Foodhub Order Analysis

Summer Boot Camp Project

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Problem Statement/Objective

The food aggregator company has stored the data of the different orders made by the registered customers in their online portal. They want to analyze the data to get a fair idea about the demand of different restaurants which will help them in enhancing their customer experience. Suppose you are hired as a Data Scientist in this company and the Data Science team has shared some of the key questions that need to be answered. Perform the data analysis to find answers to these questions that will help the company to improve the business.

Data Description

The data contains the different data related to a food order. The detailed data dictionary is given below.

Data Dictionary

• order_id: Unique ID of the order

• customer_id: ID of the customer who ordered the food

• restaurant_name: Name of the restaurant

• cuisine_type: Cuisine ordered by the customer

• cost: Cost of the order

• day_of_the_week: Indicates whether the order is placed on a weekday or weekend (The weekday is from Monday to Friday and the weekend is Saturday and Sunday)

• rating: Rating given by the customer out of 5

• food_preparation_time: Time (in minutes) taken by the restaurant to prepare the food. This is calculated by taking the difference between the timestamps of the restaurant's order confirmation and the delivery person's pick-up confirmation.

• delivery_time: Time (in minutes) taken by the delivery person to deliver the food package. This is calculated by taking the difference between the timestamps of the delivery person's pick-up confirmation and drop-off information

Basic Things

```
#importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
from scipy import stats
```

```
# Load the dataset
df = pd.read_csv('2-foodhub_order_New.csv')
```

1. Display the First 5 Rows

```
df.head()
```

	order_id	customer_id	restaurant_name	cuisine_type	cost_of_the_order	day_of_th
0	1477147	337525	Hangawi	Korean	30.75	W
1	1477685	358141	Blue Ribbon Sushi Izakaya	Japanese	12.08	W
2	1477070	66393	Cafe Habana	Mexican	12.23	W
			Blue Ribbon Fried			

	0	1	2	3	4
order_id	1477147	1477685	1477070	1477334	1478249
customer_id	337525	358141	66393	106968	76942
restaurant_name	Hangawi	Blue Ribbon Sushi Izakaya	Cafe Habana	Blue Ribbon Fried Chicken	Dirty Bird to Go
cuisine_type	Korean	Japanese	Mexican	American	American
cost_of_the_order	30.75	12.08	12.23	29.2	11.59
day_of_the_week	Weekend	Weekend	Weekday	Weekend	Weekday
rating	Not given	Not given	5	3	4
food_preparation_time	25.0	25.0	23.0	25.0	25.0
delivery_time	20	?	28	15	24

Observations:

Rating - Not Given dilvery time has error values (?).

2. Display the Last 5 Rows

```
df.tail()
```

	order_id	customer_id	restaurant_name	cuisine_type	cost_of_the_order	day_of
1893	1476701	292602	Chipotle Mexican Grill $1.99 Delivery	Mexican	22.31	
1894	1477421	397537	The Smile	American	12.18	
1895	1477819	35309	Blue Ribbon Sushi	Japanese	25.22	

	1893	1894	1895	1896	1897
order_id	1476701	1477421	1477819	1477513	1478056
customer_id	292602	397537	35309	64151	120353
restaurant_name	Chipotle Mexican Grill $1.99 Delivery	The Smile	Blue Ribbon Sushi	Jack's Wife Freda	Blue Ribbon Sushi
cuisine_type	Mexican	American	Japanese	Mediterranean	Japanese
cost_of_the_order	22.31	12.18	25.22	12.18	19.45
day_of_the_week	Weekend	Weekend	Weekday	Weekday	Weekend
rating	5	5	Not given	5	Not given
food_preparation_time	31.0	31.0	31.0	23.0	28.0
delivery_time	17	19	24	31	24

Observations:

Resturant name has $

3. Check the Shape of the Dataset:

```
df.shape
```

```
(1898, 9)
```

Observations:

Shape of the data set is Rows: 1898 & Col: 9

4. Check the Data Types of Each Feature:

```
df.dtypes
```

```
order_id                   int64
customer_id                int64
restaurant_name           object
cuisine_type              object
cost_of_the_order        float64
day_of_the_week           object
rating                    object
food_preparation_time    float64
delivery_time             object
dtype: object
```

Observations:

Here delivery_time is an object type that we need to change

5. Check the Statistical summary

```
df.describe(include='all')
```

	order_id	customer_id	restaurant_name	cuisine_type	cost_of_the_order
count	1.898000e+03	1898.000000	1898	1895	1898.000000
unique	NaN	NaN	178	14	NaN
top	NaN	NaN	Shake Shack	American	NaN
freq	NaN	NaN	219	582	NaN
mean	1.477496e+06	171168.478398	NaN	NaN	80.722007
std	5.480497e+02	113698.139743	NaN	NaN	2798.141333
min	1.476547e+06	1311.000000	NaN	NaN	0.000000
25%	1.477021e+06	77787.750000	NaN	NaN	12.080000
50%	1.477496e+06	128600.000000	NaN	NaN	14.160000
75%	1.477970e+06	270525.000000	NaN	NaN	22.310000

Observations:

Issuee in delivery_time, cost_of_the_order - Holds a outlier

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1898 entries, 0 to 1897
Data columns (total 9 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   order_id               1898 non-null   int64  
 1   customer_id            1898 non-null   int64  
 2   restaurant_name        1898 non-null   object 
 3   cuisine_type           1895 non-null   object 
 4   cost_of_the_order      1898 non-null   float64
 5   day_of_the_week        1898 non-null   object 
 6   rating                 1898 non-null   object 
 7   food_preparation_time  1896 non-null   float64
 8   delivery_time          1898 non-null   object 
dtypes: float64(2), int64(2), object(5)
memory usage: 133.6+ KB
```

Observations:

Rating - Object

- delivery - (it should be int)
- time - object (it should be int)

6. Check the null values

```
df.isnull().sum()
```

```
order_id                 0
customer_id              0
restaurant_name          0
cuisine_type             3
cost_of_the_order        0
day_of_the_week          0
rating                   0
food_preparation_time    2
delivery_time            0
dtype: int64
```

Observations:

There are 3 Null values in cuisine_type

There are 2 Null values in food_preparation_time

7. Check the duplicate values

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

```
0
```

Observations:

In This data set there is no null values

8. Check the anomalies or wrong entries.

