

Zomato Dataset Analysis

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Introduction or Project Overview

This project analyzes a large Zomato restaurant dataset for Bengaluru city to extract actionable insights about the local foodservice industry. We process and visualize over 50,000 restaurant listings to identify patterns in cuisine preferences, pricing, service offerings, and geographical distribution. By employing Python-based data science techniques (such as data cleaning, exploratory analysis, and visualization), the project highlights trends that can guide customers and businesses. The analysis aims to reveal how factors like location, cuisine type, and available services (e.g. online delivery or table booking) influence customer ratings and popularity in Bengaluru.

Problem Statement

Bengaluru's dining scene is diverse and rapidly growing, but understanding it quantitatively is challenging due to the volume and complexity of the data. Key questions — such as which neighborhoods have the most or best-rated restaurants, which cuisines dominate customer demand, and how pricing relates to popularity — are difficult to answer without systematic analysis. Customers lack clear guidance on finding affordable, high-quality dining options, and restaurant owners need data-driven insights to make strategic decisions about menus, pricing, and services. This project addresses these challenges by transforming raw restaurant listings into clear, data-driven observations. We systematically analyze the Zomato dataset to uncover trends that help stakeholders make informed choices.

Overview of the Dataset used

1. **Scope:** The dataset contains over 50,000 restaurant entries in Bengaluru, India, spanning 17 columns of information. Each row represents a unique Zomato-listed restaurant in the city.
2. **Location Data:** Key fields include the restaurant's *name*, *address*, *locality*, and *city*. The dataset focuses specifically on Bengaluru's neighborhoods.
3. **Service Availability:** Attributes such as *online_order* and *book_table* indicate whether each restaurant offers online delivery or accepts reservations. These binary fields help distinguish service options available to customers.
4. **Cuisine and Cost:** The *cuisines* column lists the cuisine types served (e.g., North Indian, Chinese). There is also an *approximate cost for two* field (in Indian rupees), allowing analysis of price ranges across restaurants.
5. **Ratings and Popularity:** Each entry includes an aggregated *rating* (on a numerical scale) and the number of *votes* (user reviews). These metrics serve as proxies for customer satisfaction and restaurant popularity.
6. **Restaurant Type and Other Features:** Additional columns capture *restaurant type* (e.g., casual dining, cafe, quick bites) and other service details. Some entries also list popular *dishes* or provide links (e.g., menu URLs, phone numbers), though these were secondary for our analysis.
7. **Data Source:** This publicly available dataset (from Zomato/Kaggle) provides a comprehensive, real-world snapshot of Bengaluru's restaurant landscape suitable for exploratory analysis and modeling.

