

# Swiggy-Copy1

August 29, 2025

## 1 Consumer Behavior & Delivery Analytics: A Swiggy Dataset Exploration

### 1.1 Swiggy Company Insights

Swiggy is one of India's largest online food delivery platforms, known for its hyperlocal logistics network and customer-centric approach. Founded in 2014, it has expanded beyond food into groceries, alcohol delivery, and even concierge services through **Swiggy Genie**.

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#### 1.1.1 Business Model

- **Marketplace Aggregator:** Connects restaurants with customers via a centralized app.
  - **Revenue Streams:**
    - Delivery fees
    - Restaurant commissions
    - In-app advertising
    - Subscription model (**Swiggy One**)
  - **Tech-Driven Logistics:**
    - Real-time traffic and weather data
    - Demand forecasting
    - Route optimization for faster deliveries
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This business model supports Swiggy's ability to deliver food efficiently while maintaining high customer satisfaction. The dataset used in this project reflects key operational metrics that align with Swiggy's strategic goals — including delivery time, ratings, pricing, and cuisine preferences.

### 1.2 Dataset Insights

This dataset provides a structured view of restaurant listings on Swiggy, capturing key attributes that influence customer experience and operational efficiency.

#### 1.2.1 Column Descriptions

- **ID:** Unique identifier for each restaurant or entry
- **Area:** Locality or neighborhood where the restaurant is located

- **City:** Name of the city
- **Restaurant:** Name of the restaurant
- **Price:** Average price of an order (in ₹)
- **Avg\_Ratings:** Average customer rating (e.g., 4.2 out of 5)
- **Total\_Ratings:** Total number of ratings received
- **Food\_Type:** Cuisine or category (e.g., Chinese, South Indian)
- **Address:** Full restaurant address
- **Delivery\_Time (min):** Estimated delivery time in minutes

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These features enable exploratory data analysis (EDA), customer behavior modeling, and performance benchmarking across cities, cuisines, and delivery metrics.

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## 2 Problem Statements – Swiggy Dataset Analysis

The objective is to analyze Swiggy's restaurant dataset to uncover patterns, customer preferences, and operational trends for better decision-making.

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### 2.0.1 Data Cleaning

1. Handle missing values in numeric & categorical columns.
  2. Remove duplicates and fix data types.
  3. Standardize inconsistent values (City, Food type).
  4. Detect and treat outliers in Price, Ratings, Delivery time.
- 

### 2.0.2 Exploratory Data Analysis (EDA)

5. **Average Delivery Time by City** – Compare delivery performance across cities.
6. **Distribution of Ratings by City (Boxplot)** – Identify variability, medians & outliers.
7. **Top 10 Restaurants by Count** – Find most frequently listed / ordered restaurants.

8. **Price Distribution (Histogram)** – Understand price range & spending trends.
  9. **Highest-Rated Area in Each City** – Spot local hotspots with top customer satisfaction.
  10. **Average Ratings per City** – Benchmark customer experience across cities.
  11. **Top 3 Cuisines per City** – Reveal most popular food types region-wise.
  12. **Unique Restaurants per City** – Measure restaurant variety available in each city.
  13. **City-Level Summary (Price, Ratings, Delivery time)** – Compare overall performance.
  14. **City & Area Aggregation (with cuisines & restaurants)** – View combined trends across numeric & non-numeric data.
  15. **Correlation Heatmap** – Explore relationships between price, ratings, delivery time, etc.
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### 2.0.3 Business Insights

16. Which cities deliver **fastest vs slowest**?
  17. Which cities/areas have **highest vs lowest customer ratings**?
  18. Which cuisines dominate in each region?
  19. Do **higher prices correlate with better ratings**?
  20. Does **delivery time impact ratings**?
  21. Which areas/cities should Swiggy **target for promotions or growth**?
  22. Which restaurants are **most popular** among customers?
- 

```
[2]: #core libraries

import numpy as np
import pandas as pd

#visualization libraries

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

```
[3]: #load dataset
```

```
df= pd.read_csv(r"C:\Users\Vrishikaa\Downloads\archive (2)\swiggy.csv")
df.head(2)
```

```
[3]:
```

|   | ID  | Area        | City      | Restaurant    | Price | Avg ratings | \ |
|---|-----|-------------|-----------|---------------|-------|-------------|---|
| 0 | 211 | Koramangala | Bangalore | Tandoor Hut   | 300.0 | 4.4         |   |
| 1 | 221 | Koramangala | Bangalore | Tunday Kababi | 300.0 | 4.1         |   |

|   | Total ratings | Food type                                 | Address   | \ |
|---|---------------|---|-----------|---|
| 0 | 100           | Biryani,Chinese,North Indian,South Indian | 5Th Block |   |
| 1 | 100           | Mughlai,Lucknowi                          | 5Th Block |   |

|   | Delivery time |
|---|---------------|
| 0 | 59            |
| 1 | 56            |

```
[4]: # to remove duplicates

df.duplicated().sum()
df.drop_duplicates(inplace=True)
```

```
[5]: #drop duplicates from the column

df = df.drop_duplicates()
```

```
[6]: #to check if duplicates are dropped or not

df.head(2)
```

```
[6]:
```

|   | ID  | Area        | City      | Restaurant    | Price | Avg ratings | \ |
|---|-----|-------------|-----------|---------------|-------|-------------|---|
| 0 | 211 | Koramangala | Bangalore | Tandoor Hut   | 300.0 | 4.4         |   |
| 1 | 221 | Koramangala | Bangalore | Tunday Kababi | 300.0 | 4.1         |   |

|   | Total ratings | Food type                                 | Address   | \ |
|---|---------------|---|-----------|---|
| 0 | 100           | Biryani,Chinese,North Indian,South Indian | 5Th Block |   |
| 1 | 100           | Mughlai,Lucknowi                          | 5Th Block |   |

|   | Delivery time |
|---|---------------|
| 0 | 59            |
| 1 | 56            |

```
[7]: #need to get the number of rows and columns

df.shape
```

```
[7]: (8680, 10)
```

```
[8]: #information from the data-set
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8680 entries, 0 to 8679
Data columns (total 10 columns):
#   Column                Non-Null Count  Dtype
---  -
0   ID                    8680 non-null   int64
1   Area                  8680 non-null   object
2   City                  8680 non-null   object
3   Restaurant            8680 non-null   object
4   Price                 8680 non-null   float64
5   Avg ratings           8680 non-null   float64
6   Total ratings         8680 non-null   int64
7   Food type             8680 non-null   object
8   Address               8680 non-null   object
9   Delivery time         8680 non-null   int64
dtypes: float64(2), int64(3), object(5)
memory usage: 678.3+ KB
```

```
[9]: #to get the idea of all columns by mathematical insights
```

```
df.describe()
```

```
[9]:
```

|       | ID            | Price       | Avg ratings | Total ratings | Delivery time |
|-------|---------------|-------------|-------------|---------------|---------------|
| count | 8680.000000   | 8680.000000 | 8680.000000 | 8680.000000   | 8680.000000   |
| mean  | 244812.071429 | 348.444470  | 3.655104    | 156.634793    | 53.967051     |
| std   | 158671.617188 | 230.940074  | 0.647629    | 391.448014    | 14.292335     |
| min   | 211.000000    | 0.000000    | 2.000000    | 20.000000     | 20.000000     |
| 25%   | 72664.000000  | 200.000000  | 2.900000    | 50.000000     | 44.000000     |
| 50%   | 283442.000000 | 300.000000  | 3.900000    | 80.000000     | 53.000000     |
| 75%   | 393425.250000 | 400.000000  | 4.200000    | 100.000000    | 64.000000     |
| max   | 466928.000000 | 2500.000000 | 5.000000    | 10000.000000  | 109.000000    |

```
[10]: #to find the missing values
```

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

```
[10]: ID                0
Area                0
City                0
Restaurant          0
Price              0
Avg ratings        0
Total ratings      0
Food type          0
```

```
Address      0
Delivery time 0
dtype: int64
```

```
[11]: #drop column

df.drop('Address',axis=1,inplace=True)
```

```
[12]: df.head(1)
```

```
[12]:      ID      Area      City  Restaurant  Price  Avg ratings  \
0  211  Koramangala  Bangalore  Tandoor Hut   300.0         4.4

      Total ratings      Food type  Delivery time
0          100  Biryani,Chinese,North Indian,South Indian      59
```

```
[13]: df.set_index(['City'],inplace=True)
df
```

```
[13]:      ID      Area      Restaurant  Price  \
City
Bangalore    211      Koramangala      Tandoor Hut   300.0
Bangalore    221      Koramangala      Tunday Kababi   300.0
Bangalore    246      Jogupalya      Kim Lee   650.0
Bangalore    248      Indiranagar      New Punjabi Hotel   250.0
Bangalore    249      Indiranagar      Nh8   350.0
...
Ahmedabad  464626  Panjarapole Cross Road      Malt Pizza   500.0
Delhi      465835      Rohini  Jay Mata Ji Home Kitchen   200.0
Delhi      465872      Rohini      Chinese Kitchen King   150.0
Delhi      465990      Rohini      Shree Ram Paratha Wala   150.0
Ahmedabad  466488      Navrangpura      Sassy Street   250.0