```
df['day_of_the_week'].unique()
df['rating'].unique()
```

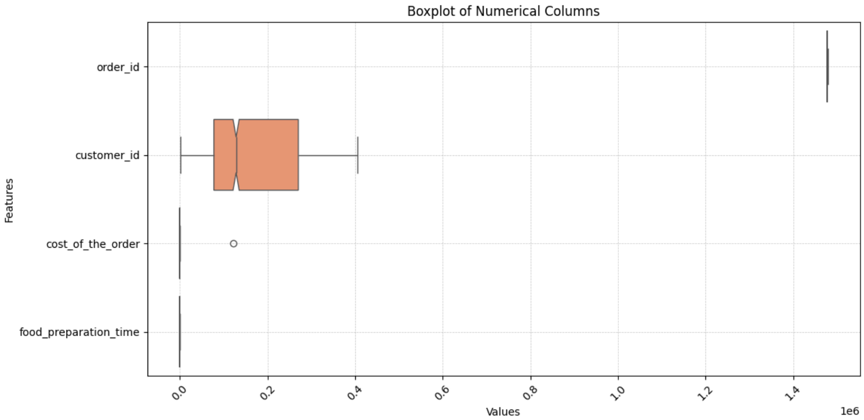
```
array(['Not given', '5', '3', '4'], dtype=object)
```

Observations:

In columnn of "rating" there are value - 5,4,3 which are considerable but also some exceptions like "Not given" values

9. Check the outliers and their authenticity.

```
def detect_iqr(df):
    Q1 = df.quantile(0.25)
    Q3 = df.quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    outliers = (df < lower_bound) | (df > upper_bound)
    return outliers

# Identify outliers in numerical columns using IQR
numerical_columns = df.select_dtypes(include=['int', 'float']).columns
outliers_iqr = df[numerical_columns].apply(detect_iqr)

# Set up the plot
plt.figure(figsize=(12, 6))

# Create the boxplot
sns.boxplot(data=df[numerical_columns], orient='h', notch=True, palette='Set2')

# Add title and labels
plt.title('Boxplot of Numerical Columns')
plt.xlabel('Values')
plt.ylabel('Features')

# Rotate x-axis labels for better readability
plt.xticks(rotation=45)

# Add grid for better visualization of values
plt.grid(True, linestyle='--', linewidth=0.5, alpha=0.7)

# Show the plot
plt.show()

# Display the outliers found using IQR
print("Outliers detected using IQR method:")
print(outliers_iqr.sum())
```




```
Outliers detected using IQR method:
order_id                 0
customer_id              0
cost_of_the_order        1
food_preparation_time    0
dtype: int64
```

Observations:

In "cost_of_the_order", "customer_id " and "order_id" outliers present that we need correct

10. Data Cleaning

```
df.duplicated().sum()
df[df.duplicated()==True]
```

order_id	customer_id	restaurant_name	cuisine_type	cost_of_the_order	day_of_the

Invalid values

```
# we will check only for
df['delivery_time'].unique()
df['delivery_time'].value_counts()
df[df['delivery_time']=='?']
df['delivery_time']= df['delivery_time'].replace('?',np.nan)
df[df['delivery_time']=='?']
```

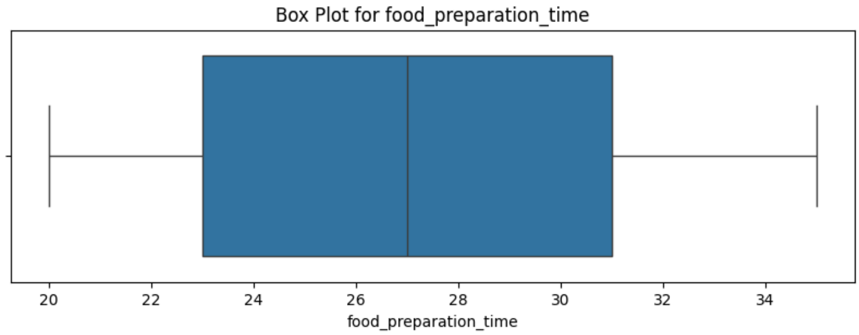
order_id	customer_id	restaurant_name	cuisine_type	cost_of_the_order	day_of_the

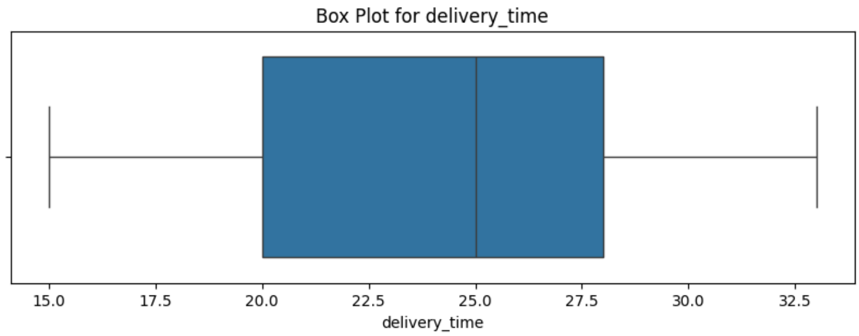
	order_id	customer_id	restaurant_name	cuisine_type	cost_of_the_order	day_of_the_week	rating	food_preparation_time	delivery_time
1	1477685	358141	Blue Ribbon Sushi Izakaya	Japanese	12.08	Weekend	Not given	25.0	?
180	1476808	84700	Pepe Giallo	Italian	14.60	Weekday	3	32.0	?

Values - Corrected

MISSING VAlUES

```
# Check for rows with any missing values
missing_rows = df[df.isnull().sum(axis=1) > 0]

# Summarize the number of missing values per column
missing_values_per_column = df.isnull().sum()

# Calculate the percentage of missing values per column
missing_values_percentage = df.isnull().sum() / len(df) * 100

# Convert 'delivery_time' to float
df['delivery_time'] = df['delivery_time'].astype('float')

# Plot box plots for 'food_preparation_time' and 'delivery_time'
for column in ['food_preparation_time', 'delivery_time']:
    plt.figure(figsize=(10, 3))
    sns.boxplot(data=df, x=column)
    plt.title(f'Box Plot for {column}')
    plt.show()

# Define the function to calculate lower and upper bounds for outlier removal
def calculate_bounds(col):
    Q1, Q3 = col.quantile([0.25, 0.75])
    IQR = Q3 - Q1
    lower_bound = Q1 - (1.5 * IQR)
    upper_bound = Q3 + (1.5 * IQR)
    return lower_bound, upper_bound

# Calculate lower and upper bounds for 'cost_of_the_order'
lower_bound, upper_bound = calculate_bounds(df['cost_of_the_order'])

# Identify outliers in 'cost_of_the_order'
outliers_upper = df[df['cost_of_the_order'] > upper_bound]
outliers_lower = df[df['cost_of_the_order'] < lower_bound]

# Replace outliers in 'cost_of_the_order' with bounds
df['cost_of_the_order'] = np.where(df['cost_of_the_order'] > upper_bound, upper_bound, df['cost_of_the_order'])
df['cost_of_the_order'] = np.where(df['cost_of_the_order'] < lower_bound, lower_bound, df['cost_of_the_order'])

# Verify the changes
print(df['cost_of_the_order'].describe())

# Fill missing values for 'cuisine_type' with the mode
mode_cuisine = df['cuisine_type'].mode().values[0]
df['cuisine_type'] = df['cuisine_type'].replace(np.nan, mode_cuisine)

# Fill missing values for 'food_preparation_time' and 'delivery_time' with the mean
mean_food_preparation_time = df['food_preparation_time'].mean()
mean_delivery_time = df['delivery_time'].mean()

df['food_preparation_time'].fillna(mean_food_preparation_time, inplace=True)
df['delivery_time'].fillna(mean_delivery_time, inplace=True)
```