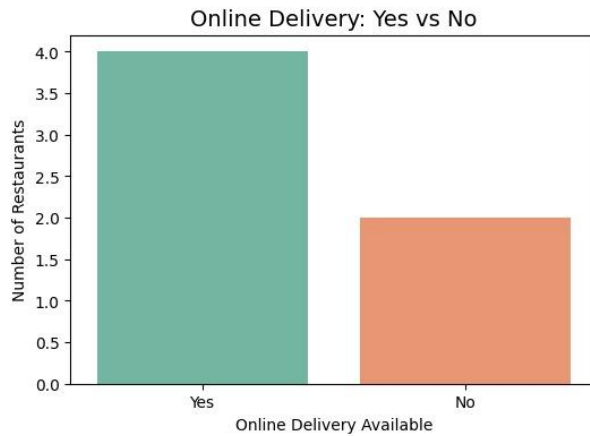
Project Workflow

1. **Data Ingestion and Preprocessing:** We loaded the Zomato CSV dataset into Python (using Pandas) and performed an initial exploration of its structure. This involved verifying row and column counts and separating variables into categorical (e.g. *cuisines*, *online_order*) and numeric (e.g. *votes*). We cleaned the data by handling missing values (for example, imputing or removing entries without key information), removing duplicate records, and renaming columns for clarity. In particular, we standardized formats for columns like *approx_cost* (converted from strings to numeric values) and parsed ratings (cleaning entries such as “3.5/5” into a numeric scale). This step ensured the dataset was consistent and ready for analysis.
2. **Exploratory Data Analysis (EDA):** With a clean dataset, we conducted statistical summaries and visual explorations of major features. We calculated descriptive statistics (means, counts, distribution ranges) for numerical fields like cost and ratings. We then created visualizations to uncover patterns: bar charts and pie charts compared the count of restaurants offering online delivery versus those not, and those allowing table booking versus those that do not. We also examined how table-booking availability relates to ratings. Location-wise, we used bar plots to show the number of restaurants by locality and identified the areas with the highest concentration of establishments. We grouped data to analyze distributions across *restaurant types* (casual dining, cafes, fast food, etc.) and plotted rating distributions to understand customer satisfaction trends. Histograms of *approximate cost* illustrated the overall price range distribution. These EDA steps revealed where restaurants cluster, which services are common, and how basic features (like cost and rating) vary across the dataset.
3. **Cuisine and Cost Analysis:** We delved deeper into customer-centric factors by analyzing cuisines and pricing. Using string parsing on the *cuisines* column, we identified the most popular cuisine categories and common cuisine pairings (for example, how often North Indian cuisine is paired with Chinese, given both are frequently listed together). We found that North Indian and Chinese cuisines dominate the offerings in the dataset. We also examined the *approximate cost* metric in context: for example, grouping restaurants into low-, medium-, and high-priced brackets (e.g., ₹300–₹800 being mid-range). Within each price bracket, we calculated average ratings and vote counts. This allowed us to identify value-for-money restaurants (those with high ratings but relatively low cost) and to check whether mid-priced venues tend to attract more customer votes compared to luxury outlets. Such analysis helps highlight affordable yet highly-regarded options and shows how price correlates with popularity.

4. **Service Features and Chain Analysis:** We investigated how operational features affect restaurant performance. An important finding was that restaurants offering online delivery or table booking generally earn higher ratings and vote counts, suggesting these services positively impact customer satisfaction. We quantified this by comparing average ratings of restaurants with and without these features. Additionally, we analyzed the presence of major restaurant chains across Bengaluru. By filtering names, we identified that popular chains such as *Domino's Pizza*, *McDonald's*, and *Café Coffee Day* appear frequently in the dataset. We examined these chains' average ratings and vote counts; their widespread presence and high vote totals indicate strong market penetration. This step of the workflow a business perspective, showing that established chains consistently perform well and that mid-priced chains tend to accumulate more customer feedback than standalone luxury venues.
5. **Geographical Insights:** To capture spatial patterns, we employed geographical visualization. Using libraries like Plotly and Folium, we plotted restaurant locations on a map of Bengaluru. These interactive maps visualized restaurant density and overlaid performance metrics (such as average rating or vote count by area). From this mapping, we identified hotspots of premium dining — for example, neighborhoods like *Koramangala* and *Indiranagar* emerged as high-density areas for well-rated restaurants. We also observed that tier-2 or suburban localities tend to have lower average costs for two (suggesting more affordable dining) compared to central urban areas. Additionally, we visualized cuisine distribution by area: for instance, South Indian cuisine dominates in certain localities (often near traditional centers), whereas fast-food outlets are widespread around student-populated regions. These geographic analyses complement the statistical results by showing *where* certain trends occur, revealing the city zones that are underserved or saturated in various categories.
6. **Validation and Use Cases (Findings Interpretation):** Finally, we synthesized the findings and considered their implications. The patterns uncovered (e.g., popular cuisines, pricing tiers, service impact) were evaluated for logical consistency and relevance. We discussed potential use cases: for instance, entrepreneurs could use the insights to decide where to open a new restaurant and what type of cuisine to offer based on demand hotspots. We also noted limitations: the analysis is based on a static snapshot of Zomato listings, so it may not capture very recent changes or user reviews outside the dataset. Moreover, unlisted or new establishments are not represented. We flagged these as areas for future improvement (such as integrating live Zomato API data or extending the study to other cities). By reflecting on these considerations, we ensured the workflow not only performs the computations but also frames the results in practical and ethical context.