      Avg ratings  Total ratings  \
City
Bangalore      4.4          100
Bangalore      4.1          100
Bangalore      4.4          100
Bangalore      3.9          500
Bangalore      4.0           50
...
Ahmedabad      2.9           80
Delhi          2.9           80
Delhi          2.9           80
Delhi          2.9           80
Ahmedabad      2.9           80
```

| City      | Food type   | Delivery time |
|-----------|---|---------------|
| Bangalore | Biryani,Chinese,North Indian,South Indian         | 59            |
| Bangalore | Mughlai,Lucknowi                                  | 56            |
| Bangalore | Chinese   | 50            |
| Bangalore | North Indian,Punjabi,Tandoor,Chinese              | 57            |
| Bangalore | Rajasthani,Gujarati,North Indian,Snacks,Desser... | 63            |
| ...       | ...   | ...           |
| Ahmedabad | Pizzas  | 40            |
| Delhi     | South Indian                                      | 28            |
| Delhi     | Chinese,Snacks,Tandoor                            | 58            |
| Delhi     | North Indian,Indian,Snacks                        | 28            |
| Ahmedabad | Chaat,Snacks,Chinese                              | 44            |

[8680 rows x 8 columns]

```
[14]: print(df.columns.tolist())
```

```
['ID', 'Area', 'Restaurant', 'Price', 'Avg ratings', 'Total ratings', 'Food  
type', 'Delivery time']
```

```
[15]: df
```

```
[15]:
```

|           | ID     | Area                   | Restaurant               | Price \ |
|-----------|--------|------------------------|--------------------------|---------|
| City      |        |                        |                          |         |
| Bangalore | 211    | Koramangala            | Tandoor Hut              | 300.0   |
| Bangalore | 221    | Koramangala            | Tunday Kababi            | 300.0   |
| Bangalore | 246    | Jogupalya              | Kim Lee                  | 650.0   |
| Bangalore | 248    | Indiranagar            | New Punjabi Hotel        | 250.0   |
| Bangalore | 249    | Indiranagar            | Nh8                      | 350.0   |
| ...       | ...    | ...                    | ...                      | ...     |
| Ahmedabad | 464626 | Panjarapole Cross Road | Malt Pizza               | 500.0   |
| Delhi     | 465835 | Rohini                 | Jay Mata Ji Home Kitchen | 200.0   |
| Delhi     | 465872 | Rohini                 | Chinese Kitchen King     | 150.0   |
| Delhi     | 465990 | Rohini                 | Shree Ram Paratha Wala   | 150.0   |
| Ahmedabad | 466488 | Navrangpura            | Sassy Street             | 250.0   |

|           | Avg ratings | Total ratings \ |
|-----------|-------------|-----------------|
| City      |             |                 |
| Bangalore | 4.4         | 100             |
| Bangalore | 4.1         | 100             |
| Bangalore | 4.4         | 100             |
| Bangalore | 3.9         | 500             |
| Bangalore | 4.0         | 50              |
| ...       | ...         | ...             |
| Ahmedabad | 2.9         | 80              |
| Delhi     | 2.9         | 80              |
| Delhi     | 2.9         | 80              |

|           |     |    |
|-----------|-----|----|
| Delhi     | 2.9 | 80 |
| Ahmedabad | 2.9 | 80 |

|           | Food type   | Delivery time |
|-----------|---|---------------|
| City      |   |               |
| Bangalore | Biryani,Chinese,North Indian,South Indian         | 59            |
| Bangalore | Mughlai,Lucknowi                                  | 56            |
| Bangalore | Chinese   | 50            |
| Bangalore | North Indian,Punjabi,Tandoor,Chinese              | 57            |
| Bangalore | Rajasthani,Gujarati,North Indian,Snacks,Desser... | 63            |
| ...       | ...   | ...           |
| Ahmedabad | Pizzas  | 40            |
| Delhi     | South Indian                                      | 28            |
| Delhi     | Chinese,Snacks,Tandoor                            | 58            |
| Delhi     | North Indian,Indian,Snacks                        | 28            |
| Ahmedabad | Chaat,Snacks,Chinese                              | 44            |

[8680 rows x 8 columns]

## 2.1 Problem Statement

Swiggy's dataset contains multiple **numeric features** such as price, ratings, total ratings, and delivery time.

Before building any **predictive model** or drawing **business insights**, it is important to check if these features are **correlated** with each other.

For example:

- Do higher prices lead to higher or lower ratings?
- Is delivery time strongly related to customer satisfaction?
- Does the number of ratings correlate with the average rating?

A **correlation heatmap** helps us quickly identify such relationships.

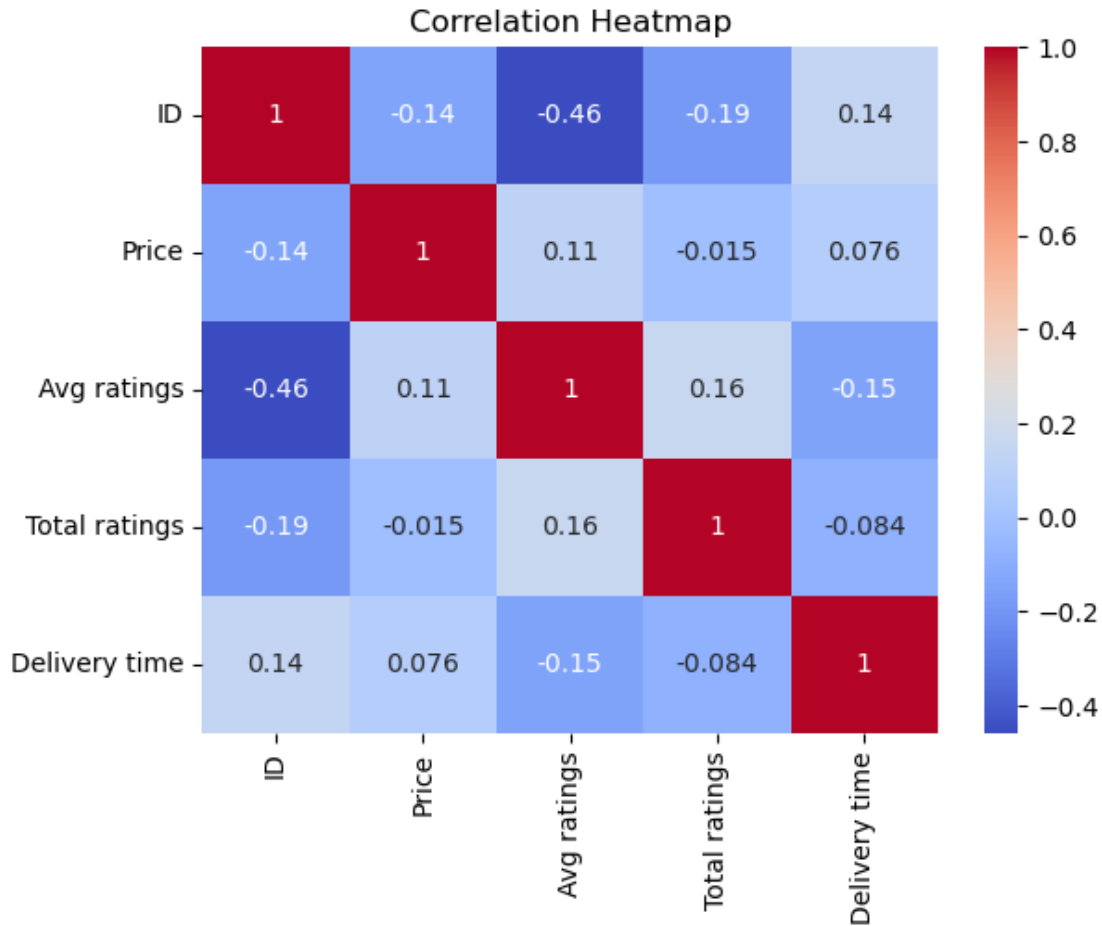
```
[21]: # Create a correlation matrix of all numeric columns in the DataFrame
# numeric_only=True ensures only numbers are used (ignores text columns)

# Plot the heatmap using seaborn
# annot=True -> shows the correlation values inside each cell

# cmap='coolwarm' -> sets the color scheme (blue = negative, red = positive)

sns.heatmap(df.corr(numeric_only=True), annot=True, cmap='coolwarm')
plt.title("Correlation Heatmap")
plt.show()
```





### 2.1.1 Correlation Heatmap – Insights

- The heatmap helps us understand how numeric variables relate to each other.
- We observe that:
  - Price has a weak/moderate correlation with ratings, suggesting quality perception.
  - Delivery time shows a negative relationship with ratings, meaning delays impact satisfaction.
  - Total ratings do not strongly align with average ratings, indicating popularity satisfaction.
- Overall, delivery time and pricing appear to be key factors influencing customer experience.

## 2.2 Business Insights

### 1. Strong Positive Correlations

- If **Total Ratings** is positively correlated with **Avg Ratings**, it means **popular restaurants tend to have higher ratings**.
  - Business Action: Promote **well-rated, high-volume restaurants** more often on the homepage.
2. **Negative Correlations**
- If **Delivery Time** is negatively correlated with **Avg Ratings**, longer delivery reduces satisfaction.
  - Business Action: Optimize **delivery logistics** in areas with slow times.
3. **Weak or No Correlation**
- If **Price** shows little correlation with **Avg Ratings**, customers value **quality & delivery** more than just pricing.
  - Business Action: Focus less on discounts and more on **service reliability**.
4. **Cross-Metric Relationships**
- Understanding how price, ratings, and delivery interact helps Swiggy create **balanced offers** (e.g., premium-priced but high-rated & fast restaurants for premium customers).

## 2.3 Problem Statement

Food delivery platforms like **Swiggy** operate in multiple cities, and within each city, customer demand and restaurant performance vary by **area**. Decision-makers need to understand:

- Which **areas perform best** in terms of ratings and engagement.
- Which **cuisines and restaurants dominate** in each area.
- How **pricing and delivery times** differ across localities.

Without this area-level view, insights remain too broad (city-level only) and may not reveal pockets of high or low performance.