```
count    1898.000000
mean       16.505809
std         7.507834
min         0.000000
25%        12.080000
50%        14.160000
75%        22.310000
max        37.655000
Name: cost_of_the_order, dtype: float64
```

```
df.describe()
```

	order_id	customer_id	cost_of_the_order	food_preparation_time	delivery
count	1.898000e+03	1898.000000	1898.000000	1898.000000	1898.(
mean	1.477496e+06	171168.478398	16.505809	27.371835	24.1
std	5.480497e+02	113698.139743	7.507834	4.631768	4.9
min	1.476547e+06	1311.000000	0.000000	20.000000	15.(
25%	1.477021e+06	77787.750000	12.080000	23.000000	20.(
50%	1.477496e+06	128600.000000	14.160000	27.000000	25.(
75%	1.477970e+06	270525.000000	22.310000	31.000000	28.(
max	1.478444e+06	405334.000000	37.655000	35.000000	33.(

Observations:

Here as we can see all the data is managed outliers were remvoed and whole data were managed

Main

1. Order Analysis

• Total number of orders in the dataset

```
total_orders = df['order_id'].nunique()
print(f'Total number of orders: {total_orders}')

df.shape
```

```
Total number of orders: 1898
(1898, 9)
```

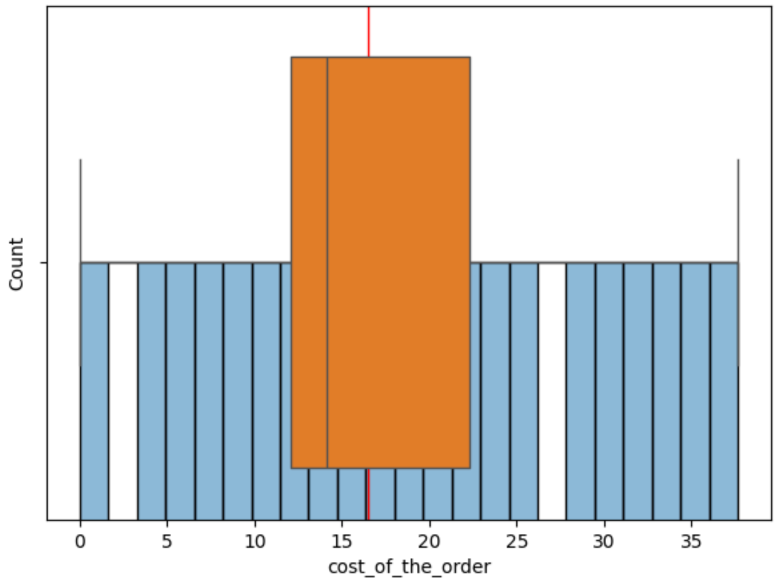
Observations:

Total number of orders placed: 1898

• The average cost of an order

```
plt.figure(figsize = (7,5))
plt.axvline(df['cost_of_the_order'].mean(), color='r', linewidth=1)
sns.histplot(data = df, x = 'cost_of_the_order', kde = True)

sns.boxplot(data = df, x = 'cost_of_the_order')


average_cost = df['cost_of_the_order'].mean()
print(f'Average cost of an order: ${average_cost:.2f}')
```

```
Average cost of an order: $16.51
```



Observations:

The Average FoodHub order cost is **$16.51** and the *majority* of the order cost ranges from **11 - 13 USD**.

• Number Of unique customers have placed orders

```
unique_customers = df['customer_id'].nunique()
print(f'Number of unique customers: {unique_customers}')

df['customer_id'].value_counts().unique()
```

```
Number of unique customers: 1200
array([13, 10,  9,  8,  7,  6,  5,  4,  3,  2,  1])
```

Observations:

- No Of unique customers is **1200**
- Among these customers there is an order count range of **1 - 13**.

• Restaurant with highest number of orders

```
#The restaurant has received the highest number of orders with numbers
```

```
restaurant_orders = df.groupby('restaurant_name')['order_id'].nunique().sort_values(ascending=False)
print("Restaurant with the highest number of orders:")
print(restaurant_orders.head(1))
```

```
Restaurant with the highest number of orders:
restaurant_name
Shake Shack    219
Name: order_id, dtype: int64
```

Observations:

Restaurant Shake Shack has received the highest number of orders: 219

2. Customer Behavior

• The average rating given by customers?

```
# Convert 'rating' column to numeric, handling non-numeric values
df['rating'] = pd.to_numeric(df['rating'], errors='coerce')

#Calculate the average rating, ignoring missing values
average_rating = df['rating'].mean()
print(f'Average rating given by customers: {average_rating:.2f}')
```

```
Average rating given by customers: 4.34
```

Observations:

Average rating given by customers is 4.34

• How does the rating vary between weekdays and weekends

```
weekday_ratings = df[(df['day_of_the_week'] == 'Weekday') & (df['rating'] != 'Not given')]['rating'].astype(float)
weekend_ratings = df[(df['day_of_the_week'] == 'Weekend') & (df['rating'] != 'Not given')]['rating'].astype(float)

avg_weekday_rating = weekday_ratings.mean()
avg_weekend_rating = weekend_ratings.mean()

print(f'Average weekday rating: {avg_weekday_rating:.2f}')
print(f'Average weekend rating: {avg_weekend_rating:.2f}')
```

```
Average weekday rating: 4.31
Average weekend rating: 4.36
```

Observations:

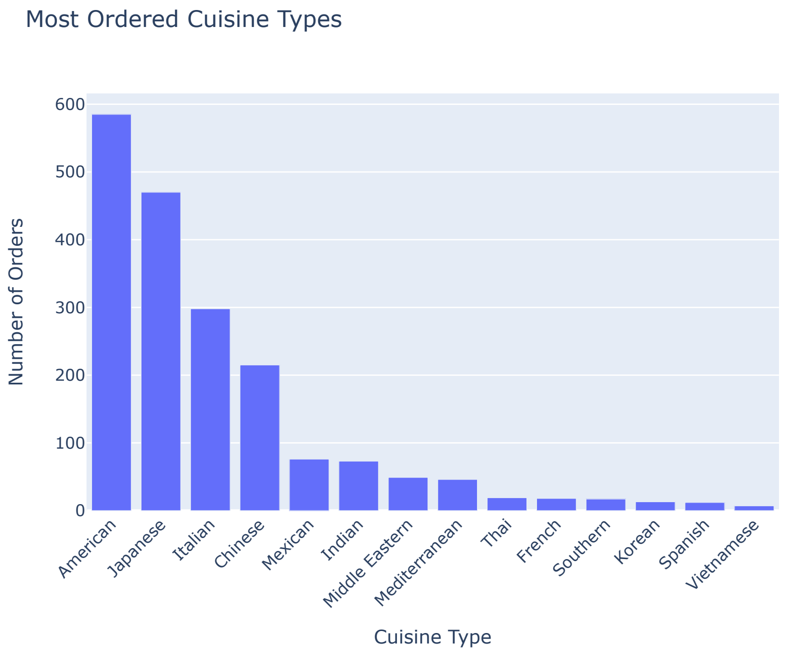
Average **weekday** rating by Customer: 4.31

Average **weekend** rating by Customer: 4.36

• Cuisine type is ordered the most?