Results

1. **Distribution by Location:** We found that a large proportion of restaurants are concentrated in central and high-density neighborhoods of Bengaluru. Major commercial and residential hubs host the majority of listings, while peripheral areas have fewer restaurants. Notably, Koramangala and Indiranagar stood out as prime dining districts with a high density of top-rated establishments.
2. **Service Offerings:** Over half of the restaurants in the dataset provide **online delivery**, whereas significantly fewer offer **table reservations**. Restaurants with delivery and booking services tend to have higher average ratings and vote counts, indicating these features enhance customer satisfaction and popularity.
3. **Cuisine Popularity:** Analysis of the cuisines column showed that **North Indian** and **Chinese** cuisines are the most commonly offered, reflecting broad local demand. Combinations of cuisines (e.g. “North Indian, Chinese”) are also frequent. South Indian and continental cuisines appear regularly as well, but North/Chinese jointly dominate the market.
4. **Pricing Patterns:** The *approximate cost for two* is mostly in the moderate range (around ₹300–₹800), suggesting that Bengaluru’s restaurant market caters primarily to mid-budget diners. Few restaurants fall into very low-cost or very high-cost extremes. Within each price segment, we saw that mid-priced restaurants generally accumulated more customer votes than upscale eateries, implying greater volume of patronage. We also identified *value-for-money* restaurants by cross-referencing low cost and high rating, highlighting affordable gems that rank highly.
5. **Ratings and Popularity:** A clear positive trend emerged between customer votes and ratings: higher-rated restaurants typically have more votes. This consistency suggests that popular consensus aligns with numeric ratings, validating the reliability of the rating system. Fast-food and casual dining venues (including major chains) often appear at the top in both votes and ratings, due to their large customer base.
6. **Restaurant Types and Chains:** **Casual dining** and quick-service restaurants are the most common types. Among them, well-known chains like **Domino’s Pizza**, **McDonald’s**, and **Café Coffee Day** feature prominently across neighborhoods. These chains collectively command a large share of customer reviews, indicating their strong presence. The analysis also showed that restaurants providing multiple services (e.g. home delivery and dine-in) tend to be more popular than single-service outlets.
7. **Key Insight Summary:** In summary, Bengaluru’s dining trends include a concentration of restaurants in urban hubs, a preference for North Indian and Chinese food, a mid-range price point for most eateries, and a strong link between service offerings and higher ratings. These findings provide a quantitative overview of the city’s restaurant landscape and can guide further strategic decisions.



Online Delivery Availability (%):