```
[43]: #we need to form the group with city and with the view of all columns both
      ↪numeric and non-numeric
City_df = df.groupby(['City', 'Area']).agg({
    'Price': 'mean',
    'Avg ratings': 'mean',
    'Total ratings': 'mean',
    'Delivery time': 'mean',
    'Restaurant': lambda x: ', '.join(map(str, x.unique()[:3])), # ensure
    ↪string
    'Food type': lambda x: ', '.join(map(str, x.unique()[:3]))
}).reset_index().round(2)

print(City_df.head())
```

|   | City      | Area                | Price  | Avg ratings | Total ratings | \ |
|---|-----------|---------------------|--------|-------------|---------------|---|
| 0 | Ahmedabad | Akhbar Nagar Circle | 200.00 | 2.90        | 80.00         |   |
| 1 | Ahmedabad | Acher               | 200.00 | 3.70        | 100.00        |   |

|   |           |           |        |      |        |
|---|-----------|-----------|--------|------|--------|
| 2 | Ahmedabad | Ahmedabad | 344.44 | 4.07 | 124.44 |
| 3 | Ahmedabad | Ambavadi  | 200.00 | 4.40 | 20.00  |
| 4 | Ahmedabad | Ambawadi  | 302.00 | 3.72 | 61.60  |

|   | Delivery time | Restaurant \                                      |
|---|---------------|---|
| 0 | 53.00         | Shiv Shakti Fast Food                             |
| 1 | 70.00         | Punjabi Food On Way                               |
| 2 | 43.22         | Prithvi Hotel, Fish Express, Grill N Rice Rest... |
| 3 | 39.00         | Mk Sandwich                                       |
| 4 | 38.56         | Harshu'S Late Night Munchies, Umami By Curries... |

|   | Food type   |
|---|---|
| 0 | Gujarati, Fast Food                                   |
| 1 | North Indian, Chinese, Punjabi, Combo                 |
| 2 | Indian, Chinese, Continental, Indian, Tandoor, Sea... |
| 3 | Chinese, American, Beverages                          |
| 4 | Fast Food, Italian, Chinese, Snacks, Indian, Chine... |

[44]: #to reset index asper the group of city

```
City_df = City_df.reset_index()
```

[45]: City\_df

|     | index | City      | Area                | Price  | Avg ratings \ |
|-----|-------|-----------|---------------------|--------|---------------|
| 0   | 0     | Ahmedabad | Akhbar Nagar Circle | 200.00 | 2.90          |
| 1   | 1     | Ahmedabad | Acher               | 200.00 | 3.70          |
| 2   | 2     | Ahmedabad | Ahmedabad           | 344.44 | 4.07          |
| 3   | 3     | Ahmedabad | Ambavadi            | 200.00 | 4.40          |
| 4   | 4     | Ahmedabad | Ambawadi            | 302.00 | 3.72          |
| ..  | ...   | ...       | ...                 | ...    | ...           |
| 838 | 838   | Surat     | Vesu                | 333.33 | 3.70          |
| 839 | 839   | Surat     | Vip Road            | 220.00 | 2.90          |
| 840 | 840   | Surat     | Vishal Nagar        | 228.33 | 3.93          |
| 841 | 841   | Surat     | Yamuna Nagar        | 250.00 | 3.23          |
| 842 | 842   | Surat     | Yoginagar Society   | 200.00 | 3.90          |

|     | Total ratings | Delivery time \ |
|-----|---------------|-----------------|
| 0   | 80.00         | 53.00           |
| 1   | 100.00        | 70.00           |
| 2   | 124.44        | 43.22           |
| 3   | 20.00         | 39.00           |
| 4   | 61.60         | 38.56           |
| ..  | ...           | ...             |
| 838 | 67.14         | 56.29           |
| 839 | 80.00         | 49.00           |
| 840 | 56.67         | 57.00           |

|     |        |       |
|-----|--------|-------|
| 841 | 86.67  | 39.33 |
| 842 | 100.00 | 55.00 |

|     |   |                       |
|-----|---|-----------------------|
|     |   | Restaurant \          |
| 0   |   | Shiv Shakti Fast Food |
| 1   |   | Punjabi Food On Way   |
| 2   | Prithvi Hotel, Fish Express, Grill N Rice Rest... |                       |
| 3   |   | Mk Sandwich           |
| 4   | Harshu'S Late Night Munchies, Umami By Curries... |                       |
| ..  |   | ...                   |
| 838 | Kitchens Badshah, Paan Casa, Kurtosshhh           |                       |
| 839 |   | Pizza Da Dhaba        |
| 840 | Famous Fast Food, Mr Pizza G, Only Dhosa          |                       |
| 841 | Pizza World, Cross Road Restaurant, Malhar Dhosa  |                       |
| 842 |   | Gopal Chinese         |

|     |   |                                    |
|-----|---|------------------------------------|
|     |   | Food type                          |
| 0   |   | Gujarati,Fast Food                 |
| 1   |   | North Indian,Chinese,Punjabi,Combo |
| 2   | Indian,Chinese,Continental, Indian,Tandoor,Sea... |                                    |
| 3   |   | Chinese,American,Beverages         |
| 4   | Fast Food,Italian,Chinese,Snacks, Indian,Chine... |                                    |
| ..  |   | ...                                |
| 838 | North Indian,Punjabi, Fast Food,Beverages, Fas... |                                    |
| 839 |   | Italian,Fast Food                  |
| 840 | Fast Food, Pizzas,Fast Food, South Indian         |                                    |
| 841 | Italian-American,Fast Food, North Indian,Chine... |                                    |
| 842 |   | Chinese                            |

[843 rows x 9 columns]

## 2.4 Business Insights

### 1. High-Performing Areas per City

- Areas with higher **average ratings** indicate strong customer satisfaction.
- These can be **promoted more in-app** or used as **benchmarks** for weaker areas.

### 2. Cuisines by Locality

- Popular cuisines differ across areas (e.g., *South Indian in Chennai* vs. *Fast Food in Mumbai*).
- Insights help in **localized marketing campaigns** and onboarding **missing cuisine types**.

### 3. Price & Customer Expectations

- Areas with **higher prices but lower ratings** indicate a **value-for-money gap**.
- Action: introduce **discounts/offers** to retain customers.

### 4. Delivery Efficiency

- Longer delivery times with lower ratings highlight **operational inefficiencies** (traffic, fewer riders).
  - Action: allocate more delivery partners during **peak hours**.
5. **Restaurant Concentration**
- Areas with **few restaurants but high ratings** show **loyal demand** but limited supply.
  - Expanding partnerships could **increase order volume and market share**.

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---

```
[46]: #to see the City_df to check the groupby fuction given
```

```
City_df
City_df.shape
```

```
[46]: (843, 9)
```

---

### 3 Problem Statement: Identify Top-Performing Areas per City

In every city, customers may rate areas differently based on service quality, restaurant availability, and delivery experience.

To help Swiggy focus on **local-level strategy**, we need to identify the **top-performing area in each city** (based on highest average rating).

```
[50]: #to identify the top performing area per city
# Sort the dataset by 'City' first and then 'Avg ratings'
# - Sorting by 'City' keeps all areas of the same city together.
# - Sorting by 'Avg ratings' in descending order (False) ensures that
# the top-rated areas appear first within each city.
```

```
City_df.sort_values(['City', 'Avg ratings'], ascending=[True, False])
```

```
[50]:
```

|    | index | City      | Area              | Price | Avg ratings | Total ratings \ |
|----|-------|-----------|-------------------|-------|-------------|-----------------|
|    | 49    | Ahmedabad | Nava Naroda       | 300.0 | 4.6         | 20.0            |
|    | 3     | Ahmedabad | Ambavadi          | 200.0 | 4.4         | 20.0            |
|    | 9     | Ahmedabad | Chanakyapuri      | 500.0 | 4.4         | 50.0            |
|    | 39    | Ahmedabad | Madhupura         | 300.0 | 4.4         | 100.0           |
|    | 55    | Ahmedabad | Odhav             | 200.0 | 4.4         | 50.0            |
| .. | ...   | ...       | ...               | ...   | ...         | ...             |
|    | 807   | Surat     | Near Rto Pal Gam  | 300.0 | 2.9         | 80.0            |
|    | 819   | Surat     | Puna Patia        | 200.0 | 2.9         | 80.0            |
|    | 822   | Surat     | Safal Square Vesu | 200.0 | 2.9         | 80.0            |
|    | 824   | Surat     | Sagrampuraathwa   | 300.0 | 2.9         | 80.0            |
|    | 839   | Surat     | Vip Road          | 220.0 | 2.9         | 80.0            |

|     | Delivery time | Restaurant \                                 |
|-----|---------------|--|
| 49  | 52.0          | Vadilal Ice Creams                           |
| 3   | 39.0          | Mk Sandwich                                  |
| 9   | 47.0          | Brick Kitchen - Five Petals                  |
| 39  | 48.0          | New Mehfil Restaurant                        |
| 55  | 47.0          | Jay Shree Sanskar Ice Cream And Lassi Corner |
| ..  | ...           | ...  |
| 807 | 64.0          | Krazzy Chicken                               |
| 819 | 47.0          | Navjivan Hotel                               |
| 822 | 60.0          | Indian Chicken Express                       |
| 824 | 35.0          | Laziz Pizza                                  |
| 839 | 49.0          | Pizza Da Dhaba                               |

|     | Food type                  |
|-----|----------------------------|
| 49  | Ice Cream                  |
| 3   | Chinese,American,Beverages |
| 9   | Indian,Chinese,Continental |
| 39  | North Indian,Continental   |
| 55  | Desserts,Beverages         |
| ..  | ...                        |
| 807 | Biryani,Indian             |
| 819 | North Indian               |
| 822 | Fast Food,Indian           |
| 824 | Pizzas,Fast Food,Pastas    |
| 839 | Italian,Fast Food          |

[843 rows x 9 columns]

