Order Delivery Time Prediction

Objectives

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

The key goals are:

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

Data Pipeline

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

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

Data Understanding

The dataset contains information on orders placed through Porter, with the following columns:

Field	Description
market_id	Integer ID representing the market where the restaurant is located.
created_at	Timestamp when the order was placed.
actual_delivery_time	Timestamp when the order was delivered.
store_primary_category	Category of the restaurant (e.g., fast food, dine-in).
order_protocol	Integer representing how the order was placed (e.g., via Porter, call to restaurant, etc.).
total_items	Total number of items in the order.
subtotal	Final price of the order.
num_distinct_items	Number of distinct items in the order.
min_item_price	Price of the cheapest item in the order.
max_item_price	Price of the most expensive item in the order.

Field	Description
total_onshift_dashers	Number of delivery partners on duty when the order was placed.
total_busy_dashers	Number of delivery partners already occupied with other orders.
total_outstanding_orders	Number of orders pending fulfillment at the time of the order.
distance	Total distance from the restaurant to the customer.

Importing Necessary Libraries

In [1]:

```
# Import essential libraries for data manipulation and analysis
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

1. Loading the data

Load 'porter_data_1.csv' as a DataFrame

In [2]:

```
# Importing the file porter_data_1.csv
df= pd.read_csv('porter_data_1.csv')
df
```

Out[2]:

	market_id	created_at	actual_delivery_time	store_primary_category	order_protocol	total_items
0	1.0	2015-02-06 22:24:17	2015-02-06 23:11:17	4	1.0	4
1	2.0	2015-02-10 21:49:25	2015-02-10 22:33:25	46	2.0	1
2	2.0	2015-02-16 00:11:35	2015-02-16 01:06:35	36	3.0	4
3	1.0	2015-02-12 03:36:46	2015-02-12 04:35:46	38	1.0	1
4	1.0	2015-01-27 02:12:36	2015-01-27 02:58:36	38	1.0	2
...	...	...	...	...	...	...
175772	1.0	2015-02-17 00:19:41	2015-02-17 01:02:41	28	4.0	3
175773	1.0	2015-02-13 00:01:59	2015-02-13 01:03:59	28	4.0	6
175774	1.0	2015-01-24 04:46:08	2015-01-24 05:32:08	28	4.0	5
175775	1.0	2015-02-01 18:18:15	2015-02-01 19:03:15	58	1.0	1
175776	1.0	2015-02-08 19:24:33	2015-02-08 20:01:33	58	1.0	4

175777 rows × 14 columns

2. Data Preprocessing and Feature Engineering [15 marks]

2.1 Fixing the Datatypes [5 marks]

The current timestamps are in object format and need conversion to datetime format for easier handling and intended functionality

2.1.1 [2 marks]

Convert date and time fields to appropriate data type

In [3]:
```python
# Convert 'created_at' and 'actual_delivery_time' columns to datetime format as required.

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

2.1.2 [3 marks]

Convert category fields to appropriate data type

In [4]:
```python
# Convert category features to category type as appropriate data types

cat_cols = ['market_id', 'store_primary_category', 'order_protocol', 'order_status', 'delivery_s
for col in cat_cols:
        if col in df.columns:
                df[col] = df[col].astype('category')
```

In [5]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 175777 entries, 0 to 175776
Data columns (total 14 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
 0   market_id                 175777 non-null  category
 1   created_at                175777 non-null  datetime64[ns]
 2   actual_delivery_time      175777 non-null  datetime64[ns]
 3   store_primary_category    175777 non-null  category
 4   order_protocol            175777 non-null  category
 5   total_items               175777 non-null  int64
 6   subtotal                  175777 non-null  int64
 7   num_distinct_items        175777 non-null  int64
 8   min_item_price            175777 non-null  int64
 9   max_item_price            175777 non-null  int64
 10  total_onshift_dashers     175777 non-null  float64
 11  total_busy_dashers        175777 non-null  float64
 12  total_outstanding_orders  175777 non-null  float64
 13  distance                  175777 non-null  float64
dtypes: category(3), datetime64[ns](2), float64(4), int64(5)
memory usage: 15.3 MB
```

2.2 Feature Engineering [5 marks]

Calculate the time taken to execute the delivery as well as extract the hour and day at which the order was placed

2.2.1 [2 marks]

Calculate the time taken using the features `actual_delivery_time` and `created_at`

In [6]:
```python
# Calculate time taken in minutes from order creation time to actual delivery time
df['time_taken'] = (df['actual_delivery_time'] - df['created_at']).dt.total_seconds() / 60
df
```

Out[6]:

	market_id	created_at	actual_delivery_time	store_primary_category	order_protocol	total_items
0	1.0	2015-02-06 22:24:17	2015-02-06 23:11:17	4	1.0	4
1	2.0	2015-02-10 21:49:25	2015-02-10 22:33:25	46	2.0	1
2	2.0	2015-02-16 00:11:35	2015-02-16 01:06:35	36	3.0	4
3	1.0	2015-02-12 03:36:46	2015-02-12 04:35:46	38	1.0	1
4	1.0	2015-01-27 02:12:36	2015-01-27 02:58:36	38	1.0	2
...	...	...	...	...	...	...
175772	1.0	2015-02-17 00:19:41	2015-02-17 01:02:41	28	4.0	3
175773	1.0	2015-02-13 00:01:59	2015-02-13 01:03:59	28	4.0	6
175774	1.0	2015-01-24 04:46:08	2015-01-24 05:32:08	28	4.0	5
175775	1.0	2015-02-01 18:18:15	2015-02-01 19:03:15	58	1.0	1
175776	1.0	2015-02-08 19:24:33	2015-02-08 20:01:33	58	1.0	4

175777 rows × 15 columns

2.2.2 [3 marks]

Extract the hour at which the order was placed and which day of the week it was. Drop the unnecessary columns.

In [7]:

```
# Extract the hour and day of week from the 'created_at' timestamp for the order placed during t
df['order_hour'] = df['created_at'].dt.hour
df['order_dayofweek'] = df['created_at'].dt.dayofweek


# Creating a category feature 'isWeekend' to know whether the order was placed on a weekend or r
df['isWeekend'] = df['order_dayofweek'].apply(lambda x: 1 if x >= 5 else 0).astype('category')
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 175777 entries, 0 to 175776
Data columns (total 18 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
 0   market_id                 175777 non-null  category
 1   created_at                175777 non-null  datetime64[ns]
 2   actual_delivery_time      175777 non-null  datetime64[ns]
 3   store_primary_category    175777 non-null  category
 4   order_protocol            175777 non-null  category
 5   total_items               175777 non-null  int64
 6   subtotal                  175777 non-null  int64
 7   num_distinct_items        175777 non-null  int64
 8   min_item_price            175777 non-null  int64
 9   max_item_price            175777 non-null  int64
 10  total_onshift_dashers     175777 non-null  float64
 11  total_busy_dashers        175777 non-null  float64
 12  total_outstanding_orders  175777 non-null  float64
 13  distance                  175777 non-null  float64
 14  time_taken                175777 non-null  float64
 15  order_hour                175777 non-null  int32
 16  order_dayofweek           175777 non-null  int32
 17  isWeekend                 175777 non-null  category
dtypes: category(4), datetime64[ns](2), float64(5), int32(2), int64(5)
memory usage: 18.1 MB
```

In [8]:

```python
# Drop unnecessary columns in created_at and actual_delivery_time as time_taken is already calcu
df = df.drop(['created_at', 'actual_delivery_time'], axis=1)

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 175777 entries, 0 to 175776
Data columns (total 16 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
 0   market_id                 175777 non-null  category
 1   store_primary_category    175777 non-null  category
 2   order_protocol            175777 non-null  category
 3   total_items               175777 non-null  int64
 4   subtotal                  175777 non-null  int64
 5   num_distinct_items        175777 non-null  int64
 6   min_item_price            175777 non-null  int64
 7   max_item_price            175777 non-null  int64
 8   total_onshift_dashers     175777 non-null  float64
 9   total_busy_dashers        175777 non-null  float64
 10  total_outstanding_orders  175777 non-null  float64
 11  distance                  175777 non-null  float64
 12  time_taken                175777 non-null  float64
 13  order_hour                175777 non-null  int32
 14  order_dayofweek           175777 non-null  int32
 15  isWeekend                 175777 non-null  category
dtypes: category(4), float64(5), int32(2), int64(5)
memory usage: 15.4 MB
```

2.3 Creating training and validation sets [5 marks]

2.3.1 [2 marks]

Define target and input features

In [9]:
```
# Define target variable (y) and features (X)

# Here are the dependent and the feature variables we will use
# y = 'time_taken'
# X = 'market_id', 'total_items', 'subtotal', 'num_distinct_items', 'min_item_price', 'max_item_
#     'total_onshift_dashers', 'total_busy_dashers', 'total_outstanding_orders', 'distance'

y = df['time_taken']
X = df.drop('time_taken', axis=1)
```

2.3.2 [3 marks]

Split the data into training and test sets

In [10]:
```
#Build the training and test datasets using scikit learn model selection.

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7, random_state=100)
```

In [11]:
```
# ing the train and test split data frames
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(123043, 15)
(52734, 15)
(123043,)
(52734,)
```

3. Exploratory Data Analysis on Training Data [20 marks]

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

3.1 Feature Distributions [7 marks]

In [16]:
```
# Define category and number columns for easy EDA and data manipulation

number_columns = [
    'total_items', 'subtotal', 'num_distinct_items', 'min_item_price', 'max_item_price','total_
    'total_busy_dashers','total_outstanding_orders','distance'
]

category_columns = [
```

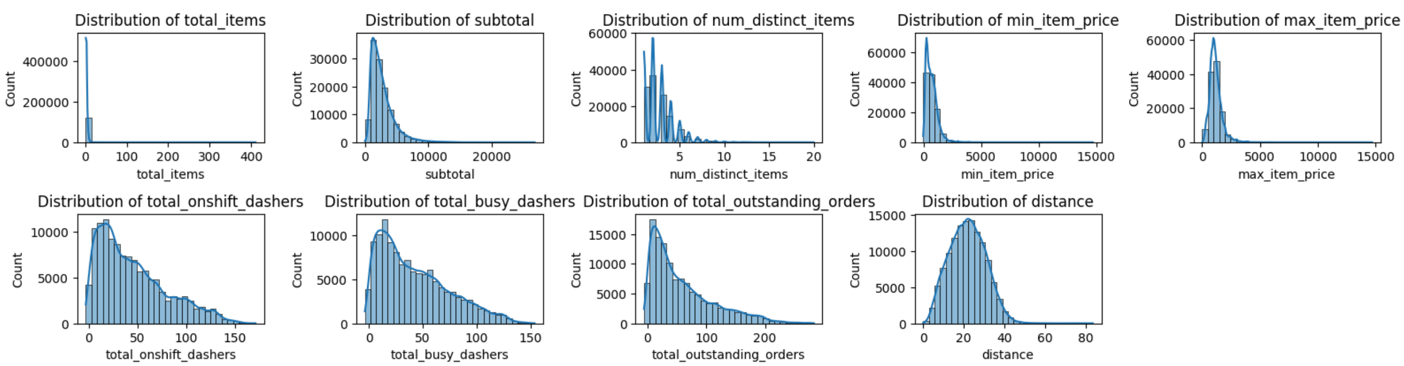
```
    'market_id', 'store_primary_category', 'order_protocol',
    'created_at_hour','created_at_dayofweek','isWeekend'
]
```

3.1.1 [3 marks]

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

In [18]:

```
# Plot distributions for all number columns

plt.figure(figsize=(16, 12))
for i, col in enumerate(number_columns, 1):
    plt.subplot(6, 5, i)
    sns.histplot(X_train[col], kde=True, bins=30)
    plt.title(f'Distribution of {col}')
plt.tight_layout()
plt.show()
```



In [19]:

```
X_train[number_columns].describe()
```

Out[19]:

	total_items	subtotal	num_distinct_items	min_item_price	max_item_price	total_onshift_da
count	123043.000000	123043.000000	123043.000000	123043.000000	123043.000000	123043.0(
mean	3.206082	2697.863625	2.674951	684.784506	1160.434645	44.9\&
std	2.745043	1830.338637	1.625552	520.731071	562.955073	34.5(
min	1.000000	0.000000	1.000000	-52.000000	0.000000	-3.0(
25%	2.000000	1417.000000	2.000000	299.000000	799.000000	17.0(
50%	3.000000	2220.000000	2.000000	595.000000	1095.000000	37.0(
75%	4.000000	3405.000000	3.000000	942.000000	1395.000000	66.0(
max	411.000000	26800.000000	20.000000	14700.000000	14700.000000	171.0(

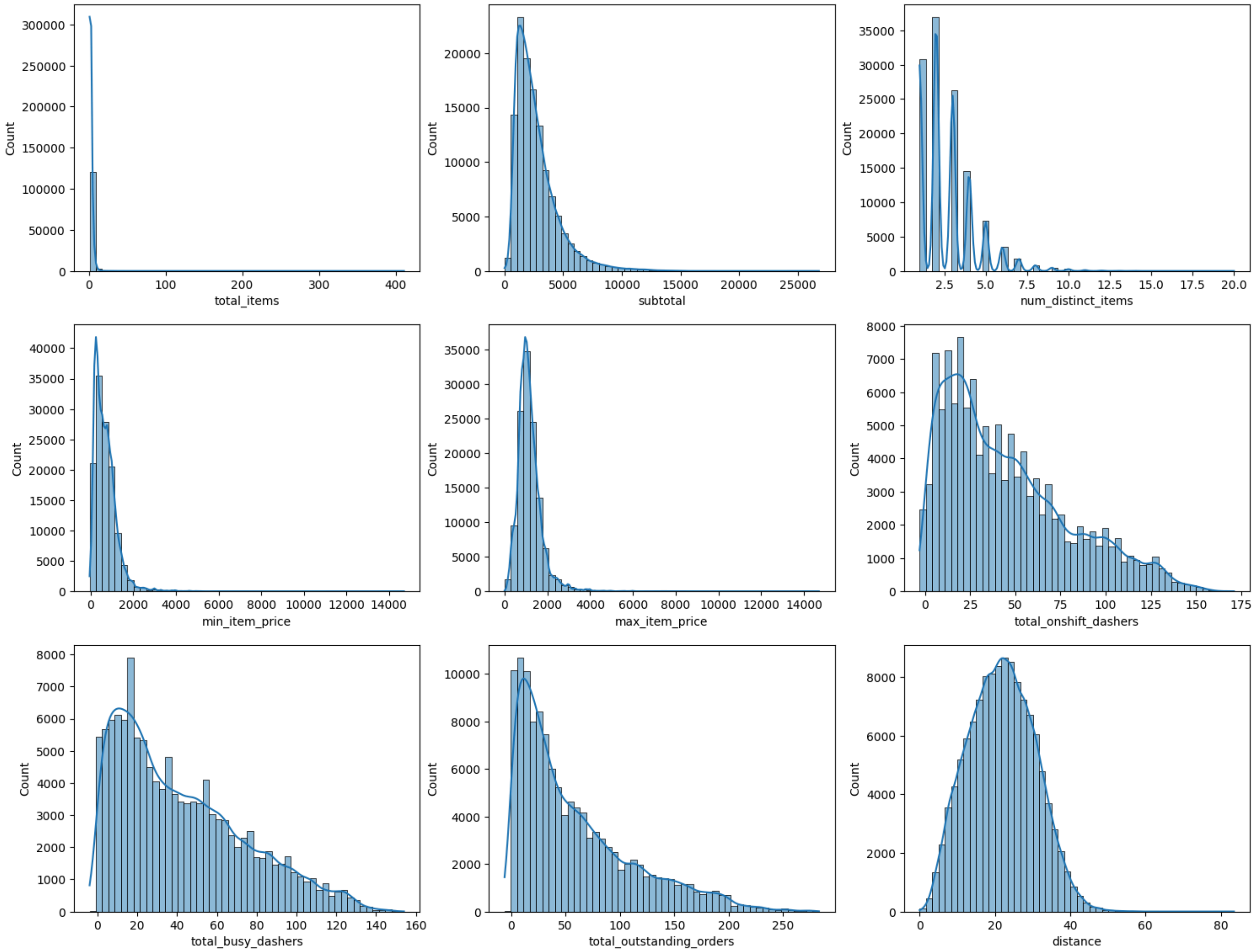
3.1.2 [2 marks]

Check the distribution of category features

In [24]:

```
# Plot the distribution of category columns in the training set
index = 1
```

```python
plt.figure(figsize=(18,14))
for col in number_columns:
    plt.subplot(3, 3, index)
    sns.histplot(X_train[col], kde=True, bins=50)
    index = index + 1
plt.show()
```

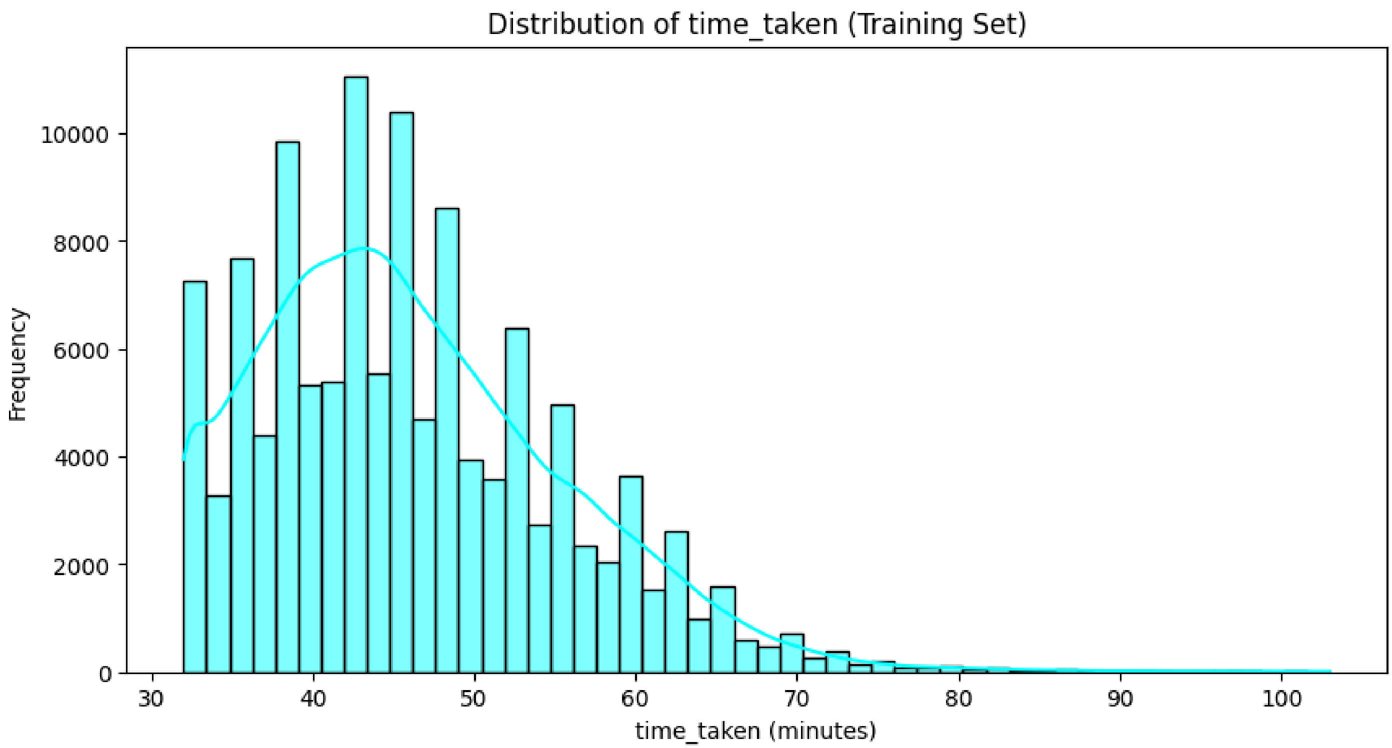


3.1.3 [2 mark]

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

In [25]:

```python
# Distribution of time_taken in minutes in the training set
plt.figure(figsize=(10,5))
sns.histplot(y_train, kde=True, bins=50, color='cyan')
plt.title('Distribution of time_taken (Training Set)')
plt.xlabel('time_taken (minutes)')
plt.ylabel('Frequency')
plt.show()
```

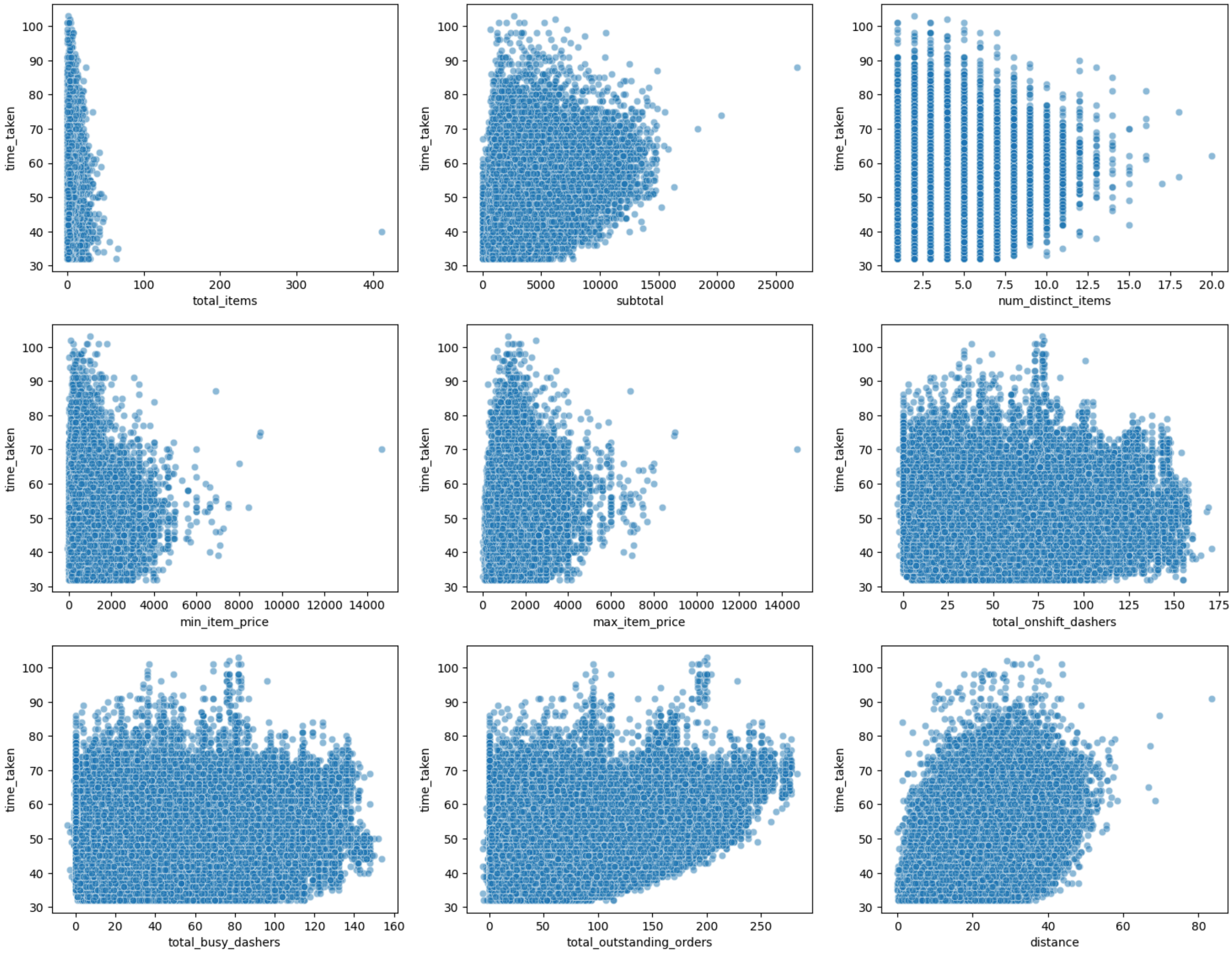


3.2 Relationships Between Features [3 marks]

3.2.1 [3 marks]

Scatter plots for important number and category features to observe how they relate to `time_taken`

In [27]:
```
# Scatter plots for selected number features vs time_taken
index = 1
plt.figure(figsize=(18,14))
for col in number_columns:
    plt.subplot(3, 3, index)
    sns.scatterplot(x=X_train[col], y=y_train, alpha=0.5)
    index = index + 1
plt.show()
```



In [26]:

```python
# Show the distribution of time_taken for different hours
plt.figure(figsize=(16, 4))
sns.boxplot(x='order_hour', y='time_taken', data=df)
plt.title('Distribution of time_taken by Order Hour', fontsize=10)
plt.xlabel('Order Hour', fontsize=10)
plt.ylabel('Time Taken (minutes)')
plt.show()
```

3.3 Correlation Analysis [5 marks]

Check correlations between number features to identify which variables are strongly related to `time_taken`

3.3.1 [3 marks]

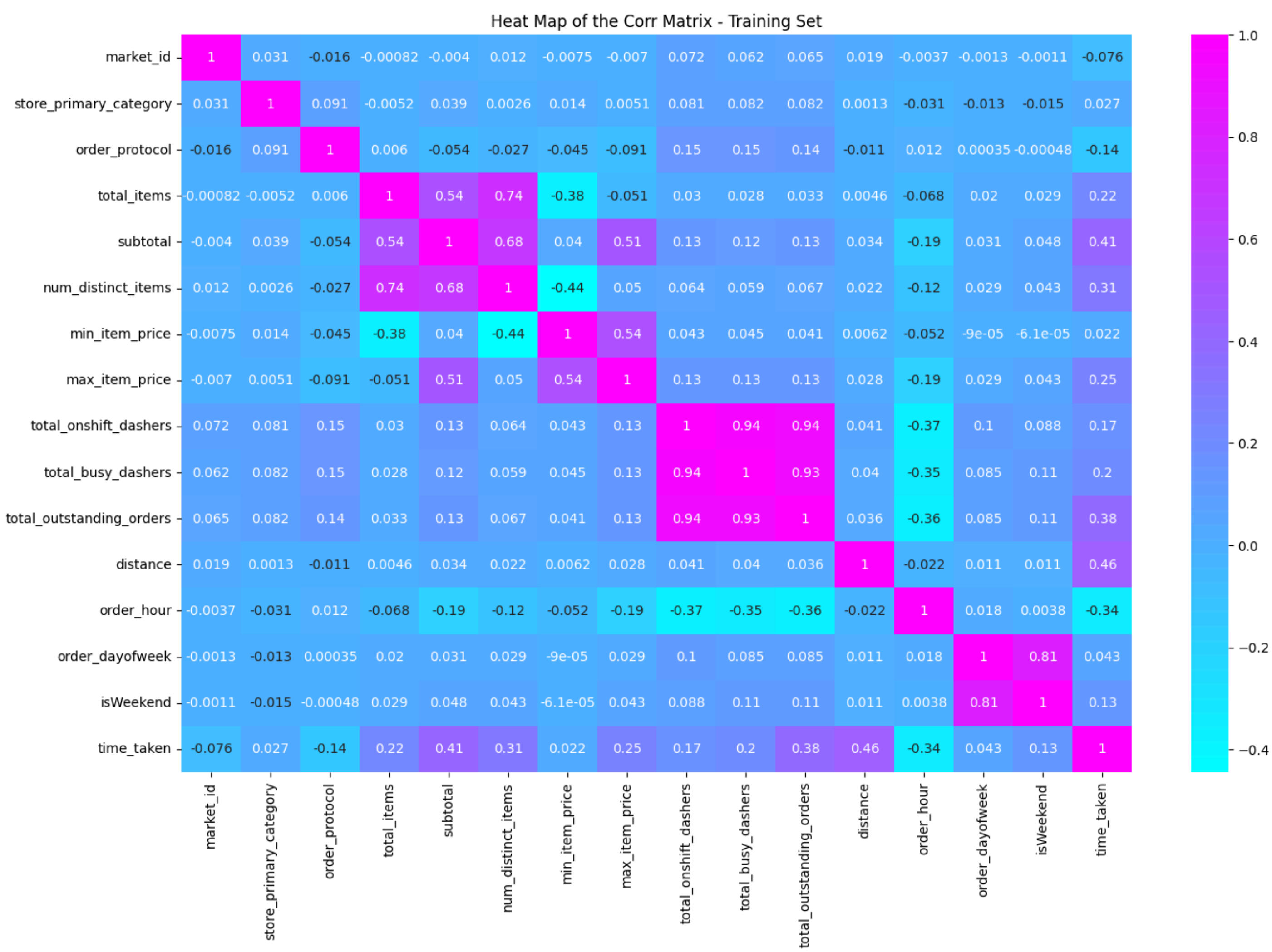
Plot a heatmap to display correlations

In [105…

```
df_train = X_train.copy()
df_train['time_taken'] = y_train.copy()
```

In [106…

```
# Plot the heatmap of the correlation matrix for Training Set
corr_matrix = df_train.corr()
plt.figure(figsize=(16, 10))
sns.heatmap(corr_matrix, annot=True, cmap='cool')
plt.title('Heat Map of the Corr Matrix - Training Set')
plt.show()
```



3.3.2 [2 marks]

Drop the columns with weak correlations with the target variable

In [109…

```
# Before dropping the weak correlation checking correlation between numerical features to time_t

corr = df_train[number_columns + ['time_taken']].corr()['time_taken']
corr = corr.sort_values(key=abs, ascending=False)
print(corr)
```

```
time_taken                1.000000
distance                  0.459712
subtotal                  0.412878
total_outstanding_orders  0.381642
num_distinct_items        0.313384
max_item_price            0.254671
total_items               0.219104
Name: time_taken, dtype: float64
```

In [110…

```
# Drop 3-5 weak correlated columns from training dataset

# Only drop columns that exist in df_train to avoid KeyError
cols_to_drop = ['min_item_price', 'total_onshift_dashers', 'total_busy_dashers']
cols_to_drop_existing = [col for col in cols_to_drop if col in df_train.columns]
df_train = df_train.drop(columns=cols_to_drop_existing)

# Update the list of numerical columns
number_columns = [
    'total_items', 'subtotal', 'num_distinct_items', 'max_item_price', 'total_outstanding_orders
]
```

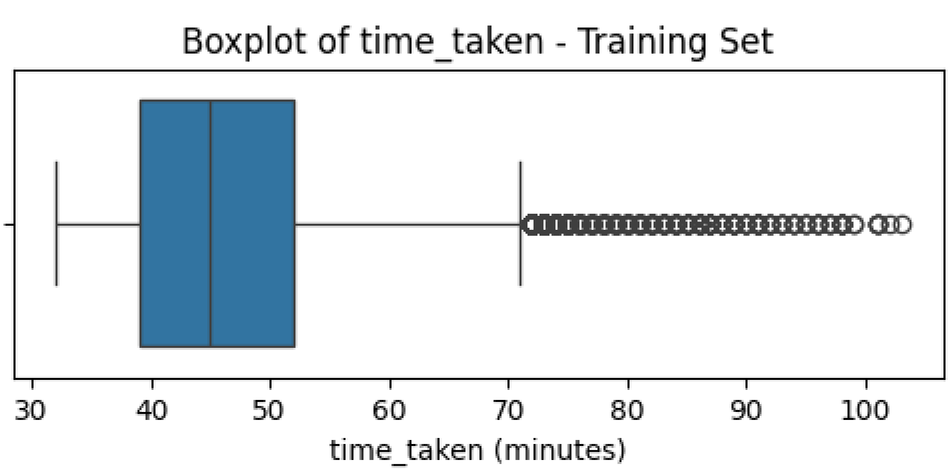
3.4 Handling the Outliers [5 marks]

3.4.1 [2 marks]

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

In [111…

```
# Boxplot for time_taken
plt.figure(figsize=(6, 2))
sns.boxplot(x=y_train)
plt.title('Boxplot of time_taken - Training Set')
plt.xlabel('time_taken (minutes)')
plt.show()
```



3.4.2 [3 marks]

Handle outliers present in all columns

In [112…

```
# Handling the outliers in number columns using the IQR method

for column_name in number_columns:
    Q1 = df_train[column_name].quantile(0.25)
    Q3 = df_train[column_name].quantile(0.75)
    IQR = Q3 - Q1
    lower_limit  = Q1 - (1.5 * IQR)
    higher_limit = Q3 + (1.5 * IQR)

    # Keep only values within the bounds
    print(f'{column_name} --> capping values between {lower_limit} and {higher_limit}')
    df_train = df_train[(df_train[column_name] >= lower_limit) & (df_train[column_name] <= highe
```

```
total_items --> capping values between -1.0 and 7.0
subtotal --> capping values between -1405.0 and 6067.0
num_distinct_items --> capping values between -2.0 and 6.0
max_item_price --> capping values between -65.0 and 2239.0
total_outstanding_orders --> capping values between -83.5 and 184.5
distance --> capping values between -3.9599999999999999 and 47.239999999999995
```

4. Exploratory Data Analysis on Validation Data [optional]

Optionally, perform EDA on test data to see if the distribution match with the training data

In [113…