online_order

Yes 66.666667

No 33.333333

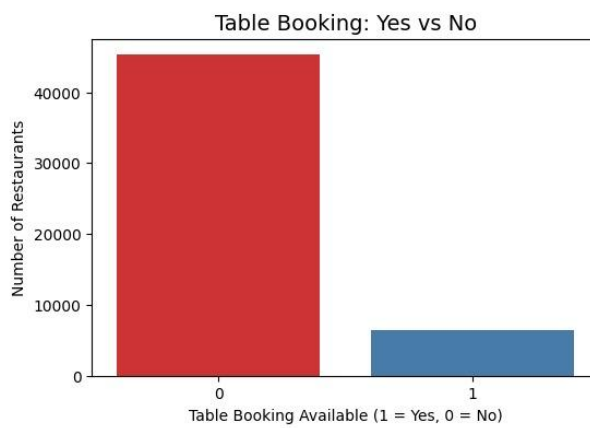


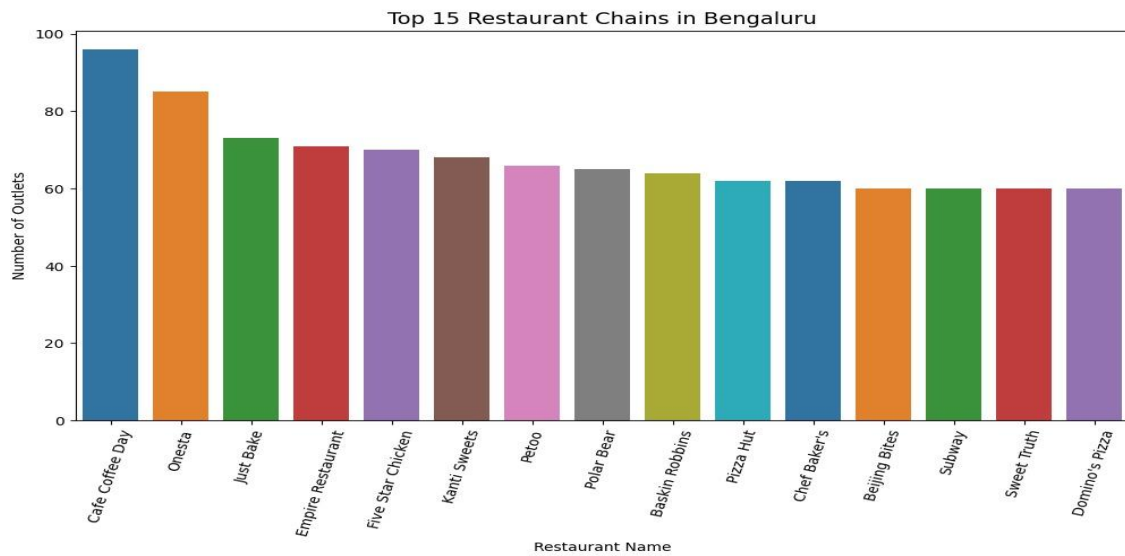
Table Booking Availability (%):

book_table

0 87.530213

1 12.469787





A scatter plot titled 'Relation Between Location Popularity and Ratings' showing the relationship between the number of restaurants and the average rating in various Bangalore neighborhoods. The x-axis represents the 'Number of Restaurants' (ranging from 1000 to 5000), and the y-axis represents the 'Average Rating' (ranging from 3.6 to 4.0). The data points are labeled with neighborhood names.

Location	Number of Restaurants (approx.)	Average Rating (approx.)
Koramangala 5th Block	2500	3.98
Koramangala 7th Block	1200	3.83
Koramangala 6th Block	1250	3.77
Indiranagar	2100	3.81
Jayanagar	1950	3.77
Brigade Road	1250	3.70
Koramangala 1st Block	1300	3.70
JP Nagar	2250	3.68
HSR	2550	3.68
Whitefield	2150	3.64
Marathahalli	1850	3.58
Electronic City	1300	3.56
Bannerghatta Road	1650	3.55
BTM	5150	3.60



Conclusion

This project demonstrates how a real-world restaurant dataset can be cleaned, explored, and analyzed to extract actionable insights. By systematically processing the Zomato listings for Bengaluru using Python tools, we have bridged the gap between raw data and operational knowledge in the food industry. The analysis highlights that customers seeking value can focus on mid-priced, high-rated restaurants (often offering delivery services), and it reveals which cuisines and neighborhoods dominate the market. Customers can use these insights to discover affordable, top-rated dining options and popular cuisine pairings. Restaurant owners and investors can leverage the findings to refine menus, set competitive pricing, and choose strategic locations (for example, by identifying underserved localities). Identified market trends (such as emerging cuisine demands and price sensitivities) also suggest opportunities for new restaurant ventures in high-demand areas. Limitations of the study include its reliance on a static dataset for one city and the absence of real-time user feedback. Future work could integrate live data (e.g. via the Zomato API) and build predictive models (such as machine learning classifiers for restaurant success factors) to further enhance decision support. Overall, the project illustrates the value of data-driven analysis in the hospitality sector, providing a transparent approach that can adapt and extend to other cities or industries.

GitHub Link

Access the dashboard and source code:

<https://github.com/21anubhav/Zomato-EDA>

https://github.com/Arora-Yash-coder/mca308/tree/main/zomato_eda