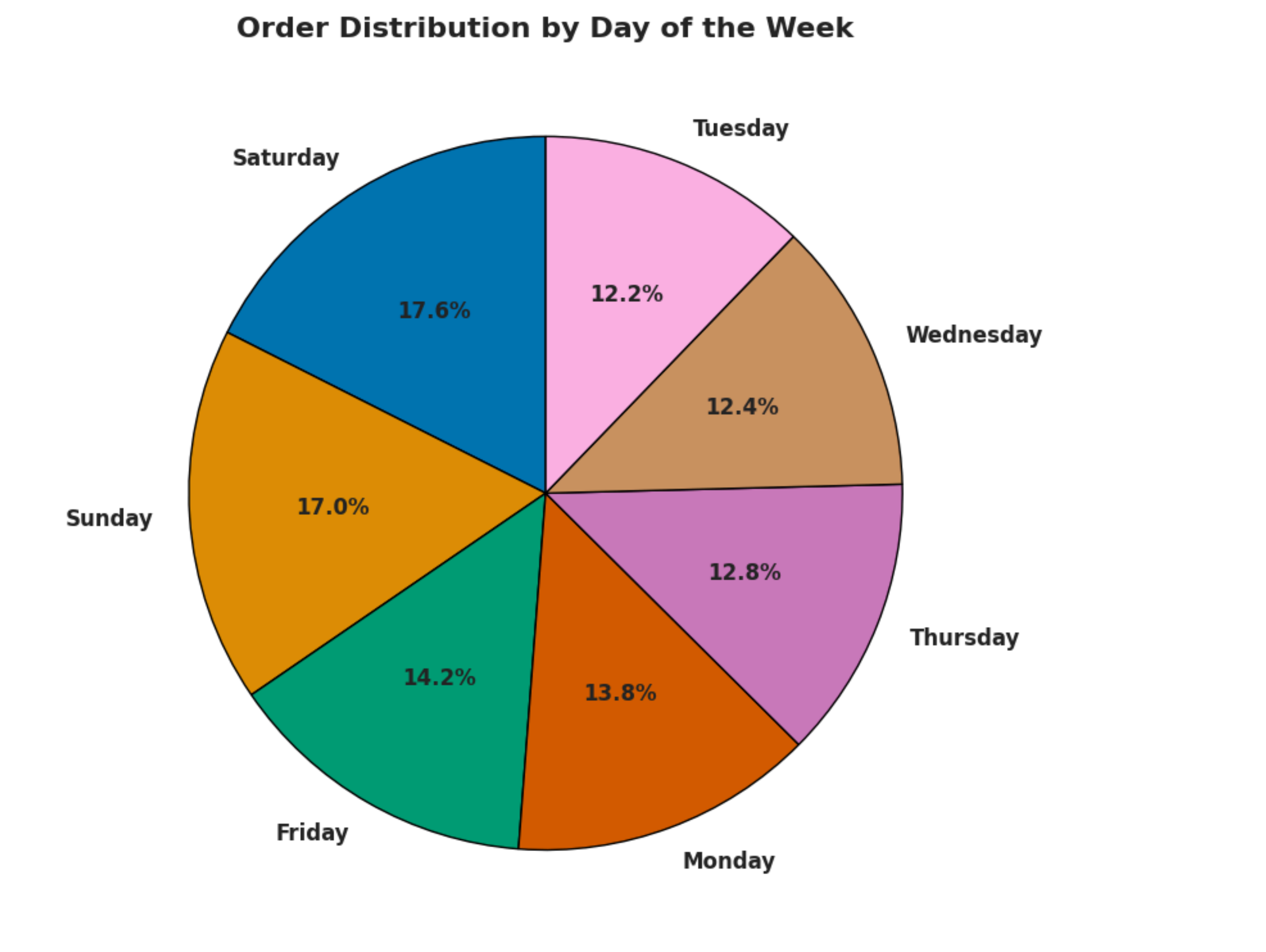
- Orders peak sharply between 1 AM and 3 AM, indicating this is the busiest time window.
- A smaller secondary peak appears around 7–11 PM, while early morning and midday hours see very low order activity.

```
plt.figure(figsize=(8, 8))
colors = sns.color_palette("colorblind")

count = df["week_of_order"].value_counts()

plt.pie(
    count,
    labels=count.index,
    autopct="%1.1f%%",
    startangle=90,
    colors=colors,
    wedgeprops={"edgecolor": "black"},
    textprops={"fontsize": 12, "fontweight": "bold"}
)

plt.title("Order Distribution by Day of the Week", fontsize=16, fontweight="bold")
plt.tight_layout()
plt.show()
```



Notes:

- Orders are slightly higher on weekends (Saturday & Sunday), indicating stronger customer activity at the end of the week.
- Weekdays show a fairly balanced distribution, with Tuesday and Wednesday being the lowest but not by a large margin.

```
df.head(5)
```