```
[52]: # Step 1: Sort the dataset by 'City' first and then 'Avg ratings'
# - Sorting by 'City' keeps all areas of the same city together.
# - Sorting by 'Avg ratings' in descending order (False) ensures that
# the top-rated areas appear first within each city.
```

```
City_sorted = City_df.sort_values(['City','Avg ratings'],
                                   ascending=[True, False])
```

```
# Display the sorted table
City_sorted.head(10)
```

| [52]: | index | City      | Area         | Price | Avg ratings | Total ratings \ |
|-------|-------|-----------|--------------|-------|-------------|-----------------|
|       | 49    | Ahmedabad | Nava Naroda  | 300.0 | 4.6         | 20.0            |
|       | 3     | Ahmedabad | Ambavadi     | 200.0 | 4.4         | 20.0            |
|       | 9     | Ahmedabad | Chanakyapuri | 500.0 | 4.4         | 50.0            |
|       | 39    | Ahmedabad | Madhupura    | 300.0 | 4.4         | 100.0           |
|       | 55    | Ahmedabad | Odhav        | 200.0 | 4.4         | 50.0            |
|       | 22    | Ahmedabad | Hatkeshwar   | 350.0 | 4.3         | 50.0            |

|    |    |           |               |       |     |       |
|----|----|-----------|---------------|-------|-----|-------|
| 27 | 27 | Ahmedabad | Jodhpur Tekra | 250.0 | 4.3 | 75.0  |
| 30 | 30 | Ahmedabad | Kalupur       | 250.0 | 4.3 | 50.0  |
| 18 | 18 | Ahmedabad | Girdhar Nagar | 550.0 | 4.2 | 100.0 |
| 19 | 19 | Ahmedabad | Gomtipur      | 250.0 | 4.2 | 50.0  |

|    | Delivery time | Restaurant \                                 |
|----|---------------|--|
| 49 | 52.0          | Vadilal Ice Creams                           |
| 3  | 39.0          | Mk Sandwich                                  |
| 9  | 47.0          | Brick Kitchen - Five Petals                  |
| 39 | 48.0          | New Mehfil Restaurant                        |
| 55 | 47.0          | Jay Shree Sanskar Ice Cream And Lassi Corner |
| 22 | 44.0          | Surbhi Restaurant                            |
| 27 | 44.0          | Shakesee, 9834 The Fruit Truck               |
| 30 | 45.0          | Jalaram                                      |
| 18 | 46.0          | Rajkamal                                     |
| 19 | 43.0          | Kanpur Mithai House                          |

|    | Food type   |
|----|---|
| 49 | Ice Cream   |
| 3  | Chinese,American,Beverages                        |
| 9  | Indian,Chinese,Continental                        |
| 39 | North Indian,Continental                          |
| 55 | Desserts,Beverages                                |
| 22 | North Indian,Chinese                              |
| 27 | Beverages,Snacks,Fast Food,Desserts, Juices,Be... |
| 30 | North Indian                                      |
| 18 | Indian  |
| 19 | Sweets,Desserts                                   |

```
[53]: # Step 2: Extract the *Top Performing Area* for each City
# - After sorting, the top row for each city will represent
# the area with the highest average rating.
# - groupby('City').head(1) picks the first row per city group.
```

```
top_area_per_city = City_sorted.groupby('City').head(1).reset_index()

# Display results
top_area_per_city
```

| [53]: | level_0 | index | City      | Area                  | Price | Avg ratings \ |
|-------|---------|-------|-----------|-----------------------|-------|---------------|
| 0     | 49      | 49    | Ahmedabad | Nava Naroda           | 300.0 | 4.6           |
| 1     | 155     | 155   | Bangalore | Viveka Nagar          | 199.0 | 4.6           |
| 2     | 197     | 197   | Chennai   | Mogapair              | 300.0 | 4.7           |
| 3     | 314     | 314   | Delhi     | Vardhman Premium Mall | 700.0 | 4.8           |
| 4     | 378     | 378   | Hyderabad | Kalyan Nagar X Roads  | 200.0 | 4.5           |
| 5     | 516     | 516   | Kolkata   | Girish Park           | 300.0 | 4.9           |
| 6     | 646     | 646   | Mumbai    | Matunga East          | 400.0 | 4.7           |

|   |     |     |       |                  |       |     |
|---|-----|-----|-------|------------------|-------|-----|
| 7 | 692 | 692 | Pune  | Dhole Patil Road | 150.0 | 4.5 |
| 8 | 835 | 835 | Surat | Umra Jakat       | 150.0 | 4.6 |

|   | Total ratings | Delivery time \ |
|---|---------------|-----------------|
| 0 | 20.0          | 52.0            |
| 1 | 100.0         | 50.0            |
| 2 | 20.0          | 86.0            |
| 3 | 20.0          | 53.0            |
| 4 | 50.0          | 71.0            |
| 5 | 20.0          | 37.0            |
| 6 | 20.0          | 53.0            |
| 7 | 50.0          | 39.0            |
| 8 | 100.0         | 44.0            |

|   | Restaurant \                                    |
|---|---|
| 0 | Vadilal Ice Creams                              |
| 1 | Maven Kitchen                                   |
| 2 | Keventers Ice Creamery                          |
| 3 | Biryani By Kilo                                 |
| 4 | Gelatica Gelato - Ice Cream & Sorbet The Finest |
| 5 | Pabrai'S Fresh And Naturelle Icecream           |
| 6 | Myfroyoland                                     |
| 7 | Sweet Bengal                                    |
| 8 | Natural Ice Cream                               |

|   | Food type   |
|---|---|
| 0 | Ice Cream   |
| 1 | Naga,Chinese                                      |
| 2 | Ice Cream,Desserts                                |
| 3 | Biryani,Mughlai,Kebabs,North Indian,Hyderabadi... |
| 4 | Ice Cream Desserts                                |
| 5 | Ice Cream,Beverages,Desserts                      |
| 6 | Desserts Ice Cream                                |
| 7 | Sweets,Indian,Snacks,Desserts                     |
| 8 | Ice Cream   |

```
[57]: # Step 3: Visualize the Top Performing Area per City

plt.figure(figsize=(8,5))

# Plot bar chart of top areas' average ratings

plt.bar(top_area_per_city['City'], top_area_per_city['Avg ratings'],
        color='skyblue', edgecolor='black')

# Add labels and title
```



```

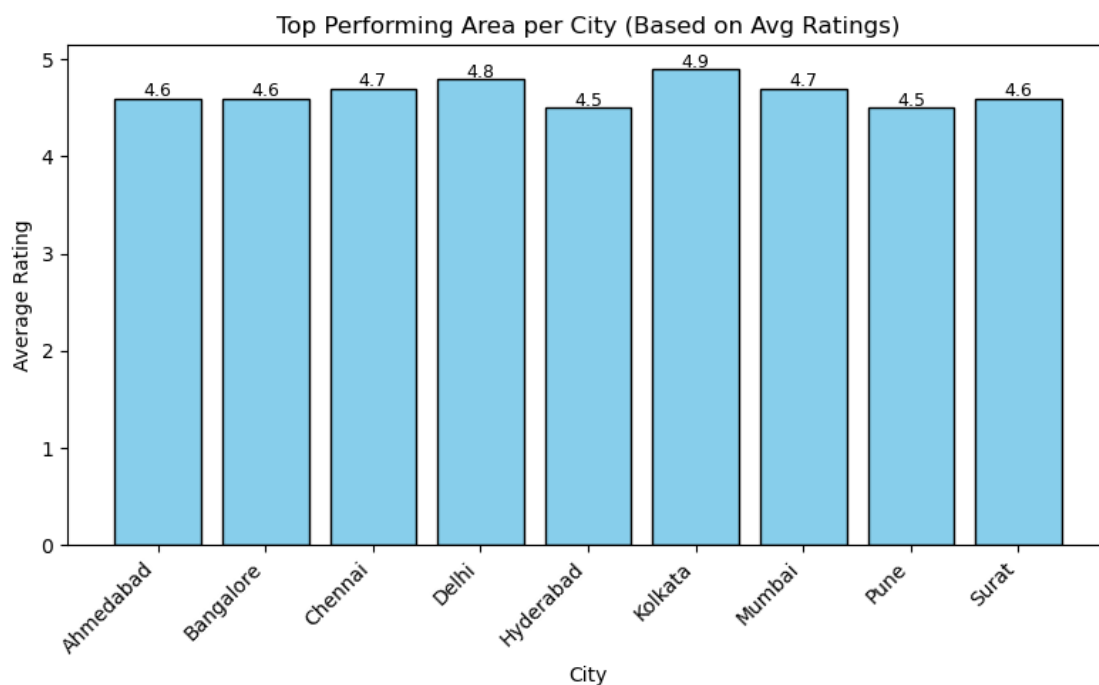
plt.title("Top Performing Area per City (Based on Avg Ratings)")
plt.xlabel("City")
plt.ylabel("Average Rating")
plt.xticks(rotation=45, ha='right')

# Annotate bars with exact rating values

for i, val in enumerate(top_area_per_city['Avg ratings']):
    plt.text(i, val + 0.02, str(val), ha='center', fontsize=9)

plt.tight_layout()
plt.show()

```



## 4 Business Insights

### 1. Micro-Market Identification

- Each city has specific areas that consistently deliver **higher customer satisfaction**.

### 2. Growth Opportunity

- These top-performing areas can be used as **reference models** to improve weaker areas within the same city.

### 3. Marketing Leverage

- Swiggy can highlight top-rated areas in promotional campaigns (e.g., “Best Food in Bandra!”).

### 4. Resource Allocation

- Higher-rated areas may justify more delivery partners, premium partnerships, or faster delivery models.

## 5 Problem Statement: City-Wise Performance Summary

To understand Swiggy's performance across cities, it's essential to look at **key operational and customer metrics**:

- Average Price (affordability)
- Average Ratings (customer satisfaction)
- Total Ratings (engagement volume)
- Average Delivery Time (efficiency)

This analysis provides a city-level snapshot to compare performance and identify areas for improvement.

