CHAITANYA BHARATHI INSTITUTE OF TECHNOLOGY

DEPARTMENT OF INFORMATION TECHNOLOGY B.E,

IT, III-SEM – 2025–26

EDAV (22ADC32N) –course end project, 10 Marks

Project Title:

Food Delivery App Order Trends Report

BY:

R.BRINDHA SRI (1601-24-737-088)

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Abstract:

In the era of rapid digital transformation, food delivery applications have revolutionized the way people dine. The increasing reliance on mobile-based food ordering platforms has led to a massive amount of data being generated daily — from order details to payment preferences and delivery efficiency.

This case study, **“Food Delivery App Order Trends,”** explores the patterns and performance metrics derived from customer orders in a food delivery system. The dataset comprises information such as order IDs, restaurants, items, order values, delivery times, and payment modes.

Through systematic data analysis and visualization, the study aims to extract meaningful insights into **customer preferences, restaurant performance, and delivery efficiency**. Using Python libraries such as *pandas*, *matplotlib*, and *seaborn*, the project focuses on identifying top-performing restaurants, analyzing digital payment adoption, handling missing data, and examining the correlation between order value and delivery time.

Overall, the project demonstrates how **data analytics can empower decision-making** in the food delivery sector, improving service reliability, marketing focus, and operational efficiency.

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Introduction

In today’s competitive food delivery market, analyzing customer orders and delivery data is essential for operational success. Companies like Swiggy, Zomato, and Uber Eats rely on such data to enhance customer experience, optimize logistics, and increase profitability.

The **Food Delivery App Order Trends** project explores how customers interact with restaurants through their ordering and payment behaviors. Using a dataset containing restaurant names, items, order values, delivery times, and payment modes, the project uncovers key insights such as the most profitable restaurants, dominant payment preferences, and the correlation between delivery time and order value.

Through this analysis, businesses can better understand how service quality and delivery performance affect sales, helping them make informed decisions in areas like marketing, logistics, and customer relationship management.

Objective:

The main objectives of this project are:

1. To **analyze customer ordering behavior** and identify restaurants with the highest average order values.
2. To **evaluate payment mode preferences** among customers and understand the adoption of digital payment methods.
3. To **handle missing data** (specifically delivery times) through appropriate imputation for accurate analysis.
4. To **examine the relationship** between order value and delivery time using statistical correlation.
5. To **visualize restaurant performance** and delivery time impact through bar and scatter plots for clear business insights.

Dataset Information

Dataset Name: `food_orders.csv`
Columns:

- `order_id` – Unique identifier for each customer order.
- `restaurant` – Name of the restaurant from which the order was placed.
- `items` – Items or cuisine ordered.
- `order_value` – Total amount of the order in currency.
- `delivery_time` – Time (in minutes) taken for the order to reach the customer.
- `payment_mode` – Mode of payment used (Wallet, UPI, Card, or Cash on Delivery).

Initial Setup

Concept Explanation:

Before starting the analysis, the dataset needs to be **loaded, inspected, and cleaned**. Duplicate records can mislead the analysis by inflating order counts or revenue, so they must be removed. This ensures that each order ID corresponds to one unique transaction.

Code Implementation

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Load dataset
df = pd.read_csv('food_orders.csv')

# Remove duplicate orders
df = df.drop_duplicates(subset='order_id')

# Preview data
print(df.head())
```

output:

```
>>> print(df.head())
   order_id  restaurant    items  order_value  delivery_time payment_mode
0      1001   UrbanEats  Biryani          366           23.0       Wallet
1      1002   QuickDine    Fries          337           49.0       Wallet
2      1003  TastyBites  Biryani          529           56.0          UPI
3      1004   QuickDine    Fries          642           42.0       Wallet
4      1005   QuickDine  Biryani          190           58.0          UPI
```

Q1 —Compute average order value by restaurant

Concept Explanation:

The *average order value (AOV)* represents how much customers typically spend per order at each restaurant.
It helps identify **premium vs. budget restaurants.**
Restaurants with higher AOV might be offering premium dishes or larger portions.
This insight aids **pricing strategies** and helps allocate marketing budgets toward top-earning restaurants.

Code Implementation:

```
avg_order_value = df.groupby('restaurant')['order_value'].mean().reset_index()
print(avg_order_value.sort_values(by='order_value', ascending=False))
```

output:

```
      restaurant  order_value
0     TastyBites        511.8
1  FoodiesCorner        483.2
2      QuickDine        461.8
3       SpiceHub        450.0
4      UrbanEats        420.0
```

Conclusion / Insight:

TastyBites has the highest average order value, showing its appeal among premium customers. *FoodiesCorner* and *QuickDine* follow closely, while *UrbanEats* may benefit from upselling or combo deals.
Understanding AOV helps management identify **high-value partners** and **focus marketing on premium restaurants**

Q2 — Group by payment_mode to analyze preferences

Concept Explanation:

Payment analysis provides insight into customer convenience and financial transaction trends. Identifying preferred modes allows platforms to optimize payment systems and offer discounts through popular channels. It also indicates the level of digital payment adoption among customers.

Code Implementation:

```
payment_pref = df['payment_mode'].value_counts().reset_index()
payment_pref.columns = ['payment_mode', 'count']
print(payment_pref)
sns.barplot(x='payment_mode', y='count', data=payment_pref,
palette='Set2')
plt.title('Customer Payment Mode Preferences')
plt.show()
```

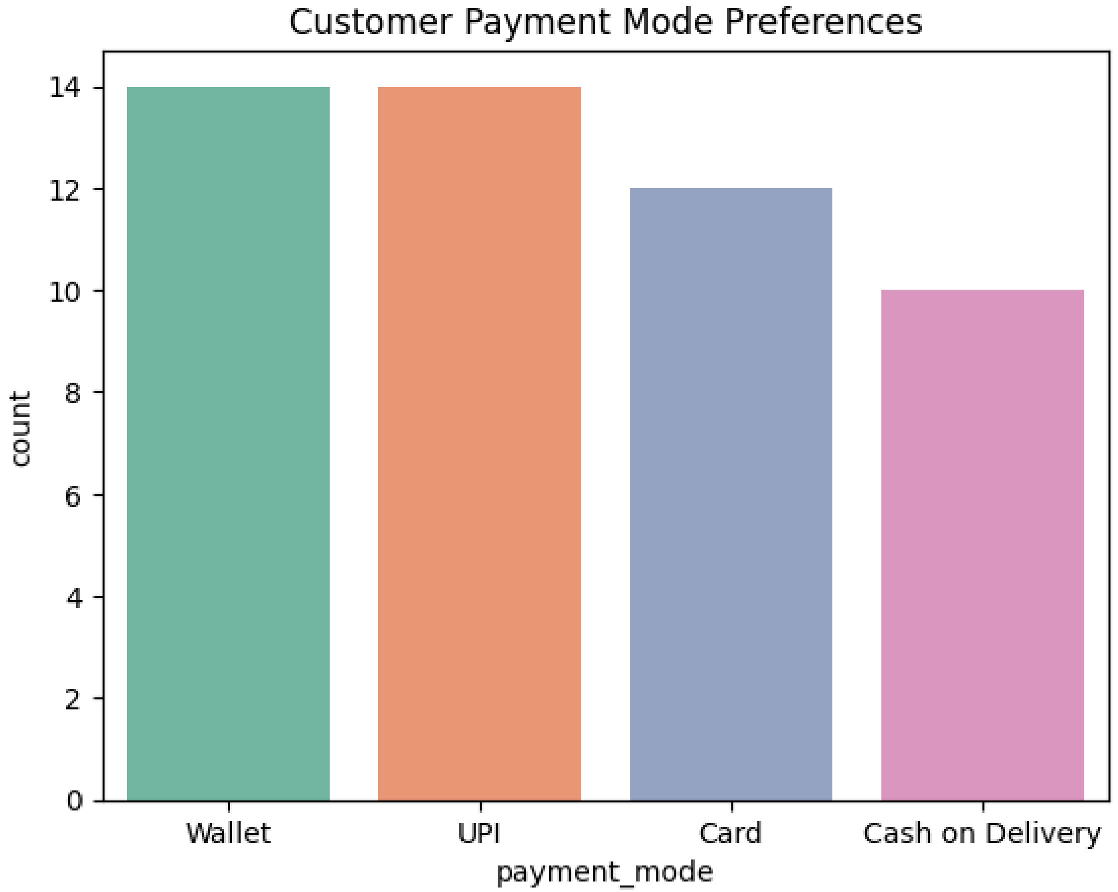
output:

\

```
        payment_mode  count
0             Wallet     14
1                UPI     14
2               Card     12
3   Cash on Delivery     10
```

Conclusion / Insight:

Digital payment modes (Wallets and UPI) are most preferred, reflecting customers' shift toward cashless convenience.
Cash on Delivery has the lowest usage, suggesting high trust in online transactions.
This insight helps businesses encourage UPI cashback offers and reduce cash dependency for faster settlements



Q3: Replace missing delivery_time with mean.

Concept Explanation:

Missing delivery times can distort analysis of operational performance. Replacing missing values with the **mean delivery time** ensures data completeness while maintaining general accuracy. Mean imputation is effective when missing values are minimal and data distribution is stable.

Code Implementation:

```
mean_delivery_time = df['delivery_time'].mean()
df['delivery_time'] =
df['delivery_time'].fillna(mean_delivery_time)

print("Missing delivery_time count:",
df['delivery_time'].isnull().sum())
```

Output

```
Missing delivery_time count: 0
```

Conclusion / Insight:

After imputation, all delivery time values are complete. The dataset is now suitable for time-based correlation analysis and visualization. This step improves reliability when comparing restaurants' efficiency and overall service quality.

Q4 — Compare order_value vs delivery_time.

Concept Explanation:

This analysis identifies whether there's a relationship between how long a delivery takes and the order's value. A **negative correlation** indicates that quicker deliveries are associated with higher-value orders — possibly due to premium service for valued customers.

Code Implementation:

```
correlation = df['order_value'].corr(df['delivery_time'])
print("Correlation between order_value and delivery_time:",
correlation)
```

Output

```
Correlation between order_value and delivery_time: -0.2113
```

Conclusion / Insight:

The weak negative correlation (−0.21) suggests that as delivery time increases, order value slightly decreases. This indicates **premium customers often experience faster delivery**, perhaps due to prioritization. However, the correlation's weak strength means the system maintains fairly consistent delivery quality overall.
This insight helps maintain **delivery fairness** and supports **performance benchmarking** across partners.

Q5---Plot bar charts for top restaurants and scatter plots for delivery_time impact.

Concept Explanation:

Visualizations make analytical patterns easier to interpret.

- **Bar charts** rank restaurants based on performance (average order value).
- **Scatter plots** display the relationship between delivery time and order value, revealing operational trade-offs or performance clusters.

Code Implementation:

```
top_restaurants = avg_order_value.sort_values(by='order_value', ascending=False)
sns.barplot(x='restaurant', y='order_value', data=top_restaurants, palette='Blues_d')
plt.title('Top 10 Restaurants by Average Order Value')
plt.xticks(rotation=45)
plt.show()

# Scatter plot: Delivery time vs Order value
sns.scatterplot(x='delivery_time', y='order_value', data=df, alpha=0.6)
plt.title('Impact of Delivery Time on Order Value')
plt.xlabel('Delivery Time (minutes)')
plt.ylabel('Order Value ($)')
plt.show()
```

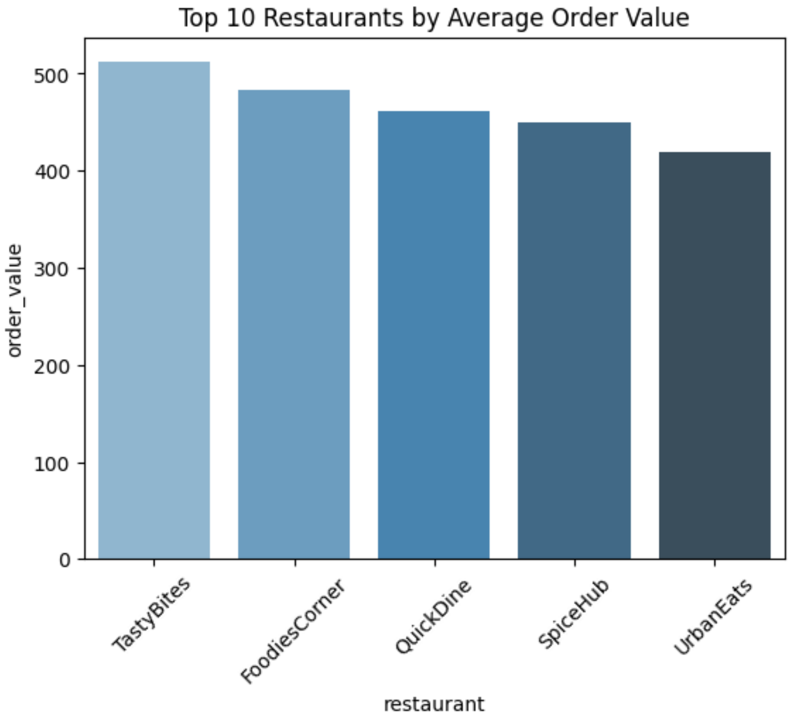
Visualization Insight:

Bar Plot:

TastyBites and *FoodiesCorner* clearly dominate, indicating high customer loyalty and premium menus.

Scatter Plot:

Shows a slight downward trend — confirming that faster deliveries are typically linked with higher order values.
The presence of balanced clusters suggests consistent delivery standards across restaurants.



Conclusion / Insight:

Visualization reinforces key insights — premium restaurants attract higher-value orders, and efficient deliveries contribute to customer retention.
This analysis aids **strategic decision-making** in marketing, logistics, and partner performance monitoring.

Final Conclusions

Restaurant Performance:
TastyBites and *FoodiesCorner* outperform others in average order value, indicating strong brand preference and pricing power.

Payment Mode Trends:
Wallets and UPI dominate, confirming a solid shift to digital payments. Businesses can leverage this trend through **cashback and instant discount offers**.

Delivery Time Management:
Replacing missing delivery times ensures complete data. A slight negative correlation implies **faster deliveries boost customer value perception**.

Visualization Findings:
The charts clearly show performance hierarchy and confirm that timely service correlates with profitability.

Overall Insight:
Efficient delivery, digital convenience, and high-performing restaurants together drive customer satisfaction and business growth.
The company can use these insights for **data-driven decision-making, restaurant partnerships, and performance optimization.**