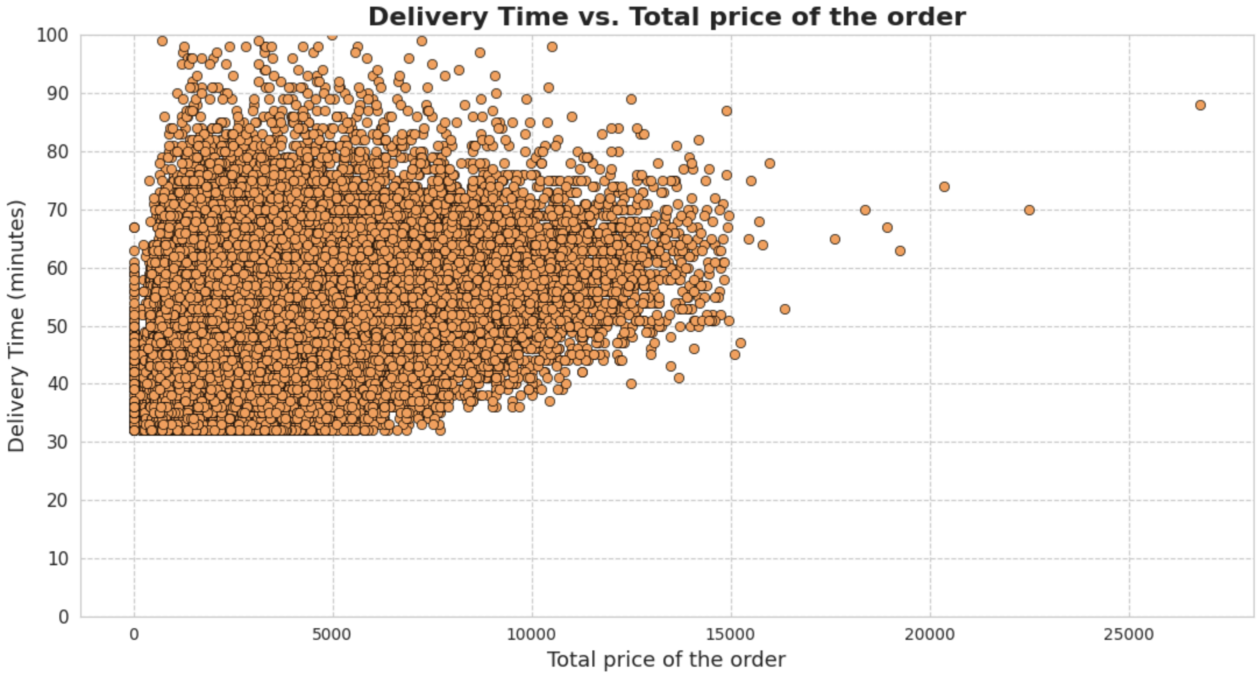
	market_id	store_primary_category	order_protocol	total_items	subtotal	num_distinct_items	min_item_price	max_item_pr
0	1.0	4	1.0	4	3441	4	557	1
1	2.0	46	2.0	1	1900	1	1400	1
2	2.0	36	3.0	4	4771	3	820	1
3	1.0	38	1.0	1	1525	1	1525	1
4	1.0	38	1.0	2	3620	2	1425	2

```
plt.figure(figsize=(11, 6))
sns.set_style("whitegrid")

# Enhanced scatter plot
sns.scatterplot(
    x="subtotal",
    y="time_taken_to_delivery_minutes",
    data=df,
    s=35,
    color="sandybrown",
    edgecolor="black"
)

# Title and axis labels
plt.title("Delivery Time vs. Total price of the order", fontsize=16, fontweight="bold")
plt.xlabel("Total price of the order", fontsize=13)
plt.ylabel("Delivery Time (minutes)", fontsize=13)
plt.yticks(range(0, 101, 10), fontsize=11)
plt.ylim(0, 100)
```

```
plt.grid(True,linestyle="--")
plt.tight_layout()
plt.show()
```



Notes:

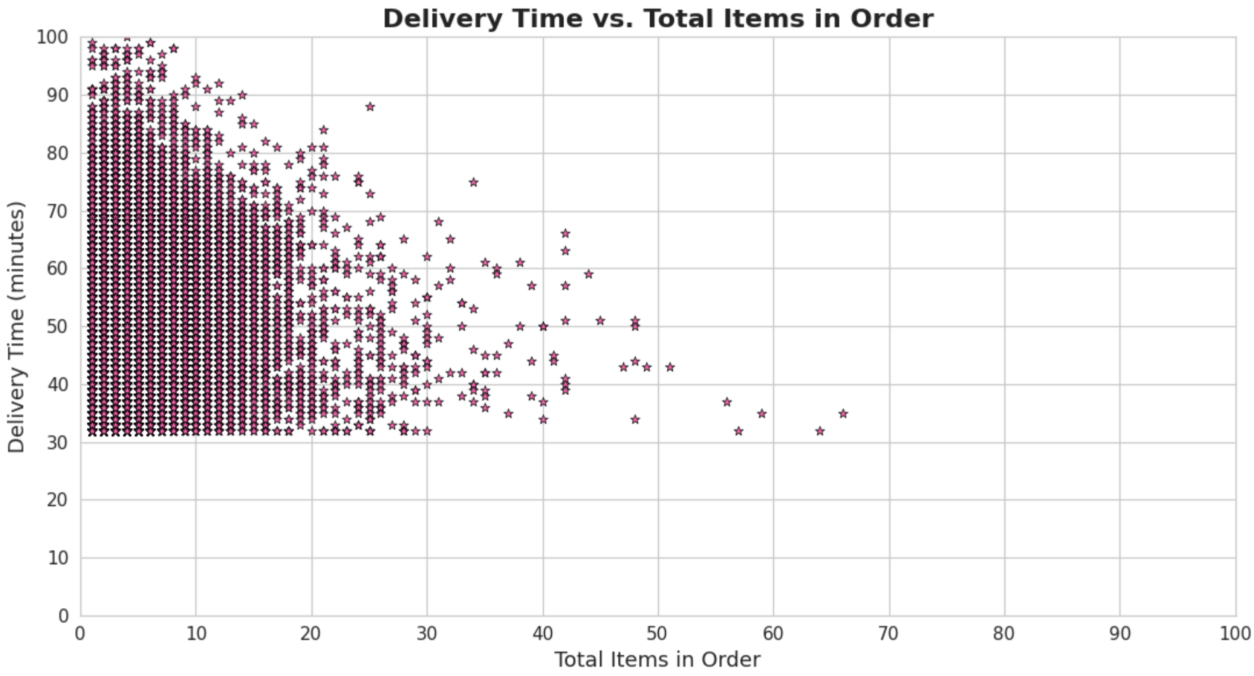
- There is no strong relationship between total order price and delivery time; higher-priced orders don't necessarily take longer to deliver.
- Most orders cluster within 40–70 minutes, even across a wide range of order prices, showing consistent delivery times regardless of spending.

```
plt.figure(figsize=(11, 6))
sns.set_style("whitegrid")

# Enhanced scatter plot
sns.scatterplot(
    x="total_items",
    y="time_taken_to_delivery_minutes",
    data=df,
    s=35,
    color="#ff69b4",
    edgecolor="black",
    marker='*'
)

# Title and axis labels
plt.title("Delivery Time vs. Total Items in Order", fontsize=16, fontweight="bold")
plt.xlabel("Total Items in Order", fontsize=13)
plt.ylabel("Delivery Time (minutes)", fontsize=13)


plt.xticks(range(0, 101, 10), fontsize=11)
plt.yticks(range(0, 101, 10), fontsize=11)
plt.xlim(0, 100)
plt.ylim(0, 100)
plt.grid(True)
plt.tight_layout()
plt.show()
```



Notes:

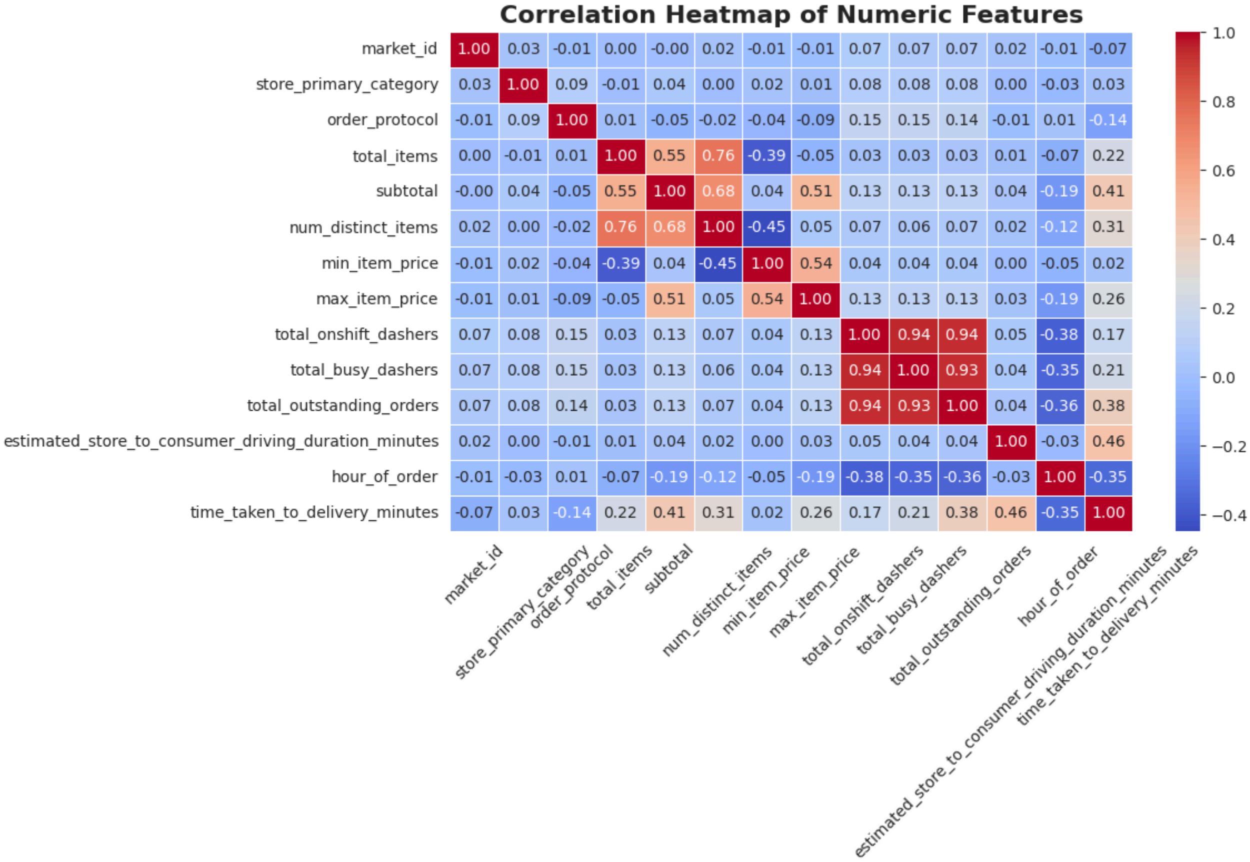
- Delivery times remain mostly within 40–70 minutes regardless of the number of items, showing no strong correlation between order size and delivery duration.
- A few larger orders (30+ items) show slightly more variability, but overall delivery time stays fairly consistent across item counts.

```
num = df.select_dtypes(include = [np.number])
# Compute correlation matrix
corr_matrix = num.corr()

# Set figure size and style
plt.figure(figsize=(12, 8))
sns.set_style("whitegrid")

# Create heatmap
sns.heatmap(
    corr_matrix,
    annot=True,
    fmt=".2f",
    cmap="coolwarm",
    linewidths=0.5
 )

plt.title("Correlation Heatmap of Numeric Features", fontsize=16, fontweight="bold")
plt.xticks(rotation=45,fontsize=10)
plt.yticks(rotation=0, fontsize=10)
plt.tight_layout()
plt.show()
```



Notes:

- Most numeric features show weak correlations with delivery time, indicating no single variable strongly predicts delivery duration.
- Strong correlations appear mainly among order-related features (e.g., subtotal ↔ total_items, num_distinct_items ↔ total_items), reflecting expected internal relationships within order composition.