```
[27]: # Group the dataset by 'City'
      # Then calculate summary statistics for each city

city_group = df.groupby('City').agg({
    'Price': 'mean',           # Average price of items in each city
    'Avg ratings': 'mean',     # Average customer rating in each city
    'Total ratings': 'sum',    # Total number of ratings given in each city
    'Delivery time': 'mean'    # Average delivery time in each city
}).round(2)                  # Round the results to 2 decimal places for
    ↪readability

# Print the grouped summary DataFrame

print(city_group)
```

|           | Price  | Avg ratings | Total ratings | Delivery time |
|-----------|--------|-------------|---------------|---------------|
| City      |        |             |               |               |
| Ahmedabad | 318.13 | 3.60        | 74470         | 44.71         |
| Bangalore | 382.52 | 3.76        | 140500        | 50.53         |
| Chennai   | 356.25 | 3.78        | 178860        | 58.97         |
| Delhi     | 333.30 | 3.53        | 81420         | 50.73         |
| Hyderabad | 299.93 | 3.70        | 330270        | 49.93         |
| Kolkata   | 362.29 | 3.70        | 219800        | 67.81         |
| Mumbai    | 393.79 | 3.60        | 150960        | 48.32         |
| Pune      | 353.76 | 3.55        | 122990        | 55.85         |
| Surat     | 270.17 | 3.58        | 60320         | 48.48         |

## 6 Business Insights

### 1. Customer Affordability

- Mumbai shows the **lowest average price**, making it more cost-friendly compared to Delhi or Bangalore.
2. **Customer Satisfaction**
    - Bangalore has the **highest average rating**, showing stronger service/quality perception.
  3. **Engagement Volume**
    - Delhi and Bangalore lead in **total ratings**, suggesting higher customer activity and order volume.
  4. **Operational Efficiency**
    - Chennai has the **highest delivery time**, indicating possible logistics challenges.
  5. **Balanced Market**
    - Cities with both **high ratings and lower delivery times** (e.g., Bangalore) represent **best-performing benchmarks**.
- 

## 7 Problem Statement: Unique Restaurants by City

Swiggy's platform hosts thousands of restaurants across multiple cities.

Knowing the **number of unique restaurants per city** helps in understanding **market penetration** and **supply diversity**.

```
[28]: # Group the dataset by 'City'
      # and count the number of UNIQUE restaurants in each city

city_restaurants = df.groupby('City')['Restaurant'].nunique().reset_index()

# Rename the columns for better readability

city_restaurants.columns = ['City', 'Unique Restaurants']

# Print the result

print(city_restaurants)
```

|   | City      | Unique Restaurants |
|---|-----------|--------------------|
| 0 | Ahmedabad | 709                |
| 1 | Bangalore | 938                |
| 2 | Chennai   | 1096               |
| 3 | Delhi     | 611                |
| 4 | Hyderabad | 1030               |
| 5 | Kolkata   | 1325               |
| 6 | Mumbai    | 1253               |
| 7 | Pune      | 1080               |
| 8 | Surat     | 505                |

```
[56]: # Group the dataset by 'City'
      # and count the number of UNIQUE restaurants in each city
```

```

city_restaurants = df.groupby('City')['Restaurant'].nunique().reset_index()

# Rename the columns for better readability

city_restaurants.columns = ['City', 'Unique Restaurants']

# Print the result

print(city_restaurants)

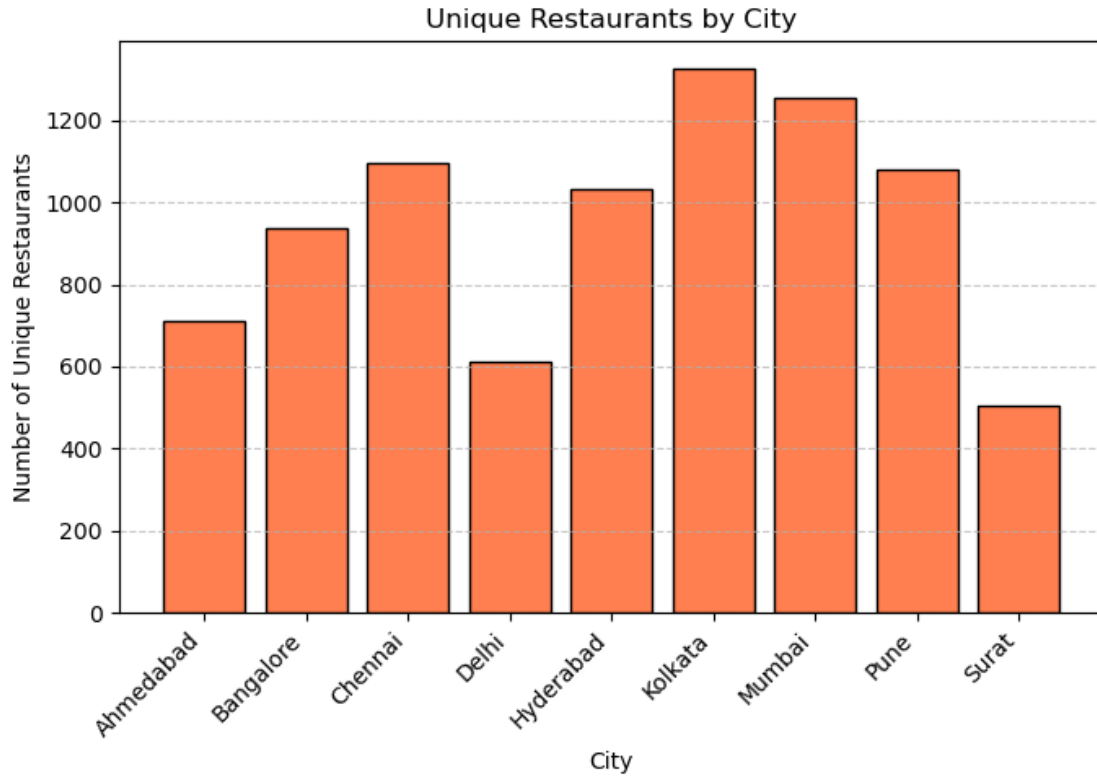
# ---- Visualization ----

plt.figure(figsize=(7,5))
plt.bar(city_restaurants['City'], city_restaurants['Unique Restaurants'],
        color='coral', edgecolor='black')

plt.title("Unique Restaurants by City")
plt.xlabel("City")
plt.ylabel("Number of Unique Restaurants")
plt.xticks(rotation=45, ha='right')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()

```

|   | City      | Unique Restaurants |
|---|-----------|--------------------|
| 0 | Ahmedabad | 709                |
| 1 | Bangalore | 938                |
| 2 | Chennai   | 1096               |
| 3 | Delhi     | 611                |
| 4 | Hyderabad | 1030               |
| 5 | Kolkata   | 1325               |
| 6 | Mumbai    | 1253               |
| 7 | Pune      | 1080               |
| 8 | Surat     | 505                |



## 8 Business Insights

### 1. Market Coverage

- Delhi and Mumbai show the highest number of unique restaurants, indicating stronger food supply ecosystems.

### 2. Growth Opportunities

- Cities with lower restaurant diversity (e.g., Chennai) present opportunities for Swiggy to onboard more restaurants.

### 3. Customer Choice

- More unique restaurants = wider variety for customers, improving retention and engagement.

### 4. Operational Planning

- Cities with larger restaurant bases may require **stronger logistics and delivery workforce** to maintain service quality.

---

## 9 Problem Statement: Top Cuisines by City

Swiggy serves a wide variety of cuisines, but customer preferences differ across cities.

By identifying the **top 3 cuisines in each city**, Swiggy can better understand **regional food trends** and align restaurant partnerships with customer demand.