```
# Import necessary libraries
import pandas as pd
import plotly.express as px

# Assuming 'df' is your DataFrame and 'cuisine_type' and 'order_id' are your columns

# Get the count of orders for each cuisine type
cuisine_order_counts = df['cuisine_type'].value_counts().reset_index()
cuisine_order_counts.columns = ['Cuisine Type', 'Number of Orders']

# Create a Plotly bar plot
fig = px.bar(cuisine_order_counts,
             x='Cuisine Type',
             y='Number of Orders',
             labels={'x': 'Cuisine Type', 'y': 'Number of Orders'},
             title='Most Ordered Cuisine Types',
             hover_data={'Number of Orders': True})
```

```
# Update layout for better appearance
fig.update_layout(
    xaxis_title='Cuisine Type',
    yaxis_title='Number of Orders',
    xaxis_tickangle=-45
)

# Show the interactive plot
fig.show()

# Print the most ordered cuisine type
cuisine_orders = df.groupby('cuisine_type')['order_id'].nunique().sort_values(ascending=False)
print("Most ordered cuisine type: ")
print(cuisine_orders.head(1))
```



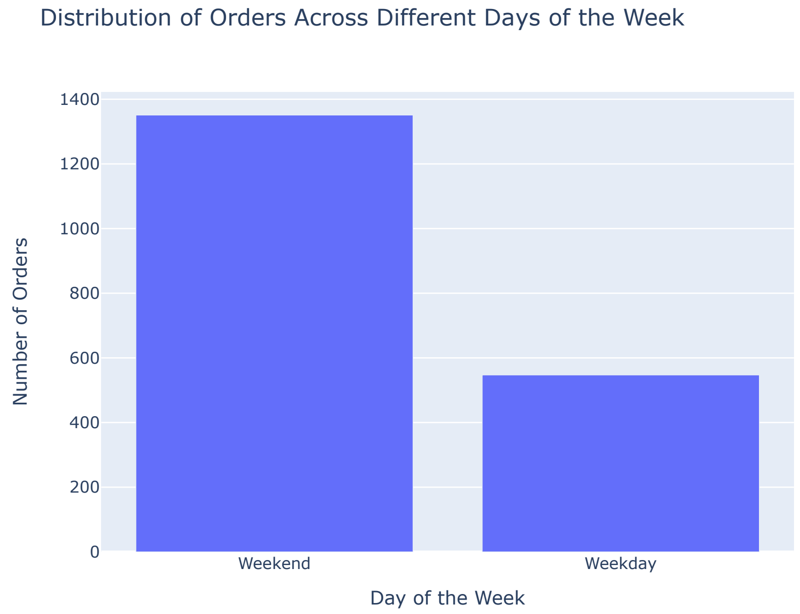

```
Most ordered cuisine type:
cuisine_type
American    585
```

Observations:

American is the most ordered cuisine type :585

• The distribution of orders across different days of the week

```
# Create a DataFrame for the distribution of orders across different days of the week
order_distribution = df['day_of_the_week'].value_counts().reset_index()
order_distribution.columns = ['day_of_the_week', 'number_of_orders']

# Sort the days to follow the natural order of the week
order_distribution['day_of_the_week'] = pd.Categorical(order_distribution['day_of_the_week'],
                                                       categories=['Weekend', 'Weekday'],
                                                       ordered=True)
order_distribution = order_distribution.sort_values('day_of_the_week')

# Create the interactive bar plot using Plotly
fig = px.bar(order_distribution,
             x='day_of_the_week',
             y='number_of_orders',
             title='Distribution of Orders Across Different Days of the Week',
             labels={'day_of_the_week': 'Day of the Week', 'number_of_orders': 'Number of Orders'},
             hover_data={'number_of_orders': True})

# Show the plot
fig.show()
```



Observations:

Number Order Placed On **Weekend** is ***Higher*** than **Weekday** : 1351 > 547

3. Restaurant Performance

• The average food preparation time for each restaurant?

```
avg_prep_time = df.groupby('restaurant_name')['food_preparation_time'].mean().sort_values()
print(avg_prep_time)
"""
Only use When Need
avg_prep_time_per_restaurant = df.groupby('restaurant_name')['food_preparation_time'].mean()
print(avg_prep_time_per_restaurant)

# Visualization
avg_prep_time_per_restaurant.plot(kind='bar', figsize=(15, 5), title='Average Food Preparation Time by Restaurant')
plt.xlabel('Restaurant Name')
plt.ylabel('Average Food Preparation Time (minutes)')
plt.show()"""
```

```
restaurant_name
Haru Gramercy Park        20.0
67 Burger                 20.0
Frank Restaurant          20.0
DespaÃ±a                  20.5
Sarabeth's West           21.0
                          ...
Taro Sushi                35.0
Cipriani Le Specialita    35.0
Kambi Ramen House         35.0
Klong                     35.0
Sushi Choshi              35.0
Name: food_preparation_time, Length: 178, dtype: float64
'\nOnly use When Need\navg_prep_time_per_restaurant = df.groupby('restaurant_name')
['food_preparation_time'].mean()\nprint(avg_prep_time_per_restaurant)\n\n# Visualiza
tion\navg_prep_time_per_restaurant.plot(kind='bar', figsize=(15, 5), title='Average
```

Observations:

Restaurants show varying average food preparation times, impacting customer wait times and operational efficiency.

Haru Gramercy Park: 20.0 minutes

67 Burger: 20.0 minutes

Frank Restaurant: 20.0 minutes

Despaña: 20.5 minutes

Sarabeth's West: 21.0 minutes

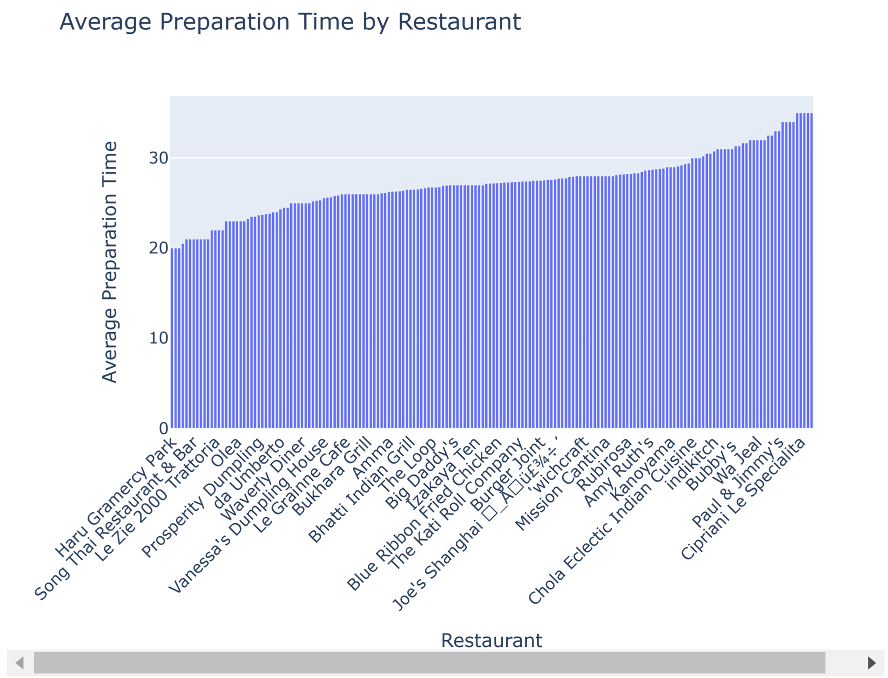
Taro Sushi: 35.0 minutes

Cipriani Le Specialita: 35.0 minutes

• Resturant has the shortest average food preparation time