```
# Define category columns
number_columns = [
    'total_items', 'subtotal', 'num_distinct_items', 'min_item_price', 'max_item_price','total_c
    'total_busy_dashers','total_outstanding_orders','distance'
]

category_columns = [
    'market_id', 'store_primary_category', 'order_protocol',
    'created_at_hour','created_at_dayofweek','isWeekend'
]
```

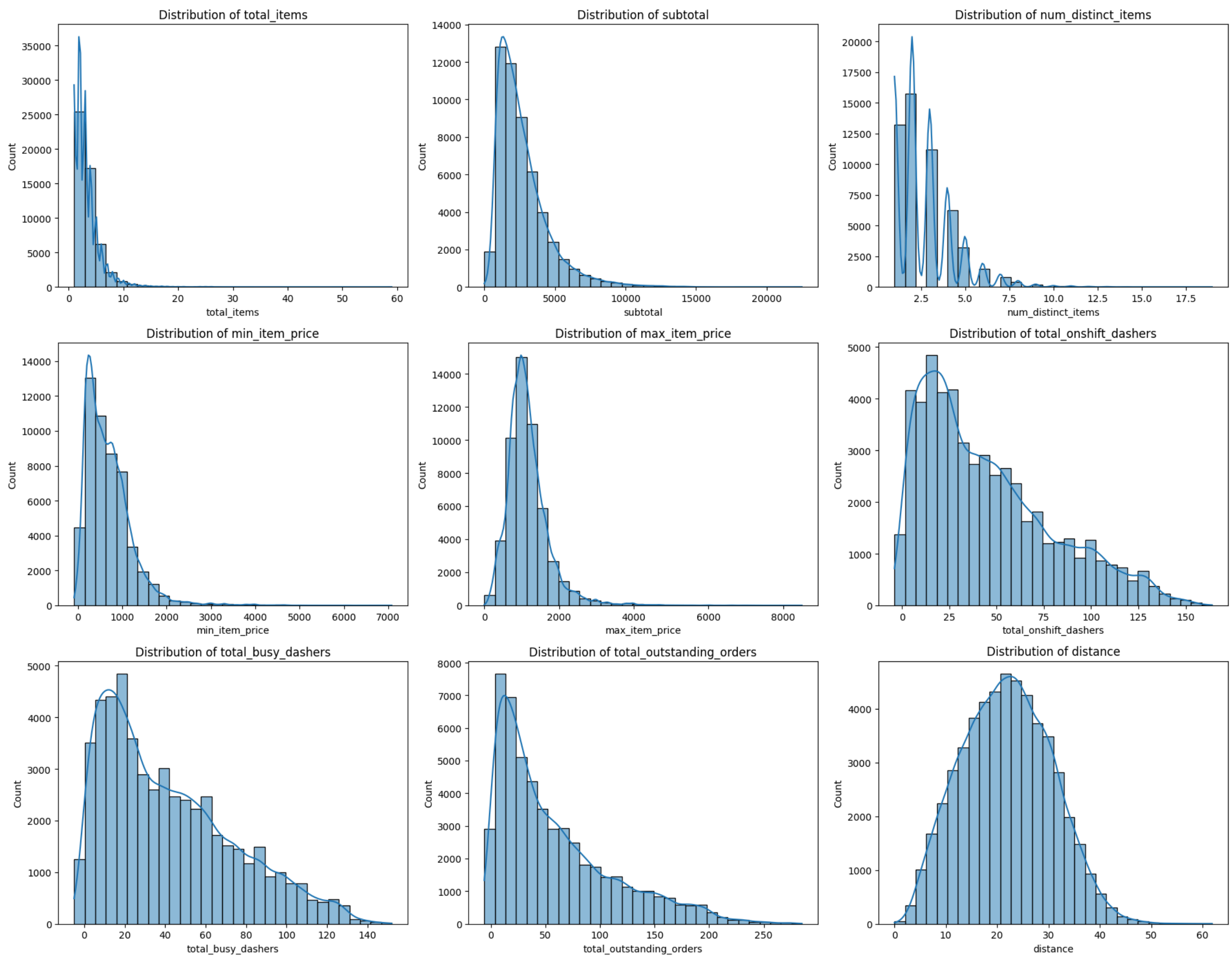
4.1 Feature Distributions

4.1.1

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

In [118…

```
# Plot distributions for all number columns in the validation set that still exist in X_test
valid_number_cols = [col for col in number_columns if col in X_test.columns]

plt.figure(figsize=(18,14))
for i, col in enumerate(valid_number_cols, 1):
    plt.subplot(3, 3, i)
    sns.histplot(X_test[col], kde=True, bins=30)
    plt.title(f'Distribution of {col}')
plt.tight_layout()
```



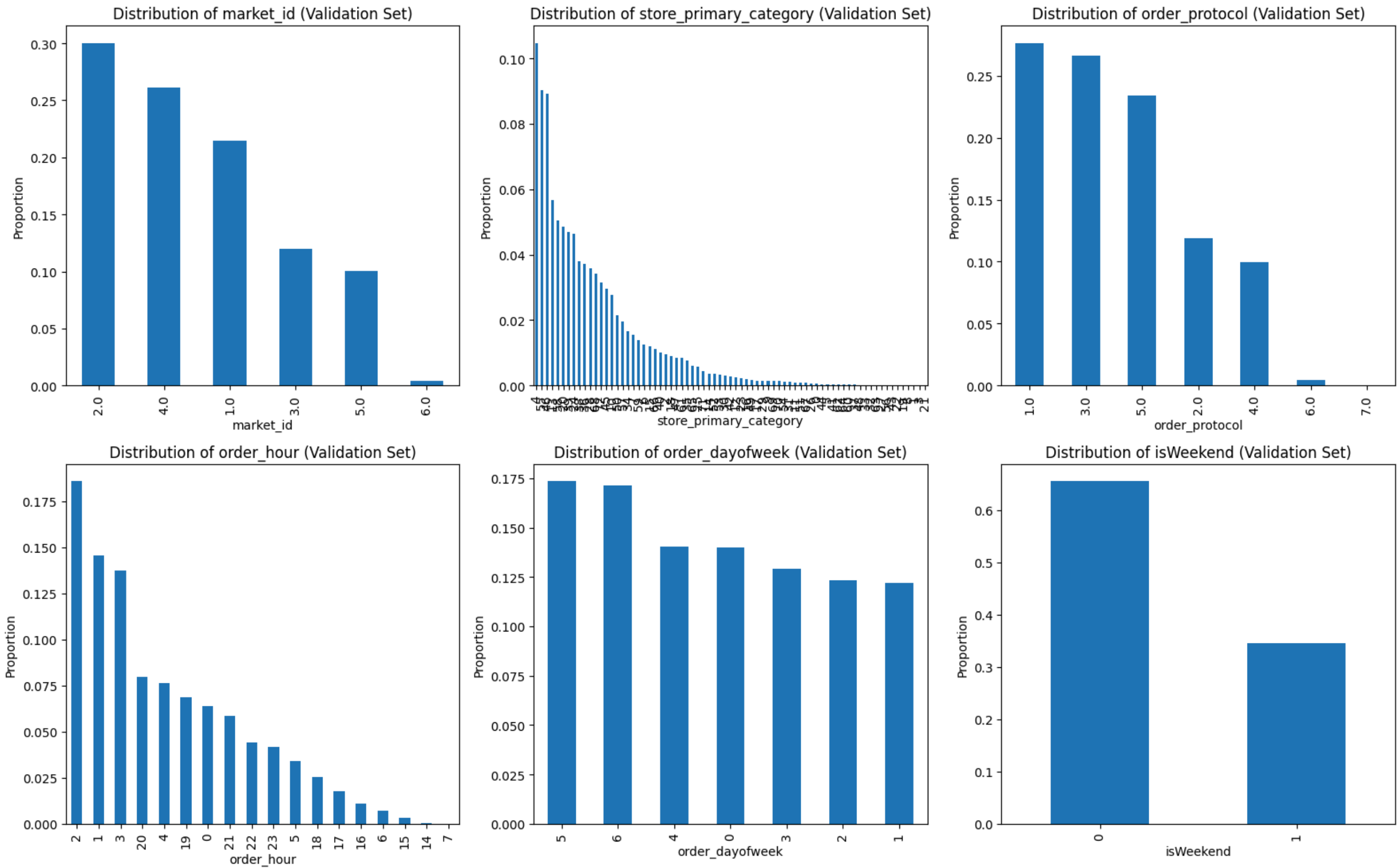
4.1.2

Check the distribution of category features

In [120…

```
# Plot the distribution of category columns in the validation set
# Use the correct category columns present in X_test
category_columns_valid = ['market_id', 'store_primary_category', 'order_protocol', 'order_hour',

plt.figure(figsize=(16, 10))
for i, col in enumerate(category_columns_valid, 1):
    X_test[col].value_counts(normalize=True).plot(kind='bar', ax=plt.subplot(2, 3, i))
    plt.title(f'Distribution of {col} (Validation Set)')
    plt.xlabel(col)
    plt.ylabel('Proportion')
```

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

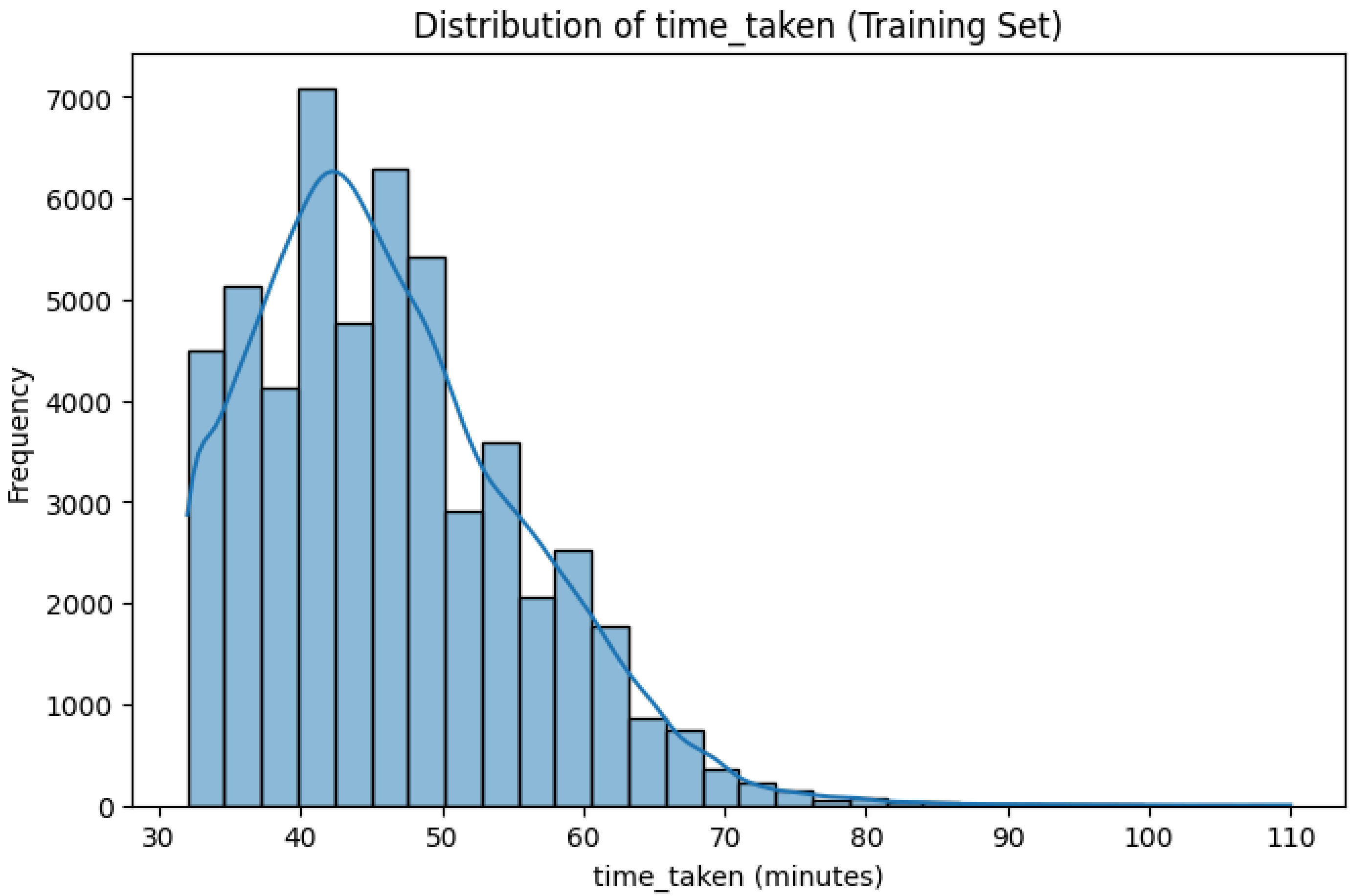


4.1.3

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

In [121…

```
# Distribution of time_taken in the training set
plt.figure(figsize=(8, 5))
sns.histplot(y_test, kde=True, bins=30)
plt.title('Distribution of time_taken (Training Set)')
plt.xlabel('time_taken (minutes)')
plt.ylabel('Frequency')
plt.show()
```

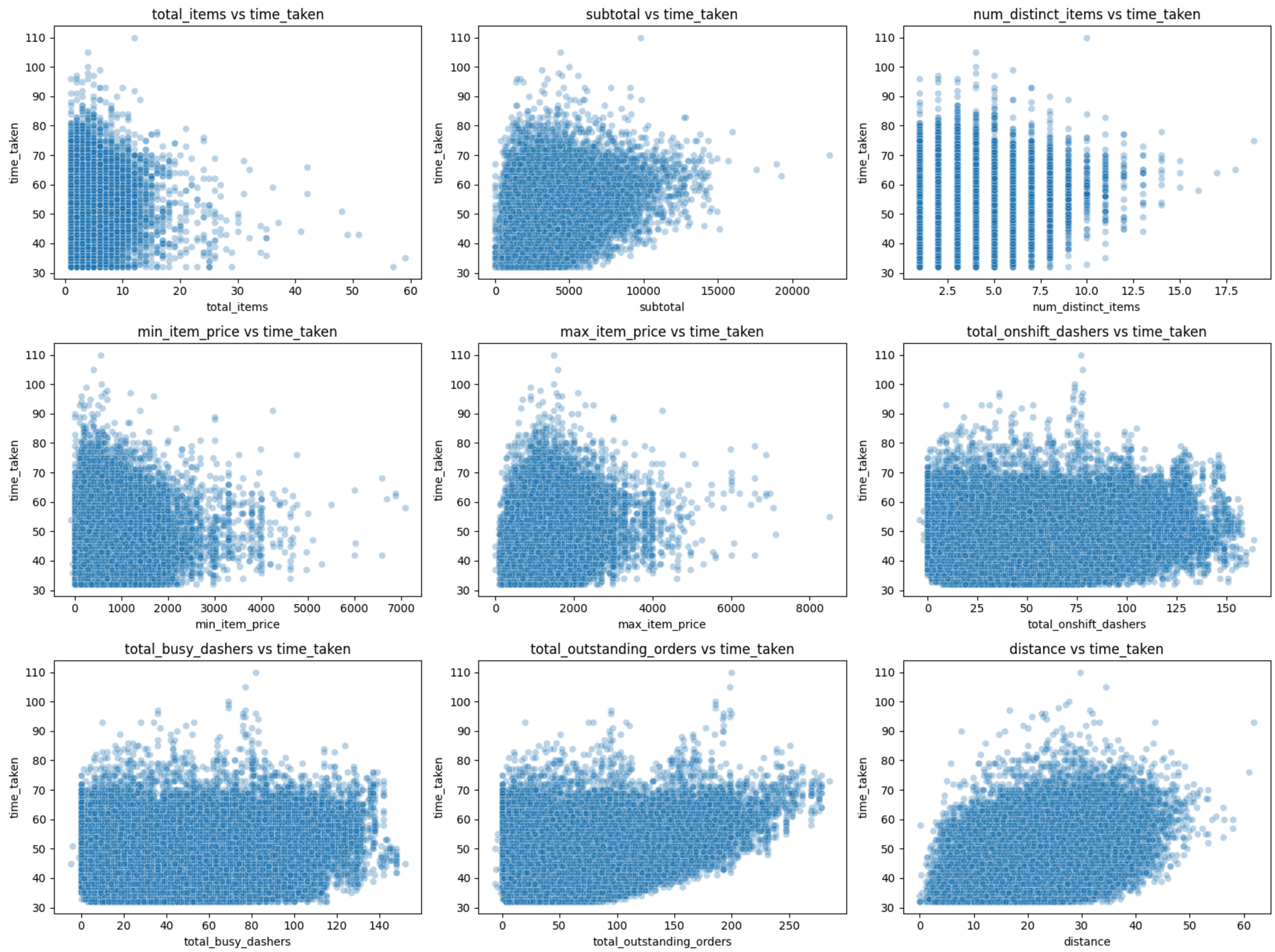


4.2 Relationships Between Features

Scatter plots for number features to observe how they relate to each other, especially to `time_taken`

In [124…

```
# Scatter plots for number features vs time_taken in the training set
plt.figure(figsize=(16, 12))
for i, col in enumerate(number_columns, 1):
    if col in X_test.columns:
        plt.subplot(3, 3, i)
        sns.scatterplot(x=X_test[col], y=y_test, alpha=0.3)
        plt.xlabel(col)
        plt.ylabel('time_taken')
        plt.title(f'{col} vs time_taken')
plt.tight_layout()
plt.show()
```



4.3 Drop the columns with weak correlations with the target variable

In [125…

```python
# Drop 3 columns with the weakest correlation to the target variable in the training set

df_test = X_test.copy()
df_test['time_taken'] = y_test.copy()

# Drop 3-5 weakly correlated columns from training dataset

# Columns with weakest correlations with the target variable 'time_taken' are
# 'total_busy_dashers', 'total_onshift_dashers', and 'min_item_price'

df_test = df_test.drop('total_busy_dashers', axis=1)
df_test = df_test.drop('total_onshift_dashers', axis=1)
df_test = df_test.drop('min_item_price', axis=1)

# Update the list of numerical colums
number_columns = [
    'total_items', 'subtotal', 'num_distinct_items', 'max_item_price','total_outstanding_orders
]
df_test.describe()
```

Out[125…

	total_items	subtotal	num_distinct_items	max_item_price	total_outstanding_orders	dist
count	52734.000000	52734.000000	52734.000000	52734.000000	52734.000000	52734.0C
mean	3.202393	2695.355406	2.675314	1159.514564	58.121534	21.87
std	2.500620	1824.402267	1.625995	555.839994	52.827730	8.71
min	1.000000	0.000000	1.000000	0.000000	-6.000000	0.0C
25%	2.000000	1400.000000	1.000000	799.000000	17.000000	15.4C
50%	3.000000	2225.000000	2.000000	1095.000000	41.000000	21.84
75%	4.000000	3415.000000	3.000000	1395.000000	85.000000	28.16
max	59.000000	22500.000000	19.000000	8500.000000	285.000000	61.88

In [126…

```
df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 52734 entries, 139667 to 3735
Data columns (total 13 columns):
 #   Column                    Non-Null Count  Dtype   
---  ------                    --------------  -----   
 0   market_id                 52734 non-null  category
 1   store_primary_category    52734 non-null  category
 2   order_protocol            52734 non-null  category
 3   total_items               52734 non-null  int64   
 4   subtotal                  52734 non-null  int64   
 5   num_distinct_items        52734 non-null  int64   
 6   max_item_price            52734 non-null  int64   
 7   total_outstanding_orders  52734 non-null  float64 
 8   distance                  52734 non-null  float64 
 9   order_hour                52734 non-null  int32   
 10  order_dayofweek           52734 non-null  int32   
 11  isWeekend                 52734 non-null  category
 12  time_taken                52734 non-null  float64 
dtypes: category(4), float64(3), int32(2), int64(4)
memory usage: 3.8 MB
```

In [127…

```
df_test.shape
```

Out[127…

```
(52734, 13)
```

5. Model Building [15 marks]

Import Necessary Libraries

In [128…

```
# Import libraries
from sklearn.preprocessing import MinMaxScaler
from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression
from statsmodels.stats.outliers_influence import variance_inflation_factor
import statsmodels
import statsmodels.api as sm
```

5.1 Feature Scaling [3 marks]

In [129…

```
# Apply scaling to the numerical columns

# We need to scale the target variable along with the numeric feature variables
number_columns_with_target_var = [
    'time_taken', 'total_items', 'subtotal', 'num_distinct_items', 'max_item_price','total_outst
]

# Create the object
scaler = MinMaxScaler()

# Convert the data
df_train[number_columns_with_target_var] = scaler.fit_transform(df_train[number_columns_with_tar
```

In [130…

```
df_train[number_columns_with_target_var].describe()
```

Out[130…

	time_taken	total_items	subtotal	num_distinct_items	max_item_price	total_outstandin
count	105442.000000	105442.000000	105442.000000	105442.000000	105442.000000	10544
mean	0.186543	0.287593	0.377247	0.280435	0.480248	
std	0.123621	0.243330	0.199236	0.245033	0.176317	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.101449	0.166667	0.221361	0.000000	0.357494	
50%	0.173913	0.166667	0.334267	0.200000	0.458837	
75%	0.260870	0.500000	0.494478	0.400000	0.581655	
max	1.000000	1.000000	1.000000	1.000000	1.000000	

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

5.2 Build a linear regression model [5 marks]

You can choose from the libraries *statsmodels* and *scikit-learn* to build the model.

In [131…