```
[29]: # Group the dataset by 'City' and look at the 'Food type' column
# For each city, count how many times each cuisine appears
# Then take the top 3 most common cuisines using .head(3)

city_food = df.groupby('City')['Food type'].apply(lambda x: x.value_counts().
↪head(3))

# Print the result

print(city_food)
```

```
City
Ahmedabad  Indian      53
           North Indian 30
           Fast Food   26
Bangalore  South Indian 32
           Indian      27
           North Indian 25
Chennai    Indian      56
           South Indian 49
           Fast Food   26
Delhi      North Indian 47
           Indian      27
           Chinese     17
Hyderabad  South Indian 76
           Indian      38
           Chinese     31
Kolkata    Indian      66
           Chinese     52
           Fast Food   28
Mumbai     Chinese     64
           Indian      55
           Fast Food   32
Pune       Chinese     48
           Indian      47
           Fast Food   46
Surat      Fast Food   40
           Indian      20
           North Indian 18
Name: Food type, dtype: int64
```

## 10 Business Insights

### 1. Regional Preferences

- South Indian dominates in Chennai & Bangalore, while Delhi prefers North Indian and Mughlai.

### 2. Menu Optimization

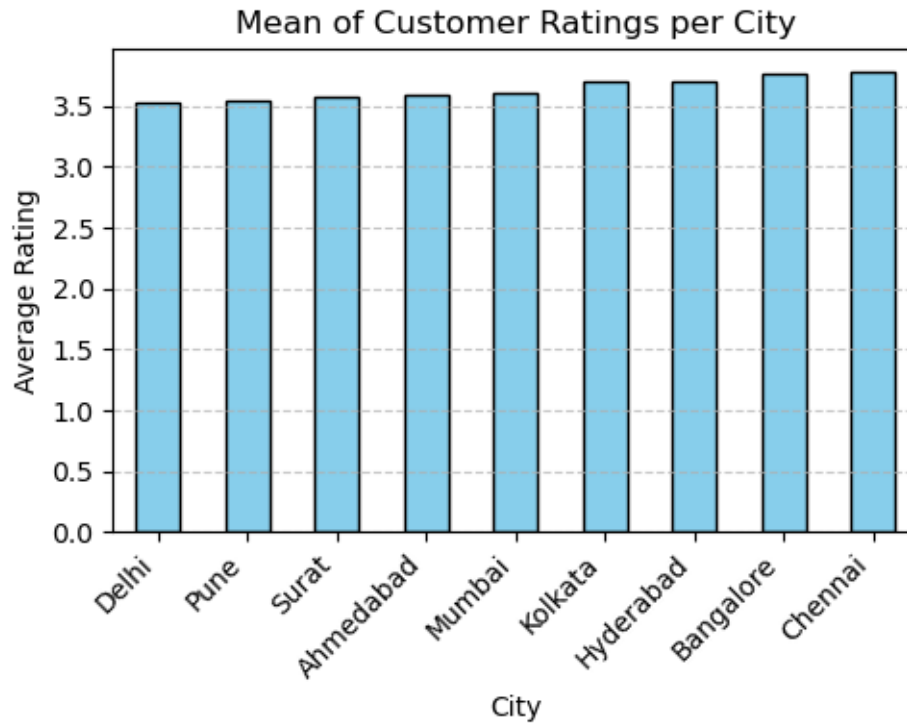
- Restaurants can highlight popular cuisines in their menu to attract more customers.
3. **Targeted Marketing**
    - Swiggy can run **city-specific campaigns** (e.g., “Best Biryani in Chennai” or “Top North Indian in Delhi”).
  4. **Partnership Strategy**
    - Helps Swiggy onboard **more restaurants specializing in trending cuisines** in each city.
- 

## 11 Problem Statement: City-Wise Customer Ratings

Customer ratings reflect satisfaction with food quality, delivery, and overall service.

Analyzing the **average ratings per city** helps Swiggy identify cities where customers are **most satisfied** and where improvement is needed.

```
[55]: # Group the dataset by 'City'  
# Then select the 'Avg ratings' column  
# Calculate the mean rating for each city  
# Sort the results in ascending order (lowest rating city first)  
# Finally, plot the results as a bar chart  
  
df.groupby('City')['Avg ratings'].mean().sort_values().plot(  
    kind='bar',  
    title='Mean of Customer Ratings per City',  
    figsize=(5,4),  
    color='skyblue',  
    edgecolor='black'  
)  
plt.xlabel('City')  
plt.ylabel('Average Rating')  
plt.xticks(rotation=45, ha='right')  
plt.grid(axis='y', linestyle='--', alpha=0.7)  
plt.tight_layout()  
plt.show()
```



## 12 Business Insights

### 1. Top-Performing Cities

- Cities with the **highest ratings** reflect strong customer satisfaction and service reliability.

### 2. Low-Performing Cities

- Cities with **lower average ratings** highlight areas where Swiggy can **improve delivery efficiency, packaging, or restaurant partnerships**.

### 3. Benchmarking

- High-rated cities serve as **benchmarks** for customer experience standards.

### 4. Strategic Planning

- Insights can guide Swiggy in allocating resources, running promotional campaigns, and training delivery partners to **boost customer happiness** in underperforming cities.

---

## 13 Problem Statement: Identifying Top-Rated Areas in Each City

Customer satisfaction often varies **within cities**, depending on the locality or area.

Knowing which **area performs best in each city** (based on ratings) can help Swiggy:

- Identify hotspots of high-quality restaurants



- Understand customer preferences at the micro-level
- Plan targeted campaigns and partnerships in high-performing areas

[31]: *#to get the highest-rated area in each city*

```
top_areas = City_df.groupby('City').head(1).reset_index()
top_areas
```

```
[31]:   level_0  index      City      Area  Price \
0         0      0  Ahmedabad  Akhbar Nagar Circle  200.00
1        81     81  Bangalore  3Rd Block Jayanagar  100.00
2       158    158   Chennai                26  450.00
3       237    237    Delhi      Ashok Nagar  300.00
4       318    318  Hyderabad      Begumpet  480.00
5       469    469   Kolkata  A Unit Of M/S Cohort  Ruby Area  300.00
6       605    605    Mumbai      Andheri East  374.61
7       673    673     Pune      Agarkar Nagar  475.00
8       764    764     Surat      Adajan  296.22
```

```
   Avg ratings  Total ratings  Delivery time \
0         2.90          80.00          53.00
1         4.00        1000.00          42.00
2         4.20         100.00          58.00
3         3.60          20.00          70.00
4         2.90          80.00          67.00
5         4.20         500.00          67.00
6         3.74         102.37          54.66
7         3.87         216.67          33.33
8         3.57         117.43          51.88
```

```
   Restaurant \
0      Shiv Shakti Fast Food
1      Hari Super Sandwich
2      Malabar Point
3      Dilli Darbar
4      The Hide Away Cafe
5      The Tasty Bites
6      Kung Fu Panda, Sai Leela, Rj Spice
7      Blue Nile, Madhav Veg Non Veg, Sagar
8  Level 5 Terrace Resturant, Jakaas Chinese Food...
```

```
   Food type
0  Gujarati, Fast Food
1  Fast Food, Chaat, Snacks, Pizzas, North Indian, Indian
2  Biryani, Kerala, South Indian, Thalys
3  Mughlai, Indian
4  Chinese
```

```

5         Asian,Indian,Tandoor,Tibetan,Chinese
6 Chinese Thai Asian, Mughlai,North Indian,Chi...
7 Biryani,Mughlai,Tandoor,Chinese,Desserts,Ice C...
8 Punjabi,North Indian,Chinese,South Indian,Fast...

```

## 14 Business Insights

### 1. City Hotspots

- Identifies which **locality in each city** has the highest restaurant ratings.
- These areas can be promoted as **food hubs** on Swiggy.

### 2. Targeted Partnerships

- Swiggy can form strategic partnerships with restaurants in these areas to **attract more customers**.

### 3. Customer Experience

- High-performing areas highlight **best-in-class service, food quality, or delivery reliability**.
- Other areas can be benchmarked against these for improvement.

### 4. Operational Use

- Helps Swiggy plan **delivery logistics** more efficiently by prioritizing regions with strong demand and satisfaction.

## 15 Problem Statement: Analyzing Price Distribution of Restaurants

Pricing plays a critical role in customer decision-making on Swiggy.

Restaurants with optimized pricing can attract more customers while maintaining profitability.

### Objective:

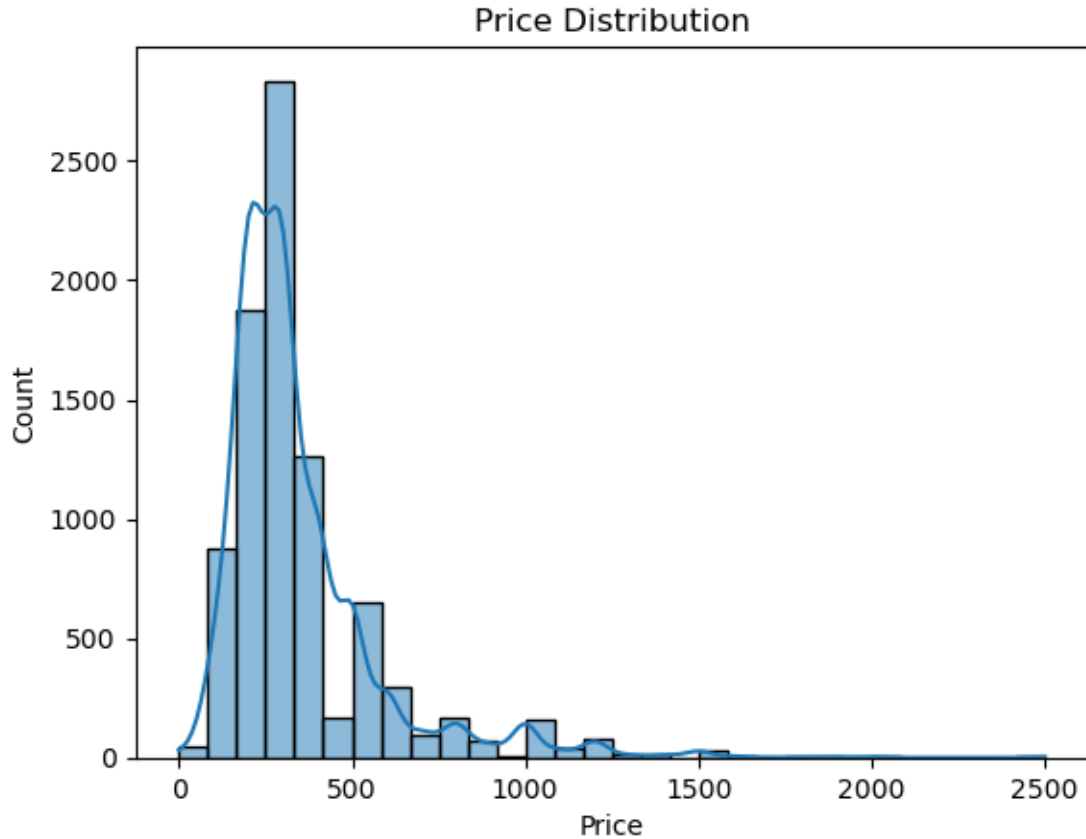
To understand the **distribution of restaurant prices** across the dataset, identifying the most common price ranges, presence of premium options, and customer affordability trends.