```
# Calculate the average preparation time by restaurant name
avg_prep_time = df.groupby('restaurant_name')['food_preparation_time'].mean().reset_index()

# Sort the data by average preparation time in ascending order
avg_prep_time = avg_prep_time.sort_values(by='food_preparation_time')

# Find the top 5 restaurants with the shortest average preparation time
top_5_restaurants = avg_prep_time.head(5)
print("Top 5 Restaurants with the Shortest Average Preparation Time:")
for index, row in top_5_restaurants.iterrows():
    print(f"{row['restaurant_name']}: {row['food_preparation_time']:.2f} minutes")

# Create the bar chart
fig = px.bar(avg_prep_time, x='restaurant_name', y='food_preparation_time',
             title='Average Preparation Time by Restaurant',
             labels={'restaurant_name': 'Restaurant', 'food_preparation_time': 'Average Preparation Time'},
             hover_data={'food_preparation_time': ':.2f'})

# Update the layout for better visualization
fig.update_layout(xaxis_tickangle=-45)

# Show the figure
fig.show()
```

```
Top 5 Restaurants with the Shortest Average Preparation Time:
Haru Gramercy Park: 20.00 minutes
67 Burger: 20.00 minutes
Frank Restaurant: 20.00 minutes
DespaÌ±a: 20.50 minutes
Sarabeth's West: 21.00 minutes
```



Observations:

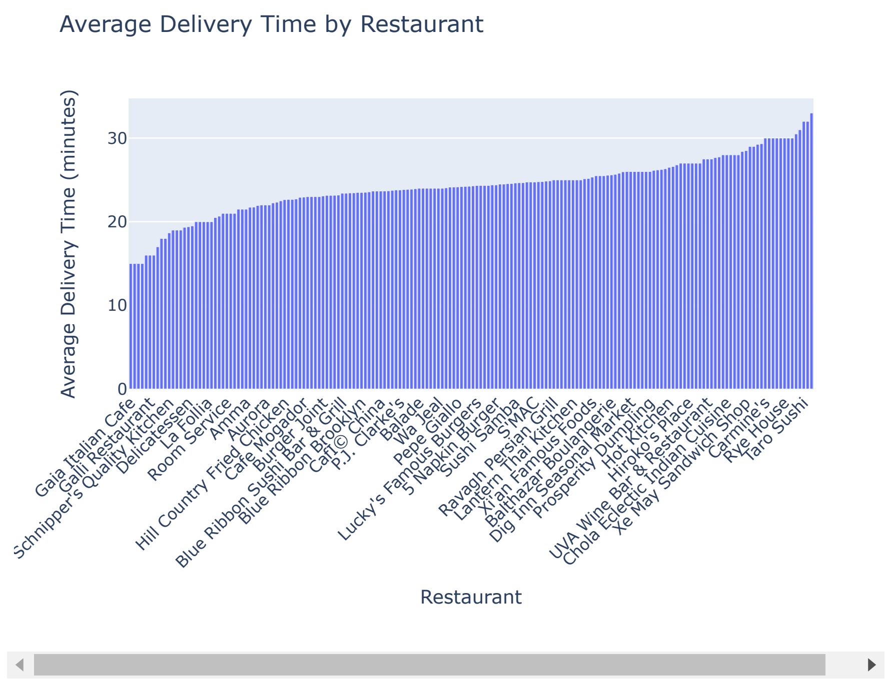
Restaurants with the Shortest Average Preparation Time:

- Haru Gramercy Park: 20.00 minutes
- 67 Burger: 20.00 minutes
- Frank Restaurant: 20.00 minutes
- DespaÌ±a: 20.50 minutes
- Sarabeth's West: 21.00 minutes

• The average delivery time compare across different restaurants?

```
# Calculate the average delivery time by restaurant name
avg_delivery_time = df.groupby('restaurant_name')['delivery_time'].mean().reset_index().sort_values(by='delivery_time')

# Print the average delivery time for each restaurant
print("Average Delivery Time by Restaurant:")
print(avg_delivery_time)

# Create the bar chart
fig = px.bar(avg_delivery_time, x='restaurant_name', y='delivery_time',
             title='Average Delivery Time by Restaurant',
             labels={'restaurant_name': 'Restaurant', 'delivery_time': 'Average Delivery Time (minutes)'},
             hover_data={'delivery_time': ':.2f'})

# Update the layout for better visualization
fig.update_layout(xaxis_tickangle=-45)

# Show the figure
fig.show()
```

```
Average Delivery Time by Restaurant:
          restaurant_name  delivery_time
60      Gaia Italian Cafe           15.0
110        Paul & Jimmy's           15.0
152        The MasalaWala           15.0
71                 Hibino           15.0
40         Coppola's East           16.0
..                    ...            ...
64                 Haandi           30.5
58       Frank Restaurant           31.0
148            Taro Sushi           32.0
68     Haru Gramercy Park           32.0
132        Sarabeth's West          33.0