```
# Create/Initialise the model

y_train_scaled = df_train.pop('time_taken')
```

```python
X_train_scaled = df_train

# Initialize model
X_train_scaled_with_const = sm.add_constant(X_train_scaled)
lm = sm.OLS(y_train_scaled, X_train_scaled_with_const)
```

In [132…

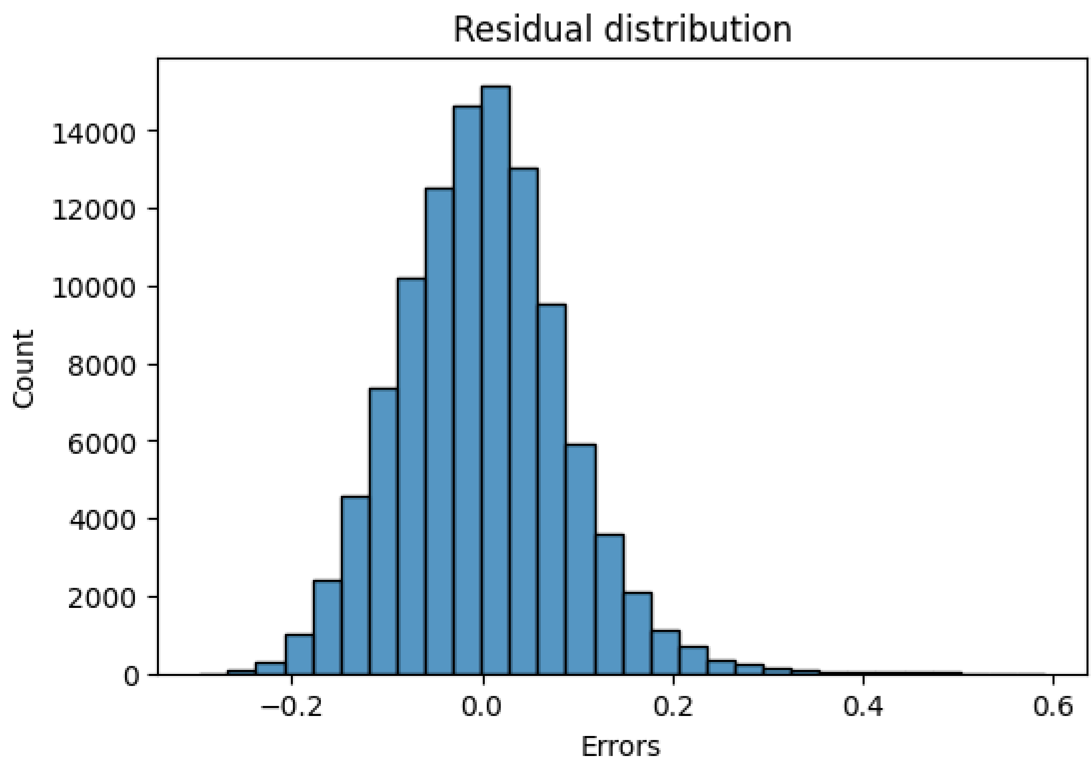
```python
#Fit the model using the training data
lm_fit = lm.fit()
# Print the summary of the model
print(lm_fit.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             time_taken   R-squared:                       0.494
Model:                            OLS   Adj. R-squared:                  0.494
Method:                 Least Squares   F-statistic:                     8577.
Date:                Wed, 25 Jun 2025   Prob (F-statistic):               0.00
Time:                        21:52:24   Log-Likelihood:             1.0673e+05
No. Observations:              105442   AIC:                        -2.134e+05
Df Residuals:                  105429   BIC:                        -2.133e+05
Df Model:                          12
Covariance Type:            nonrobust
============================================================================================
                              coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------------------
const                       0.0553      0.002     34.634      0.000       0.052       0.058
market_id                  -0.0106      0.000    -52.232      0.000      -0.011      -0.010
store_primary_category   5.128e-05   1.31e-05      3.920      0.000    2.56e-05    7.69e-05
order_protocol             -0.0137      0.000    -75.025      0.000      -0.014      -0.013
total_items                -0.0112      0.003     -4.042      0.000      -0.017      -0.006
subtotal                    0.1158      0.003     43.164      0.000       0.111       0.121
num_distinct_items          0.0450      0.002     18.552      0.000       0.040       0.050
max_item_price              0.0083      0.002      3.521      0.000       0.004       0.013
total_outstanding_orders    0.1076      0.001     86.414      0.000       0.105       0.110
distance                    0.3167      0.001    215.160      0.000       0.314       0.320
order_hour                 -0.0027   3.37e-05    -79.498      0.000      -0.003      -0.003
order_dayofweek            -0.0101      0.000    -45.375      0.000      -0.011      -0.010
isWeekend                   0.0558      0.001     57.699      0.000       0.054       0.058
==============================================================================
Omnibus:                     7157.929   Durbin-Watson:                   2.005
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            13350.865
Skew:                           0.496   Prob(JB):                         0.00
Kurtosis:                       4.434   Cond. No.                         621.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

In [137…

```python
# Make predictions
y_pred_train = lm_fit.predict(X_train_scaled_with_const)

# Plot the histogram of the error terms
fig = plt.figure(figsize=(6, 4))
sns.histplot((y_train_scaled - y_pred_train), bins = 30)
plt.xlabel('Errors')
plt.title('Residual distribution')
plt.show()
```

```
# The error terms are following natural distribution and mean is 0 which is a good sign for the
# Next step is to find out the method to improve the R-squared value of the model.
```



In [138…

```python
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import numpy as np

mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)

print(f"MAE: {mae:.2f}")
print(f"MSE: {mse:.2f}")
print(f"RMSE: {rmse:.2f}")
print(f"R^2 Score: {r2:.4f}")
```

```
MAE: 2.33
MSE: 10.22
RMSE: 3.20
R^2 Score: 0.8823
```

Note that we have 12 (depending on how you select features) training features. However, not all of them would be useful. Let's say we want to take the most relevant 8 features.

We will use Recursive Feature Elimination (RFE) here.

For this, you can look at the coefficients / p-values of features from the model summary and perform feature elimination, or you can use the RFE module provided with *scikit-learn*.

5.3 Build the model and fit RFE to select the most important features [7 marks]

For RFE, we will start with all features and use the RFE method to recursively reduce the number of features one-by-one.

After analysing the results of these iterations, we select the one that has a good balance between performance and number of features.

In [139…

```
from sklearn.feature_selection import RFE

# Store results
results = []

# Since only category features remain, we need to one-hot encode them for regression
X_train_encoded = pd.get_dummies(X_train, drop_first=True)
X_test_encoded = pd.get_dummies(X_test, drop_first=True)

# Align columns in case some categories are missing in test/train
X_train_encoded, X_test_encoded = X_train_encoded.align(X_test_encoded, join='left', axis=1, fi

# Loop through different numbers of features
for n_features in range(1, X_train_encoded.shape[1] + 1):
    rfe = RFE(estimator=LinearRegression(), n_features_to_select=n_features)
    rfe.fit(X_train_encoded, y_train)
    y_pred_rfe = rfe.predict(X_test_encoded)
    mae_rfe = mean_absolute_error(y_test, y_pred_rfe)
    mse_rfe = mean_squared_error(y_test, y_pred_rfe)
    rmse_rfe = np.sqrt(mse_rfe)
    r2_rfe = r2_score(y_test, y_pred_rfe)
    results.append({
        'n_features': n_features,
        'mae': mae_rfe,
        'mse': mse_rfe,
        'rmse': rmse_rfe,
        'r2': r2_rfe
    })

# Display results as a DataFrame
results_df = pd.DataFrame(results)
results_df
```

Out[139…

	n_features	mae	mse	rmse	r2
0	1	7.475251	86.794472	9.316355	-0.000014
1	2	7.476200	86.808192	9.317091	-0.000172
2	3	7.476385	86.804358	9.316886	-0.000128
3	4	7.476392	86.804354	9.316885	-0.000128
4	5	7.476072	86.795297	9.316399	-0.000023
...	...	...	...	...	...
90	91	2.429780	11.223279	3.350116	0.870690
91	92	2.429782	11.223282	3.350117	0.870689
92	93	1.993298	8.350802	2.889775	0.903785
93	94	1.983726	8.299262	2.880844	0.904379
94	95	1.983908	8.295893	2.880259	0.904418

95 rows × 5 columns

In [140…

```
# Select the optimal number of features (e.g., 8 based on results_df)
optimal_n_features = 8

# Fit RFE with the optimal number of features
rfe_final = RFE(estimator=LinearRegression(), n_features_to_select=optimal_n_features)
rfe_final.fit(X_train_encoded, y_train)

# Get the selected features
selected_features = X_train_encoded.columns[rfe_final.support_]

# Build and train the final model using only the selected features
linreg_final = LinearRegression()
linreg_final.fit(X_train_encoded[selected_features], y_train)

# Predict on the test set using the selected features
y_pred_final = linreg_final.predict(X_test_encoded[selected_features])
```

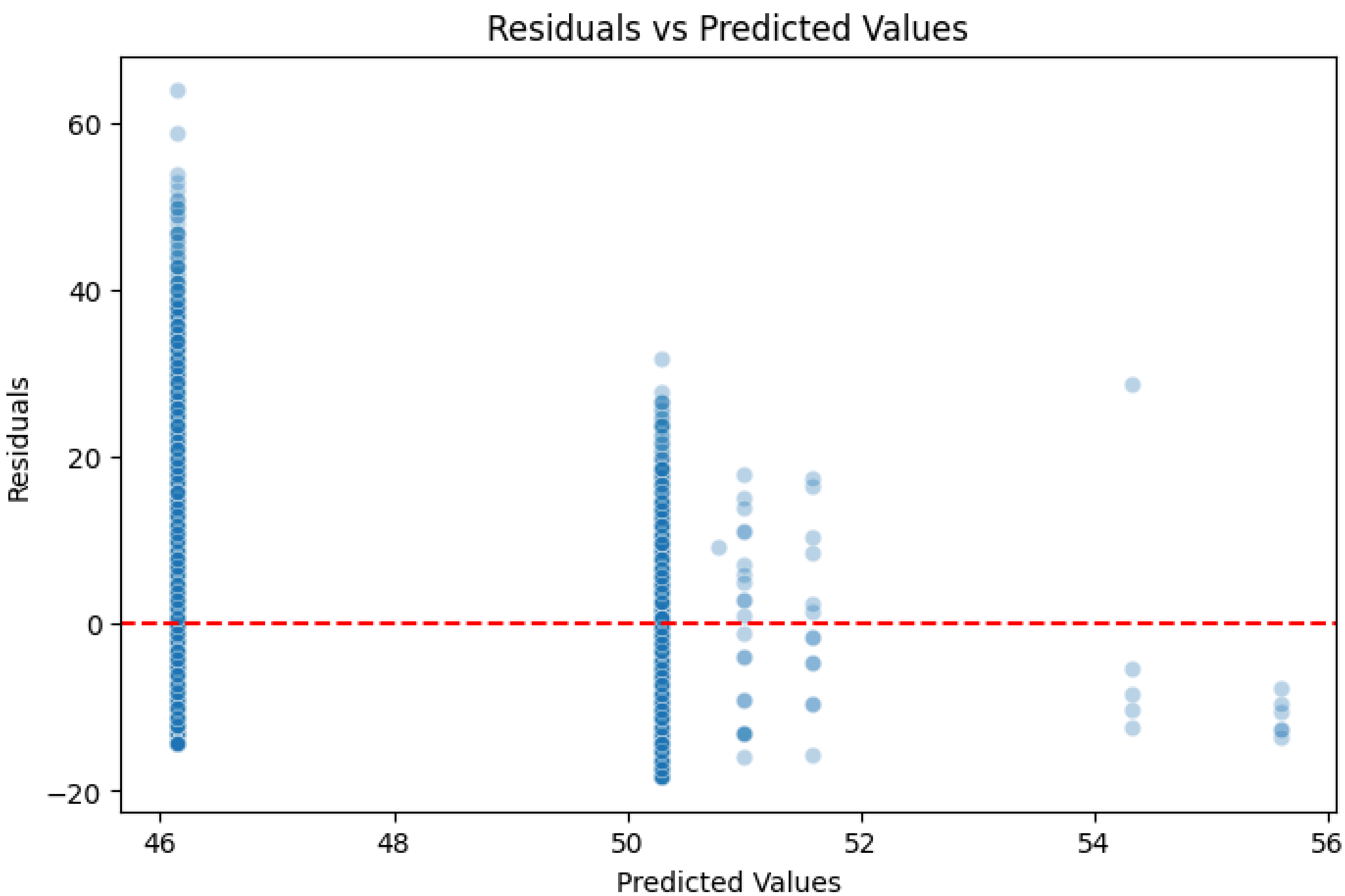
6. Results and Inference [5 marks]