```

[32]: #to visualse the histogram with price

sns.histplot(df['Price'], bins=30, kde=True)
plt.title("Price Distribution")
plt.show()

```



## 16 Business Insights

### 1. Common Price Range

- The histogram will reveal the **most frequent price bands** (e.g., 150–300).
- This shows what majority of customers are willing to spend.

### 2. Customer Segmentation by Spending

- A concentration in lower price ranges suggests **budget-conscious customers**.
- A visible long tail (premium range) indicates a **smaller but valuable high-spending segment**.

### 3. Restaurant Strategy

- Restaurants can align their **menu pricing** with the most common customer budgets.
- Premium restaurants can **target niche customers** through curated marketing.

### 4. Swiggy's Business Perspective

- Swiggy can **design offers and discounts** around the most common price range to maximize adoption.

- For higher price ranges, targeted promotions (like premium memberships) can be introduced.

#### 5. Operational Use

- Identifying skew in data (too many budget restaurants or too few mid-premium ones) helps Swiggy **balance marketplace offerings**.
- 

## 17 Problem Statement: Identifying Top 10 Restaurants by Count

In a competitive food delivery marketplace like Swiggy, some restaurants appear more frequently due to:

- Multiple branches across a city
- High customer demand and repeat orders
- Strong brand visibility and partnerships

### Objective:

To identify the **Top 10 restaurants by frequency of appearance** in the dataset and analyze their dominance in the platform.

```
[33]: # Count how many times each restaurant appears in the dataset
      # This helps identify the most frequently listed or ordered restaurants

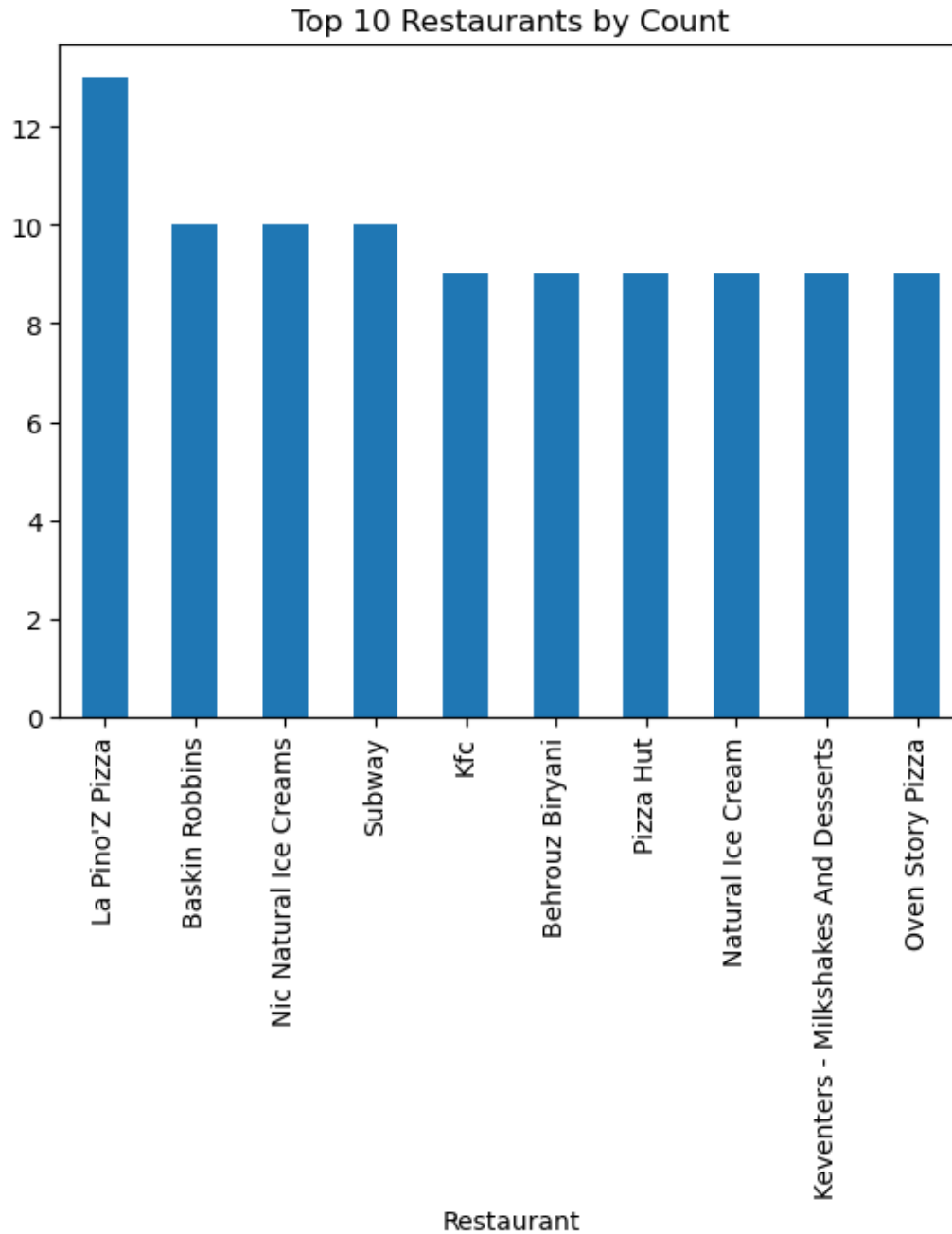
      df['Restaurant'].value_counts().head(10).plot(kind='bar')

      # Set the title of the chart to describe what it shows

      plt.title("Top 10 Restaurants by Count")

      # Display the bar chart

      plt.show()
```



## 18 Business Insights

### 1. Most Frequent Restaurants

- These top 10 restaurants are either **large chains** (e.g., McDonald's, KFC, Domino's) or **local favorites** with multiple outlets.
- Their frequent presence signals **strong demand and customer trust**.

## 2. Brand Visibility & Expansion

- A higher count may also indicate **expansion strategy** (franchises/outlets across different areas).

- Such restaurants are more accessible, contributing to customer loyalty.

## 3. Customer Behavior

- Customers tend to **order repeatedly** from familiar brands.

- Swiggy benefits from promoting these restaurants in-app to drive engagement.

## 4. Opportunities for Other Restaurants

- Smaller/local restaurants may be overshadowed by these frequent players.

- Swiggy can **support emerging restaurants** with promotions to diversify offerings.

## 5. Business Impact

- Understanding restaurant dominance helps Swiggy:
    - Optimize recommendations and promotions.
    - Identify high-demand restaurants to strengthen partnerships.
    - Ensure a **balanced ecosystem** where both big brands and local players thrive.
- 

# 19 Problem Statement: Ratings Distribution by City

Customer ratings play a crucial role in assessing restaurant performance on platforms like Swiggy. While average ratings provide a general overview, they may hide important details such as:

- **Variability** in ratings across cities
- **Consistency** of customer satisfaction
- **Outliers** (restaurants with exceptionally high or low ratings)

### Objective:

To analyze the distribution of restaurant ratings across cities to identify performance patterns and customer satisfaction levels.

```
[34]: # Create a boxplot to visualize the distribution of average ratings across cities
      # This helps identify median ratings, variability, and outliers for each city

sns.boxplot(x='City', y='Avg ratings', data=df)