[178 rows x 2 columns]
```



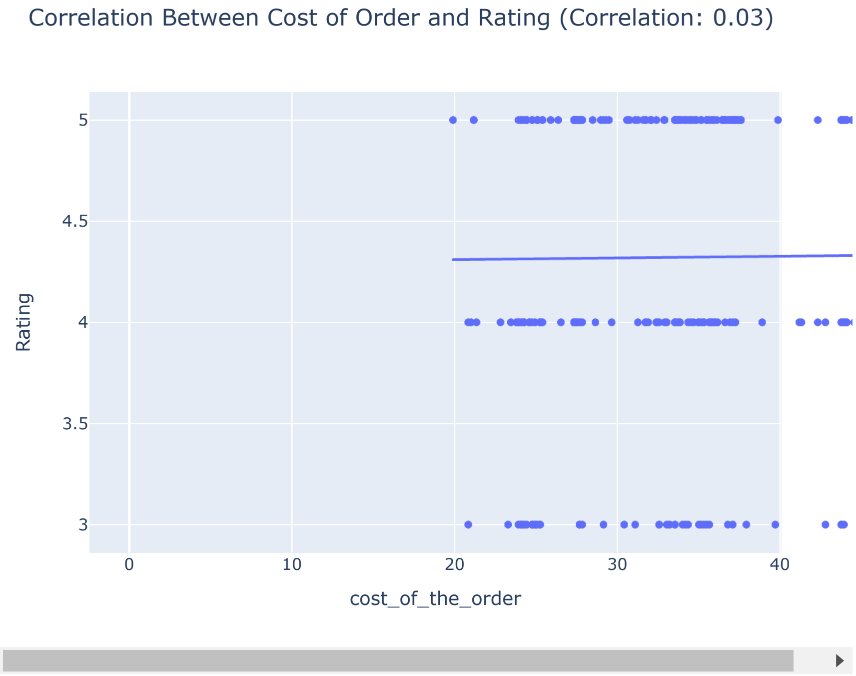
Observations:

Restaurants have varied average delivery times, with some delivering in 15 minutes and others taking over 30 minutes.

• Checking is there a correlation between the cost of the order and the rating given

```
# Calculate the correlation between cost and rating
correlation = df[['cost_of_the_order', 'rating']].corr().iloc[0, 1]
print(f'Correlation between cost of the order and the rating given: {correlation:.2f}')

# Create a scatter plot with a trendline
fig = px.scatter(df, x='cost_of_the_order', y='rating', trendline='ols',
                 title=f'Correlation Between Cost of Order and Rating (Correlation: {correlation:.2f})',
                 labels={'cost': 'Cost of Order', 'rating': 'Rating'})

# Show the figure
fig.show()
```

```
Correlation between cost of the order and the rating given: 0.03
```



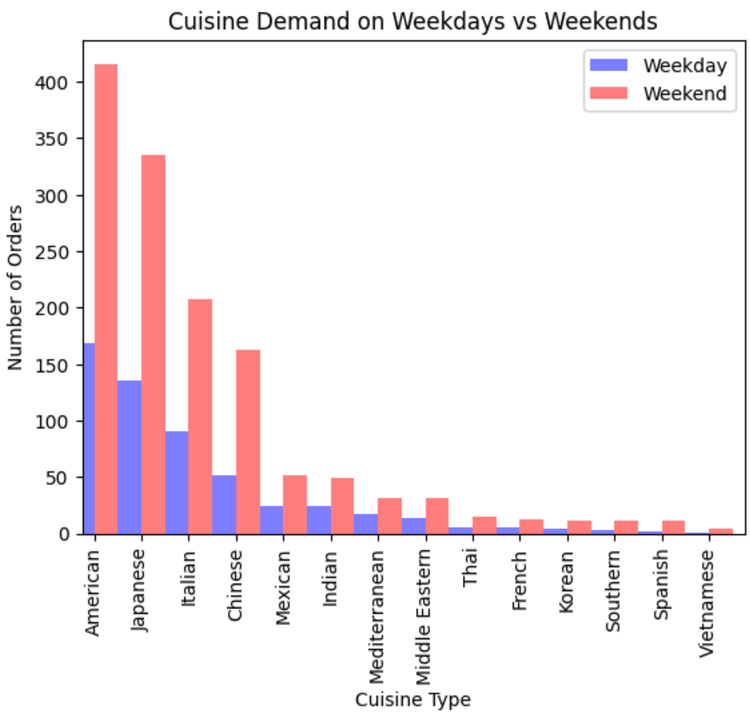
Observations:

The scatter plot indicates a very weak positive correlation (0.03) between the cost of the order and the rating given, suggesting minimal relationship.

4. Demand Patterns

• Howing the demand for different cuisine types vary on weekdays versus weekends?

```
cuisine_demand_weekday = df[df['day_of_the_week'] == 'Weekday']['cuisine_type'].value_counts()
cuisine_demand_weekend = df[df['day_of_the_week'] == 'Weekend']['cuisine_type'].value_counts()

"""print("Cuisine demand on weekdays:")
print(cuisine_demand_weekday)
print("\nCuisine demand on weekends:")
print(cuisine_demand_weekend)"""

# Visualization
cuisine_demand_weekday.plot(kind='bar', alpha=0.5, color='blue', position=1, label='Weekday')
cuisine_demand_weekend.plot(kind='bar', alpha=0.5, color='red', position=0, label='Weekend')
plt.legend()
plt.title('Cuisine Demand on Weekdays vs Weekends')
plt.xlabel('Cuisine Type')
plt.ylabel('Number of Orders')
plt.show()
```



Observations:

The bar chart reveals that demand for all cuisine types is generally higher on weekends compared to weekdays, with American and Japanese cuisines being the most popular.

• Which day of the week has the highest average order cost?

```
avg_cost_per_day = df.groupby('day_of_the_week')['cost_of_the_order'].mean()
highest_avg_cost_day = avg_cost_per_day.idxmax()
highest_avg_cost = avg_cost_per_day.max()
print(f'Day with the highest average order cost: {highest_avg_cost_day} (${highest_avg_cost:.2f})')
```

```
Day with the highest average order cost: Weekend ($16.58)
```

Observations:

Day with the highest average order cost: ***Weekend*** **$16.58**

• What is the most common day for orders to be placed?

```
most_common_order_day = df['day_of_the_week'].value_counts().idxmax()
print(f'Most common day for orders: {most_common_order_day}')
```

```
Most common day for orders: Weekend
```

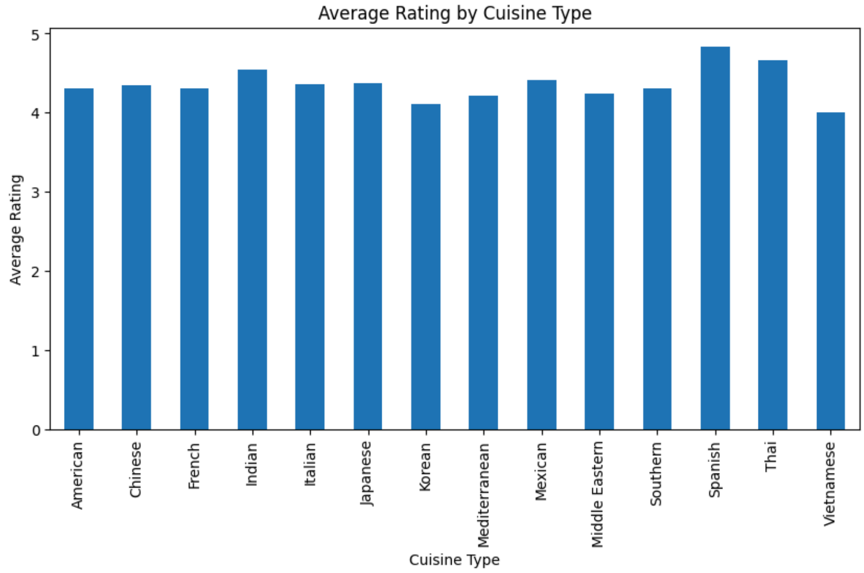
Observations:

Most common day for orders: **Weekend**

• The average rating vary by cuisine type?