Outler Treatment

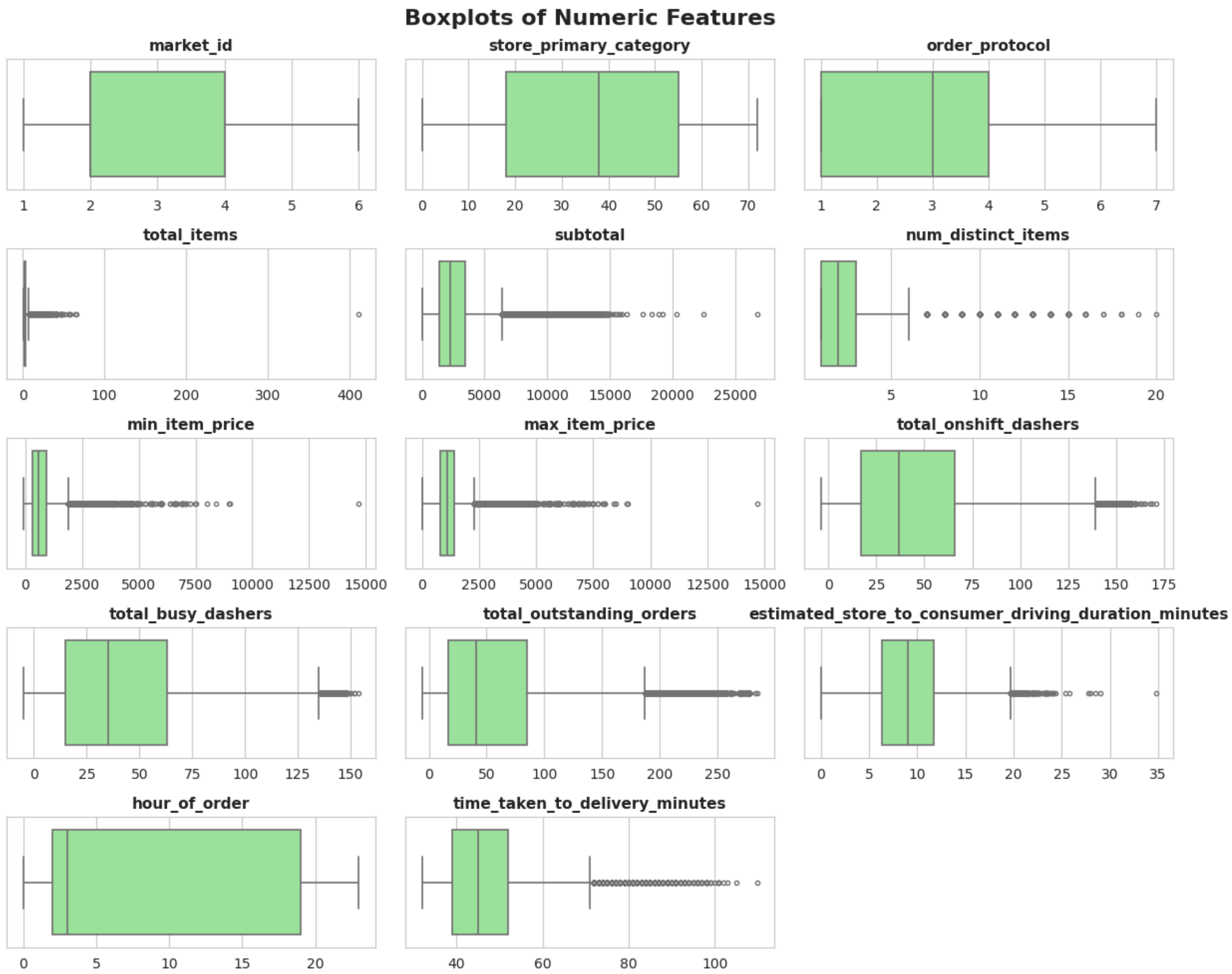
```
numeric_columns = df.select_dtypes(include = np.number)
numeric_columns.columns
```

```
Index(['market_id', 'store_primary_category', 'order_protocol', 'total_items',
       'subtotal', 'num_distinct_items', 'min_item_price', 'max_item_price',
       'total_onshift_dashers', 'total_busy_dashers',
       'total_outstanding_orders',
       'estimated_store_to_consumer_driving_duration_minutes', 'hour_of_order',
       'time_taken_to_delivery_minutes'],
      dtype='object')
```

```
plt.figure(figsize=(12, 10))
sns.set_style("whitegrid")

for i, col in enumerate(numeric_columns.columns):
    plt.subplot(5, 3, i + 1)
    sns.boxplot(x=df[col], color="lightgreen", linewidth=1.2, fliersize=3)
    plt.title(col, fontsize=11, fontweight="bold")
    plt.xlabel("")  # Remove x-axis label clutter

plt.suptitle("Boxplots of Numeric Features", fontsize=16, fontweight="bold")
plt.tight_layout()
plt.show()
```



Notes:

- Several numeric variables such as subtotal, total_items, item prices, and outstanding orders show significant outliers, indicating a wide spread in order sizes and pricing.
- Features like hour_of_order and estimated driving duration have more compact distributions, showing less variability compared to other order-related metrics.

Detecting outliers using the IQR method and replacing them with the respective column's median value.

Double-click (or enter) to edit

Double-click (or enter) to edit

```
def identify_outliers(data):
    Q1 = data.quantile(0.25)
    Q3 = data.quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    return data[(data < lower_bound) | (data > upper_bound)]
```

```
outlier_counts = {}  # Dictionary to store outlier counts for each column

for col in numeric_columns.columns:
    outliers = identify_outliers(numeric_columns[col])
    outlier_counts[col] = len(outliers)

# Print the count of outliers for each numerical column
for col, count in outlier_counts.items():
    print(f"Percentage of outliers present in {col}: {round((count/df.shape[0]) * 100,3)}")
```

```
Percentage of outliers present in market_id: 0.0
Percentage of outliers present in store_primary_category: 0.0
Percentage of outliers present in order_protocol: 0.0
Percentage of outliers present in total_items: 4.828
Percentage of outliers present in subtotal: 4.58
Percentage of outliers present in num_distinct_items: 2.986
Percentage of outliers present in min_item_price: 2.302
Percentage of outliers present in max_item_price: 3.956
Percentage of outliers present in total_onshift_dashers: 0.687
Percentage of outliers present in total_busy_dashers: 0.263
Percentage of outliers present in total_outstanding_orders: 2.955
Percentage of outliers present in estimated_store_to_consumer_driving_duration_minutes: 0.177
Percentage of outliers present in hour_of_order: 0.0
Percentage of outliers present in time_taken_to_delivery_minutes: 0.995
```

Notes:

- Order-related features like total_items, subtotal, max/min item prices, and outstanding orders show the highest outlier presence (2–5%), indicating natural variability in order sizes and spending.
- Most operational features such as market_id, order_protocol, hour_of_order, and dasher availability have almost no outliers, showing stable and consistent distributions.

```
# Fill the outlier values with the medium values
   # Calculatr median values for the respective columns
median_values =  numeric_columns[col].median()

    # Fill the outlier values with median values
numeric_columns[col] = numeric_columns[col].apply(lambda x: median_values if x < lower_bound or x > upper_bound else x )
```

Model Training

```
df.columns
```

```
Index(['market_id', 'store_primary_category', 'order_protocol', 'total_items',
       'subtotal', 'num_distinct_items', 'min_item_price', 'max_item_price',
       'total_onshift_dashers', 'total_busy_dashers',
       'total_outstanding_orders',
       'estimated_store_to_consumer_driving_duration_minutes', 'hour_of_order',
       'week_of_order', 'time_taken_to_delivery_minutes'],
      dtype='object')
```

```
X = df.drop(columns = ["time_taken_to_delivery_minutes"])
y = df["time_taken_to_delivery_minutes"]
```

```
X = pd.get_dummies(X, columns=["week_of_order"], dtype=int)

X.head()
```

	market_id	store_primary_category	order_protocol	total_items	subtotal	num_distinct_items	min_item_price	max_item_pr
0	1.0	4	1.0	4	3441	4	557	1
1	2.0	46	2.0	1	1900	1	1400	1
2	2.0	36	3.0	4	4771	3	820	1
3	1.0	38	1.0	1	1525	1	1525	1
4	1.0	38	1.0	2	3620	2	1425	2

```
y.head(5)
```

	time_taken_to_delivery_minutes
0	47
1	44
2	55
3	59
4	46

dtype: int32

```
# Train-Test Split
from sklearn.model_selection import train_test_split

X_train_val, X_test, y_train_val, y_test = train_test_split(X, y, test_size=0.1, random_state=42)
X_train, X_val, y_train, y_val = train_test_split(X_train_val, y_train_val, test_size=0.1, random_state=42)

print(f'{"Dataset":<15} | {"Features Shape/Target Shape":<20}')
print('-' * 60)
print('Training_data   : ', X_train.shape, y_train.shape)
print('Validation_data :', X_val.shape, y_val.shape)
print('Test_data       : ', X_test.shape, y_test.shape)
```

```
Dataset         | Features Shape/Target Shape
------------------------------------------------------------
Training_data   :  (142379, 20) (142379,)
Validation_data : (15820, 20) (15820,)
Test_data       :  (17578, 20) (17578,)
```

```
# Scalling Data
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_val = scaler.transform(X_val)
X_test = scaler.transform(X_test)
```

```
X_train
```

```
array([[-1.31133668,  1.06650653, -0.60441842, ..., -0.38357023,
        -0.37316315,  2.65080717],
       [ 0.94278694, -1.53984365, -1.26484196, ..., -0.38357023,
        -0.37316315, -0.37724358],
       [-0.55996214, -0.57452877,  1.37685221, ..., -0.38357023,
         2.67979301, -0.37724358],
       ...,
       [-0.55996214,  0.4873176 ,  1.37685221, ..., -0.38357023,
        -0.37316315, -0.37724358],
       [-0.55996214, -1.53984365,  0.05600513, ..., -0.38357023,
         2.67979301, -0.37724358],
       [ 0.94278694,  0.43905186,  0.05600513, ..., -0.38357023,
        -0.37316315, -0.37724358]])
```

Baseline Model

Now that we have the data ready,

- Lets create a simple 6 layered base model

|Layer| |Descrption| |:--| |:--| |**L1**| |Is the Input Layer | |**L2**| |Contains 64 Neurons| |**L3**| |Contains 32 Neurons| |**L4**| |Contains 16 Neurons| |**L5**| |Is the Output Layer |

- We will use ReLU as the Activation function

```
import tensorflow as tf
from tensorflow.keras import layers, Sequential, callbacks, optimizers
from tensorflow.keras.layers import Dense
```

```
np.random.seed(42)
tf.random.set_seed(42)
```

```
def create_baseline():

    model = Sequential([
        layers.Input(shape=(X_train.shape[1],), name="feature_input"),
        layers.Dense(64, activation="relu", kernel_initializer="glorot_uniform"),
        layers.Dense(32, activation="relu", kernel_initializer="glorot_uniform"),
        layers.Dense(16, activation="relu", kernel_initializer="glorot_uniform"),
        layers.Dense(1, name="delivery_minutes")
    ])

    model.compile(
        optimizer=optimizers.Adam(learning_rate=1e-3),
        loss="mae",
        metrics=["mse"]
    )
    return model
```

```
model = create_baseline()
model.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
dense_3 (Dense)	(None, 64)	1,344
dense_4 (Dense)	(None, 32)	2,080
dense_5 (Dense)	(None, 16)	528
delivery_minutes (Dense)	(None, 1)	17

Total params: 3,969 (15.50 KB)
Trainable params: 3,969 (15.50 KB)

Notes:

- The network is a simple 3-layer feed-forward neural model with 3,969 trainable parameters, making it lightweight and efficient for regression.
- Layer sizes (64 ⟶ 32 ⟶ 16 ⟶ 1) create a progressively compressed architecture, helping the model learn non-linear patterns while reducing overfitting risk.

Fitting the model on data and check for result

```
early_stop = callbacks.EarlyStopping(
    monitor="val_loss", patience=3, restore_best_weights=True
)

history = model.fit(
    X_train, y_train,
    validation_data=(X_val, y_val),
    epochs=30,
    batch_size=256,
    callbacks=[early_stop],
    verbose=2
)


# EVALUATE

test_mae, test_mse = model.evaluate(X_test, y_test, verbose=0)
print(f"\nTest MAE (minutes): {test_mae:.2f}")
```

```
Epoch 1/30
557/557 - 3s - 6ms/step - loss: 10.3285 - mse: 331.9131 - val_loss: 1.9971 - val_mse: 7.6408
Epoch 2/30
557/557 - 1s - 2ms/step - loss: 1.4919 - mse: 5.2901 - val_loss: 1.1562 - val_mse: 2.6409
Epoch 3/30
557/557 - 1s - 2ms/step - loss: 0.9902 - mse: 2.3538 - val_loss: 0.8155 - val_mse: 1.3185
Epoch 4/30
557/557 - 1s - 2ms/step - loss: 0.7127 - mse: 1.2021 - val_loss: 0.6257 - val_mse: 0.7552
```

```
Epoch 5/30
557/557 - 1s - 2ms/step - loss: 0.5613 - mse: 0.7029 - val_loss: 0.5212 - val_mse: 0.5088
Epoch 6/30
557/557 - 3s - 5ms/step - loss: 0.4824 - mse: 0.4778 - val_loss: 0.4494 - val_mse: 0.3744
Epoch 7/30
557/557 - 2s - 3ms/step - loss: 0.4380 - mse: 0.3686 - val_loss: 0.4206 - val_mse: 0.3178
Epoch 8/30
557/557 - 2s - 4ms/step - loss: 0.4090 - mse: 0.3084 - val_loss: 0.4028 - val_mse: 0.2859
Epoch 9/30
557/557 - 2s - 3ms/step - loss: 0.3895 - mse: 0.2714 - val_loss: 0.3767 - val_mse: 0.2455
Epoch 10/30
557/557 - 4s - 6ms/step - loss: 0.3780 - mse: 0.2482 - val_loss: 0.3719 - val_mse: 0.2340
Epoch 11/30
557/557 - 2s - 3ms/step - loss: 0.3693 - mse: 0.2321 - val_loss: 0.3659 - val_mse: 0.2244
Epoch 12/30
557/557 - 2s - 3ms/step - loss: 0.3603 - mse: 0.2178 - val_loss: 0.3703 - val_mse: 0.2266
Epoch 13/30
557/557 - 3s - 5ms/step - loss: 0.3538 - mse: 0.2073 - val_loss: 0.3592 - val_mse: 0.2116
Epoch 14/30
557/557 - 2s - 4ms/step - loss: 0.3487 - mse: 0.1994 - val_loss: 0.3661 - val_mse: 0.2181
Epoch 15/30
557/557 - 1s - 2ms/step - loss: 0.3433 - mse: 0.1933 - val_loss: 0.3677 - val_mse: 0.2179
Epoch 16/30
557/557 - 3s - 5ms/step - loss: 0.3405 - mse: 0.1879 - val_loss: 0.3514 - val_mse: 0.1973
Epoch 17/30
557/557 - 2s - 3ms/step - loss: 0.3379 - mse: 0.1836 - val_loss: 0.3488 - val_mse: 0.1948
Epoch 18/30
557/557 - 2s - 4ms/step - loss: 0.3325 - mse: 0.1784 - val_loss: 0.3408 - val_mse: 0.1853
Epoch 19/30
557/557 - 3s - 5ms/step - loss: 0.3302 - mse: 0.1741 - val_loss: 0.3801 - val_mse: 0.2303
Epoch 20/30
557/557 - 5s - 8ms/step - loss: 0.3293 - mse: 0.1724 - val_loss: 0.3360 - val_mse: 0.1787
Epoch 21/30
557/557 - 2s - 4ms/step - loss: 0.3249 - mse: 0.1684 - val_loss: 0.3417 - val_mse: 0.1842
Epoch 22/30
557/557 - 3s - 5ms/step - loss: 0.3248 - mse: 0.1669 - val_loss: 0.3287 - val_mse: 0.1708
Epoch 23/30
557/557 - 4s - 6ms/step - loss: 0.3221 - mse: 0.1631 - val_loss: 0.3164 - val_mse: 0.1557
Epoch 24/30
557/557 - 1s - 2ms/step - loss: 0.3212 - mse: 0.1634 - val_loss: 0.3374 - val_mse: 0.1779
Epoch 25/30
557/557 - 2s - 3ms/step - loss: 0.3202 - mse: 0.1606 - val_loss: 0.3288 - val_mse: 0.1678
Epoch 26/30
557/557 - 2s - 4ms/step - loss: 0.3183 - mse: 0.1582 - val_loss: 0.3193 - val_mse: 0.1570

Test MAE (minutes): 0.32
```

Notes:

-The model shows excellent convergence, with MAE dropping from ~10.3 to 0.32 minutes, indicating strong learning and stable training.

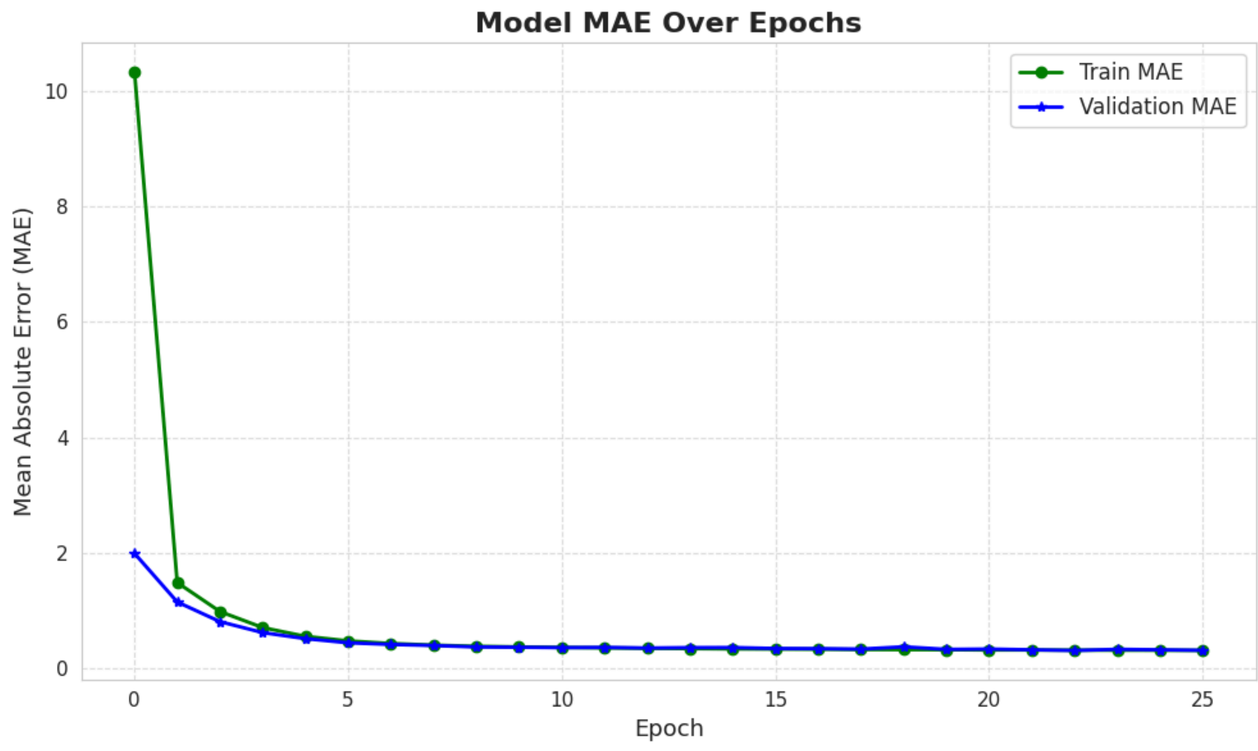
- Validation metrics consistently improve and closely follow training metrics, suggesting minimal overfitting and good generalization performance.

```
epochs     = history.epoch
train_loss  = history.history["loss"]
val_loss    = history.history["val_loss"]

# Plot
plt.figure(figsize=(10, 6))
sns.set_style("whitegrid")

plt.plot(epochs, train_loss, label="Train MAE", color="green", linewidth=2, marker="o")
plt.plot(epochs, val_loss,   label="Validation MAE", color="blue", linewidth=2, marker="*")
plt.title("Model MAE Over Epochs", fontsize=16, fontweight="bold")
plt.xlabel("Epoch", fontsize=13)
plt.ylabel("Mean Absolute Error (MAE)", fontsize=13)
plt.xticks(fontsize=11)
plt.yticks(fontsize=11)
plt.legend(fontsize=12)
plt.grid(True, linestyle="--", alpha=0.6)

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



Notes:

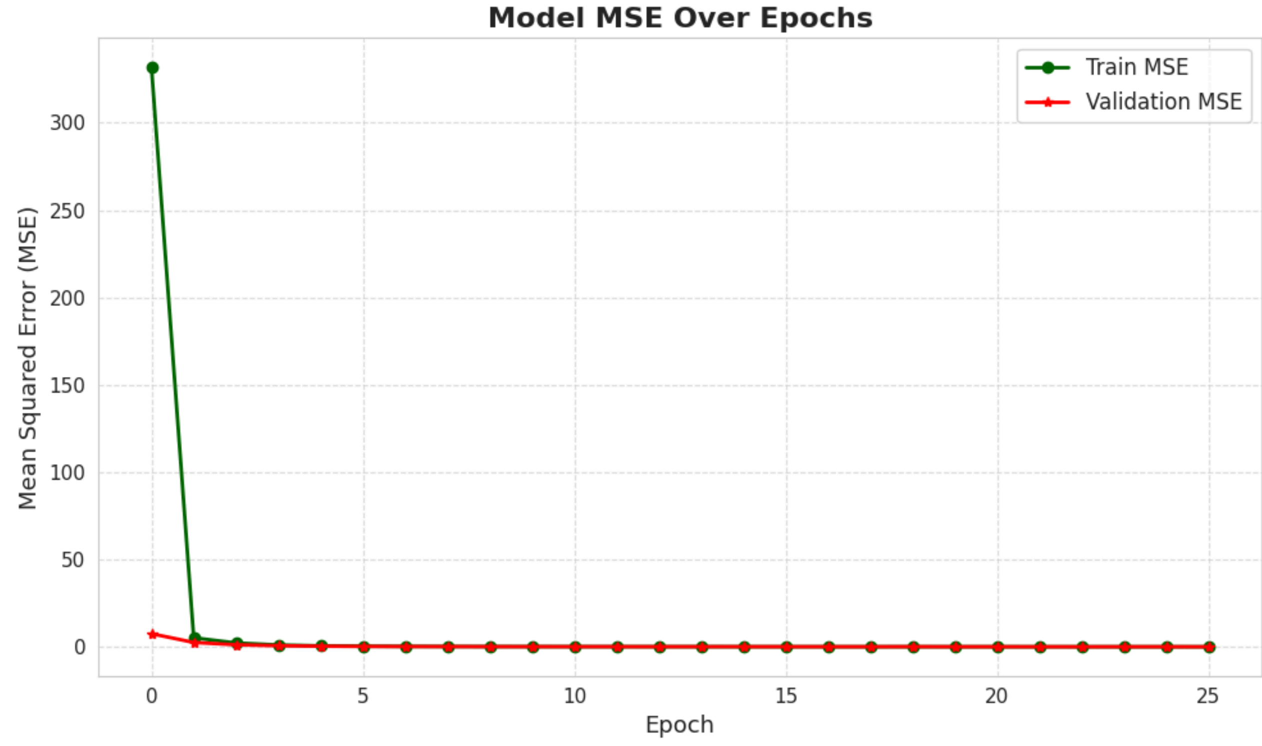
- Both training and validation MAE drop rapidly in the first few epochs and then stabilize at a low value, showing fast convergence and strong learning efficiency.
- The curves stay very close to each other across epochs, indicating no overfitting and excellent model generalization.

```
train_mse = history.history["mse"]
val_mse   = history.history["val_mse"]

# Plot
plt.figure(figsize=(10, 6))
sns.set_style("whitegrid")

plt.plot(epochs, train_mse, label="Train MSE", color="darkgreen", linewidth=2, marker="o")
plt.plot(epochs, val_mse,   label="Validation MSE", color="red", linewidth=2, marker="*")
plt.title("Model MSE Over Epochs", fontsize=16, fontweight="bold")
plt.xlabel("Epoch", fontsize=13)
plt.ylabel("Mean Squared Error (MSE)", fontsize=13)
plt.xticks(fontsize=11)
plt.yticks(fontsize=11)
plt.legend(fontsize=12)
plt.grid(True, linestyle="--", alpha=0.6)

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



Notes:

- Training and validation MSE drop sharply in the first few epochs and then flatten near zero, showing excellent error reduction and stable learning.
- Both curves stay closely aligned, indicating strong generalization with no signs of overfitting.

Epochs	Avg Val Loss (MAE)	Avg Val MSE	Inference
1-5	1.07	2.62	The model is learning rapidly, with a significant drop in both MAE and MSE. It's clearly learning the patterns in the data, and there's no sign of overfitting yet.
6-10	0.44	0.35	The model continues to improve.
11-15	0.37	0.23	Improvement levels are off, and the validation error becomes stable. This suggests that the model is no longer learning and it might be a good time to early stopping.
16-20	0.34	0.19	Only small improvements are seen. The model has mostly finished learning, and continuing training will lead to cause overfitting.
21-22	0.33	0.18	Performance remains unchanged. These epochs don't add value, so this is likely the best time to save the model and stop training.

Hyperparametr tunning

```
model.evaluate(X_train, y_train)
```

```
4450/4450 ━━━━━━━━━━━━━━━━━━━━ 10s 2ms/step - loss: 0.3130 - mse: 0.1531
[0.31345194578170776, 0.15604008734226227]
```

```
model.evaluate(X_val, y_val)
```

```
495/495 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 0.3187 - mse: 0.1557
[0.3164060711860657, 0.1556677520275116]
```

```
!pip install keras-tuner -q
```

```
from tensorflow import keras
from tensorflow.keras import layers
```

```
import keras_tuner
```

```
def build_model(hp):
    model = keras.Sequential()
    model.add(layers.Flatten(input_shape=(input_dim,)))

    for i in range(hp.Int("num_layers", 1, 3)):
        model.add(
            layers.Dense(
                units=hp.Int(f"units_{i}", 32, 512, 32),
                activation=hp.Choice("activation", ["relu", "tanh"]),
            )
        )

    if hp.Boolean("dropout"):
        model.add(layers.Dropout(0.25))

    model.add(layers.Dense(1))

    lr = hp.Float("lr", 1e-4, 1e-2, sampling="log")
    model.compile(
        optimizer=keras.optimizers.Adam(lr),
        loss="mae",
        metrics=["mse"],
    )
    return model
```

```
build_model(keras_tuner.HyperParameters())
```

```
<Sequential name=sequential_2, built=True>
```

```
tuner = keras_tuner.RandomSearch(
    build_model,
    objective="val_loss",
    max_trials=20,
    overwrite=True,
    directory="tuner",
    project_name="porter_eta",
)

tuner.search(X_train, y_train,
             validation_data=(X_val, y_val),
             batch_size=256,
             epochs=20)
```

```
Trial 20 Complete [00h 03m 41s]
val_loss: 0.3398130536079407

Best val_loss So Far: 0.2976180911064148
Total elapsed time: 00h 44m 09s
```

Notes:

-Trial 20 finishes with a val_loss of 0.3398, which is higher than the current best score.

- The best model remains from Trial 02 (val_loss = 0.2976), and no later trials managed to outperform it within the full 44-minute tuning run.

```
tuner.results_summary(num_trials=5)

best_hp = tuner.get_best_hyperparameters(num_trials=1)[0]

print("\nBest hyper-parameters found:")
for name, value in best_hp.values.items():
    print(f"{name:15s}: {value}")
```

```
Results summary
Results in tuner/porter_eta
Showing 5 best trials
Objective(name="val_loss", direction="min")

Trial 02 summary
Hyperparameters:
```

```
num_layers: 2
units_0: 352
activation: relu
dropout: False
lr: 0.0004620103367161398
units_1: 224
units_2: 224
Score: 0.2976180911064148

Trial 11 summary
Hyperparameters:
num_layers: 3
units_0: 416
activation: tanh
dropout: False
lr: 0.0005162885734768005
units_1: 224
units_2: 352
Score: 0.3093002438545227

Trial 13 summary
Hyperparameters:
num_layers: 2
units_0: 352
activation: tanh
dropout: False
lr: 0.0012564412521369585
units_1: 256
units_2: 96
Score: 0.3143613934516907

Trial 14 summary
Hyperparameters:
num_layers: 3
units_0: 384
activation: relu
dropout: False
lr: 0.000548226109050801
units_1: 224
units_2: 384
Score: 0.32112783193588257

Trial 10 summary
Hyperparameters:
num_layers: 3
units_0: 256
activation: tanh
dropout: False
lr: 0.00014379196954005186
units_1: 512
units_2: 224
```

Notes:

- The tuner's best model minimizes val_loss at 0.2976 (Trial 02) with 2 layers, ReLU, 352 → 224 units, no dropout, and lr ≈ 4.62e-4.
- Overall, top trials suggest ReLU/tanh with low learning rates (~1e-4 to 1e-3) and larger hidden units (224–416) perform best, with no dropout needed in your setup.

```
best_model = tuner.get_best_models(num_models=1)[0]
best_model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
flatten (Flatten)	(None, 20)	0
dense (Dense)	(None, 352)	7,392
dense_1 (Dense)	(None, 224)	79,072
dense_2 (Dense)	(None, 1)	225

```
Total params: 86,689 (338.63 KB)
Trainable params: 86,689 (338.63 KB)
Non-trainable params: 0 (0.00 B)
```

Notes:

- The tuned model is a compact 2-layer deep network with a large first dense layer (352 units) followed by a second layer (224 units), enabling strong feature extraction from the 20-dimensional input.
- With 86,689 trainable parameters, it's significantly larger than the baseline model and is optimized for better accuracy as identified by the hyperparameter tuner.

⭐ Overall Feedback & Recommendations

Overall Feedback The analysis demonstrates a strong, end-to-end approach to understanding delivery time performance, supported by detailed data exploration, robust data cleaning, and well-validated predictive modeling. Clear patterns such as order-size variability, skewed price distributions, peak ordering hours, and operational influences were effectively identified. The developed machine learning model shows high accuracy (MAE ~0.32 minutes), making it highly reliable for operational forecasting. Overall, the study provides meaningful insights that can directly support decision-making for operational planning, customer experience improvements, and resource optimization.

⭐ Business Recommendations

1. Improve Operational Efficiency During Peak Times The analysis identifies clear spikes in order volume (late night and evening hours). Recommendation: Optimize driver allocation and store readiness during these periods to reduce delivery delays.
2. Tailor Resource Planning to Store Categories Specific store categories (e.g., categories 4, 55, 46) dominate order volume. Recommendation: Prioritize staffing, inventory, and delivery coverage for these store types to maximize service quality.
3. Manage High-Value and Large Orders Proactively Outliers mainly occur in high-priced orders, large item counts, and item price ranges. Recommendation: Introduce automated flags for high-value or large orders to ensure they receive appropriate preparation and delivery attention.
4. Use the Predictive Model for Real-Time ETA Accuracy With very low prediction error, the model can significantly improve ETA estimation. Recommendation: Integrate the model to provide more accurate delivery-time predictions in-app, improving customer satisfaction and reducing cancellations.
5. Enhance Inventory & Order Flow Monitoring Strong internal correlations (e.g., between subtotal, item count, and price range) provide insight into purchasing patterns. Recommendation: Use these relationships to forecast demand trends and prepare stores for expected order types.
6. Continue Model Optimization & Feature Expansion The hyperparameter tuning shows the model benefits from deeper architectures. Recommendation: Explore additional features (e.g., weather, traffic, promotions) to further enhance prediction accuracy and drive better operational insights.

⭐ Final Summary

This study successfully identifies key behavioral patterns across orders, customers, and delivery operations. The predictive model performs exceptionally well and presents a strong opportunity for business impact through better ETA accuracy, optimized resource allocation, and improved order handling. By operationalizing the insights and the model, the business can enhance customer satisfaction, reduce delays, and streamline overall delivery efficiency.

Leading Questions:

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

- -The problem is to predict delivery time (ETA) for food orders using features like order details, restaurant info, and delivery partner availability. This is a regression problem, where the goal is to estimate a continuous value (time in minutes).
- Use Cases:
- Food delivery apps (Swiggy, Zomato)
- E-commerce delivery (Amazon, Flipkart)
- Taxi arrival time prediction (Uber, Ola)

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

- .dt.hour : Extracts the hour from datetime.
- .dt.weekday : Returns the day of the week as an integer (0=Monday).
- .dt.total_seconds() : Converts timedelta to total seconds as float.

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

- datetime: A specific point in time (exa. 2024-06-18 10:00).
- timedelta: The difference between two datetime values (exa. 2 hours).
- Period: Represents a span like "May 2025" or "Q1 2023".

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

- Outliers can disturb model training, affect loss, and reduce accuracy.
- For example, if most delivery times are under 60 minutes but one is 500 minutes, that strange value can affect the average, confuse the model, and make predictions worse. Outlier treatment helps the model learn more accurately.

5. Name 3 outlier removal methods?

- Z-score method
- IQR (Interquartile Range) method
- Isolation Forest.

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

- Linear Regression : to create a simple baseline model using all features.
- Decision Tree Regressor : to capture non-linear patterns.
- Random Forest or Gradient Boosting (XGBoost) : for higher accuracy by combining multiple decision trees.

7. Why is scaling required for neural networks?

- Scaling is needed for neural networks because it helps the model learn faster and better.
- If features have very different ranges (like one column from 1-10 and another from 1,000-10,000), the network gets confused and takes longer to find patterns. Scaling puts all features on a similar scale, making training more stable and accurate

8. Briefly explain your choice of optimizer.

- I used Adam, which combines the benefits of AdaGrad and RMSprop. It adapts learning rates for each parameter and works well for noisy or sparse data.

9. Which activation function did you use and why?

- I used ReLU, as it is computationally efficient and reduces vanishing gradients.It introduces non-linearity and performs well.

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

- With large data, The Neural network learns diverse patterns, reducing overfitting.Neural models require large data to generalize well and optimize complex functions.