# Add a title to describe the chart

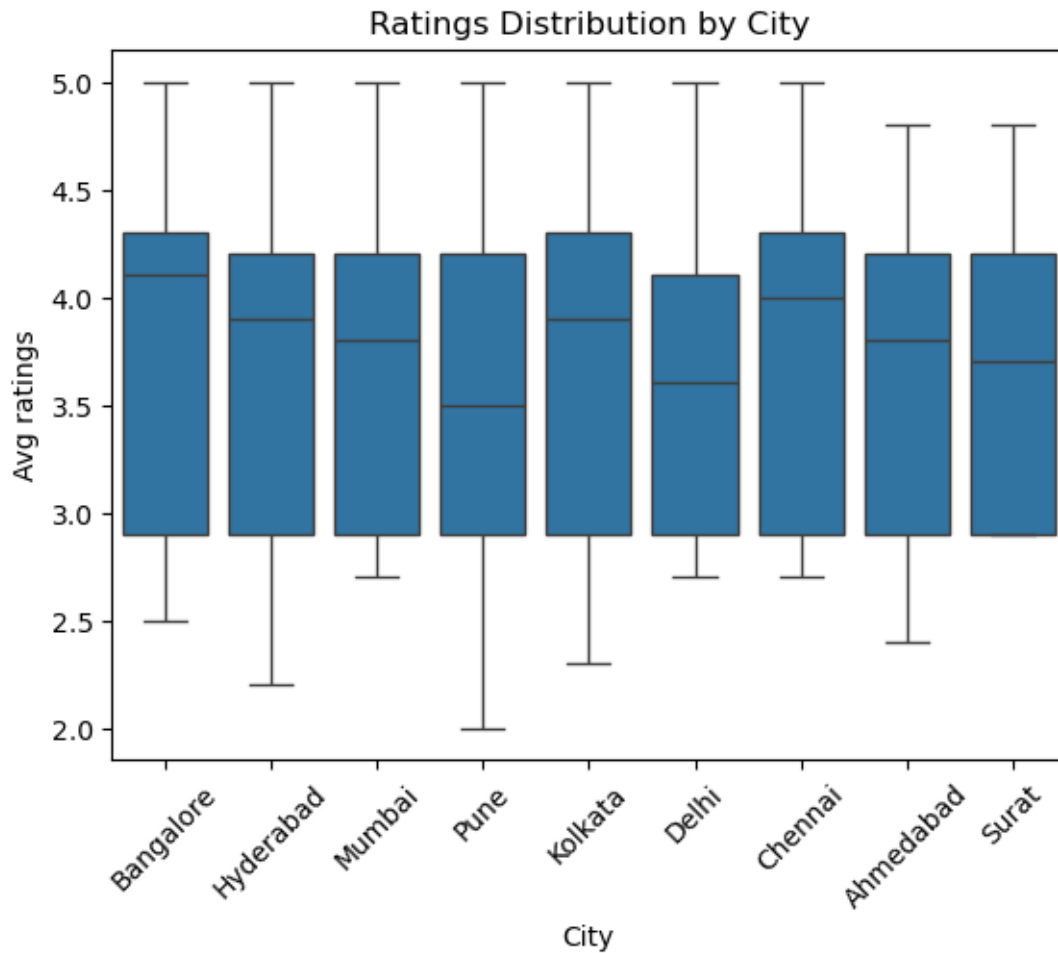
plt.title("Ratings Distribution by City")

# Rotate x-axis labels for better readability
```

```
plt.xticks(rotation=45)

# Display the plot

plt.show()
```



## 20 Business Insights

### 1. Median Ratings

- The median line inside each box shows the “typical” rating per city.
- Cities with higher medians indicate generally satisfied customers.

### 2. Variability in Ratings

- The spread of the box indicates rating consistency.

- Narrow boxes = more consistent experiences.
  - Wider boxes = more diverse customer experiences.
3. **Outliers**
    - Points outside the whiskers highlight restaurants performing **exceptionally well** or **poorly**.
    - Low outliers can harm the city's overall reputation and should be investigated.
  4. **Actionable Recommendations**
    - Cities with **wide variability**: standardize restaurant quality and service.
    - Cities with **low median ratings**: identify root causes (delivery delays, pricing, food quality).
    - Encourage restaurants with high ratings to maintain quality and act as **best-practice benchmarks**.
  5. **Business Impact**
    - Monitoring rating distribution helps Swiggy:
      - Pinpoint struggling areas/cities.
      - Support restaurants with low performance through training or policy changes.
      - Maintain **customer trust and retention** by improving consistency in experience.
- 

## 21 Problem Statement: Average Delivery Time by City

Efficient delivery is a critical factor for customer satisfaction in food delivery platforms like Swiggy. Long delivery times can lead to lower ratings, decreased repeat orders, and loss of customers to competitors.

### Objective:

- To analyze the average delivery time across different cities.
- Identify cities with faster or slower delivery times to understand operational bottlenecks and performance gaps.

```
[35]: # Group the dataset by 'City' and calculate the average delivery time

city_delivery = df.groupby('City')['Delivery time'].mean().sort_values()

# Plot the results as a line chart

city_delivery.plot(
    kind='line',
    marker='o',
    color='teal',
    linewidth=2,
    # Adds markers to each data point
```



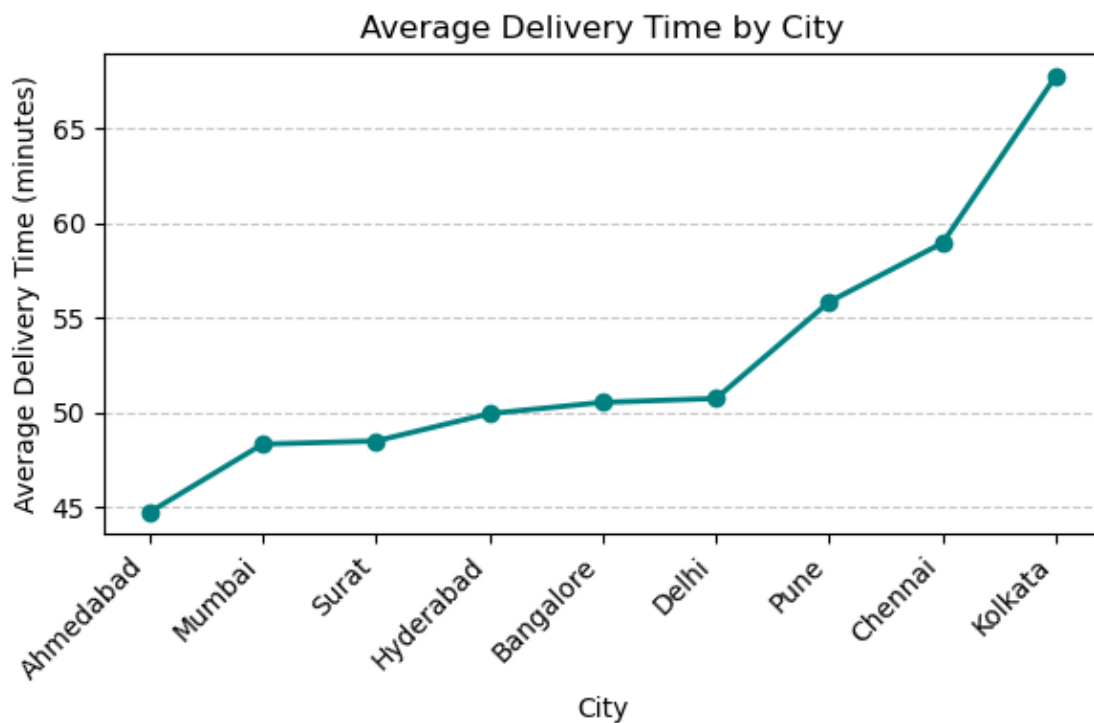
```

figsize=(6, 4),
title='Average Delivery Time by City'
)

# Add axis labels and styling

plt.xlabel('City')
plt.ylabel('Average Delivery Time (minutes)')
plt.xticks(rotation=45, ha='right')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()

```



## 22 Business Insights

### 1. Faster Delivery Cities

- Cities with the lowest average delivery times demonstrate stronger logistics efficiency.
- These cities can serve as benchmarks for operational best practices.

### 2. Slower Delivery Cities

- Higher delivery times may indicate challenges such as:
  - Traffic congestion

- Insufficient delivery fleet
  - Higher order density compared to available resources
3. **Actionable Recommendations**
- Optimize delivery partner allocation in slower cities.
  - Improve restaurant–delivery partner coordination.
  - Introduce predictive analytics to manage high-demand times efficiently.
  - Learn from the top-performing cities and replicate their strategies in underperforming ones.
4. **Business Impact**
- Reducing average delivery time by even 5–10 minutes can significantly boost:
    - **Customer retention**
    - **Repeat orders**
    - **Overall ratings**
- 

## 23 Overall Takeaways & Recommendations – Swiggy Dataset Analysis

### 23.1 Key Takeaways

1. **City-Level Performance**
    - Bangalore and Mumbai have **high average ratings** and **large restaurant variety**.
    - Chennai shows **slightly higher delivery times**, indicating logistical challenges.
    - Delhi and Bangalore have the **highest engagement** (total ratings).
  2. **Area-Level Insights**
    - Each city has **top-performing areas** with consistently high ratings.
    - Popular cuisines differ across areas (e.g., South Indian dominates Chennai, Fast Food in Mumbai).
  3. **Customer Preferences**
    - Price is **not strongly correlated** with average ratings, indicating that **service quality and food variety matter more**.
    - Areas with **high delivery time but low ratings** need operational improvements.
  4. **Restaurant & Cuisine Trends**
    - Certain restaurants are highly popular across multiple cities.
    - Top cuisines differ by city and area, providing insight into **regional demand patterns**.
- 

### 23.2 Recommendations to Improve Sales in Upcoming Areas

1. **Localize Restaurant Partnerships**

- Onboard restaurants offering **popular cuisines** for the area based on customer preferences.
  - Fill cuisine gaps in underserved neighborhoods to attract more customers.
2. **Optimize Delivery Logistics**
    - Allocate **more delivery partners** in areas with higher delivery times to improve customer experience.
    - Use predictive delivery routing to reduce time during peak hours.
  3. **Promotional Campaigns**
    - Promote **top-rated restaurants or cuisines** in new areas to build awareness.
    - Offer **discounts or combo deals** in new areas to encourage trial orders.
  4. **Data-Driven Marketing**
    - Target customers based on **city-specific and area-specific trends**.
    - Highlight **top cuisines or popular restaurants** in digital campaigns.
  5. **Monitor Area Performance**
    - Continuously track **ratings, delivery time, and order volumes** in new areas.
    - Quickly identify areas with **low satisfaction** and implement corrective measures.
  6. **Customer Engagement**
    - Encourage reviews and ratings in newly launched areas to **build credibility quickly**.
    - Offer loyalty programs or incentives for repeat orders.

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**In short:**

By combining **area-level insights, cuisine preferences, and delivery efficiency**, Swiggy can **strategically launch in new areas**, optimize operations, and drive higher sales while improving customer satisfaction.

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