```
avg_rating_per_cuisine = df[df['rating'] != 'Not given'].groupby('cuisine_type')['rating'].mean()
print(avg_rating_per_cuisine)

# Visualization
avg_rating_per_cuisine.plot(kind='bar', figsize=(10, 5), title='Average Rating by Cuisine Type')
plt.xlabel('Cuisine Type')
plt.ylabel('Average Rating')
plt.show()
```

```
cuisine_type
American          4.300813
Chinese           4.338346
French            4.300000
Indian            4.540000
Italian           4.360465
Japanese          4.373626
Korean            4.111111
Mediterranean     4.218750
Mexican           4.404255
Middle Eastern    4.235294
Southern          4.307692
Spanish           4.833333
Thai              4.666667
Vietnamese        4.000000
Name: rating, dtype: float64
```



Observations:

Average ratings are generally high across all cuisine types, with Spanish and Indian cuisines receiving the highest average ratings, while Vietnamese cuisine has the lowest.

5. Operational Efficiency

• Average Delivery Time for All Orders

```
average_delivery_time = df['delivery_time'].mean()
print(f'Average delivery time for all orders: {average_delivery_time:.2f} minutes')
```

```
Average delivery time for all orders: 24.16 minutes
```

Observations:

Average delivery time for all orders: 24.16 minutes

• Restaurant with Longest Average Delivery Time

```
# Calculate average delivery time per restaurant
avg_delivery_time_per_restaurant = df.groupby('restaurant_name')['delivery_time'].mean()

# Now you can proceed with the rest of your code
longest_delivery_time_restaurant = avg_delivery_time_per_restaurant.idxmax()
longest_delivery_time = avg_delivery_time_per_restaurant.max()
print(f'Restaurant with the longest average delivery time: {longest_delivery_time_restaurant} ({longest_delivery_time:.2f} minutes)')
```

```
Restaurant with the longest average delivery time: Sarabeth's West (33.00 minutes)
```

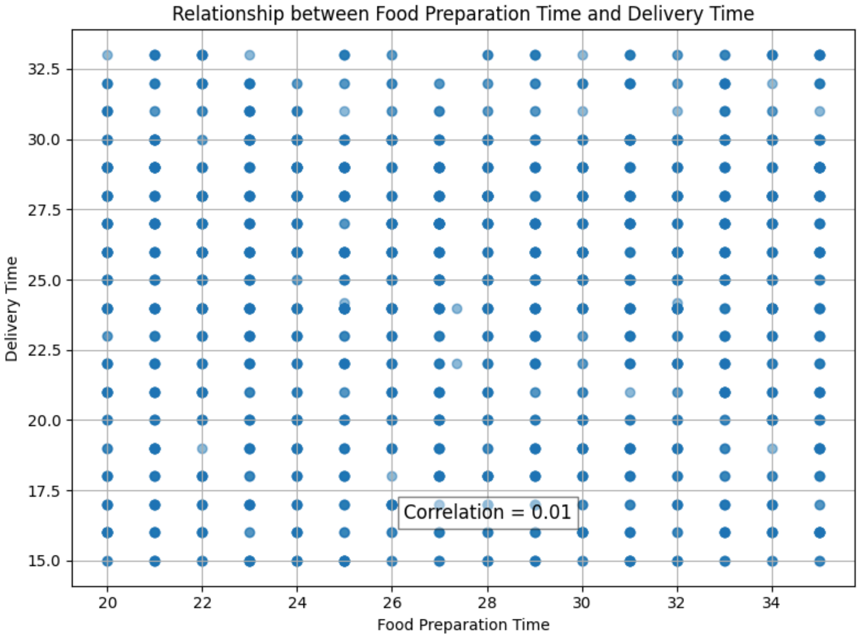
Observations:

The restaurant with the longest average delivery time is Sarabeth's West, taking an average of 33.00 minutes for delivery.

• Relationship Between Food Preparation Time and Delivery Time

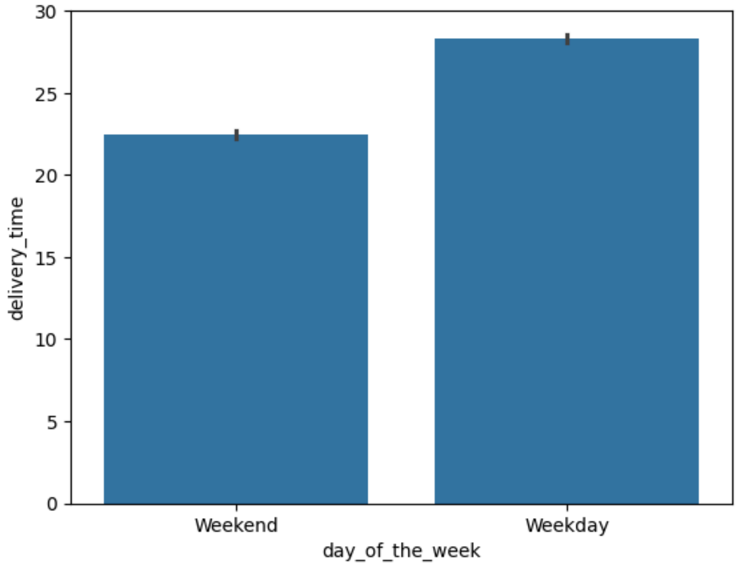
```
prep_delivery_correlation = df[['food_preparation_time', 'delivery_time']].corr().iloc[0, 1]
print(f'Relationship between food preparation time and delivery time: {prep_delivery_correlation:.2f}')

# Compute correlation
prep_delivery_correlation = df[['food_preparation_time', 'delivery_time']].corr().iloc[0, 1]

# Print correlation
print(f'Relationship between food preparation time and delivery time: {prep_delivery_correlation:.2f}')

# Visualize the relationship with a scatter plot
plt.figure(figsize=(8, 6))
plt.scatter(df['food_preparation_time'], df['delivery_time'], alpha=0.5)
plt.title('Relationship between Food Preparation Time and Delivery Time')
plt.xlabel('Food Preparation Time')
plt.ylabel('Delivery Time')
plt.grid(True)
plt.tight_layout()

# Optionally, show correlation coefficient on the plot
plt.text(df['food_preparation_time'].max() * 0.75, df['delivery_time'].min() * 1.1,
         f'Correlation = {prep_delivery_correlation:.2f}', fontsize=12, bbox=dict(facecolor='white', alpha=0.5))

plt.show()


#delivery time and food prepration - to mean
```

```
Relationship between food preparation time and delivery time: 0.01
Relationship between food preparation time and delivery time: 0.01
```



```
sns.barplot(data = df, x = 'day_of_the_week', y = 'delivery_time')
df.groupby(['day_of_the_week'])['delivery_time'].mean()
```