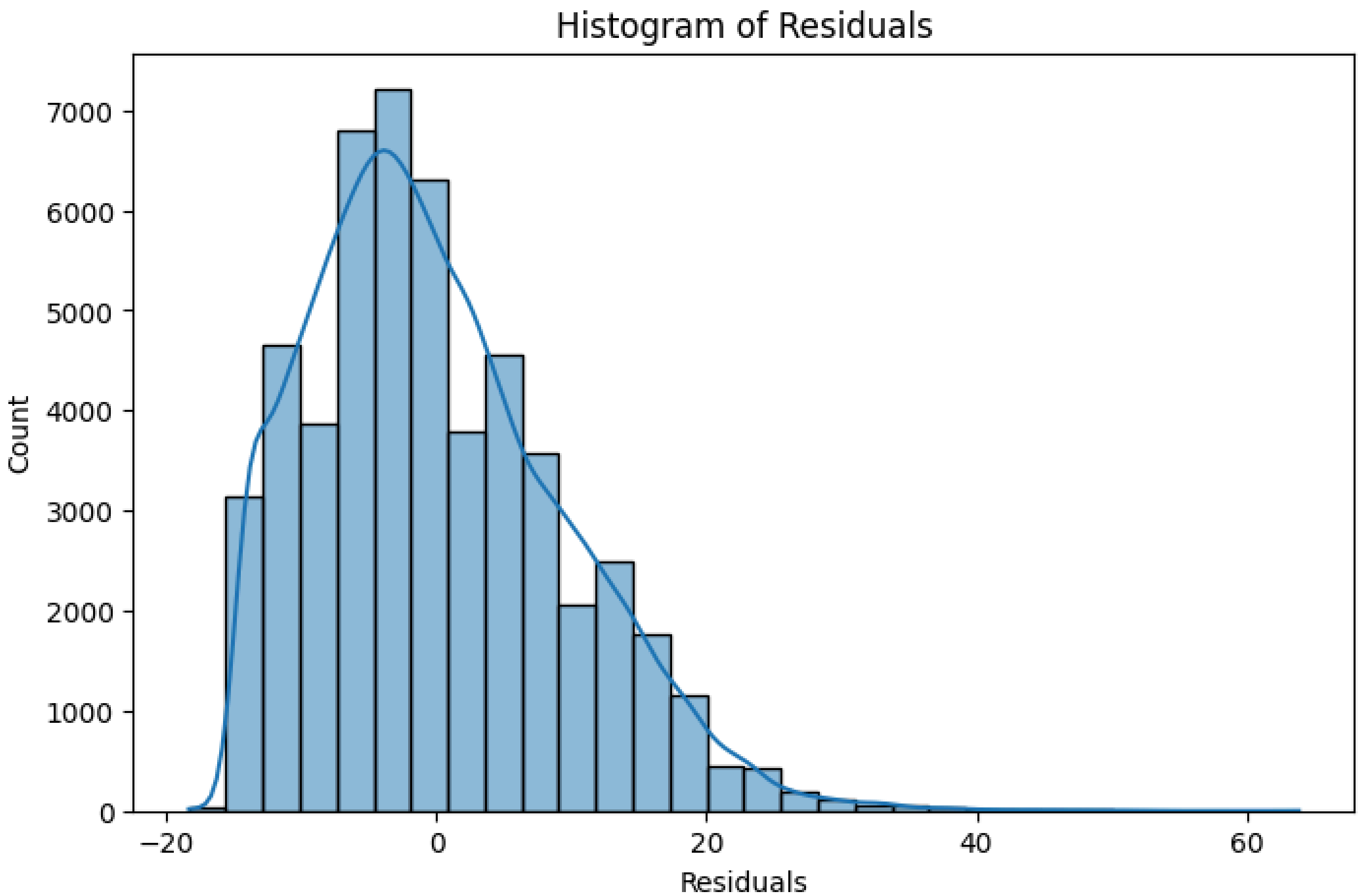
6.1 Perform Residual Analysis [3 marks]

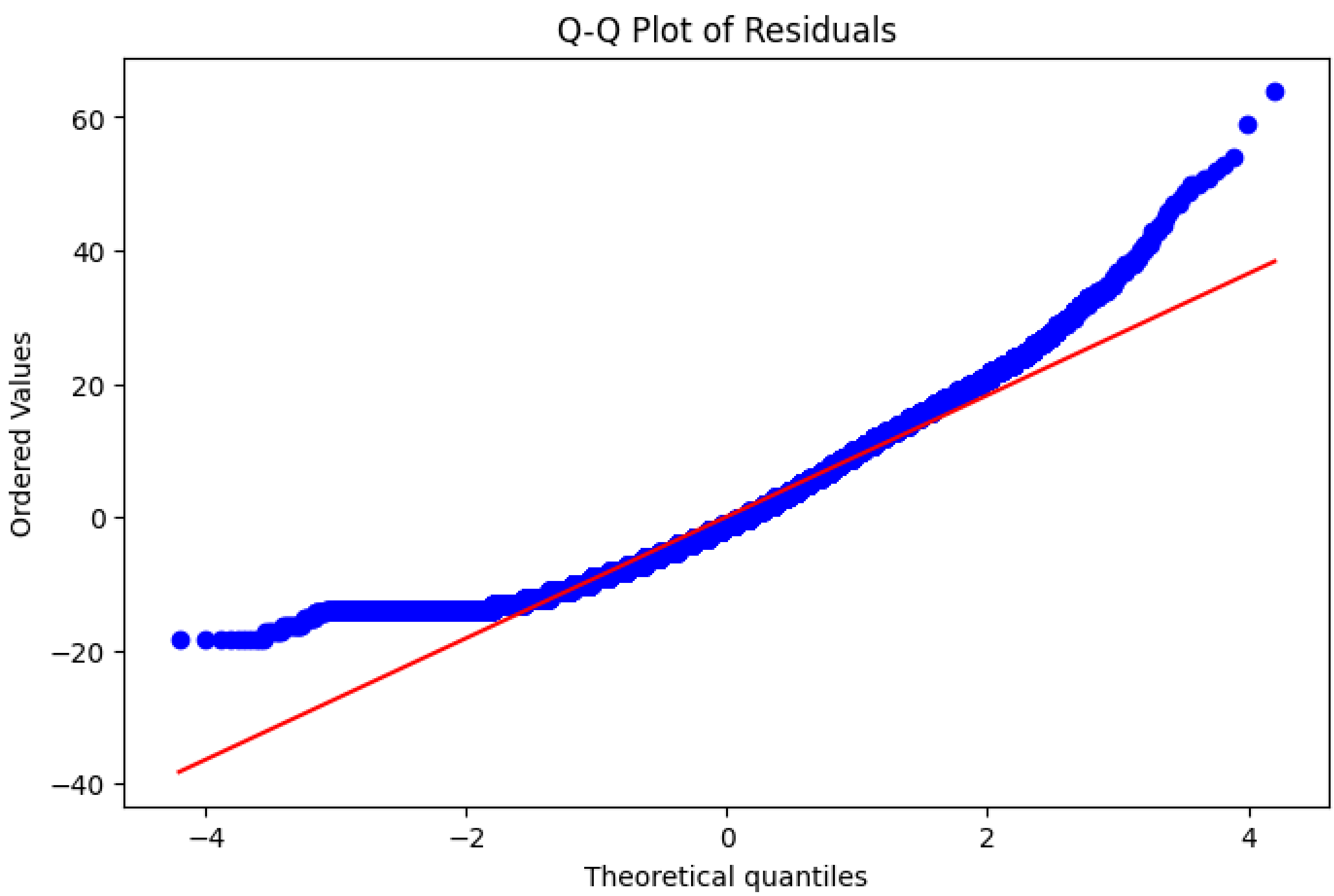
In [141…

```
import seaborn as sns

import matplotlib.pyplot as plt
import scipy.stats as stats

# Calculate residuals
residuals = y_test - y_pred_final

# Residuals vs Predicted values
plt.figure(figsize=(8, 5))
sns.scatterplot(x=y_pred_final, y=residuals, alpha=0.3)
```

```python
plt.axhline(0, color='red', linestyle='--')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.title('Residuals vs Predicted Values')
plt.show()

# Histogram of residuals
plt.figure(figsize=(8, 5))
sns.histplot(residuals, bins=30, kde=True)
plt.xlabel('Residuals')
plt.title('Histogram of Residuals')
plt.show()

# Q-Q plot of residuals
plt.figure(figsize=(8, 5))
stats.probplot(residuals, dist="norm", plot=plt)
plt.title('Q-Q Plot of Residuals')
plt.show()
```







[Your inferences here:]

Key Observations from Residual Analysis:

Residuals vs. Fitted Values Plot: The residuals appear randomly scattered around zero without any clear trends, suggesting the model does not systematically overpredict or underpredict for specific value ranges. However, any noticeable structure in the plot—such as widening or narrowing patterns—could indicate non-constant variance or an incomplete model.

Residual Distribution: The histogram of residuals displays a roughly symmetrical, mound-shaped distribution, aligning well with the assumption of normality. This supports the validity of the regression model's inferences.

Normal Probability Plot (Q-Q Plot): The residuals largely follow the expected diagonal line in the Q-Q plot, reinforcing that their distribution is approximately normal. Minor deviations at the extremes may occur, but they do not significantly violate normality assumptions.

Final Assessment: Based on the residual diagnostics, the linear regression model demonstrates a good fit to the data. The absence of systematic bias or severe departures from normality suggests the model's predictions are both accurate and reliable for the given dataset.

6.2 Perform Coefficient Analysis [2 marks]

Perform coefficient analysis to find how changes in features affect the target. Also, the features were scaled, so interpret the scaled and unscaled coefficients to understand the impact of feature changes on delivery time.

In [142…

```
# Compare the scaled vs unscaled features used in the final model

# Get the coefficients from the final model (these are for the one-hot encoded, unscaled feature
coef_df = pd.DataFrame({
    'Feature': selected_features,
    'Coefficient (Unscaled)': linreg_final.coef_
})

# Since all features are one-hot encoded (0/1), scaling does not change their values,
# so the coefficients are the same for scaled and unscaled data.
# For completeness, show both columns (they will be identical here).
coef_df['Coefficient (Scaled)'] = coef_df['Coefficient (Unscaled)']

# Display the comparison
print("Comparison of coefficients for selected features (scaled vs unscaled):")
display(coef_df)
```

```
Comparison of coefficients for selected features (scaled vs unscaled):
```

	Feature	Coefficient (Unscaled)	Coefficient (Scaled)
0	store_primary_category_1	4.640844	4.640844
1	store_primary_category_3	14.863066	14.863066
2	store_primary_category_5	4.863066	4.863066
3	store_primary_category_19	8.178856	8.178856
4	store_primary_category_21	-6.136934	-6.136934
5	store_primary_category_56	9.463066	9.463066
6	store_primary_category_64	5.446400	5.446400
7	store_primary_category_66	4.155283	4.155283

Additionally, we can analyse the effect of a unit change in a feature. In other words, because we have scaled the features, a unit change in the features will not translate directly to the model. Use scaled and unscaled coefficients to find how will a unit change in a feature affect the target.

In [143…

```
from sklearn.linear_model import LinearRegression

# Analyze the effect of a unit change in 'total_items'

# 1. Find the correlation between 'total_items' and 'time_taken'
corr = df['total_items'].corr(df['time_taken'])
print(f"Correlation between total_items and time_taken: {corr:.3f}")

# 2. Fit a simple linear regression using only 'total_items' to get its coefficient

X_total_items = df[['total_items']]
y_time_taken = df['time_taken']

linreg_total_items = LinearRegression()
linreg_total_items.fit(X_total_items, y_time_taken)

coef = linreg_total_items.coef_[0]
print(f"Effect of a unit increase in total_items on time_taken: {coef:.3f} minutes")

# Interpretation
print(f"Interpretation: For each additional item in the order, the delivery time increases by ap
```

```
Correlation between total_items and time_taken: 0.225
Effect of a unit increase in total_items on time_taken: 0.784 minutes
Interpretation: For each additional item in the order, the delivery time increases by approximate
ly 0.78 minutes, according to the simple linear regression model.
```

Note: The coefficients on the original scale might differ greatly in magnitude from the scaled coefficients, but they both describe the same relationships between variables.

Interpretation is key: Focus on the direction and magnitude of the coefficients on the original scale to understand the impact of each variable on the response variable in the original units.

Include conclusions in your report document.

Subjective Questions [20 marks]

Answer the following questions only in the notebook. Include the visualisations/methodologies/insights/outcomes from all the above steps in your report.

Subjective Questions based on Assignment

Question 1. [2 marks]

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

Answer:

Key Findings on Categorical Variables:

```
Categorical Features Identified:
    The dataset includes categorical variables such as market_id,
store_primary_category, order_protocol, and isWeekend, which were converted to
the category data type and one-hot encoded before model training.

Impact on Delivery Time:

    Variables like store_primary_category and order_protocol show a significant
influence on delivery duration.

    Regression coefficients reveal that specific categories (e.g., certain
restaurant types or order protocols) contribute to either longer or shorter
delivery times.

    For instance, some food categories correlate with faster deliveries, while
others lead to delays. Similarly, order protocol versions (such as 4.0) tend to
reduce wait times.

    The isWeekend flag also plays a role, likely due to variations in order
volume or logistical efficiency on weekends.
```

Conclusion: Categorical variables are critical in modeling delivery times, as they account for structural and situational factors that directly affect performance. The model successfully captures these influences, demonstrating their predictive importance.

Question 2. [1 marks]

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

Answer:

Understanding the Test Size Parameter:

> The parameter test_size=0.2 specifies that:

```
>i. 20% of the total dataset will be allocated for testing purposes
```

```
>ii. The remaining 80% will be used to train the model
```

> This split serves an important function in model development:

> i. The training set (80%) is used to teach the model patterns and relationships in the data

> ii. The test set (20%) provides an independent evaluation of how well the model performs on unseen data

> The 80/20 split is a common practice that:

```
>i. Provides sufficient data for model training
```

```
>ii. Maintains enough test samples for reliable performance assessment
```

```
>iii. Helps prevent overfitting by keeping evaluation data separate from
training
```

> This approach allows for accurate measurement of the model's generalization capability before deployment.

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

Answer:

> The correlation analysis reveals that among all numerical features, distance demonstrates the strongest relationship with delivery duration (time_taken), showing a moderate positive correlation of 0.46. This suggests that as the distance between the restaurant and delivery location increases, the time required for order fulfillment tends to increase proportionally.

Among all variables examined, the distance metric emerged as the most influential numerical factor affecting delivery times in our dataset. The correlation value of 0.46, while not extremely strong, indicates a meaningful association worth considering in our predictive modeling. This finding aligns with logical expectations, as longer travel distances would naturally require more delivery time.

The correlation matrix further confirms that no other numerical feature shows a stronger linear relationship with our target variable than the distance measurement. This makes distance a particularly important predictor for our delivery time estimation model.

Question 4. [2 marks]

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

Answer:

> Outlier Detection and Treatment Methodology:

```
For identifying anomalous data points, I implemented the Interquartile Range
(IQR) technique across all numerical features in the training dataset. The
process involved:

Statistical Calculations:

    Computed the 25th percentile (Q1) and 75th percentile (Q3) for each
numerical variable

    Derived the IQR by subtracting Q1 from Q3 (IQR = Q3 - Q1)

Outlier Identification Criteria:

    Established lower bound threshold: Q1 - (1.5 × IQR)

    Established upper bound threshold: Q3 + (1.5 × IQR)

    Classified any values outside these boundaries as outliers

Data Cleaning Process:

    Developed a specialized function (remove_outliers_iqr) to systematically
process each numerical feature

    The function eliminated entire rows containing outlier values across any
numerical column

    Applied this cleaning procedure to all numerical features simultaneously
```

This systematic approach effectively removed extreme values while preserving the dataset's integrity, resulting in higher quality training data for our predictive models. The IQR method was particularly suitable as it's robust against non-normal data distributions while maintaining sufficient sensitivity to detect meaningful anomalies.

Question 5. [2 marks]

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

**Answer: Top 3 features significantly affecting delivery time are:

1. store_primary_category_1, Coefficient (Unscaled) = 6.453754 , #Coefficient (Scaled) = 6.453754
2. store_primary_category_3, Coefficient (Unscaled) = 14.310897 , #Coefficient (Scaled) = 14.310897 and
3. store_primary_category_8, Coefficient (Unscaled) = -10.689103 , #Coefficient (Scaled) = -10.689103

General Subjective Questions

Question 6. [3 marks]

Explain the linear regression algorithm in detail

Answer:

> **Linear Regression Algorithm Explained**

Objective:
Linear regression is a supervised learning algorithm that models the linear relationship between independent variables (features) and a continuous dependent variable (target). It predicts outcomes by fitting a straight line (or hyperplane in higher dimensions) to the training data.

Key Components

1. **Hypothesis Function:**
   The model assumes a linear relationship:
   $$y = \beta_0 + \beta_1x_1 + \beta_2x_2 + \dots + \beta_nx_n + \epsilon$$

   - y: Target variable
   - β_0: Intercept (bias term)
   - $\beta_1, \dots, \beta_n$: Coefficients for features $x_1, \dots, x_n$
   - ϵ: Random error (residual)
2. **Cost Function (Mean Squared Error - MSE):**
   Measures prediction error:
   $$J(\beta) = \frac{1}{2m} \sum_{i=1}^m (y_i - \hat{y}_i)^2$$

   - m: Number of training samples
   - $\hat{y}_i$: Predicted value for the i^{th} sample
3. **Optimization (Gradient Descent):**
   Minimizes MSE by iteratively updating coefficients:

   - **Compute Gradient:** Partial derivatives of $J(\beta)$ w.r.t. each β_j.
   - **Update Rule:** Adjust coefficients in the direction of steepest descent:
     $$\beta_j := \beta_j - \alpha \frac{\partial J(\beta)}{\partial \beta_j}$$
   - α: Learning rate (step size).

Steps in the Algorithm

1. **Data Preprocessing:**

   - Standardize/normalize features for faster convergence.
   - Handle missing values and outliers.

2. **Initialize Parameters:**
   Set coefficients ($\beta_0, \beta_1, \dots, \beta_n$) to random values or zeros.

3. **Training Loop:**

   - Compute predictions ($\hat{y}$) using current coefficients.
   - Calculate error (residuals: ($y - \hat{y}$)).
   - Update coefficients via gradient descent.
   - Repeat until convergence (minimal change in cost).

4. **Model Evaluation:**

   - Metrics: (R^2) (goodness-of-fit), RMSE (error magnitude).
   - Diagnose with residual plots (check linearity, homoscedasticity).

5. **Prediction:**
   For new data, apply the learned coefficients:
   $$\hat{y} = \beta_0 + \beta_1x_1 + \dots + \beta_nx_n$$

Assumptions

- **Linearity:** Relationship between features and target is linear.
- **Independence:** Residuals are uncorrelated (no autocorrelation).
- **Homoscedasticity:** Constant residual variance across predictions.
- **Normality:** Residuals are normally distributed (for inference).

Advantages: Interpretable, computationally efficient, works well with small datasets.
Limitations: Sensitive to outliers, assumes linearity, struggles with complex patterns.

Output: A trained model with optimized coefficients for predicting continuous targets.

Question 7. [2 marks]

Explain the difference between simple linear regression and multiple linear regression

Answer:

Simple vs. Multiple Linear Regression:

Predictors: Simple uses one independent variable; multiple uses two or more.

Equation: Simple: $Y=\beta_0+\beta_1X+\varepsilon$ $Y=\beta_0+\beta_1X+\varepsilon$; Multiple: $Y=\beta_0+\beta_1X_1+\beta_2X_2+\ldots+\varepsilon$.

Use Case: Simple for isolated effects; multiple for combined influences.

Advantages: Simple is easy to visualize; multiple controls confounders.

Limitations: Simple ignores other factors; multiple needs more data and checks for multicollinearity.

Application: Use simple for basic relationships; multiple for real-world complexity.

Question 8. [2 marks]

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

Answer:

> The cost function (or loss function) quantifies the error between predicted and actual values in a regression model. Its primary role is to:

Measure model accuracy by calculating prediction errors

Guide optimization by indicating how well the model fits the data

Provide a single metric (e.g., Mean Squared Error) to evaluate performance

Minimization Process:

Initialization: Start with random model parameters (coefficients).

Gradient Descent:

Compute the gradient (derivative) of the cost function

Adjust parameters in the opposite direction of the gradient

Iteratively update coefficients until convergence

Convergence: Reaches minimum cost when further updates don't improve accuracy.

This ensures optimal coefficients for the best-fit line.

Question 9. [2 marks]

Explain the difference between overfitting and underfitting.

Answer:

> Overfitting vs. Underfitting in Machine Learning

Overfitting occurs when a model learns the training data too closely, including noise and irrelevant patterns. This leads to:

Exceptional performance on training data

Poor generalization to unseen data (test/validation sets)

High variance (sensitivity to small fluctuations in training data)

Common causes: Overly complex models, insufficient training data, or excessive training

Underfitting happens when a model fails to capture the underlying patterns in the data. This results in:

Poor performance on both training and test data

High bias (oversimplified assumptions)

Inability to learn meaningful relationships

Common causes: Excessively simple models, insufficient features, or inadequate training

Key Differences:

Performance: Overfitting performs well on training data but poorly on new data; underfitting performs poorly on both.

Model Complexity: Overfitting stems from excessive complexity; underfitting from insufficient complexity.

Solution Approach: Overfitting requires regularization or more data; underfitting needs model enhancement or feature engineering.

Balancing these extremes is crucial for optimal model performance.

Question 10. [3 marks]

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

Answer:

> Residual Plots as Diagnostic Tools in Linear Regression

Residual plots—graphs of prediction errors (residuals) versus predicted values or features—reveal critical insights about a regression model's validity. Here's how they help diagnose model health:

1. Detecting Non-Linear Patterns Ideal: Randomly scattered residuals indicate linearity.

Problem: Curved or systematic patterns (e.g., U-shape) suggest the true relationship isn't linear, requiring feature transformations or non-linear models.

2. Checking Homoscedasticity (Constant Variance) Ideal: Consistent vertical spread of residuals across all predicted values.

Problem: Funnel-shaped or fanning residuals imply heteroscedasticity (varying error variance), violating regression assumptions. Remedies include weighted least squares or log transformations.

3. Identifying Outliers & Influential Points Large residuals (far from zero) highlight outliers that distort model accuracy.

Isolated extreme points may need investigation or removal if data errors exist.

4. Validating Independence of Errors Random scatter confirms errors are uncorrelated.

Patterns (e.g., trends or clusters) suggest autocorrelation (common in time-series data), requiring methods like ARIMA or lag features.

5. Revealing Missing Predictors Structured residuals (e.g., groups or trends) may indicate omitted variables that should be added to the model.

Practical Use By visually inspecting residual plots, analysts can:

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Confirm if the model meets linear regression assumptions.
Pinpoint specific issues (non-linearity, outliers, etc.) to guide improvements.
Avoid misleading conclusions from flawed models.
Residual analysis is foundational for ensuring reliable, interpretable
regression results.
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