```
day_of_the_week
Weekday    28.340334
Weekend    22.470883
Name: delivery_time, dtype: float64
```



Observations:

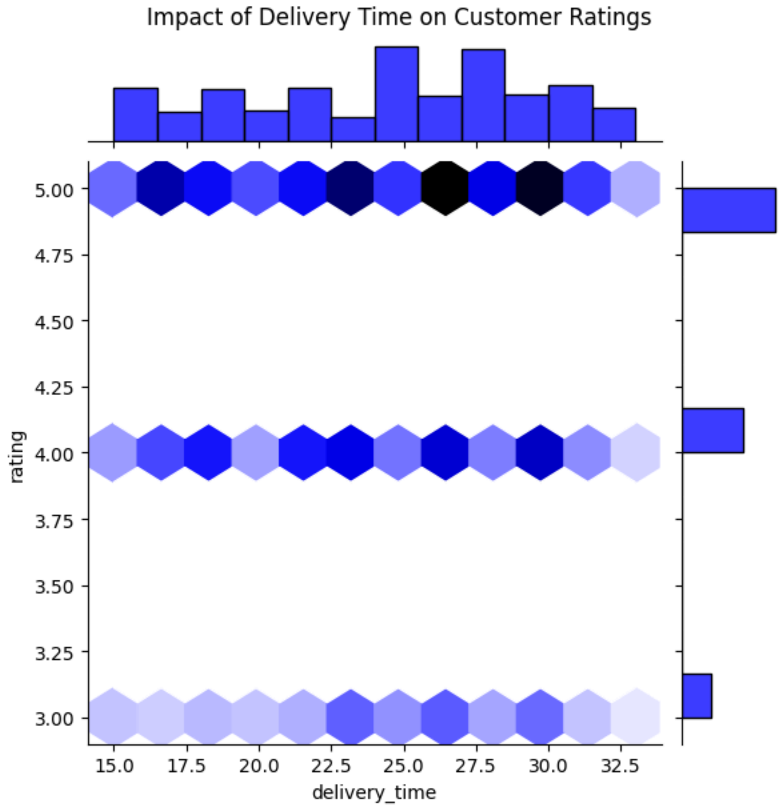
On average delivery times are higher during the weekday than on the weekend.

1. Weekday - 28 minutes
2. Weekend - 22 minutes

• Impact of Delivery Time on Customer Ratings

```
"""plt.figure(figsize=(10, 8))
sns.jointplot(data=df, x='delivery_time', y='rating', kind='reg')
plt.suptitle('Impact of Delivery Time on Customer Ratings', y=1.02)
plt.show()"""
plt.figure(figsize=(10, 8))
sns.jointplot(data=df, x='delivery_time', y='rating', kind='hex', color='b')
plt.suptitle('Impact of Delivery Time on Customer Ratings', y=1.02)
plt.show()
```

```
<Figure size 1000x800 with 0 Axes>
```



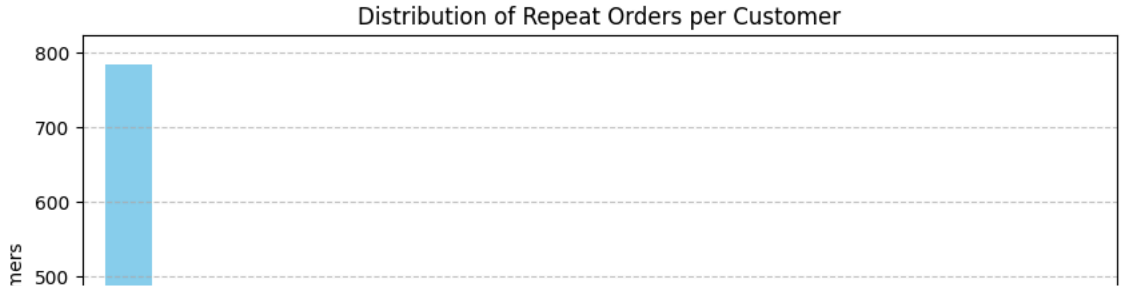
Observations:

Customer ratings are evenly spread across various delivery times, indicating that delivery time has little to no effect on the ratings given.

6. Customer Insights

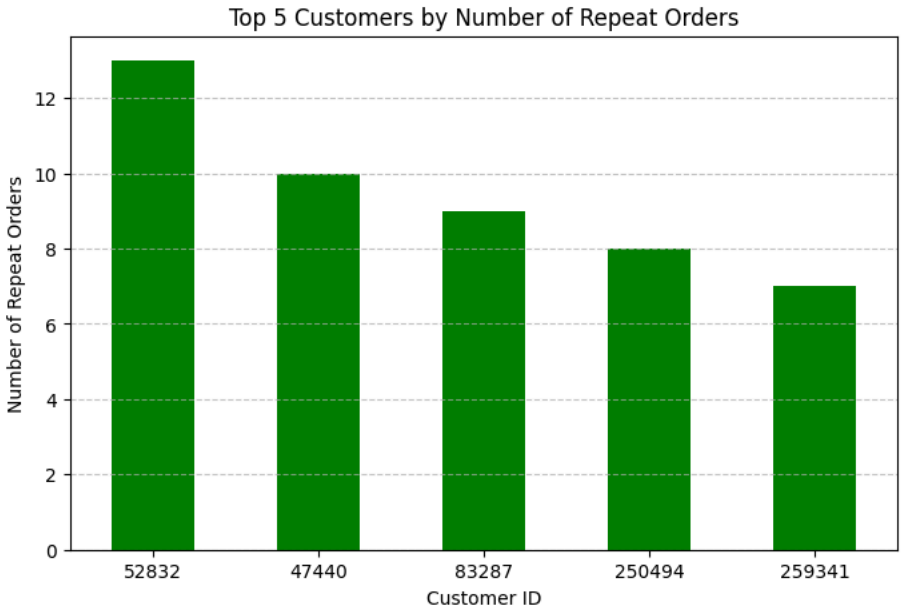
• Repeat Order Rate

```
import matplotlib.pyplot as plt

# Calculate repeat customer counts
repeat_customers = df['customer_id'].value_counts()

# Plotting
plt.figure(figsize=(10, 6))
repeat_customers.value_counts().sort_index().plot(kind='bar', color='skyblue')
plt.title('Distribution of Repeat Orders per Customer')
plt.xlabel('Number of Repeat Orders')
plt.ylabel('Number of Customers')
plt.xticks(rotation=0)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```




```
# Get top 5 customers by customer_id
top_5_customers = repeat_customers.head(5)

# Displaying customer_id of the top 5
print("Top 5 Customers by customer_id:")
print(top_5_customers)

# Optionally, visualize the top 5 customers
plt.figure(figsize=(8, 5))
top_5_customers.plot(kind='bar', color='green')
plt.title('Top 5 Customers by Number of Repeat Orders')
plt.xlabel('Customer ID')
plt.ylabel('Number of Repeat Orders')
plt.xticks(rotation=0)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```

```
Top 5 Customers by customer_id:
customer_id
52832     13
47440     10
83287      9
250494     8
259341     7
Name: count, dtype: int64
```



Observations: