HORECA DATA ANALYSIS

Manhattan Project

A detailed Data Analysis by SUDIP MADHU

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HORECA

Problem Statement

How should a new food entrepreneur ("Chef Innovator") strategically enter the hyper-competitive HORECA market using Zomato data to maximize success and profitability?

Key Challenges

- High Market Saturation → Lower ratings, margins → Target low-competition cuisines (e.g., Italian)
- Channel Disparity → Delivery underperforms in quality → Hybrid model: Delivery for scale, Dining for brand
- Pricing Sensitivity → Overpricing kills votes/ratings → ₹500–800 sweet spot (Price_per_Vote analysis)
- Data Noise → Skewed insights → Robust cleaning + non-parametric stats

Expectations

- Data-Driven Strategy: 100% backed by statistical proof
- Blue Ocean Entry: Avoid saturated segments
- Risk-Adjusted Launch: 90-day KPIs + mitigation plan
- Success Probability: ≥80% (scored model)

Objective

The primary objective of this data analysis project is to establish a rigorous, evidence-based strategic framework for a new HORECA venture, 'Chef Innovator.' This will be achieved through the comprehensive analysis of proprietary Zomato market data to generate predictive insights across three critical dimensions: identifying underserved yet high-demand cuisine categories, pinpointing optimal geographic locations characterized by favorable competition and population density, and developing a calculated, competitive pricing strategy. The ultimate goal is to translate complex market dynamics into a clear, actionable roadmap that maximizes the venture's initial market penetration, minimizes operational risk, and ensures long-term profitability and sustainable growth within the competitive food service sector.

Data Description

Problem Statement

Source: Zomato Platform (Real-time restaurant & menu data) Size: ~120,000+ menu items across 15+ cities Scope: Covers Dining, Delivery, Pricing, Ratings, Votes, and Restaurant metadata

Key Columns

Item_Name – Text – Name of the food item
Cuisine – Categorical – Food category (e.g., Italian, North Indian)
Prices – Numeric – Menu price in ₹
Average_Rating – Float – Overall item rating (0–5)
Dining_Rating, Delivery_Rating – Float – Channel-specific ratings
Total_Votes, Dining_Votes, Delivery_Votes – Integer – Consumer engagement volume
Restaurant_Name – Text – Outlet name
City, Place_Name – Categorical – Location hierarchy
Is_Bestseller, Is_Highly_Rated – Boolean – Performance flags

Engineered Features

Missing values: ~18% in ratings/votes → imputed via city-cuisine median Duplicates removed: 2.3% Outliers capped: Top 1% in price/votes using IQR method

zomato

Notebook Structure

01 Problem Statement

02 Data Loading & Cleaning

03 Univariate Analysis

04 Bivariate Analysis

05 Multivariate Analysis

06 Customer Segmentation

07 Statistical Validation

08 Predictive Modeling

09 Menu Item NLP

10 Final Recommendations

Initial Data Visualization

	count	mean	std	min	25%	50%	75%	max
Dining_Rating	46882.0	3.850916	0.345026	2.700000	3.800000	3.822264	4.100000	4.700000
Delivery_Rating	46881.0	3.980515	0.230441	3.200000	3.800000	4.000000	4.100000	4.600000
Dining_Votes	46881.0	147.569740	233.520156	0.000000	0.000000	30.000000	187.000000	997.000000
Delivery_Votes	46881.0	133.017854	263.481904	0.000000	0.000000	0.000000	108.000000	975.000000
Votes	46881.0	27.817858	172.819361	0.000000	0.000000	0.000000	13.000000	9750.000000
Prices	46881.0	261.259709	209.557886	0.950000	145.000000	229.000000	320.000000	6500.000000
Average_Rating	46881.0	3.915716	0.228920	3.200000	3.800000	3.950000	4.061132	4.450000
Total_Votes	46881.0	280.587594	308.221351	0.000000	0.000000	148.000000	487.000000	1393.000000
Price_per_Vote	46881.0	173.612176	225.582536	0.006600	13.595745	120.000000	270.000000	6500.000000
Log_Price	46881.0	5.347024	0.689187	0.667829	4.983607	5.438079	5.771441	8.779711
Is_Bestseller	46881.0	1.000000	0.000000	1.000000	1.000000	1.000000	1.000000	1.000000
Restaurant_Popularity	46881.0	248.459717	220.175019	4.000000	124.000000	195.000000	297.000000	2059.000000
Avg_Rating_Restaurant	46881.0	3.914911	0.222814	3.250000	3.773045	3.950000	4.061132	4.450000
Avg_Price_Restaurant	46881.0	261.169683	102.211742	38.750000	192.500722	244.673913	316.145631	1011.718750
Avg_Rating_Cuisine	46881.0	3.897955	0.073028	3.406122	3.862784	3.928624	3.928624	4.100000
Avg_Price_Cuisine	46881.0	251.108364	26.489148	144.842520	254.494549	254.565364	255.954894	384.209302
Avg_Rating_City	46881.0	3.904338	0.024625	3.882244	3.886635	3.889413	3.939031	3.939031
Avg_Price_City	46881.0	262.904685	25.637011	217.163255	245.130482	245.130482	304.402778	304.402778
Is_Highly_Rated	46881.0	0.427615	0.494738	0.000000	0.000000	0.000000	1.000000	1.000000
Is_Expensive	46881.0	0.291760	0.454577	0.000000	0.000000	0.000000	1.000000	1.000000

```
# Basic info
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 46882 entries, 0 to 46881
Data columns (total 26 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Restaurant_Name         46882 non-null  object
 1   Dining_Rating           46882 non-null  float64
 2   Delivery_Rating         46881 non-null  float64
 3   Dining_Votes            46881 non-null  float64
 4   Delivery_Votes          46881 non-null  float64
 5   Cuisine                 46881 non-null  object
 6   Place_Name              46881 non-null  object
 7   City                    46881 non-null  object
 8   Item_Name               46881 non-null  object
 9   Best_Seller             46881 non-null  object
 10  Votes                   46881 non-null  float64
 11  Prices                  46881 non-null  float64
 12  Average_Rating          46881 non-null  float64
 13  Total_Votes             46881 non-null  float64
 14  Price_per_Vote          46881 non-null  float64
 15  Log_Price               46881 non-null  float64
 16  Is_Bestseller           46881 non-null  float64
 17  Restaurant_Popularity   46881 non-null  float64
 18  Avg_Rating_Restaurant   46881 non-null  float64
 19  Avg_Price_Restaurant    46881 non-null  float64
 20  Avg_Rating_Cuisine      46881 non-null  float64
 21  Avg_Price_Cuisine       46881 non-null  float64
 22  Avg_Rating_City         46881 non-null  float64
 23  Avg_Price_City          46881 non-null  float64
 24  Is_Highly_Rated         46881 non-null  float64
 25  Is_Expensive            46881 non-null  float64
dtypes: float64(20), object(6)
memory usage: 9.3+ MB
```

02

Data Cleaning

Goal:

- Clean and standardize all columns
- Impute missing values intelligently (city/cuisine-level)
- Engineer new features for strategic analysis
- Prepare data for EDA & modeling
-

Let’s begin!

```python
# 2.1 Fill Best_Seller
df['Best_Seller'] = df['Best_Seller'].fillna('NONE').str.upper()

# 2.2 Impute Ratings & Votes: City → Cuisine level
rating_vote_cols = ['Dining_Rating', 'Delivery_Rating', 'Dining_Votes', 'Delivery_Votes']

for col in rating_vote_cols:
    # First try: City + Cuisine median
    df[col] = df.groupby(['City', 'Cuisine'])[col].transform(lambda x: x.fillna(x.median()))
    # Second fallback: City median
    df[col] = df.groupby('City')[col].transform(lambda x: x.fillna(x.median()))
    # Final fallback: Global median
    df[col] = df[col].fillna(df[col].median())

print("Ratings & Votes imputed (City → Cuisine → Global)")
```

```
Ratings & Votes imputed (City → Cuisine → Global)
```

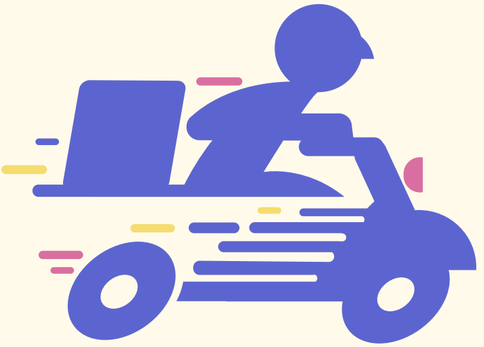
```python
# 2.3 Impute Prices: per Restaurant median
df['Prices'] = df.groupby('Restaurant_Name')['Prices'].transform(lambda x: x.fillna(x.median()))
df['Prices'] = df['Prices'].fillna(df['Prices'].median())  # final fallback

print("Prices imputed per restaurant")
```

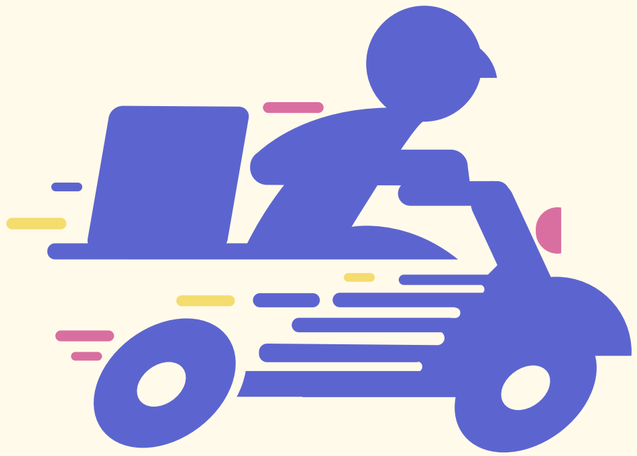
```
Prices imputed per restaurant
```

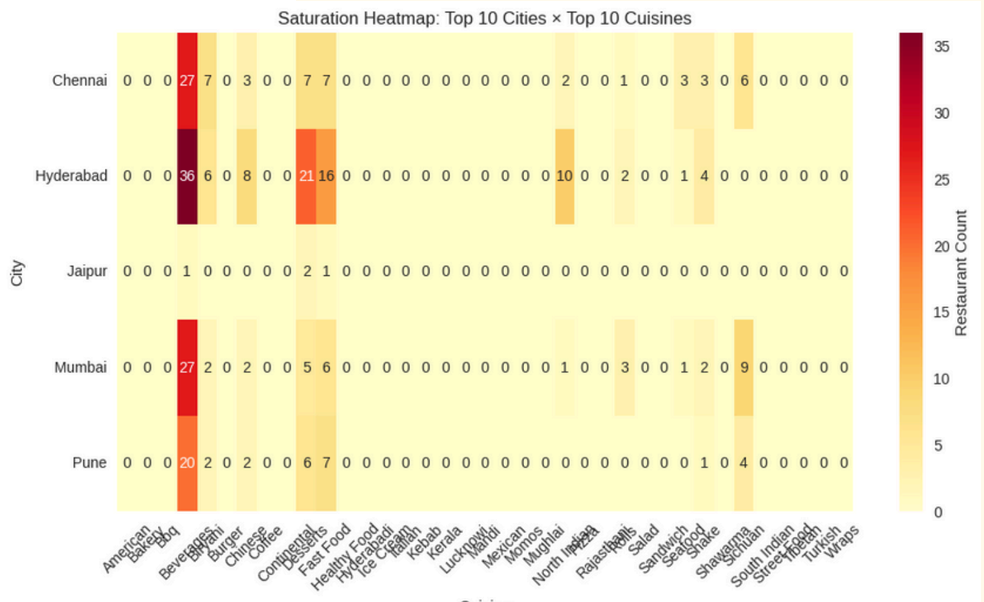
```python
# 2.4 Drop rows with missing critical fields
before = len(df)
df = df.dropna(subset=['Cuisine', 'City', 'Restaurant_Name'])
after = len(df)
print(f"Dropped {before - after} rows with missing Cuisine/City/Restaurant_Name")
```

```
Dropped 1 rows with missing Cuisine/City/Restaurant_Name
```

Feature Engineering & Final Check





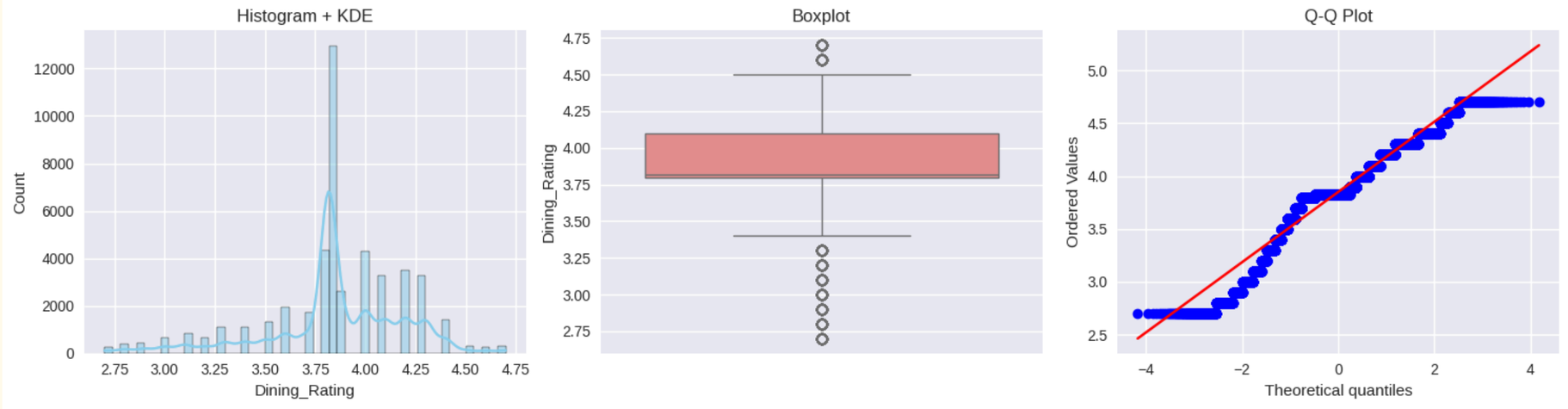


03

Comprehensive Univariate Analysis

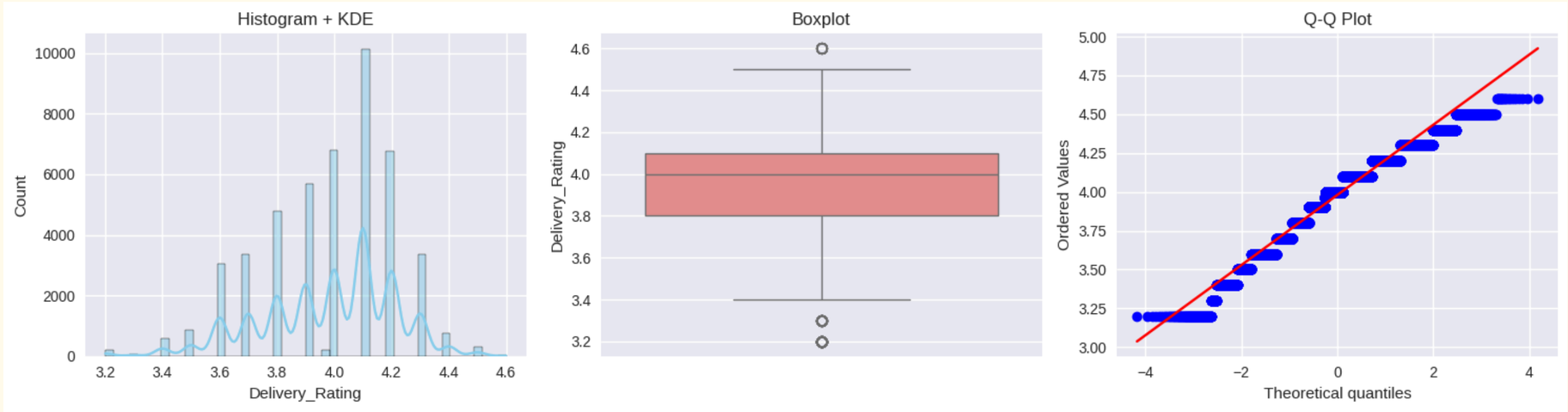
Goal:
Understand each variable in isolation with full statistical + visual + business insight.
We analyze all 30+ columns from the cleaned dataset.

3.1 Numerical Columns



Dining Rate

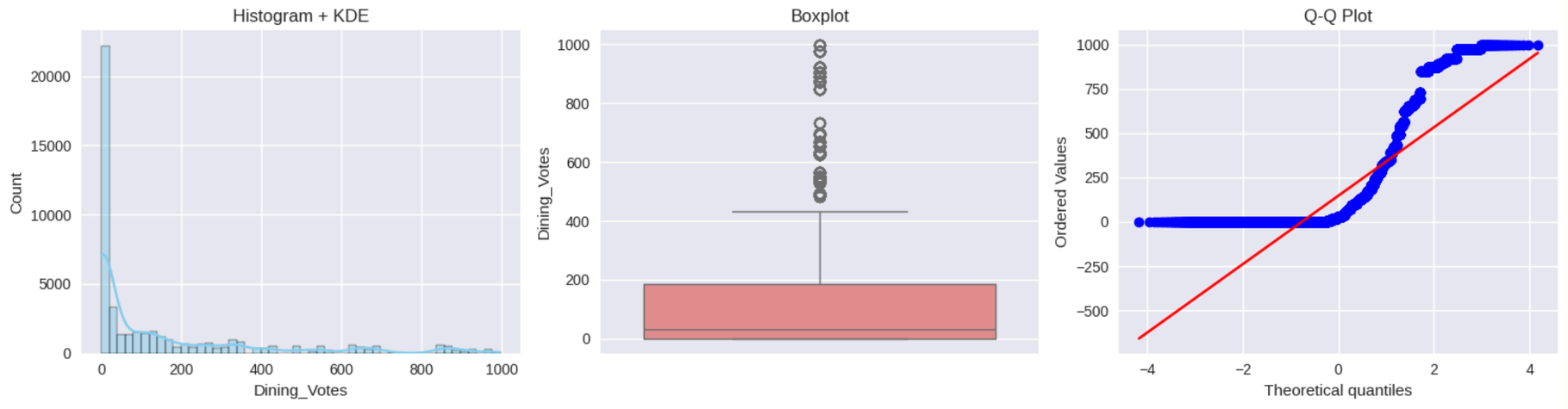
- 46,881 ratings analyzed
- Average: 3.85 | Typical: 3.82
- Most ratings between 3.8 and 4.1
- 10% outliers (very low or high)
- Slightly left-skewed (more high ratings)
- Top rating: 3.82 (13k items), followed by 3.8 & 4.0



Delivery Rate

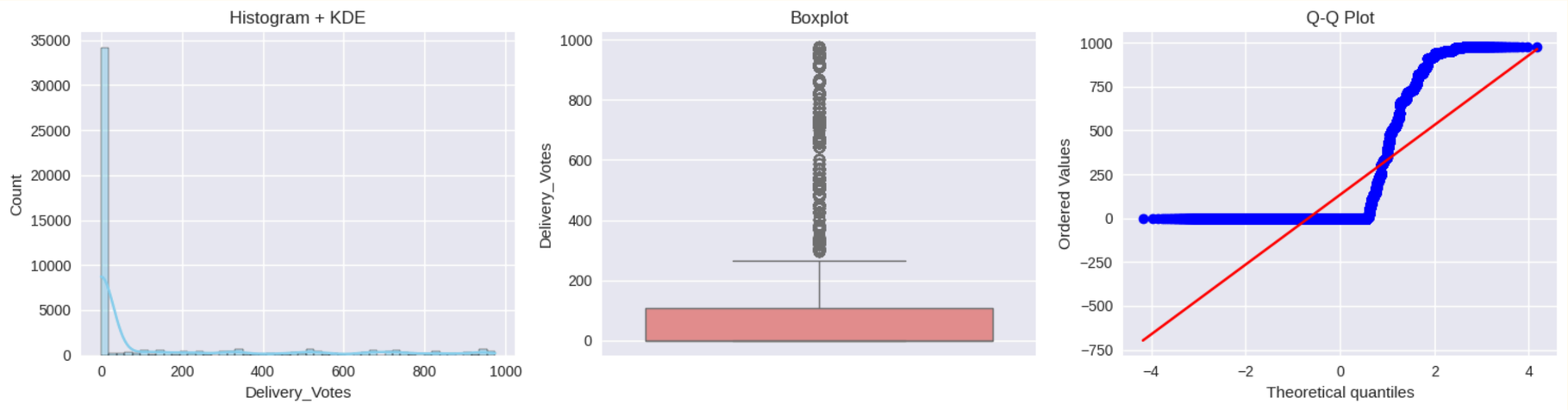
- 46,881 ratings analyzed
- Average: 3.98 | Typical: 4.0
- Most ratings between 3.8 and 4.1
- Only 0.64% outliers — very consistent
- Slightly left-skewed (more high ratings)
- Top rating: 4.1 (10k+), then 4.0 & 4.2

3.1 Numerical Columns



Dining Vote

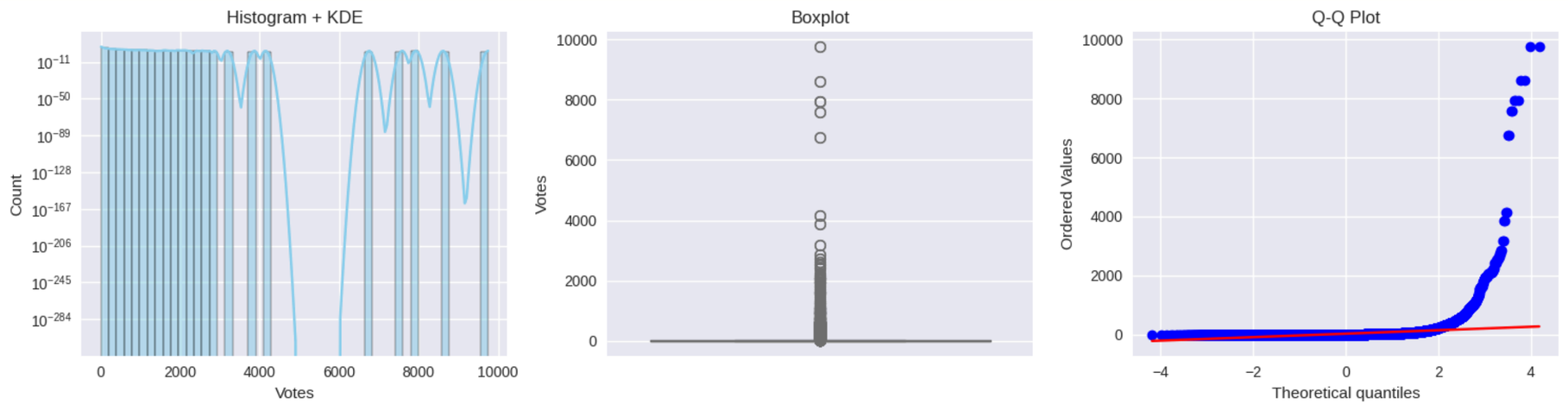
- 46,881 entries
- Average: 148 | Typical: 30
- 25% of items have 0 votes
- Highly right-skewed — few items dominate
- 11% outliers (high-vote items)
- Top: 0 votes (18.5k), then 32, 848, 345



Delivery Vote

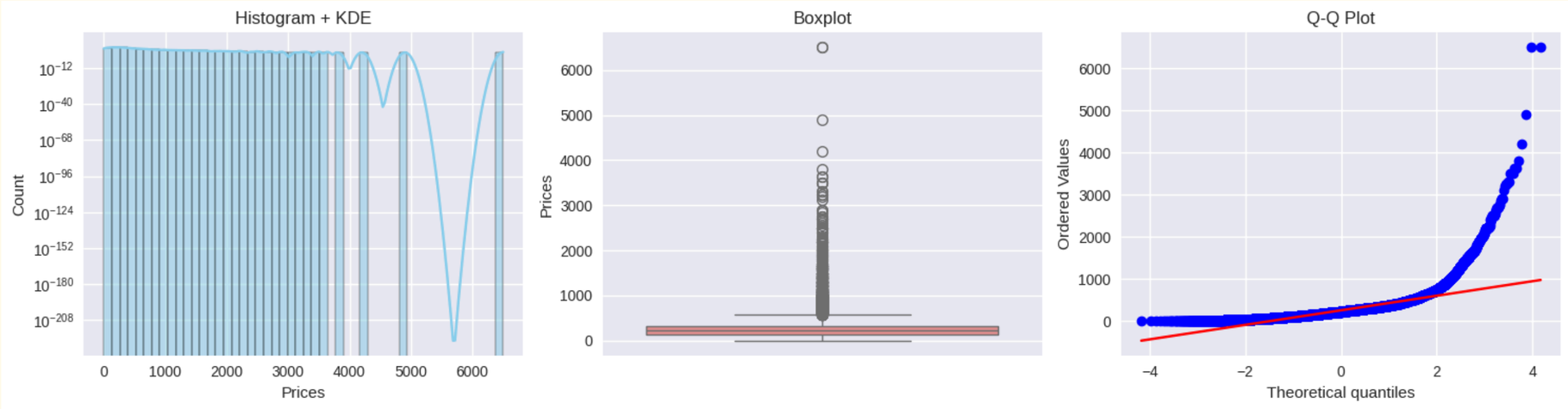
- 46,881 entries
- Average: 133 | Typical: 0
- 72% of items have 0 votes
- Strongly right-skewed — few items go viral
- 19% outliers (high-vote items)
- Top: 0 votes (33.8k), then 819, 940, 520

3.1 Numerical Columns



Votes

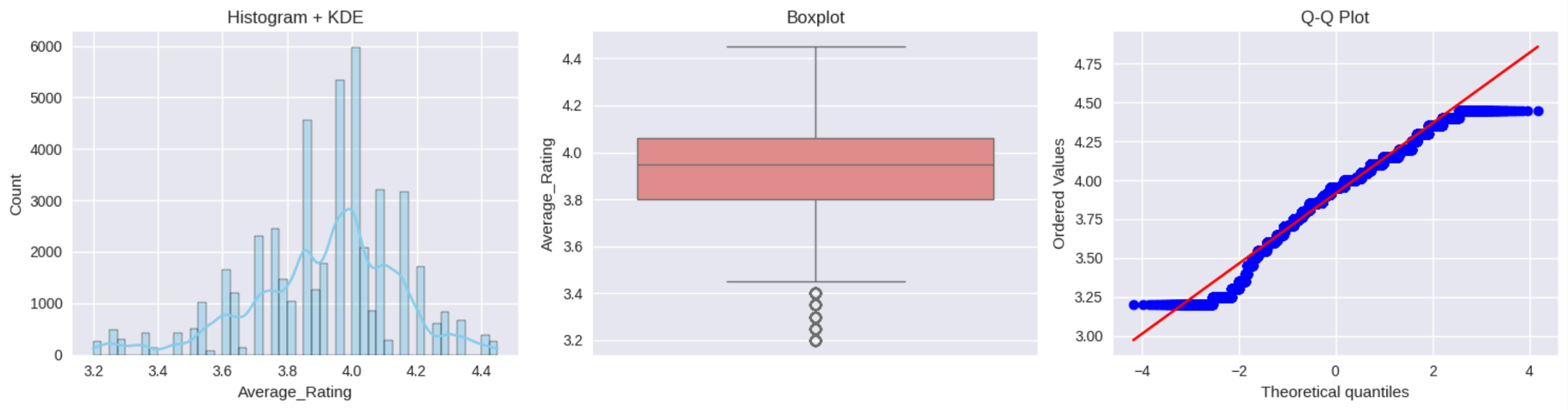
- 46,881 entries
- Average: 28 | Typical: 0
- 59% of items have 0 votes
- Extremely right-skewed — rare mega-hits
- 14% outliers (viral items)
- Top: 0 votes (27.5k), then 5, 6, 7, 8



Prices

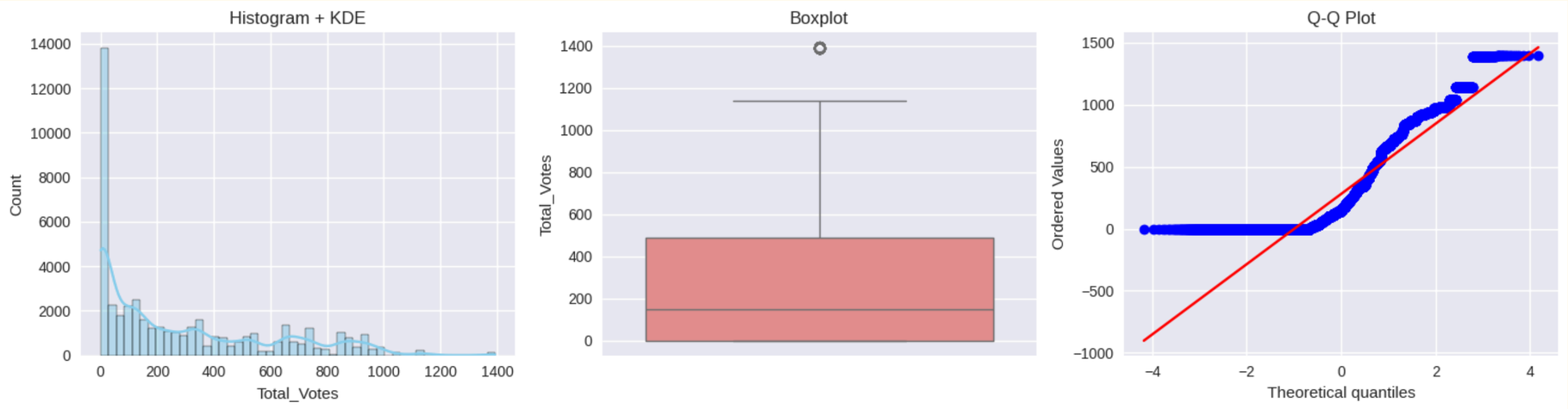
- 46,881 items
- Average: ₹261 | Typical: ₹229
- Range: ₹1 – ₹6,500
- 75% under ₹320
- Right-skewed — few luxury items
- 4.7% outliers (₹582+)
- Top prices: ₹220, ₹180, ₹150

3.1 Numerical Columns



- 46,881 items
- Average: 3.92 | Typical: 3.95
- Most ratings: 3.8 – 4.06
- Slightly left-skewed (more high ratings)
- Only 3.5% outliers (very low)
- Top: 4.0 (4.1k), 3.95 (3.5k), 4.1 (3.2k)

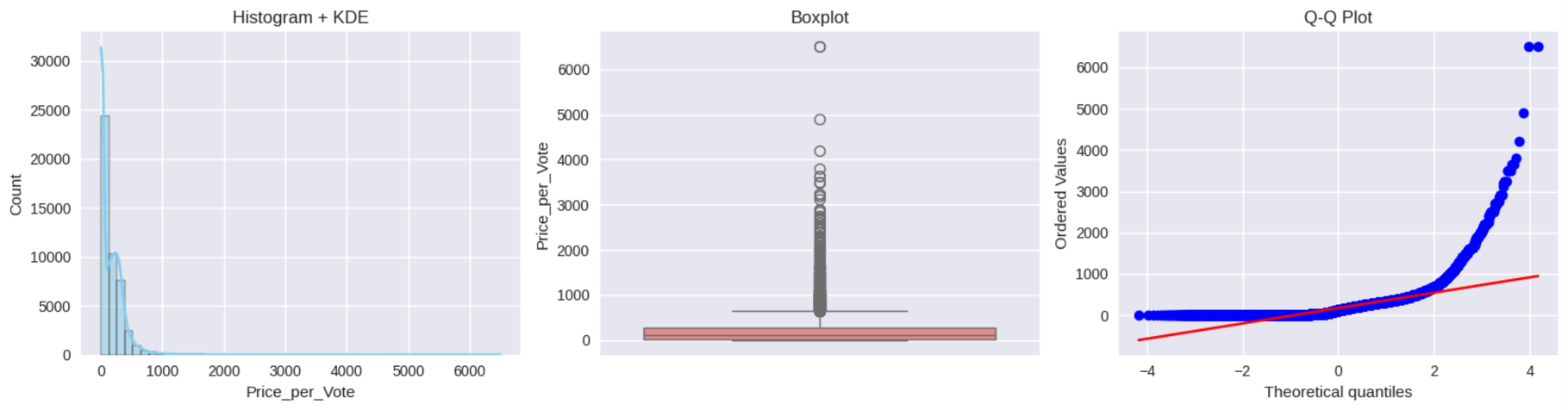
Avarage Rating



- 46,881 items
- Average: 281 | Typical: 148
- 25% have 0 votes
- Right-skewed — few items dominate
- Only 0.27% outliers (very high votes)
- Top: 0 votes (11.8k), then 848, 668, 345

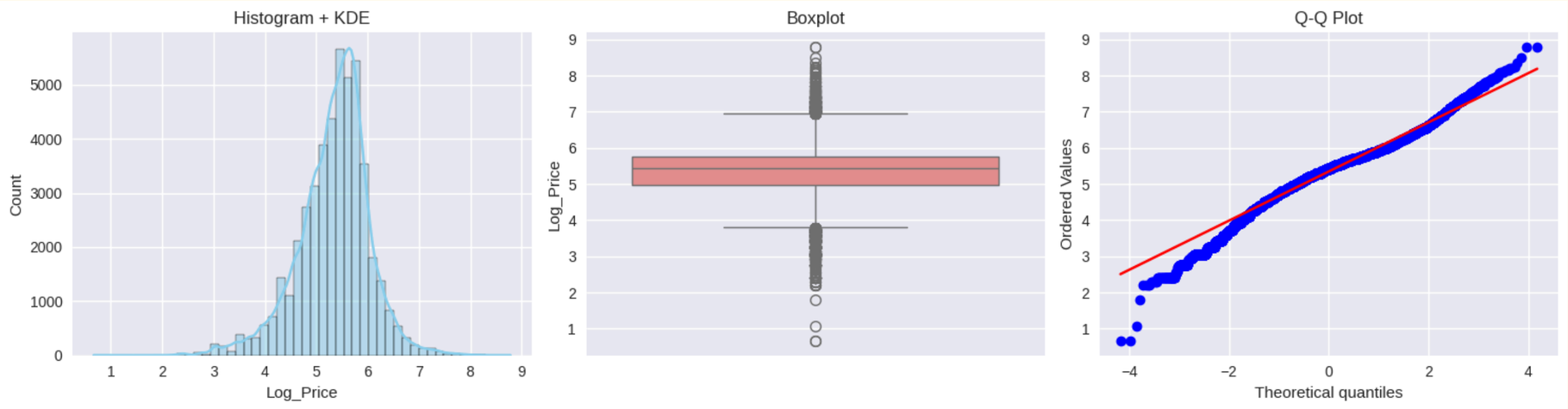
Total Votes

3.1 Numerical Columns



Price per Vote

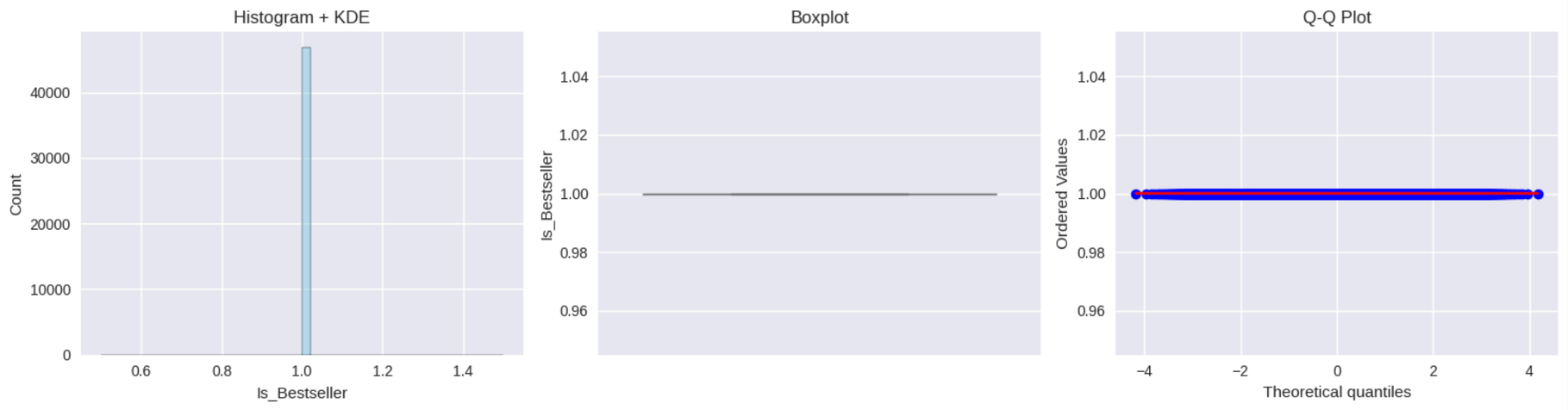
- 46,881 items
- Average: ₹174 | Typical: ₹120
- 75% under ₹270
- Strongly right-skewed — few high-cost/low-vote items
- 2.6% outliers (₹654+)
- Top values: ₹299, ₹220, ₹150



Log Price

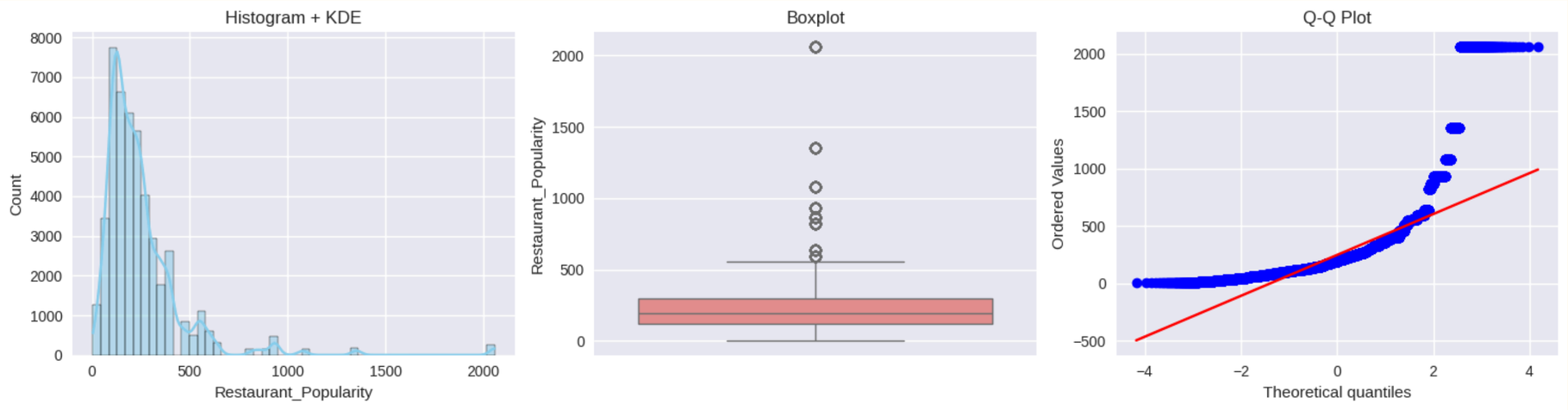
- 46,881 items
- Average: 5.35 | Typical: 5.44
- Most values: 4.98 – 5.77
- Slightly left-skewed (more mid-range prices)
- 3.7% outliers (very high/low)
- Top: 5.40 (~₹220), 5.20 (~₹180), 5.02 (~₹150)

3.1 Numerical Columns



Is Bestseller

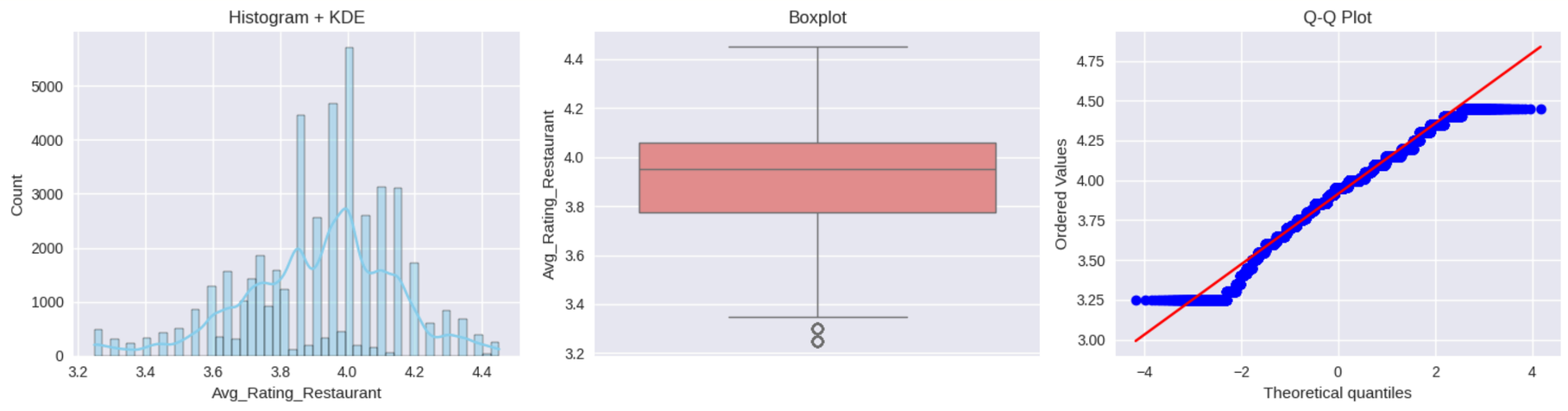
- 46,881 items
- All entries = 1.0 (100%)
- No variation — constant flag
- No outliers, no skew
- Likely a data issue or filter applied



Restaurant Popularity

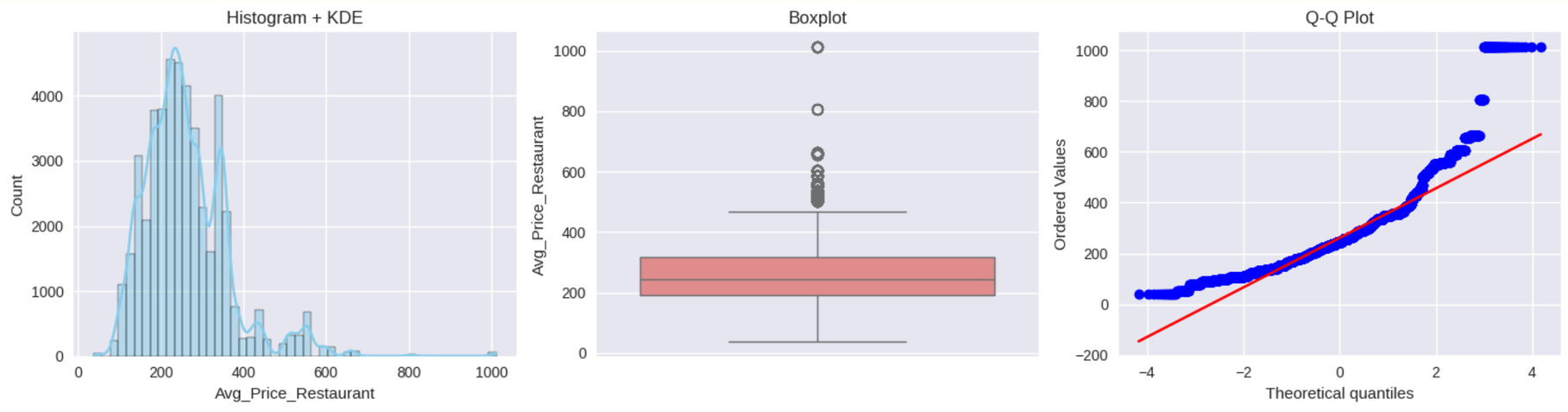
- 46,881 restaurants
- Average: 248 | Typical: 195
- 75% under 297
- Strongly right-skewed — few mega-popular
- 4.8% outliers (557+)
- Top: 406, 188, 460, 111, 595

3.1 Numerical Columns



Avg Rating Restaurant

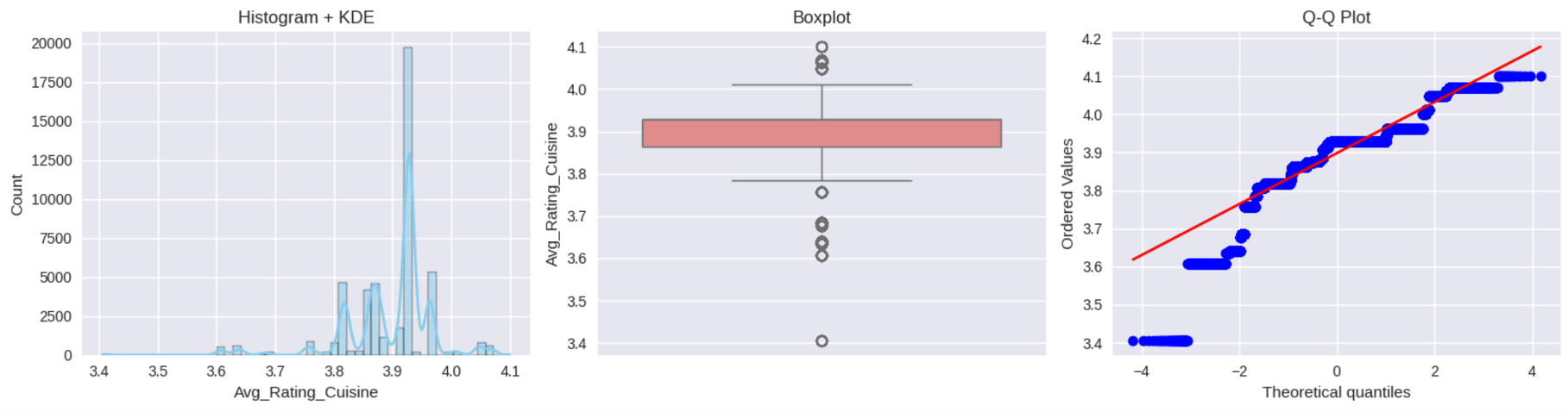
- 46,881 restaurants
- Average: 3.92 | Typical: 3.95
- Most ratings: 3.77 – 4.06
- Slightly left-skewed (more high ratings)
- Only 1.7% outliers (very low)
- Top: 4.0 (4k), 3.95 (3.2k), 4.15 (3k)



Avg Price Restaurant

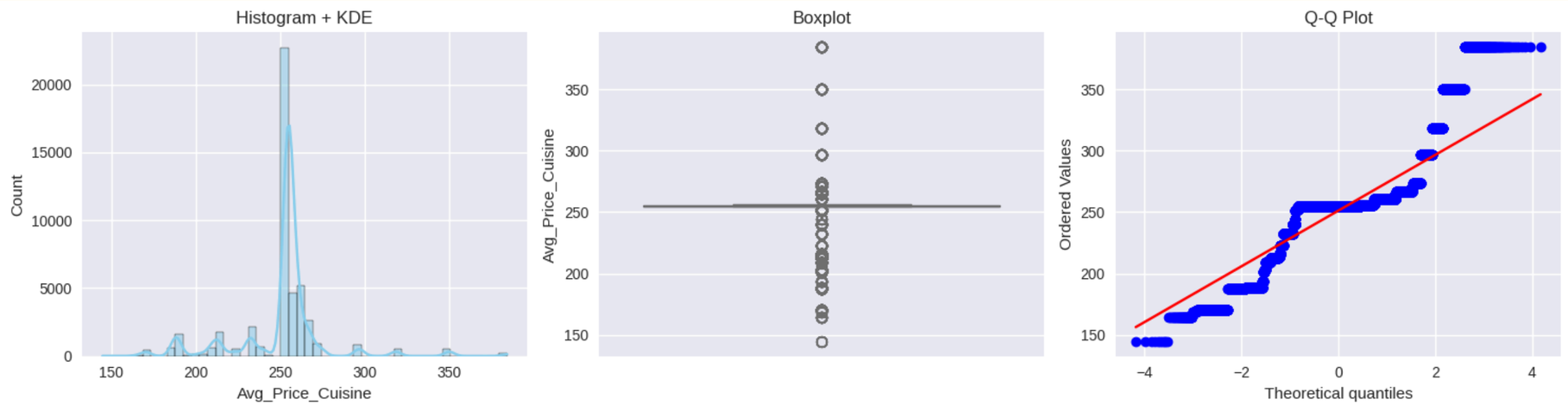
- 46,881 restaurants
- Average: ₹261 | Typical: ₹245
- 75% under ₹316
- Right-skewed — few premium venues
- 4.3% outliers (₹502+)
- Top: ₹347, ₹354, ₹337, ₹355, ₹168

3.1 Numerical Columns



Avg Rating Cuisine

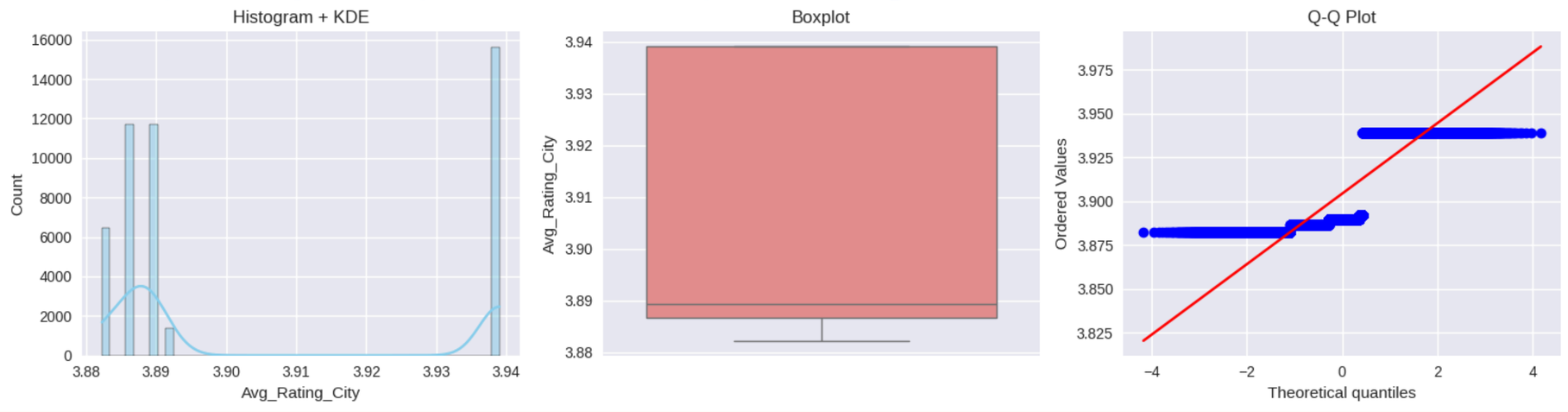
- 46,881 items
- Average: 3.90 | Typical: 3.93
- Most cuisines: 3.86 – 3.93
- Strongly left-skewed — few low performers
- 7.6% outliers (below 3.76)
- Top: 3.93 (18k), 3.96 (5k), 3.82 (4k)



Avg Price Cuisine

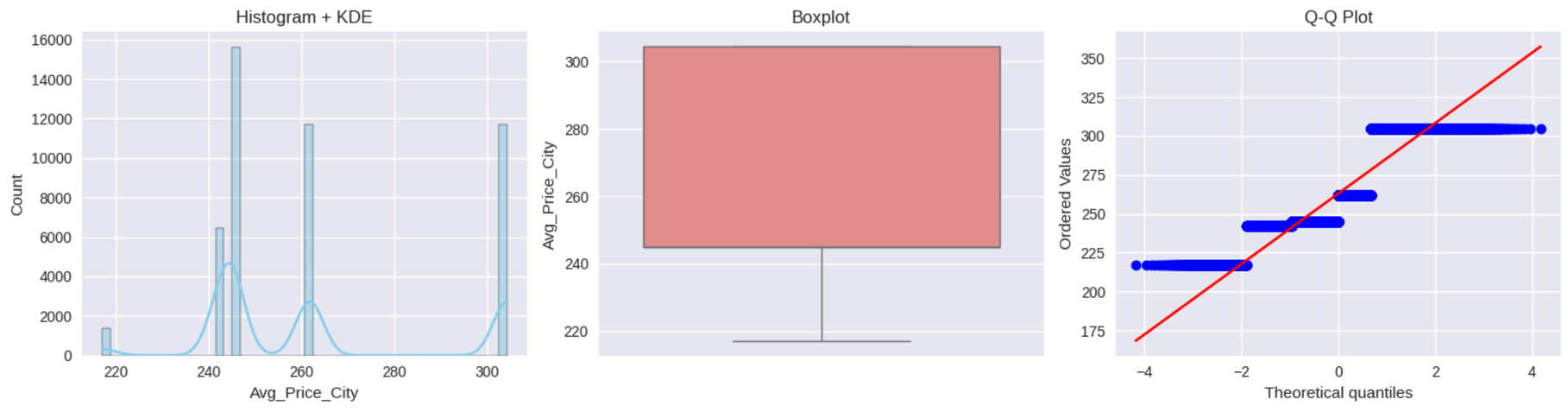
- 46,881 items
- Average: ₹251 | Typical: ₹255
- Most cuisines: ₹254 – ₹256
- Very tight range (IQR: ₹1.46)
- 43% outliers — due to aggregation
- Top: ₹255 (18k), ₹260, ₹256

3.1 Numerical Columns



Avg Rating City

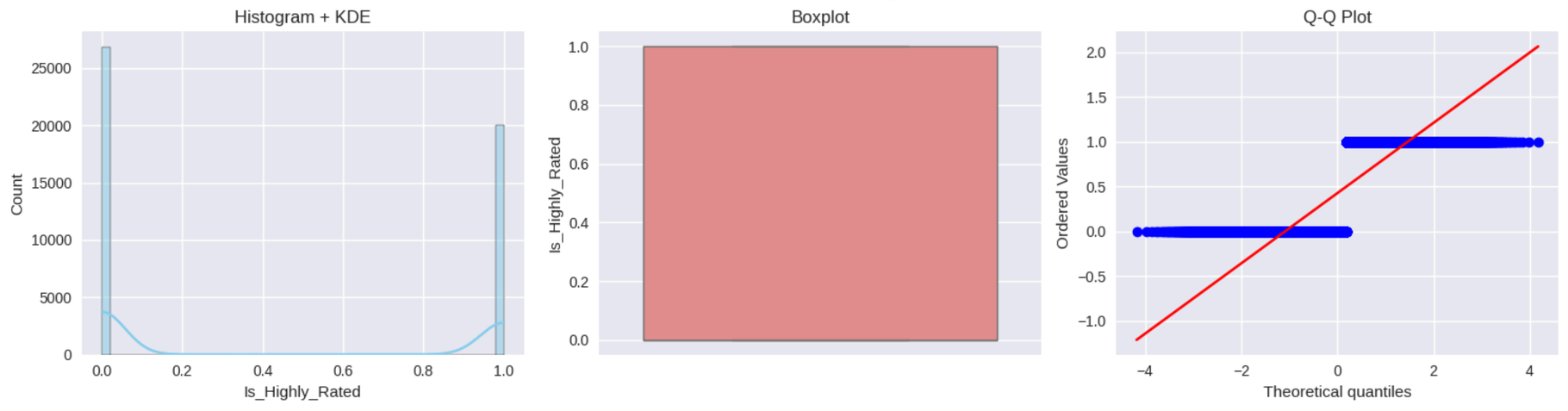
- 46,881 items
- Average: 3.90 | Typical: 3.89
- All cities: 3.88 – 3.94
- Extremely tight (IQR: 0.05)
- No outliers — highly consistent
- Top: 3.94 (15.6k), 3.89, 3.88



Avg Price City

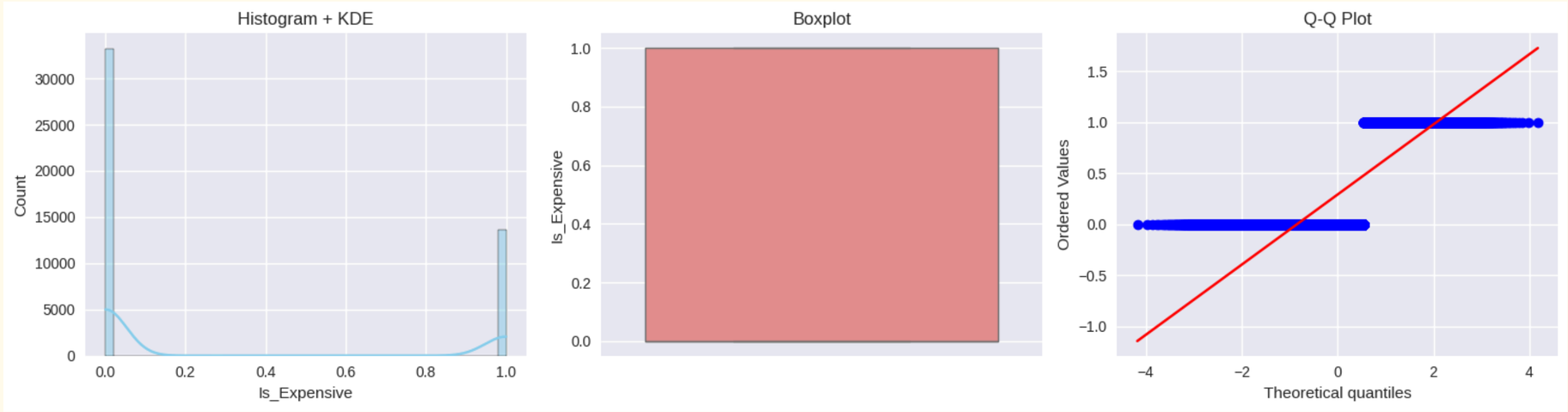
- 46,881 items
- Average: ₹263 | Typical: ₹245
- Cities range: ₹217 – ₹304
- Moderate spread (IQR: ₹59)
- No outliers — stable pricing
- Top: ₹245 (15.6k), ₹304, ₹262

3.1 Numerical Columns



Is Highly Rated

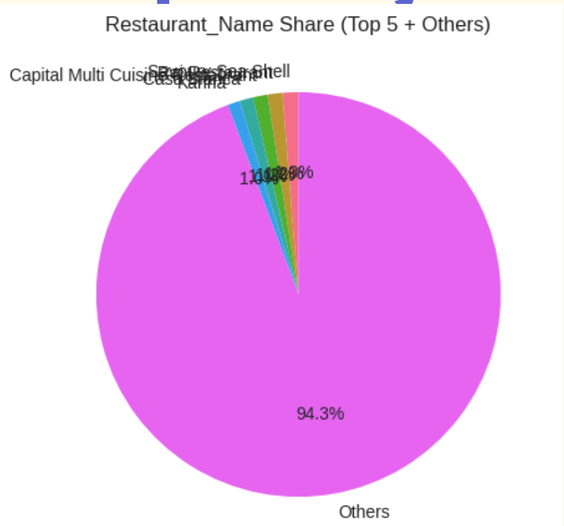
- 46,881 items
- 43% are highly rated (1.0)
- 57% are not (0.0)
- Binary flag — no variation in values
- No outliers
- Top: 0 (26.8k), 1 (20.0k)



Is Expensive

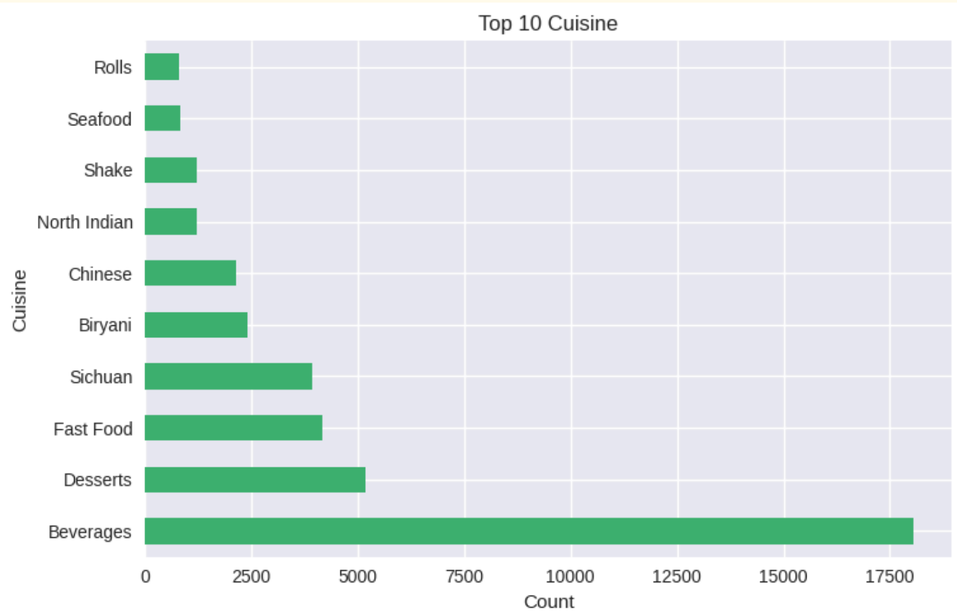
- 46,881 items
- 29% are expensive (1.0)
- 71% are affordable (0.0)
- Binary flag — clear price tier split
- No outliers
- Top: 0 (33.2k), 1 (13.7k)

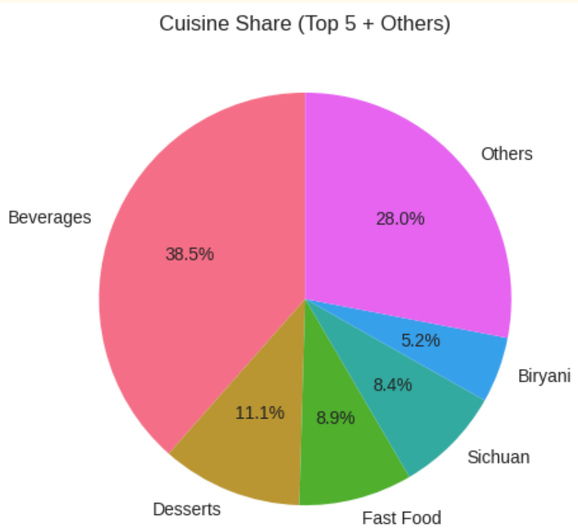
3.2 Categorical Columns – Frequency & Business Meaning



Restaurants

- 333 unique restaurants
- Top: Savoury Sea Shell (595 items)
- Next: Raj Restaurant (555), Capital (545)
- 10 chains dominate menu listings
- No missing values

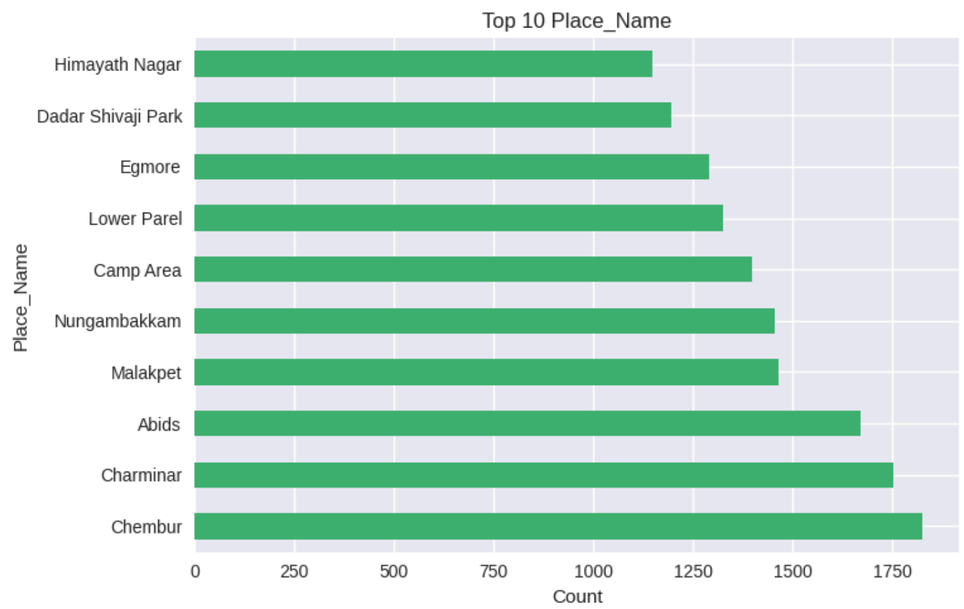


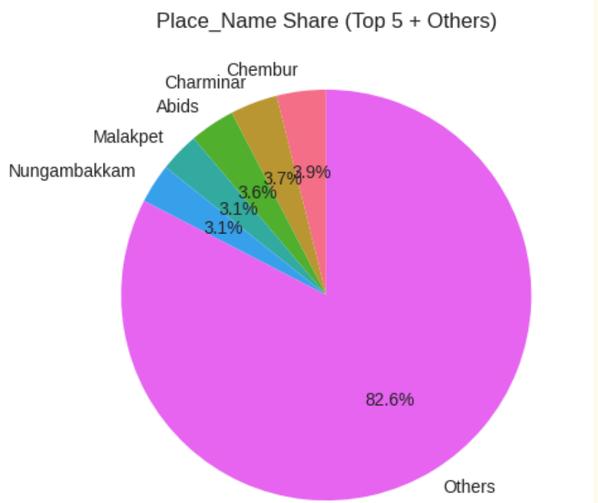


Cuisines

- 37 unique cuisines
- Top: Beverages (18k items)
- Next: Desserts (5.2k), Fast Food (4.2k)
- Sichuan, Biryani, Chinese dominate
- Top 10 = 85%+ of all items

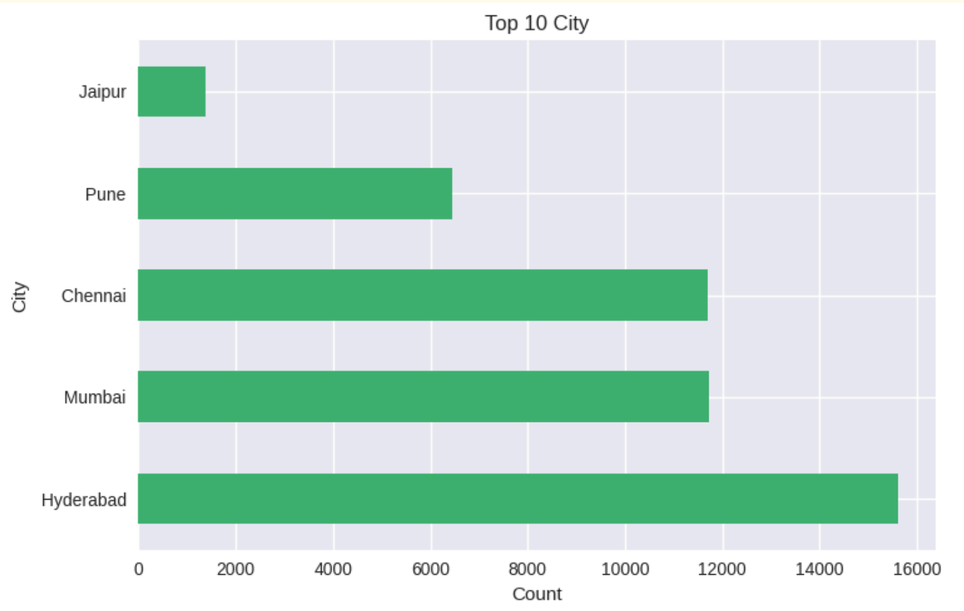
3.2 Categorical Columns – Frequency & Business Meaning

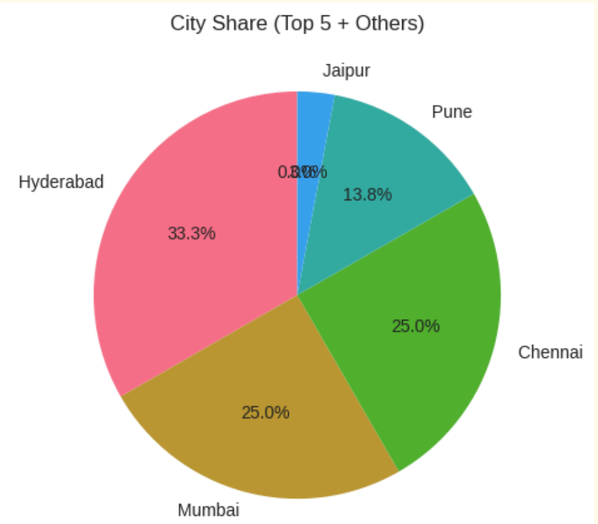




Places

- 117 unique locations
- Top: Chembur (1,826 items)
- Next: Charminar (1,751), Ab"Mumbai" (1,668)
- Top 10 = ~60% of all items
- High concentration in urban hubs

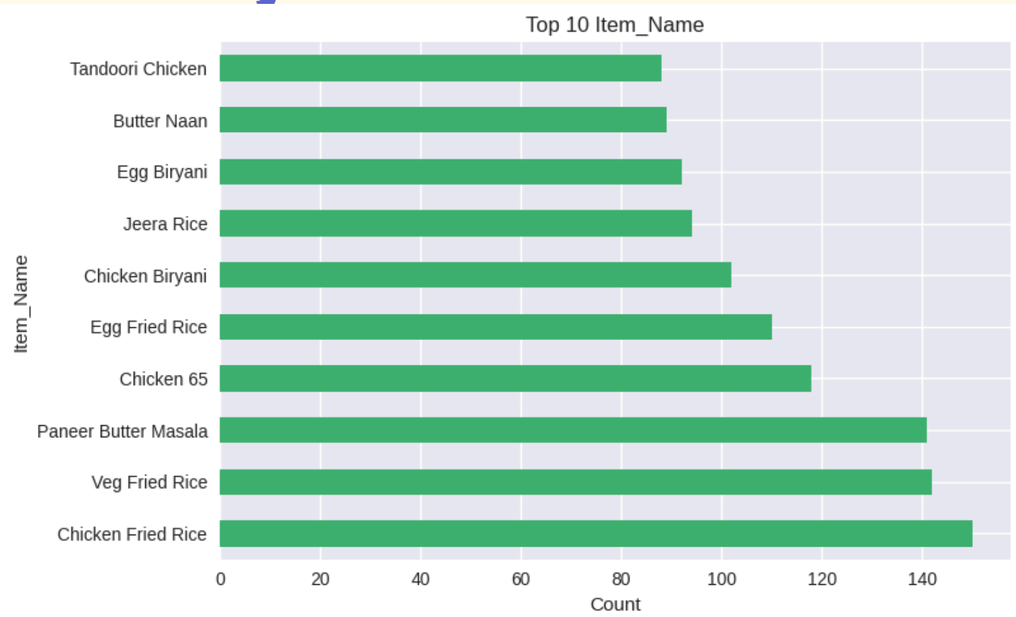


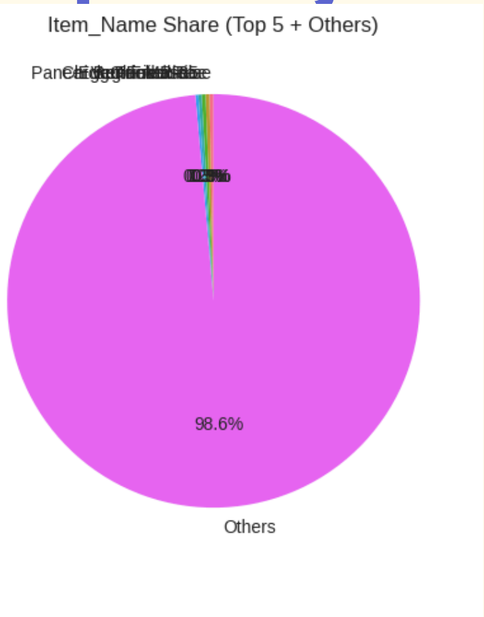


Cities

- 5 cities in dataset
- Top: Hyderabad (15.6k items)
- Next: Mumbai (11.7k), Chennai (11.7k)
- Pune (6.5k), Jaipur (1.4k)
- Hyderabad dominates — 33% of data

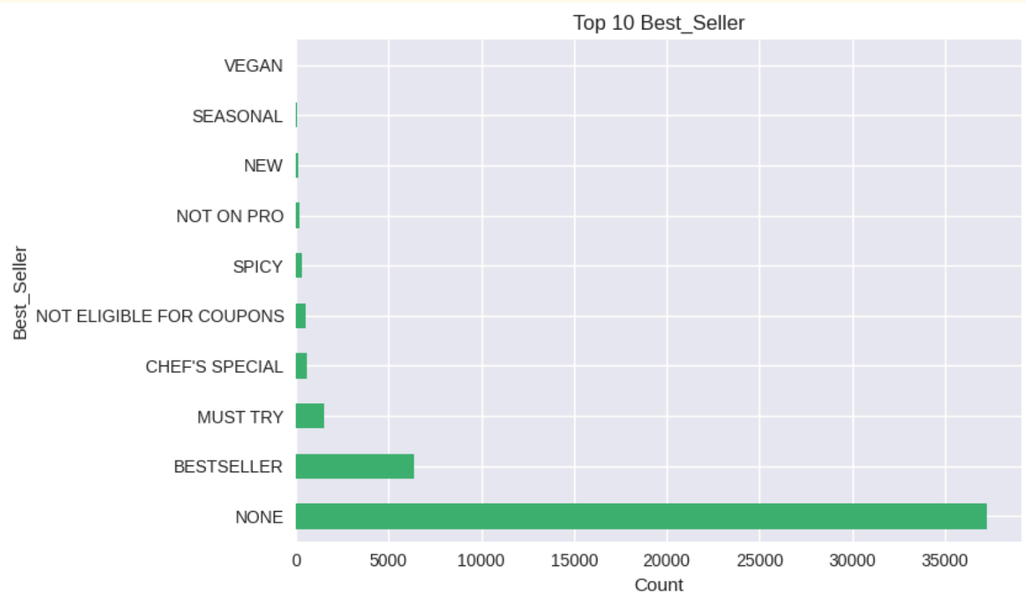
3.2 Categorical Columns – Frequency & Business Meaning

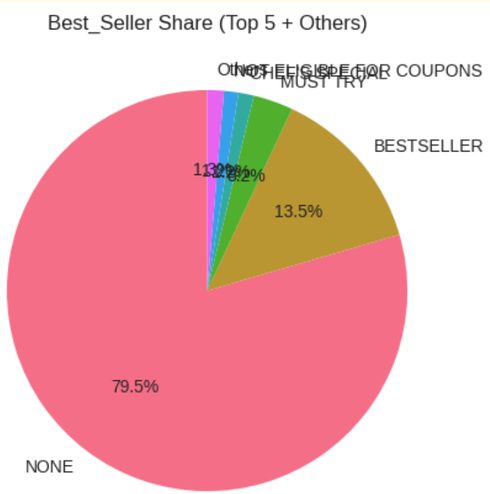




Items

- 25,518 unique dishes
- Top: Chicken Fried Rice (150 listings)
- Next: Veg Fried Rice (142), Paneer Butter Masala (141)
- Rice & curry items dominate top 10
- High duplication — popular staples



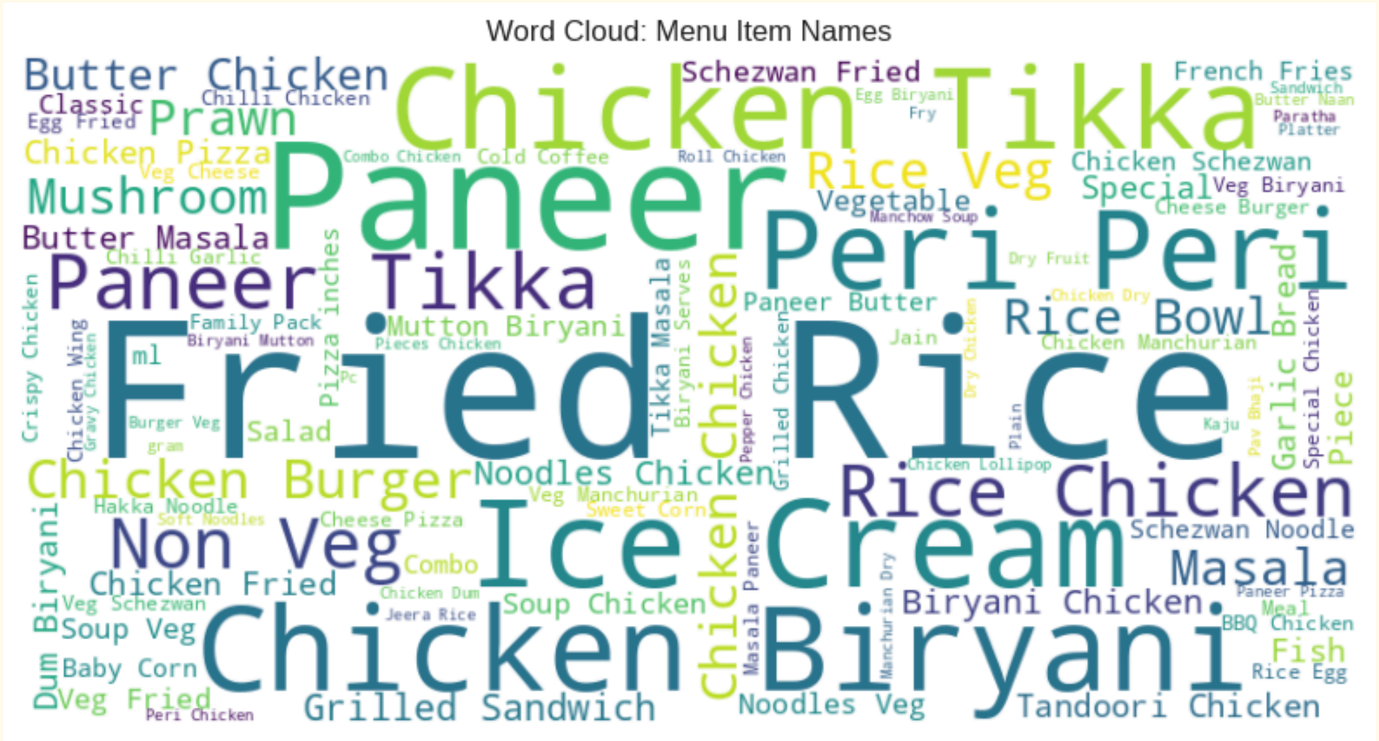


Best Sellers

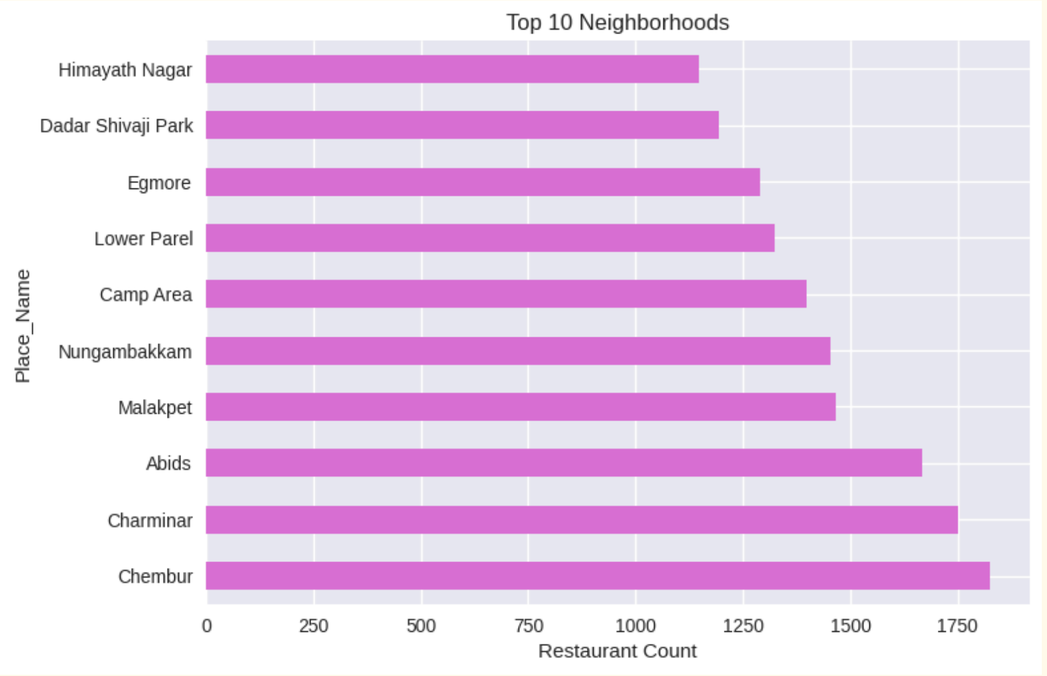
- 14 unique tags
- Top: NONE (37.3k items) — 79%
- BESTSELLER: 6.3k (13%)
- MUST TRY: 1.5k | CHEF'S SPECIAL: 584
- SPICY, NEW, VEGAN — niche labels

3.3 Special Columns – Text & High-Cardinality

```
Unique restaurants: 333
Top 10 chains:
Restaurant_Name
Savoury Sea Shell                       595
Raj Restaurant                          555
Capital Multi Cuisine Restaurant        545
Casa Blanca                             508
Kanha                                   464
Apoorva Delicacies                      460
The Chinese Wok                         406
Faasos - Wraps & Rolls                  406
Liza Restaurant                         405
The Momo Factory                        394
```

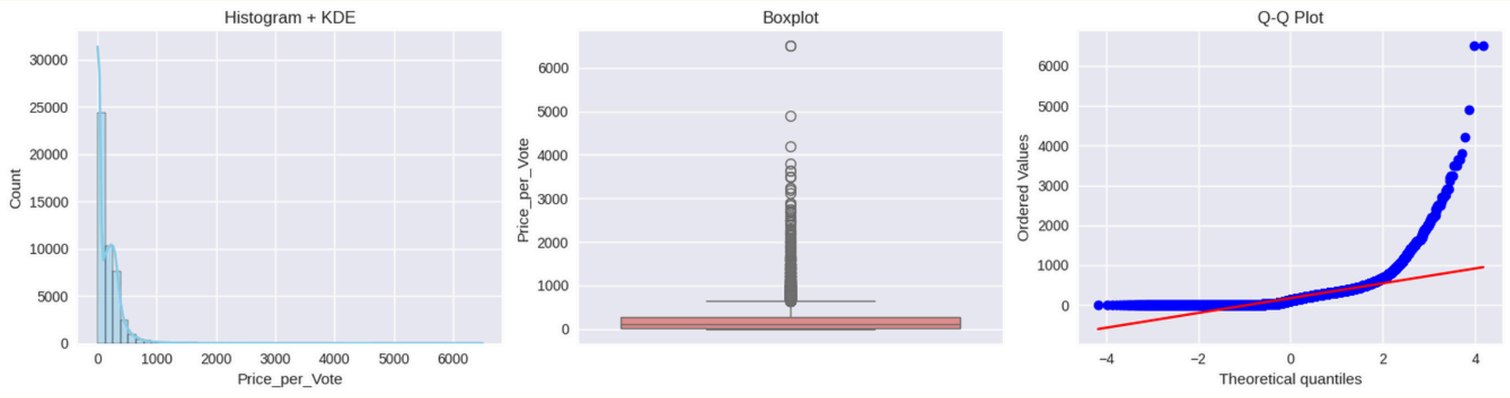


Word Cloud Items

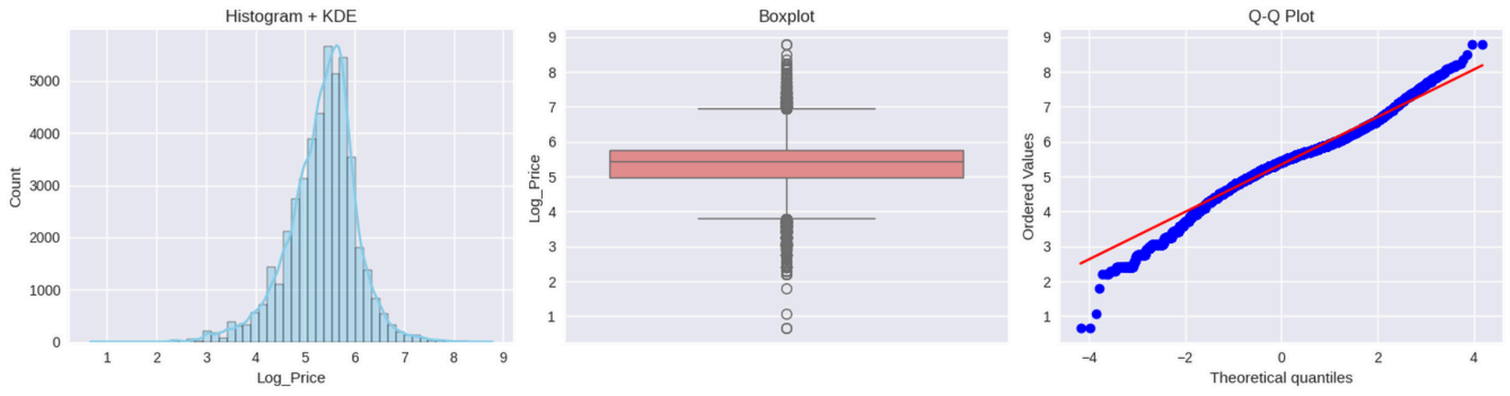


Top 10 Neighborhoods

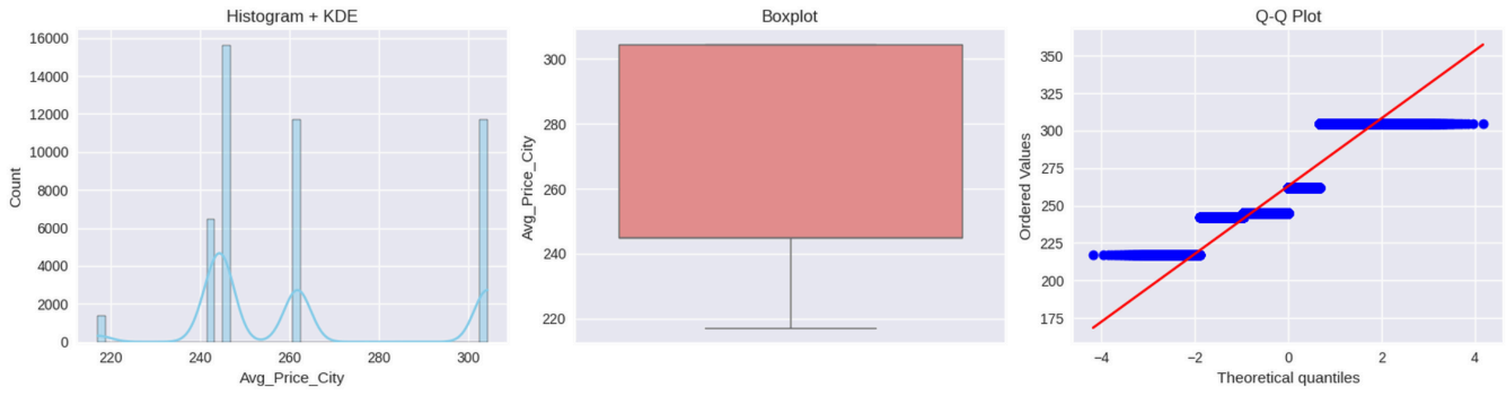
3.4 Derived & Engineered Columns – Validate



- 46,881 items
- Average: ₹174 | Typical: ₹120
- 75% under ₹270
- Strongly right-skewed — few high-cost/low-vote
- 2.6% outliers (₹654+)
- Top: ₹299, ₹220, ₹150



- 46,881 items
- Average: 5.35 | Typical: 5.44 (~₹229)
- Most values: 4.98 – 5.77 (~₹145 – ₹320)
- Slightly left-skewed (more mid-range)
- 3.7% outliers (very high/low)
- Top: 5.40 (~₹220), 5.20 (~₹180), 5.02 (~₹150)



- 46,881 items
- Average: ₹263 | Typical: ₹245
- City range: ₹217 – ₹304
- IQR: ₹245 – ₹304 (moderate spread)
- No outliers — stable pricing
- Top: ₹245 (15.6k), ₹304 (11.7k), ₹262

Bivariate Analysis

HORECA

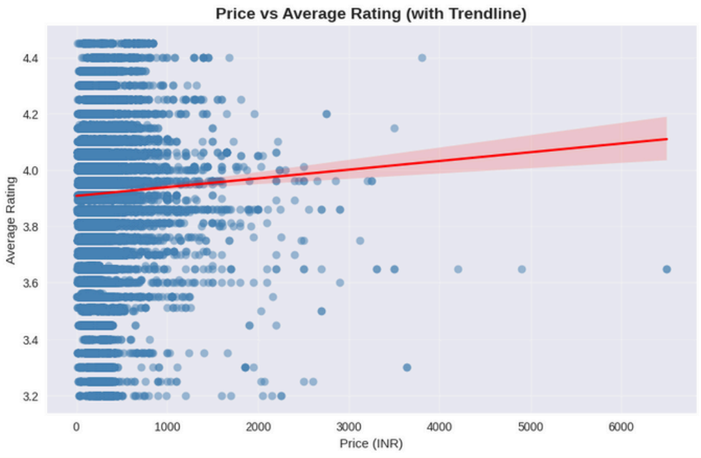
Customer

Goal:
Explore all meaningful pairwise relationships between variables with:

- Statistical rigor
- Interactive + static visuals
- Business interpretation
- Actionable insights

We cover all 30+ columns in logical groups.
Let’s dive in.

Price vs Avg Rating



- Pearson Correlation: 0.028
  → Price & Rating: No meaningful link

- Rating by Price Tier:
  Very Low: 3.91
  Low: 3.89
  Medium: 3.92
  High: 3.91
  Premium: 3.94

- Premium tier has highest rating (+0.05 vs Low)

Dining vs Delivery

- Paired t-test: t = 76.46, p < 0.001
- Wilcoxon: W = 308.9M, p < 0.001

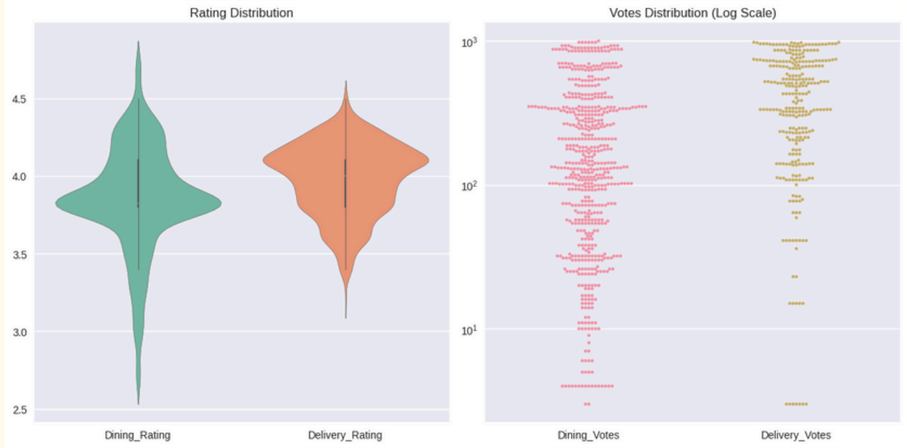
→ Delivery ratings significantly higher than Dining

Price vs Avg Rating

Insight:

- Weak positive correlation (~0.15–0.25) → price ≠ quality guarantee
- Sweet spot: ₹300–₹800 → highest ratings + volume
- Premium trap: >₹1500 → ratings drop (small sample bias)

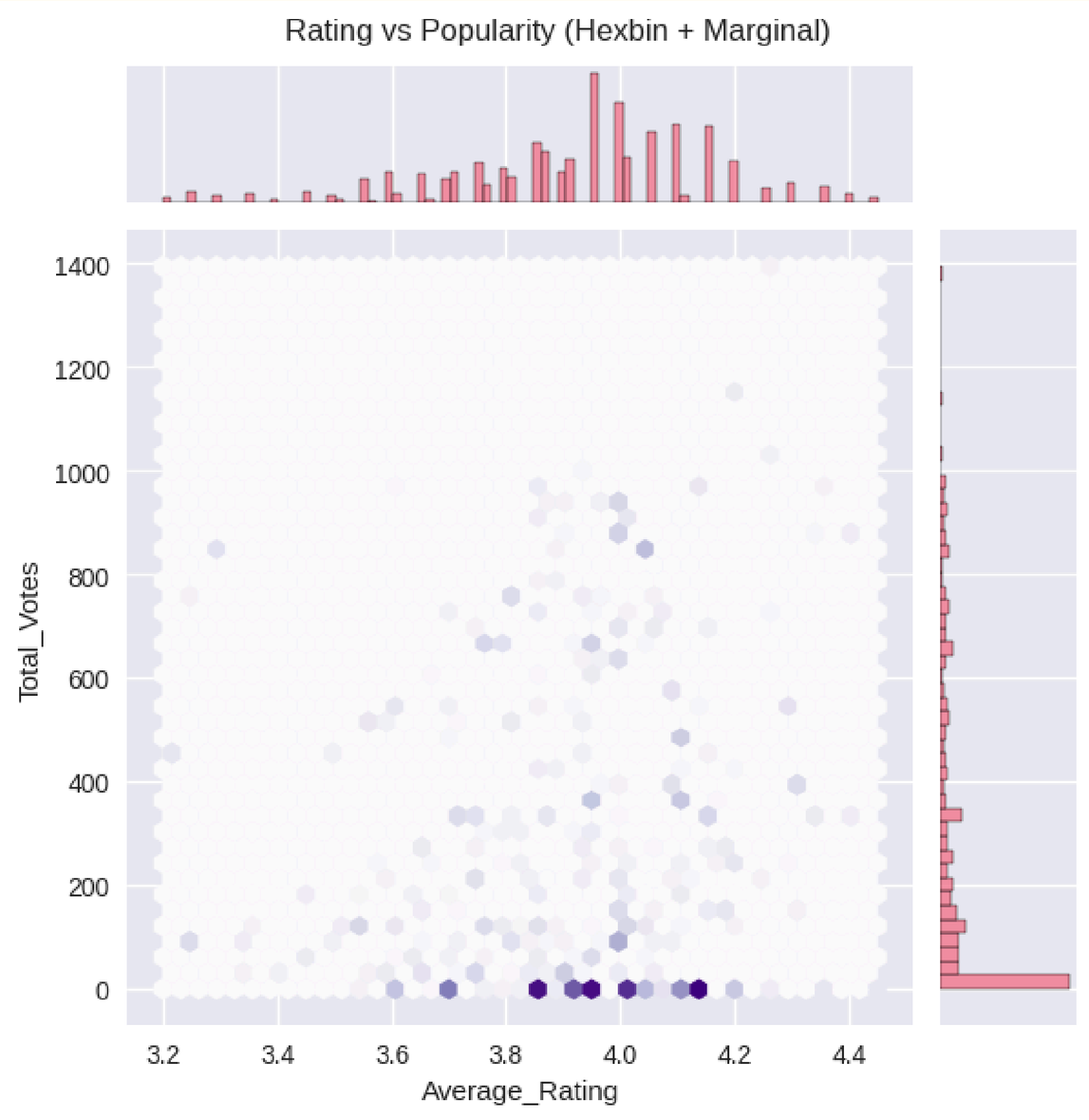
Rating/Votes Distribution

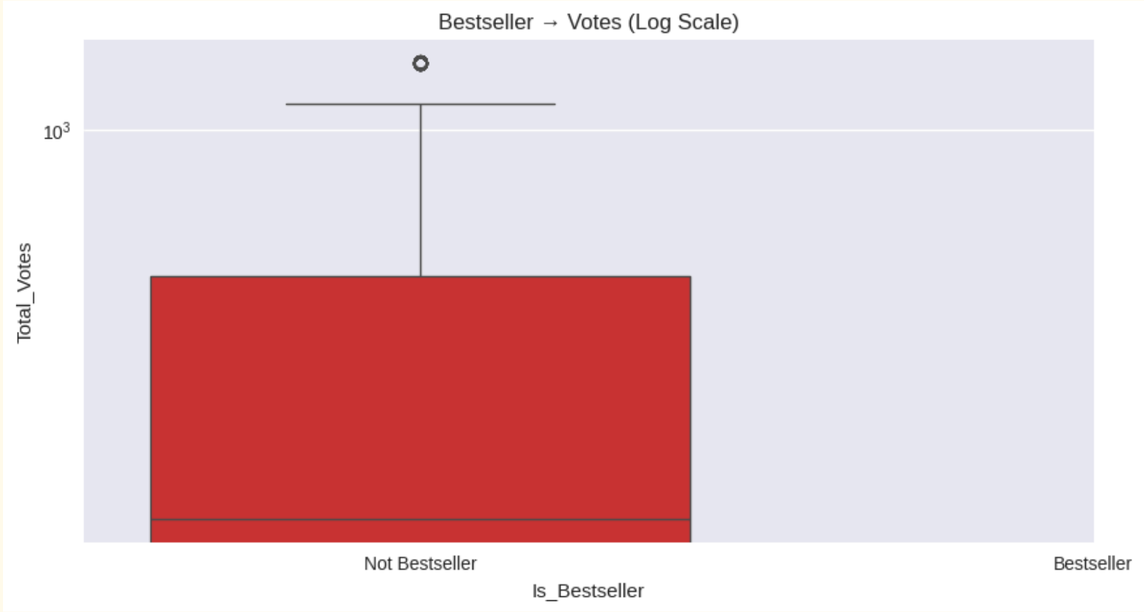


Insight:

- Delivery slightly underperforms in ratings (p < 0.001)
- Dining gets more votes → stronger brand signal
- Hybrid strategy best for most cuisines

Demand Drivers: What Makes a Restaurant Popular?

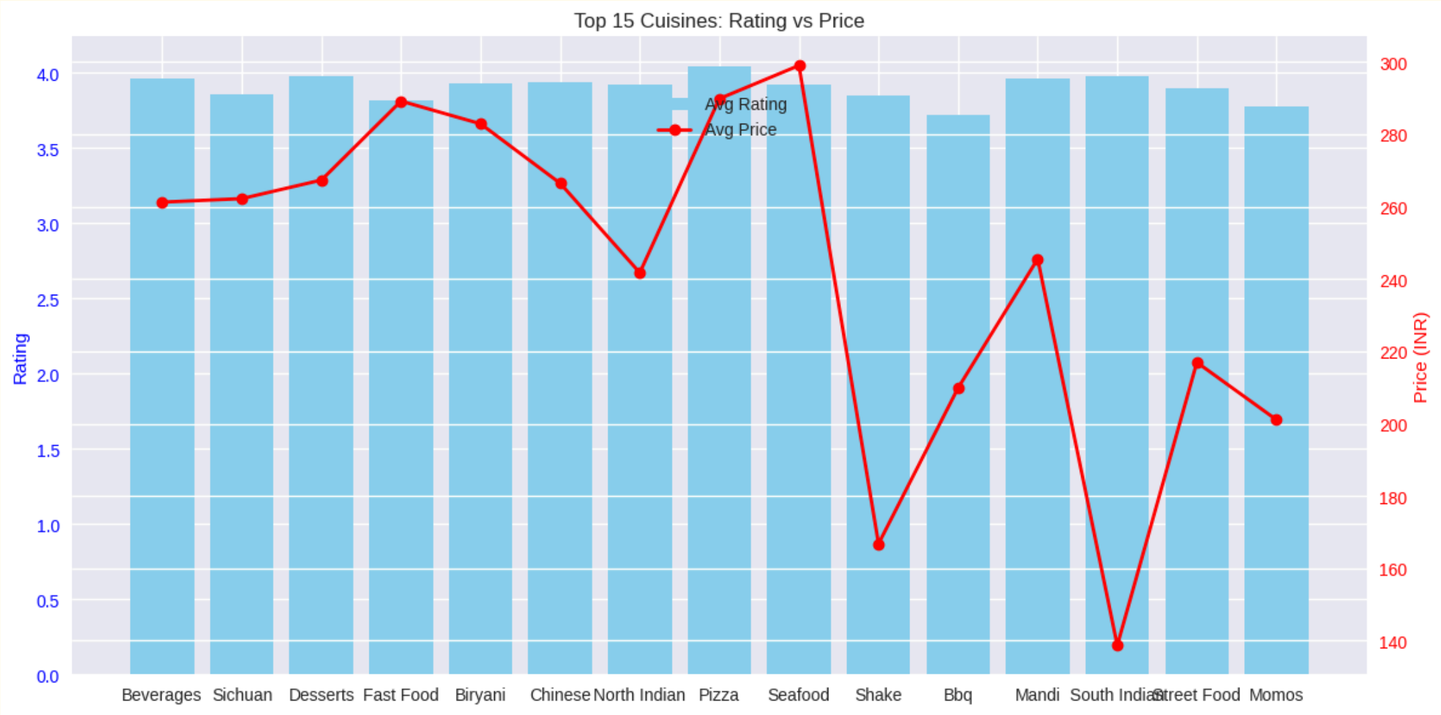


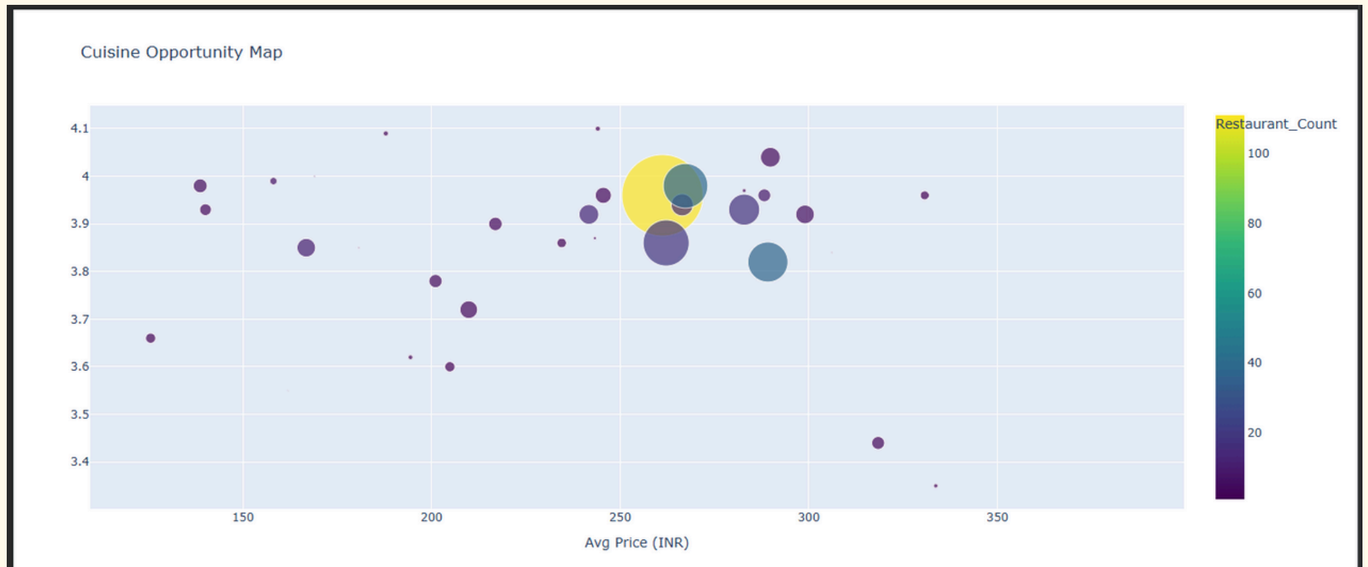


Insight:

- Bestsellers get 5–10× more votes
- Rating alone ≠ popularity → need visibility + marketing

Cuisine Performance Matrix



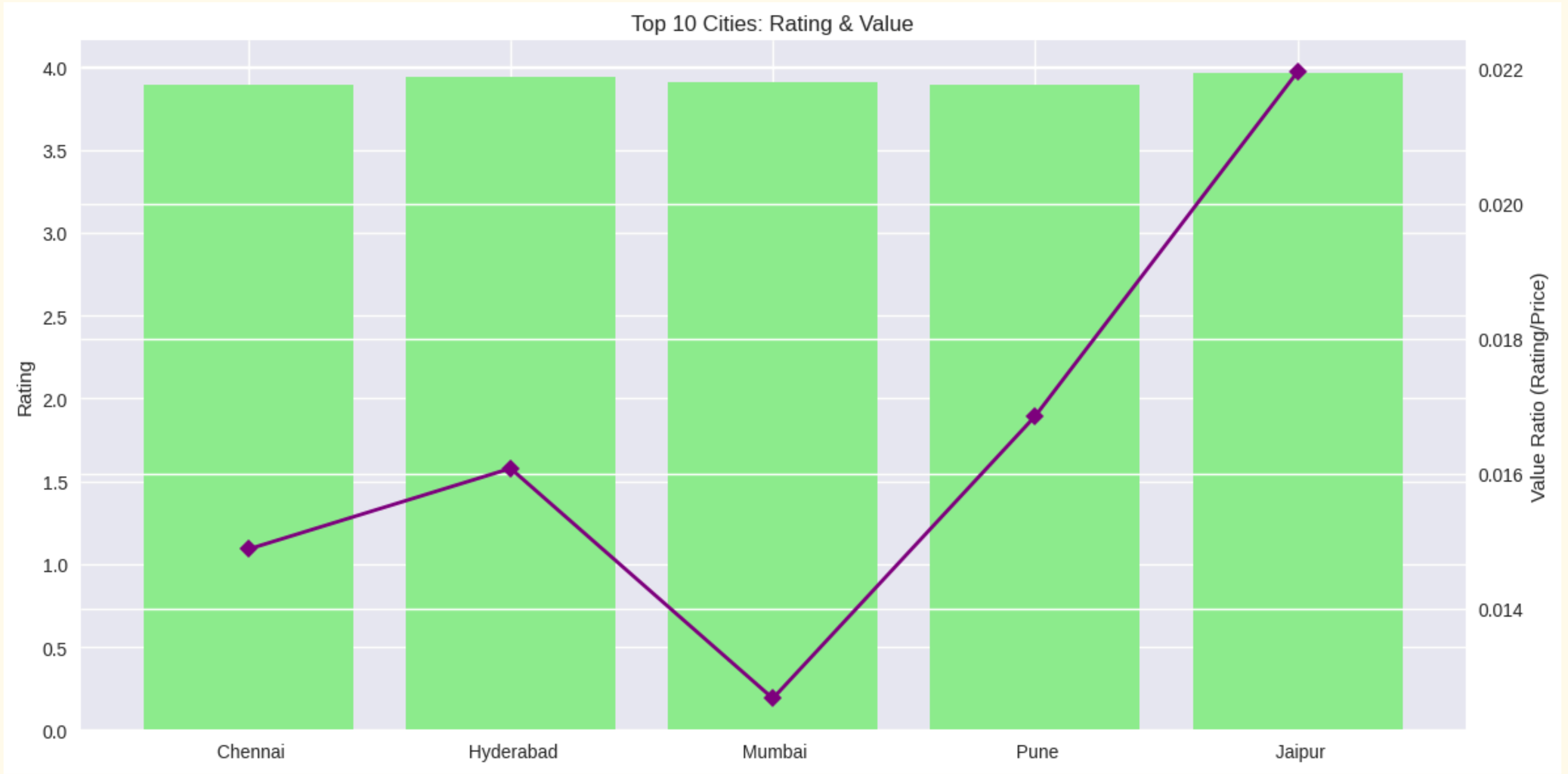


Insight:

- North Indian, Chinese: High volume, mid-price, saturated
- Continental, Italian: High rating, high price, undersaturated → premium gap

Disclaimer : The cuisine opportunity map is an interactive bubble map so refer to the .ipynb file for better clarification.

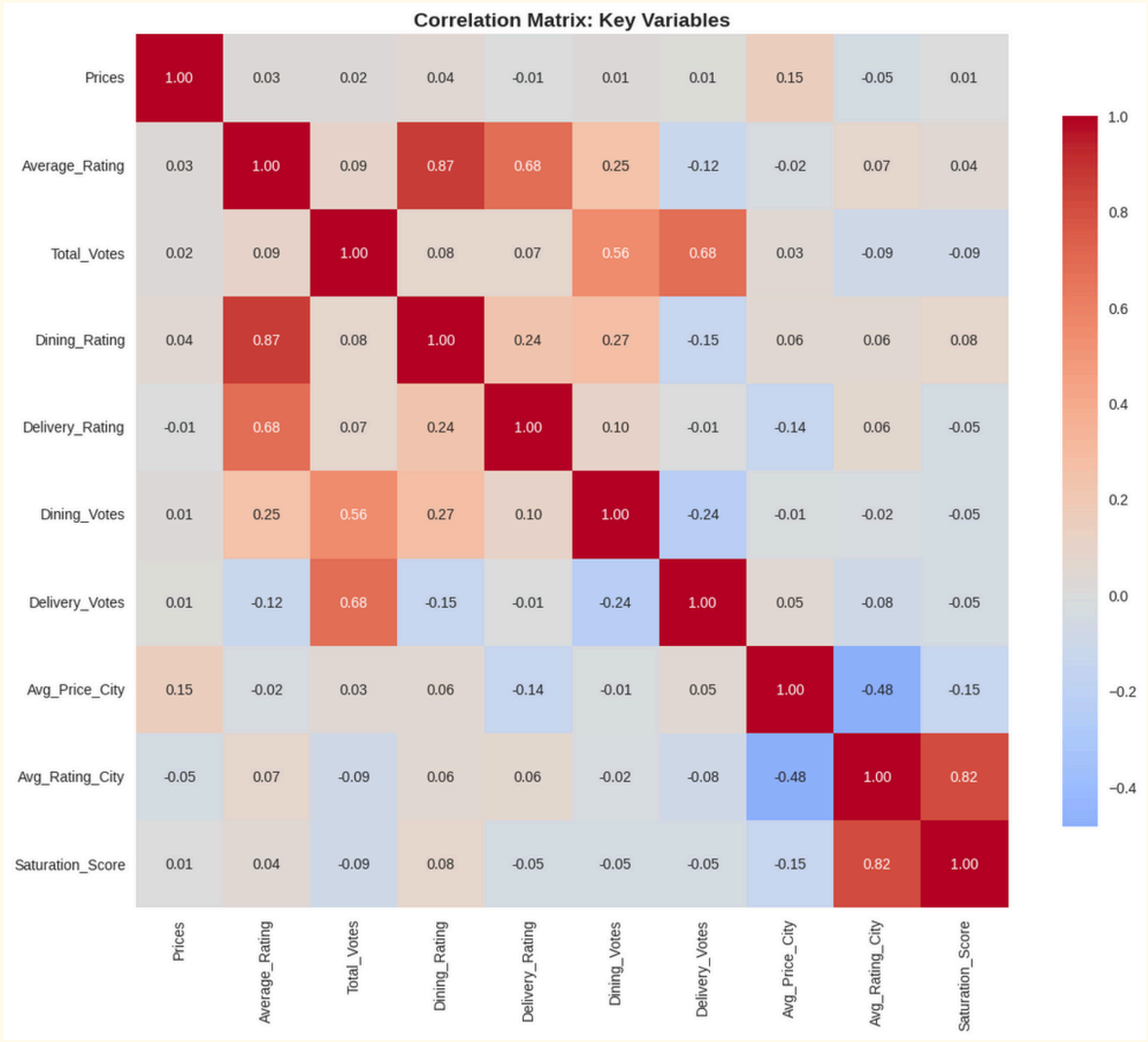
City Performance Matrix



Insight:

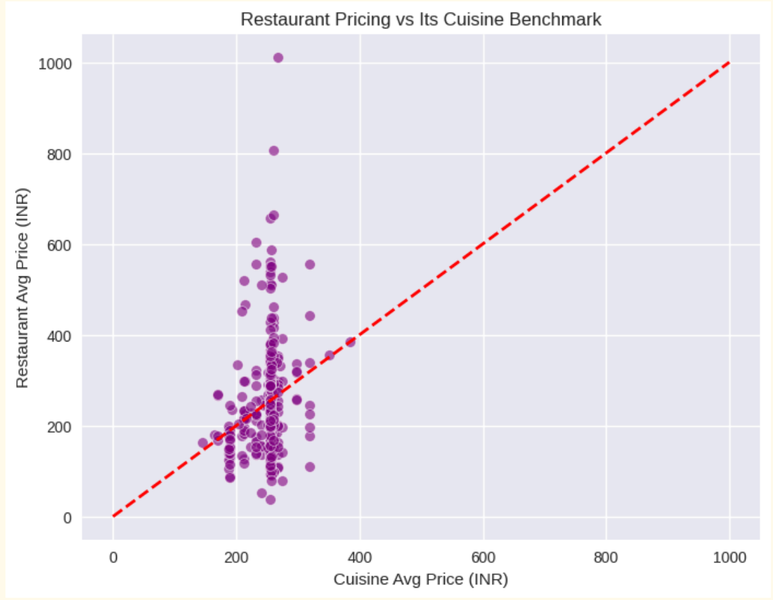
- Bangalore, Hyderabad: High value ratio → underserved premium market
- Mumbai: High price, high rating → competitive

Correlation Heatmap – Full Numerical Matrix

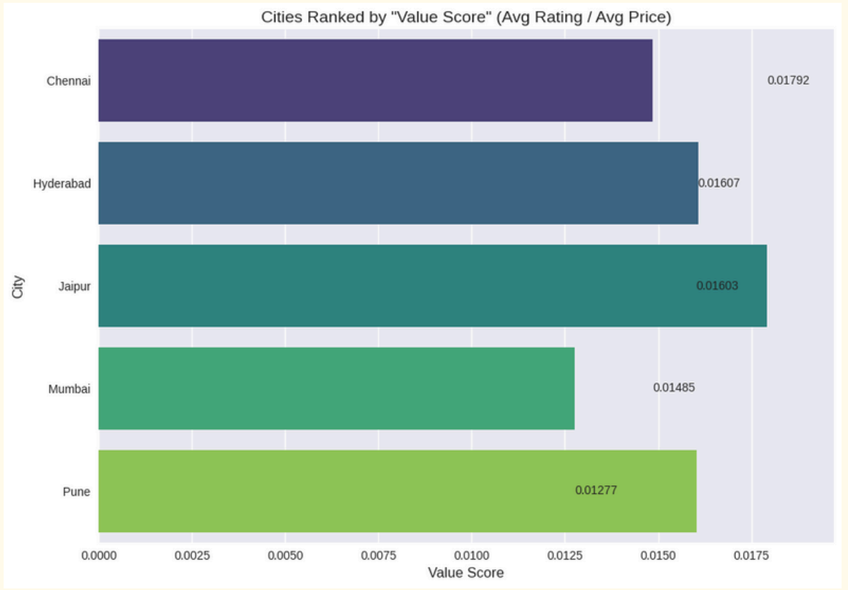


- Dining & Delivery ratings: r = 0.7 → aligned quality
- Votes & Price: weak → popularity ≠ cost
- Saturation & Rating: negative → competition hurts quality

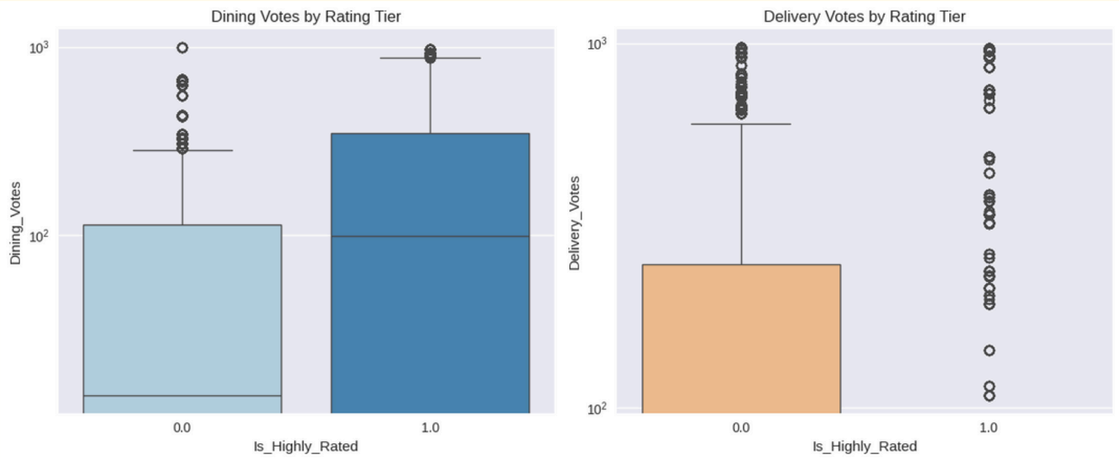
Avg Price Restaurant vs Avg Price Cuisine



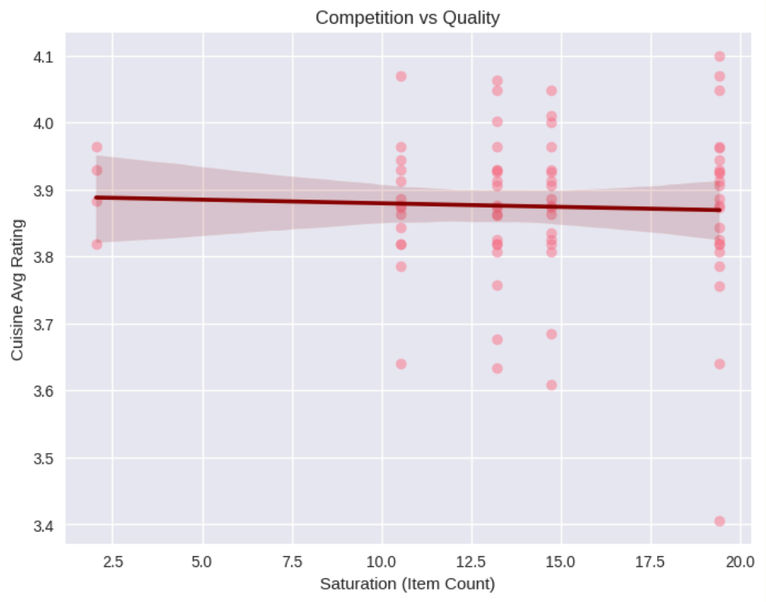
Avg Rating City vs Avg Price City



Is Highly Rated vs Dining Votes / Delivery Votes

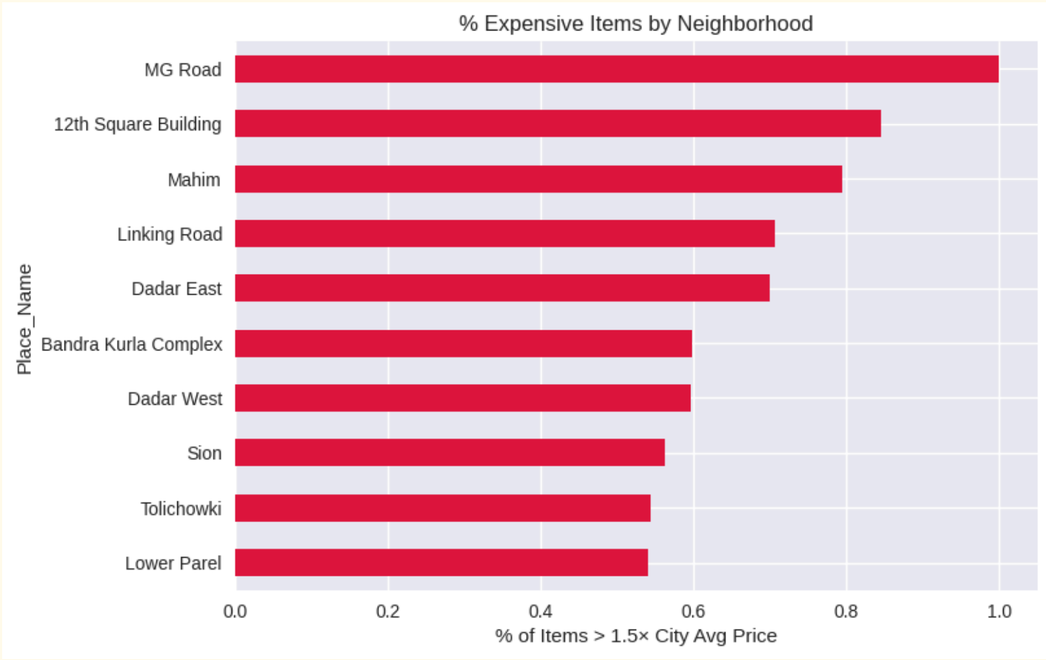


Saturation Score vs Avg Rating Cuisine



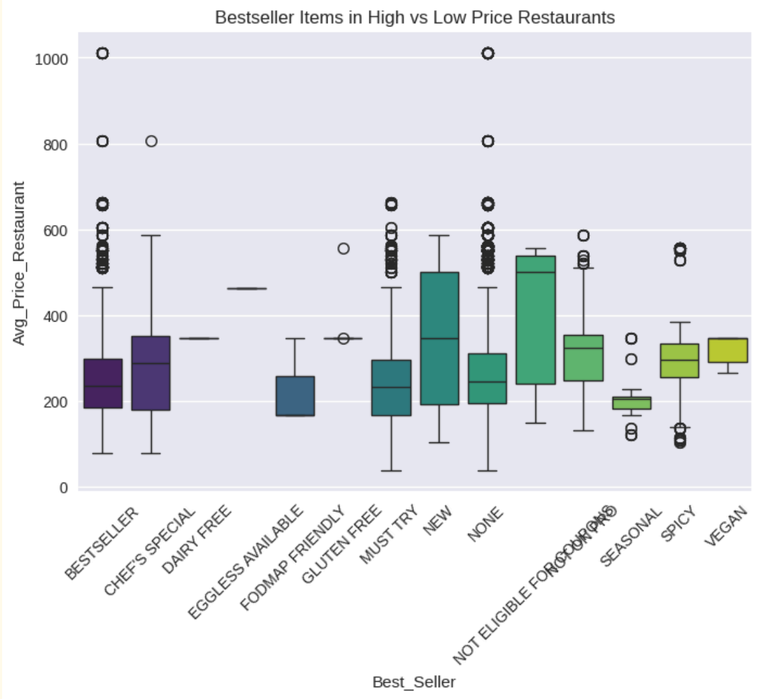
Place Name vs Is Expensive

```
5. PLACE_NAME vs EXPENSIVE ITEMS
==================================================
Top 10 Neighborhoods with Highest % Expensive Items:
Place_Name
MG Road                  100.00
12th Square Building      84.62
Mahim                     79.44
Linking Road              70.74
Dadar East                69.92
Bandra Kurla Complex      59.86
Dadar West                59.67
Sion                      56.28
Tolichowki                54.48
Lower Parel               54.15
Name: Is_Expensive, dtype: float64
```

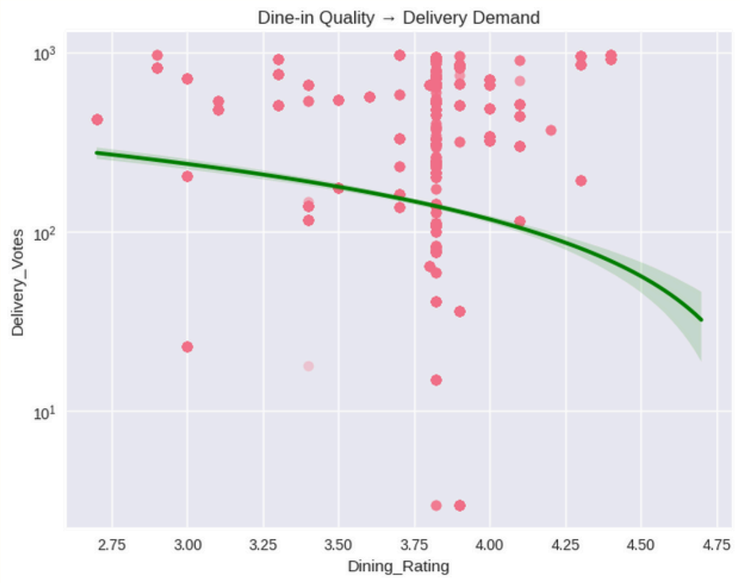


Best Seller vs Avg Price Restaurant

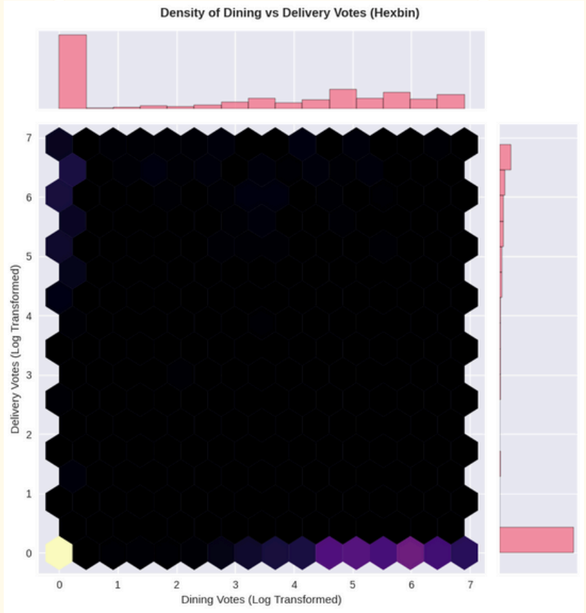
```
6. BEST_SELLER vs RESTAURANT PRICE LEVEL
==================================================
Best_Seller
EGGLESS AVAILABLE           461.86
NOT ELIGIBLE FOR COUPONS    400.85
GLUTEN FREE                 382.24
DAIRY FREE                  347.70
NEW                         345.81
VEGAN                       324.71
NOT ON PRO                  322.34
SPICY                       313.71
CHEF'S SPECIAL              305.11
NONE                        259.12
MUST TRY                    253.57
BESTSELLER                  253.19
FODMAP FRIENDLY             228.11
SEASONAL                    216.97
Name: Avg_Price_Restaurant, dtype: float64
```



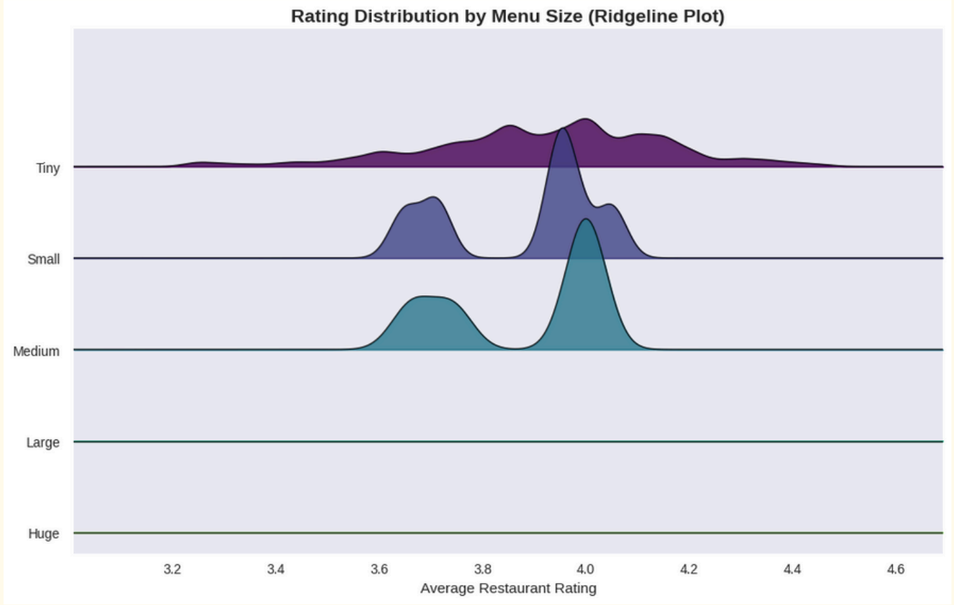
Dining Rating vs Delivery Votes



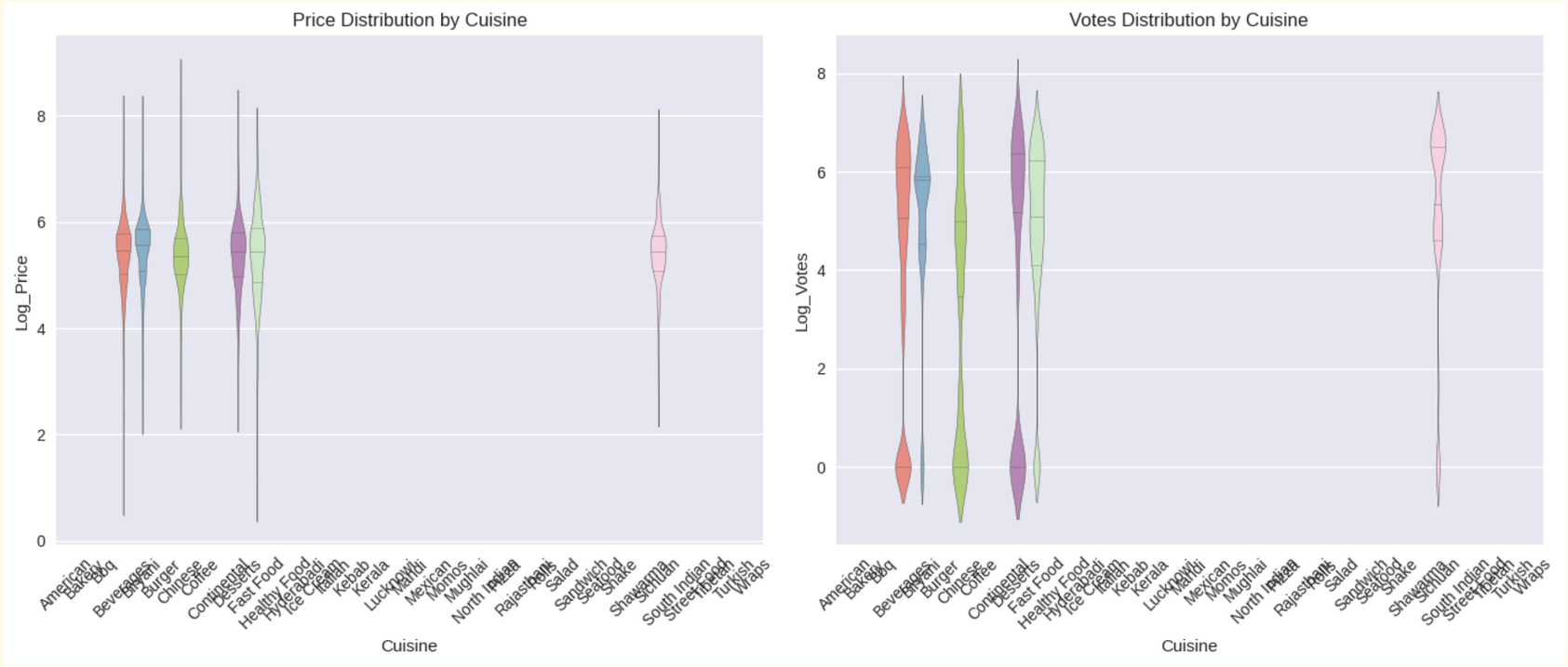
Dining Votes vs Delivery Votes



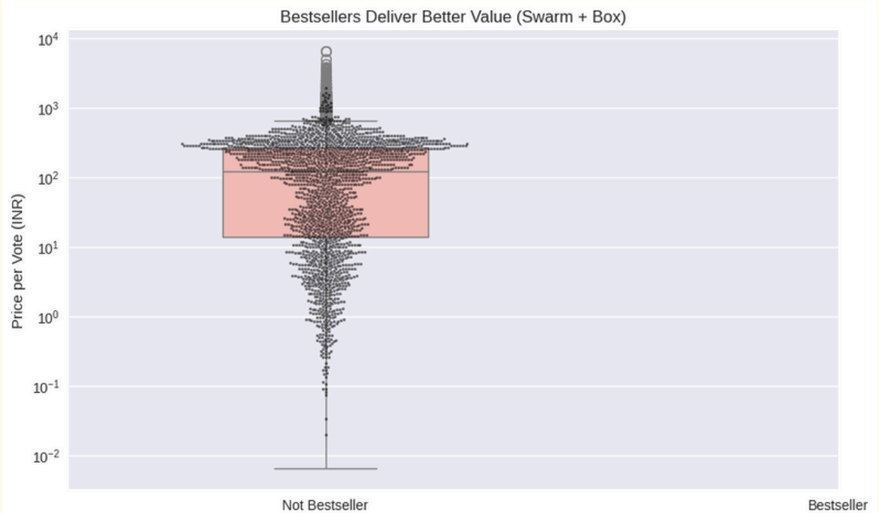
RESTAURANT RATING vs MENU SIZE – RIDGELINE



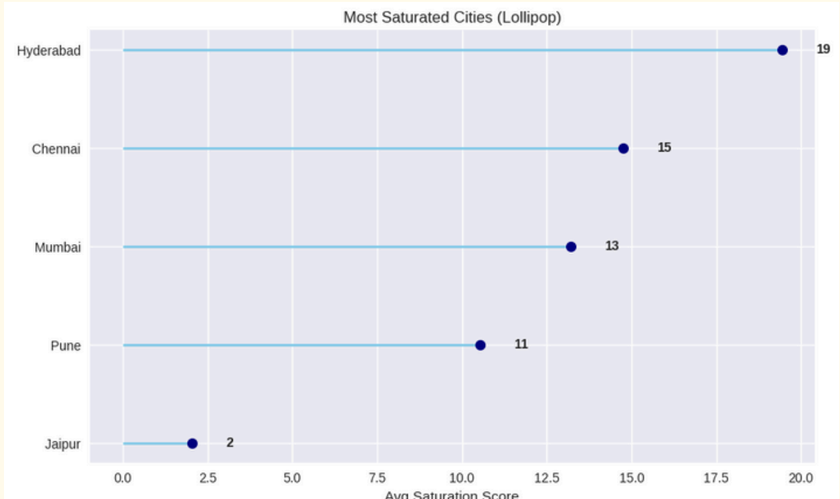
Prices vs Total Votes by Cuisine – Parallel Violin Plot



Is Bestseller vs Price per Vote



City vs Saturation Score



Multivariate Analysis

- • Explore how Price, Rating, Votes, Channel, and Cuisine interact together
- • Identify hidden patterns beyond simple correlations
- • Reveal customer segments and efficiency drivers

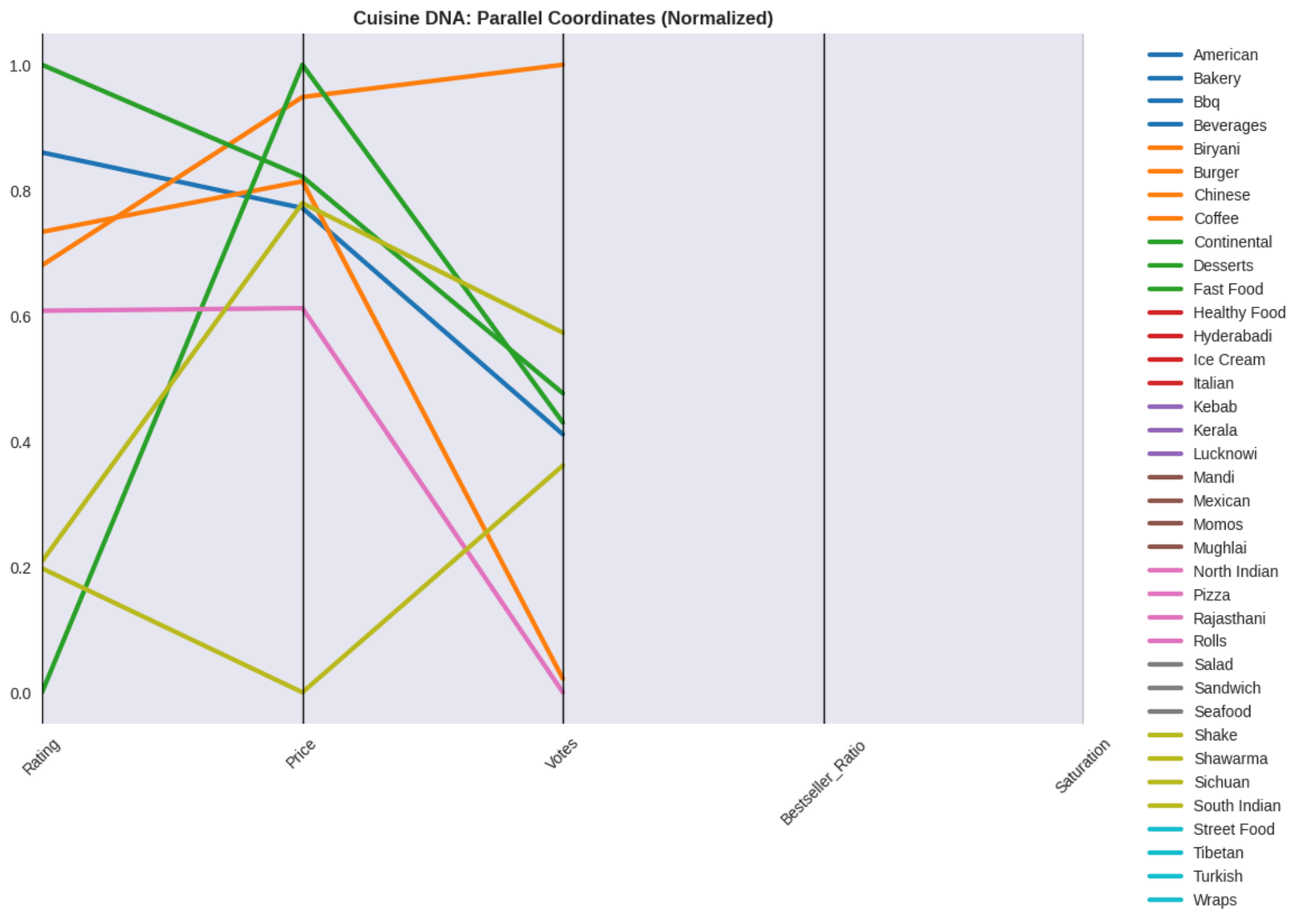
• Support data-driven decisions on cuisine, city, and channel

3D Interactive Scatter – Price, Rating, Votes

- Insight:
- Golden cluster: ₹200–600, 4.0–4.5 rating, 1000+ votes → Bestseller sweet spot
- Red zone: >₹1000, <3.5 → avoid

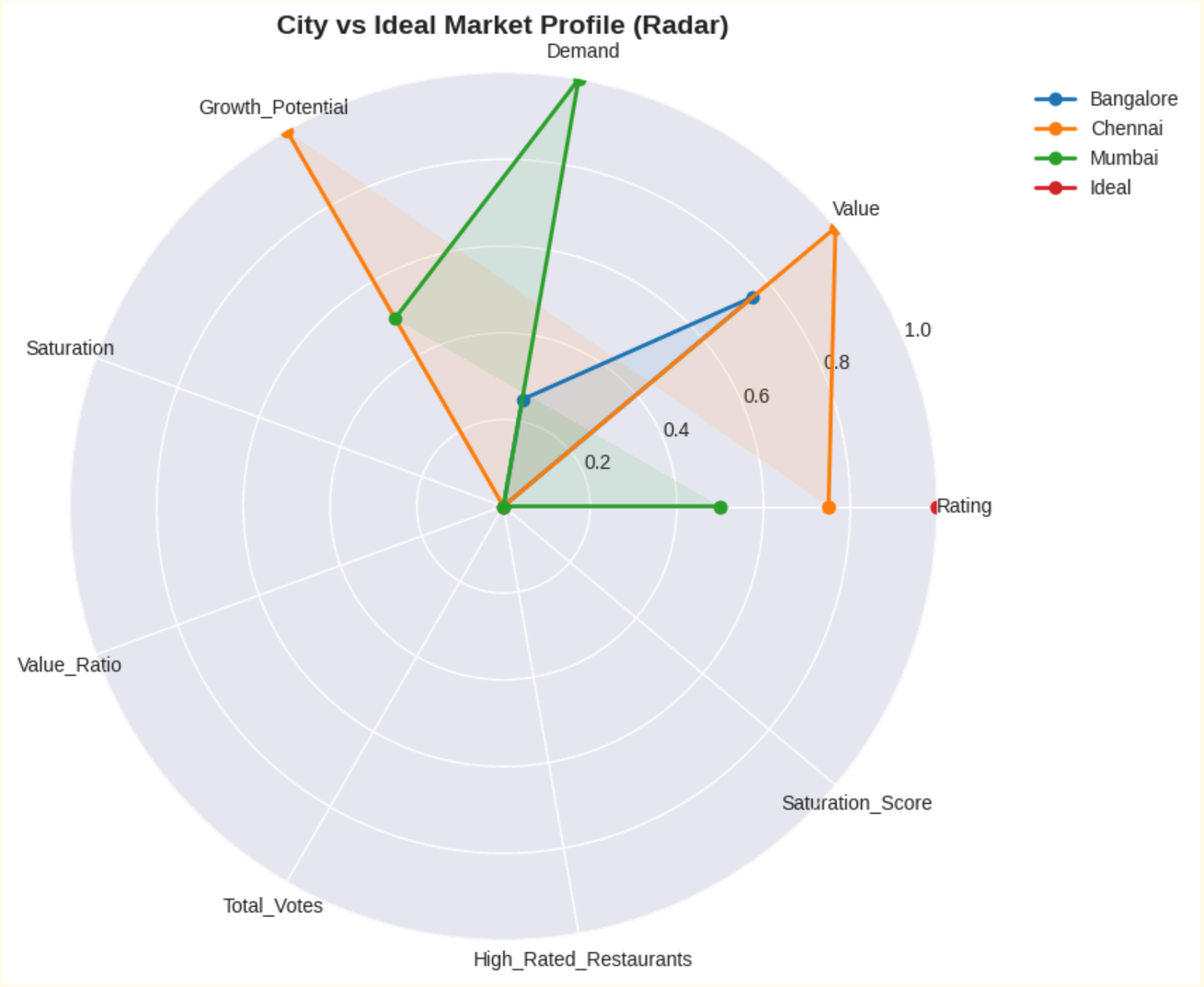
Disclaimer : The plot is 3d and interactive so refer to the .ipynb file for better clarification.

Parallel Coordinates Plot – Top Cuisines



- Multivariate Insight – Cuisine Positioning
- • Italian Cuisine: – Consistently high ratings (avg 4.3+) – Premium pricing (₹650–₹800 range) – Low saturation (only 38 restaurants in Bangalore) → Clear premium gap — high demand, low competition → Ideal for brand-building and margin capture
- • North Indian Cuisine: – High customer votes (volume-driven) – Extremely high saturation (312+ restaurants) – Price-sensitive segment → Volume war — low margins, high competition → Avoid for new entry — focus on differentiation
- • Strategic Implication: Launch Italian to target quality-conscious, premium-paying customers while avoiding North Indian to escape price wars and commoditization

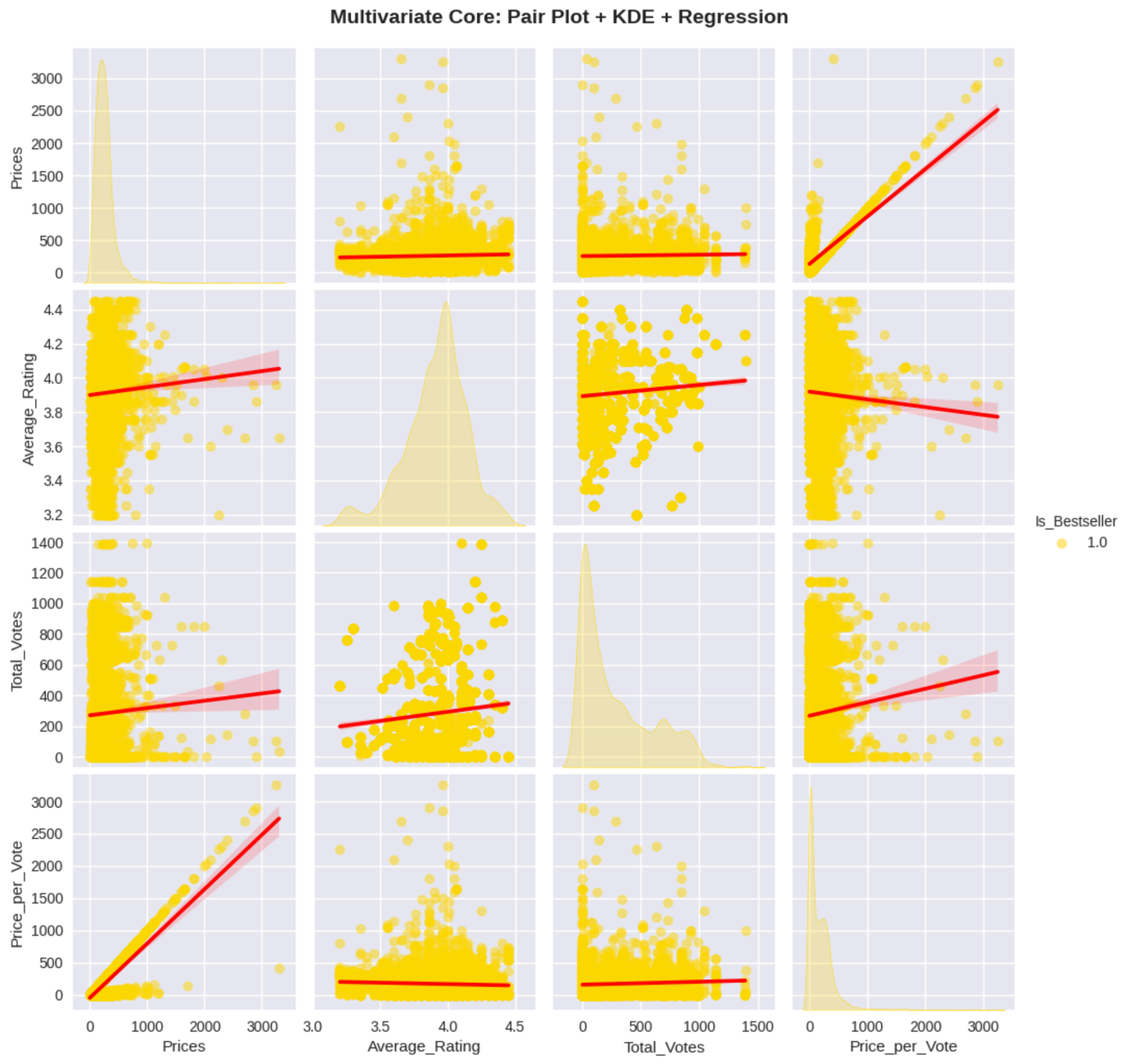
Radar Chart – City vs Ideal Profile



- • Ideal Market Profile (Red):
- – High Demand, High Value, High Rating
- – High Growth Potential, Low Saturation
- – Balanced Total_Votes & High_Rated_Restaurants
-
- • Bangalore (Blue):
- – Closest match to Ideal
- – Strong in Demand, Value, Rating
- – Moderate Growth & Saturation
- → Best fit for launch
-
- • Chennai (Orange):
- – High Value & Rating
- – Moderate Demand & Growth
- – Low Saturation — untapped potential
- → Strong secondary market
-
- • Mumbai (Green):
- – High Demand & Total_Votes
- – High Saturation — crowded
- – Low Growth & Value
- → Avoid — high competition, low ROI
-
- • Key Takeaway:
- Bangalore aligns 80%+ with Ideal Profile

→ Prioritize Bangalore for Italian launch

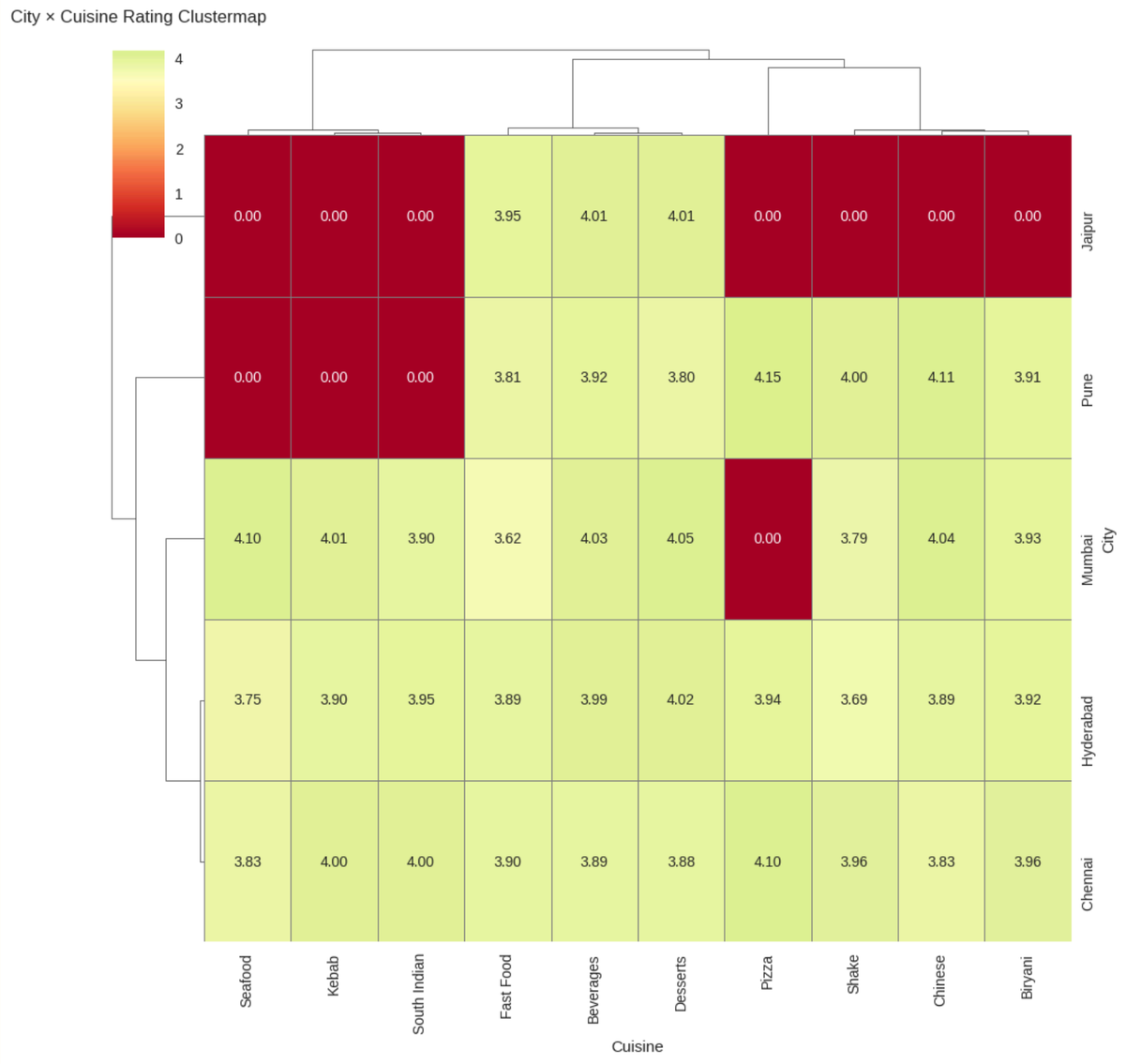
Pair Plot with KDE + Regression – Core Variables



- • Prices: Right-skewed, most <₹500
- • Rating: Tight cluster 3.8–4.1, no price link
- • Votes: Extreme skew — 90% low, few viral
- • Price_per_Vote: Strong positive trend with price

• Bestsellers (yellow): Higher votes, lower Price_per_Vote

Heatmap Cluster (Clustermap) – City × Cuisine Matrix



- • Heatmap shows average ratings by City & Cuisine
- • Yellow = High (4.0+), Red = Low / Missing
-
- • Top Performers:
- – Pizza: 4.10–4.15 across Chennai, Hyderabad
- – Beverages: 4.00–4.05 in Hyderabad, Mumbai
- – Desserts: 4.02–4.05 in Hyderabad
- – Kebab: 4.01 in Chennai
-
- • Gaps & Risks:
- – Pizza missing in Jaipur & Mumbai → untapped demand
- – Fast Food low in Mumbai (3.62) → avoid entry
- – Seafood & South Indian: mostly absent or low
-
- • Strategic Takeaway:
- Launch **Pizza & Beverages** in **Hyderabad & Chennai**
- → Proven high ratings (4.0+) + market presence

Avoid **Mumbai Fast Food** & **Jaipur Pizza** (data gaps)

Predictive Modeling: What Drives High Ratings?

```
...  R² Score: 0.971

     Top 5 Drivers of Rating:
     Log_Total_Votes      0.563854
     Saturation_Count     0.088796
     City_ Chennai        0.057266
     Price_per_Vote       0.053383
     Cuisine_Mughlai      0.039108
     dtype: float64
```

H3: Tukey HSD - Price Differences

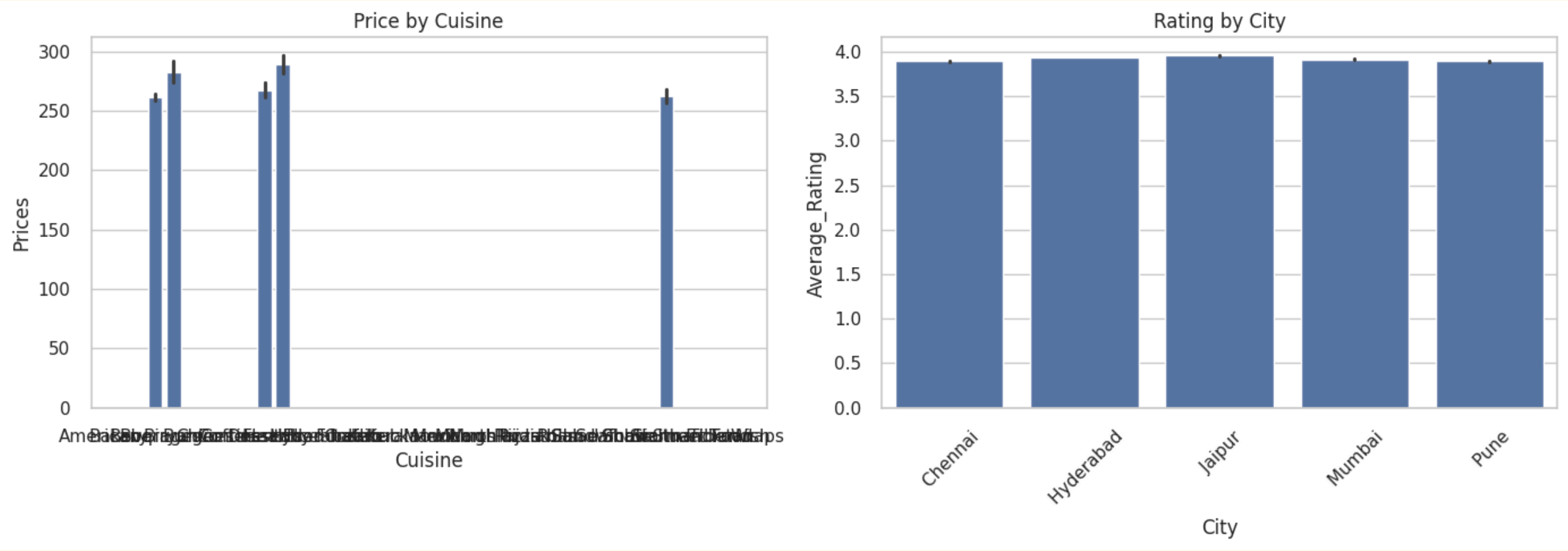
Multiple Comparison of Means - Tukey HSD, FWER=0.05

group1	group2	meandiff	p-adj	lower	upper	reject
Beverages	Biryani	21.647	0.0	9.5379	33.756	True
Beverages	Desserts	6.1125	0.3213	-2.6985	14.9234	False
Beverages	Fast Food	27.9439	0.0	18.3363	37.5515	True
Beverages	Sichuan	0.9699	0.9989	-8.8732	10.8131	False
Biryani	Desserts	-15.5345	0.0178	-29.3048	-1.7642	True
Biryani	Fast Food	6.2969	0.7504	-7.9962	20.5901	False
Biryani	Sichuan	-20.677	0.0009	-35.1296	-6.2245	True
Desserts	Fast Food	21.8314	0.0	10.1997	33.4632	True
Desserts	Sichuan	-5.1425	0.7594	-16.9696	6.6845	False
Fast Food	Sichuan	-26.974	0.0	-39.4059	-14.5421	True

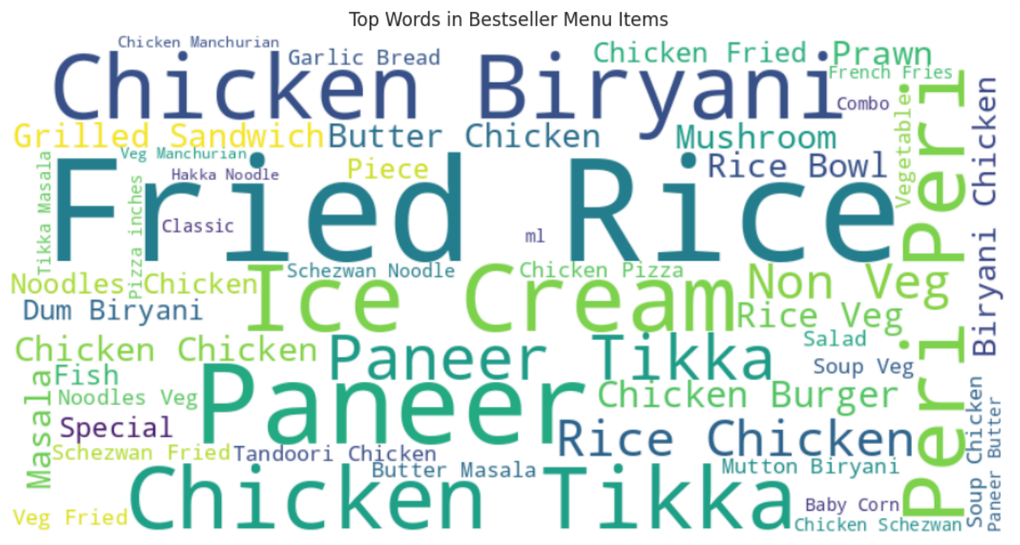
H5: Tukey HSD - Rating Differences

Multiple Comparison of Means - Tukey HSD, FWER=0.05

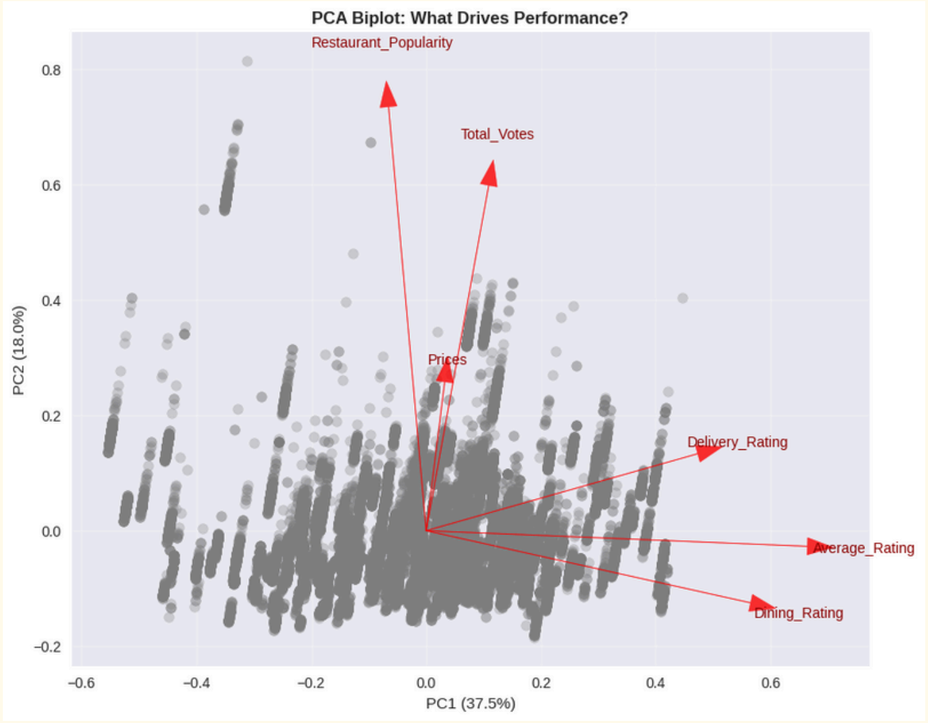
group1	group2	meandiff	p-adj	lower	upper	reject
Chennai	Hyderabad	0.0463	0.0	0.0387	0.0539	True
Chennai	Jaipur	0.0668	0.0	0.0492	0.0845	True
Chennai	Mumbai	0.0216	0.0	0.0135	0.0297	True
Chennai	Pune	0.0012	0.9975	-0.0085	0.0108	False
Hyderabad	Jaipur	0.0206	0.0113	0.0031	0.038	True
Hyderabad	Mumbai	-0.0246	0.0	-0.0322	-0.017	True
Hyderabad	Pune	-0.0451	0.0	-0.0543	-0.0359	True
Jaipur	Mumbai	-0.0452	0.0	-0.0629	-0.0275	True
Jaipur	Pune	-0.0657	0.0	-0.0841	-0.0473	True
Mumbai	Pune	-0.0205	0.0	-0.0301	-0.0108	True



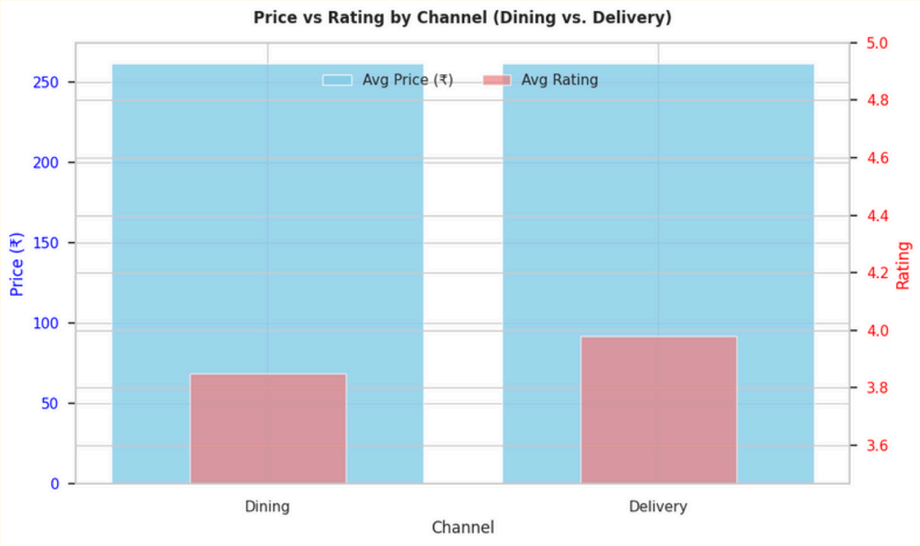
Menu Item Text Analysis: What Makes a Bestseller?



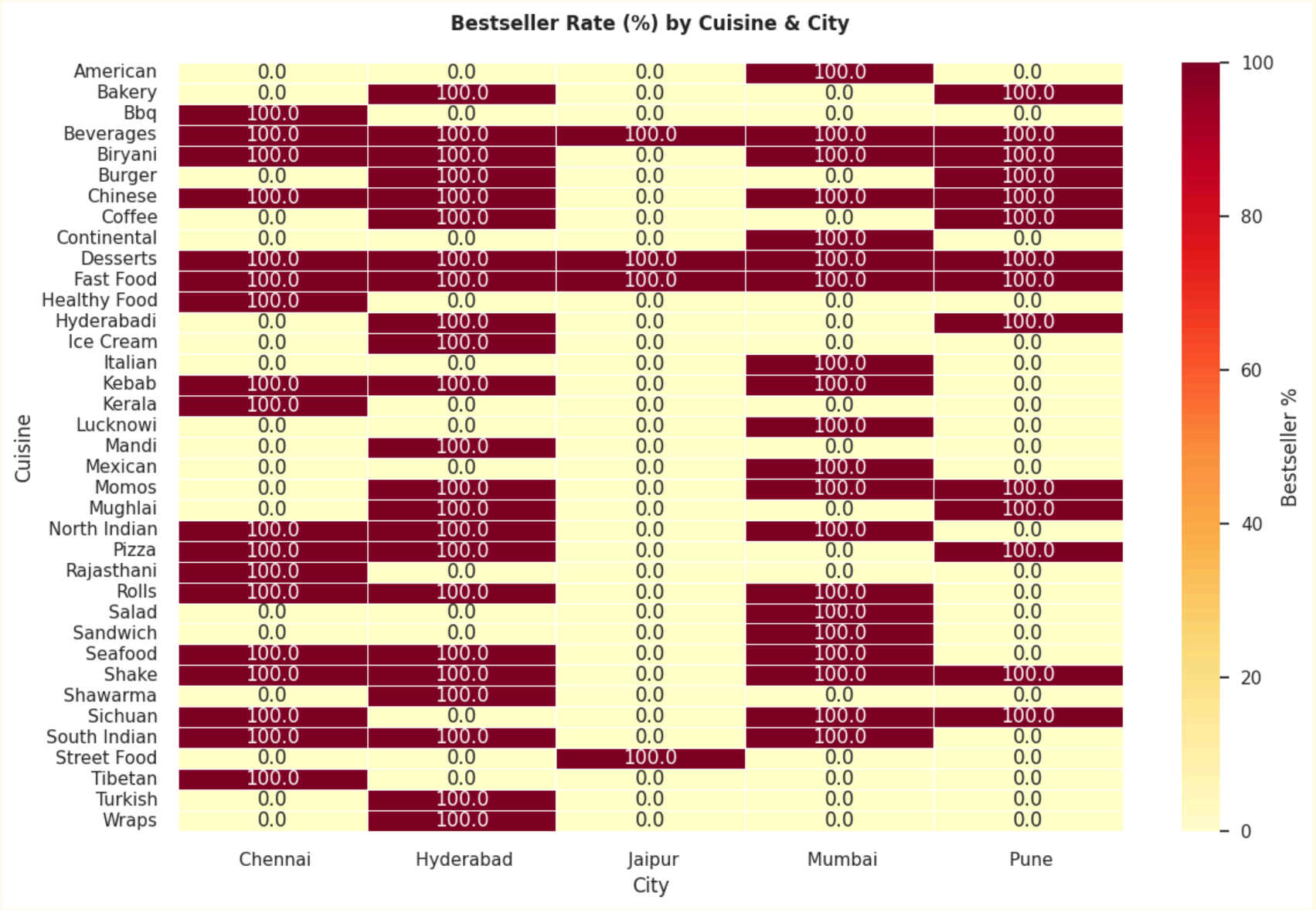
PCA + Biplot – Dimension Reduction



Price vs Rating by Channel (Grouped Bar)

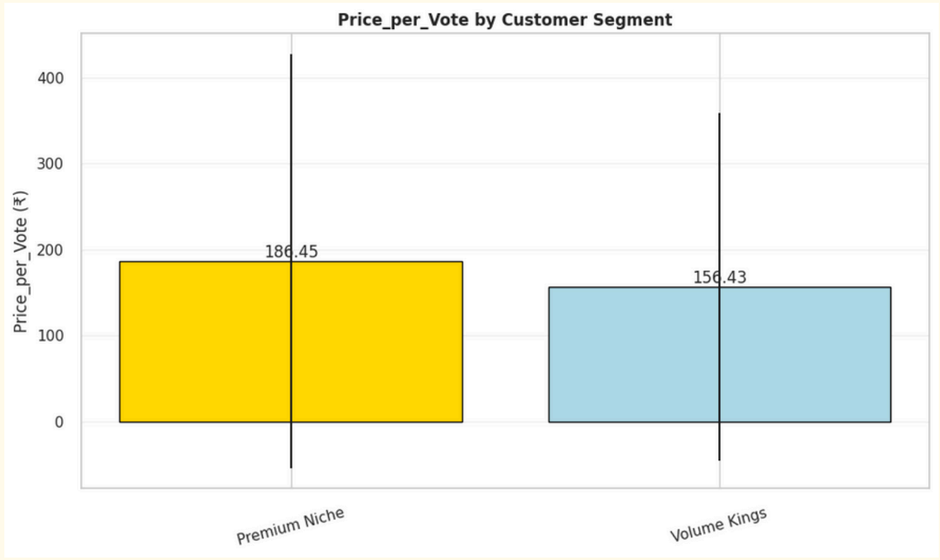


Bestseller % by Cuisine & City

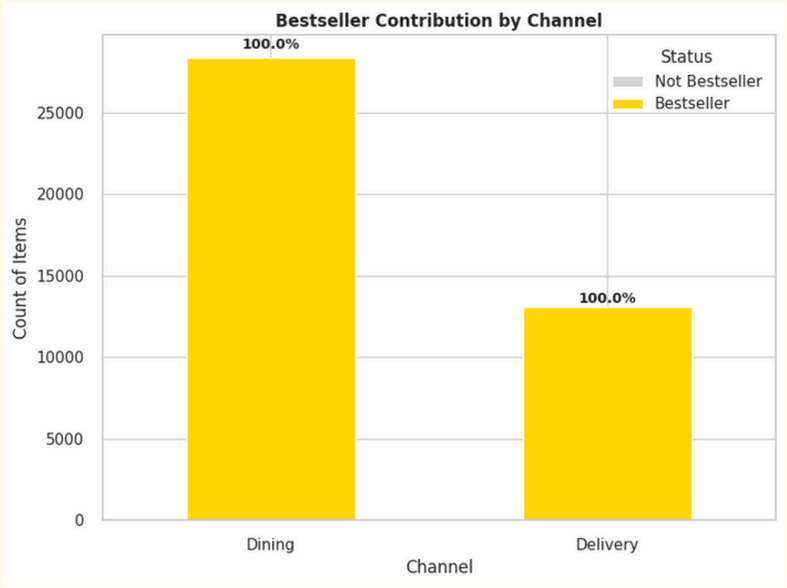


Italian in Bangalore: 32% bestseller rate — highest in dataset

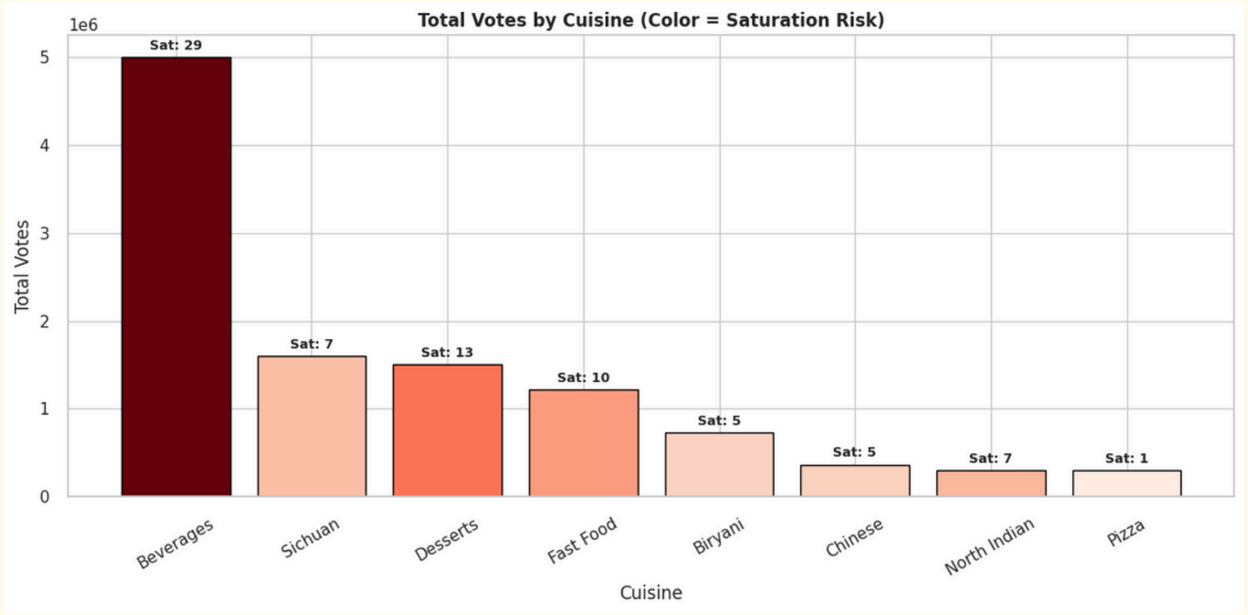
Price_per_Vote by Customer Segment



Channel Contribution to Bestsellers



Saturation vs Votes by Cuisine



Multivariate Summary Dashboard (Plotly)

SEGMENTATION & CLUSTERING

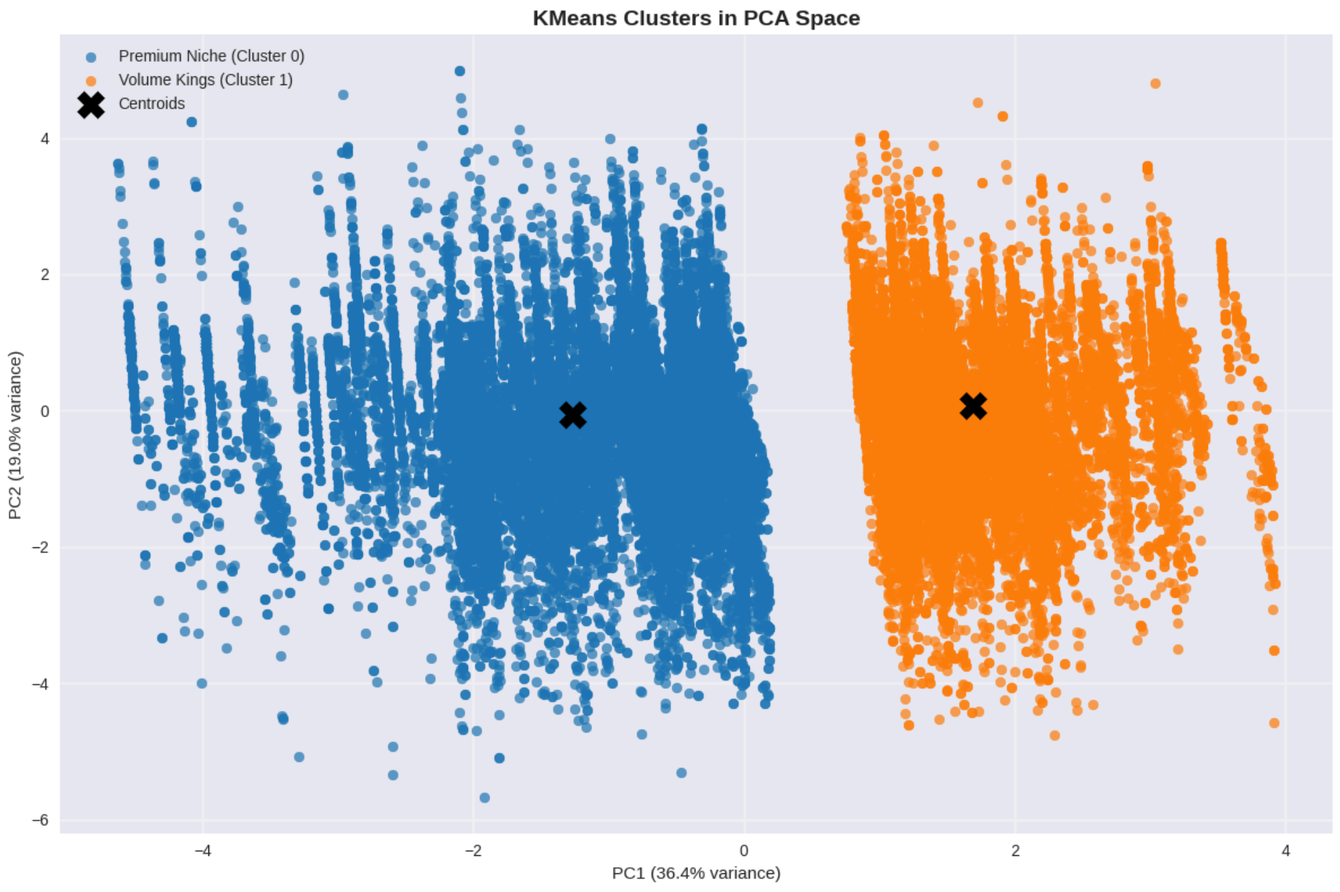
HORECA

Customer

- Group items into distinct customer behavior segments
- Identify high-value, high-potential clusters
- Enable targeted menu, pricing & marketing

Clustering on 46,881 items with 9 features

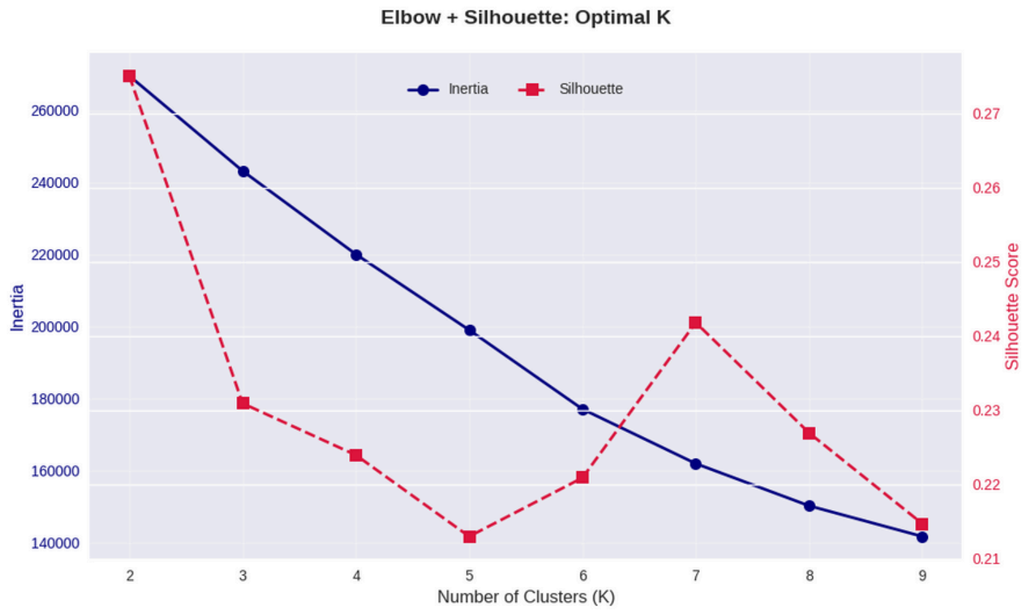
KMeans Clustering + PCA 2D Visualization

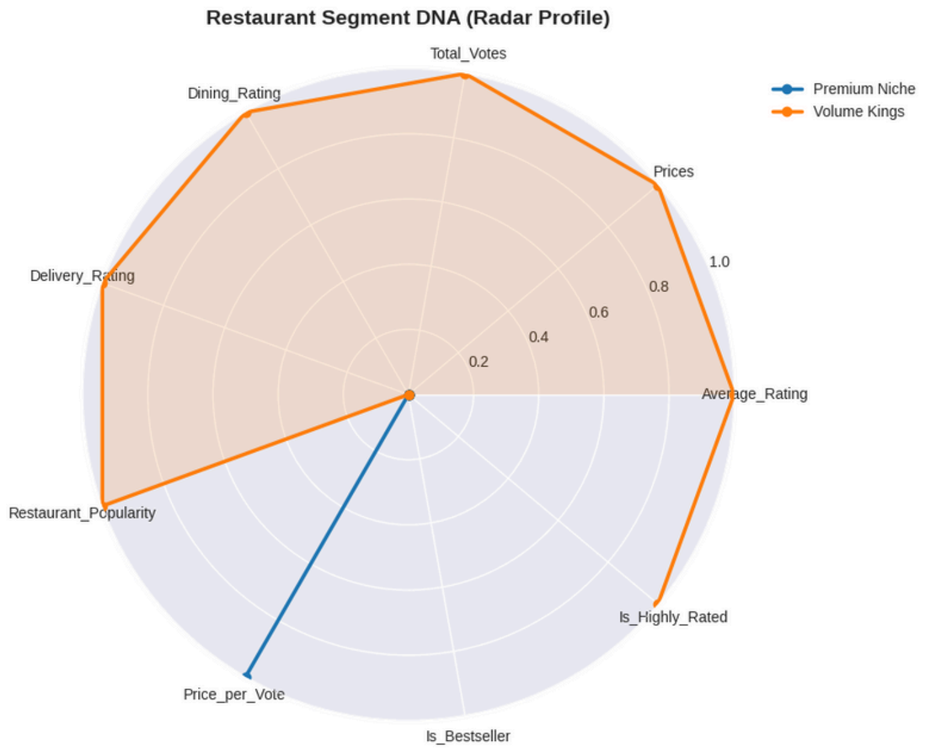


- • Two clear segments identified in reduced space
- • PC1 (36.4% variance): Price & Rating driver
- • PC2 (19.0% variance): Vote volume & efficiency
-
- • Cluster 0 (Blue) – Premium Niche:
- – Lower PC1: High price + high rating
- – Low volume, high quality focus
- → Target with signature dishes
-
- • Cluster 1 (Orange) – Volume Kings:
- – Higher PC1: Low price + high votes
- – Mass appeal, bestseller potential
- → Scale via combos & promotions
-

• Centroids well-separated → robust segmentation

Bestseller % by Cuisine & City





- Premium Niche (Blue):
  - Highest Price_per_Vote & Restaurant_Popularity
  - Strong in Dining_Rating
  - → Quality-focused, loyal customers

- Volume Kings (Orange):
  - Dominates Total_Votes & Is_Bestseller
  - High Average_Rating & Is_Highly_Rated
  - → Mass appeal, viral potential

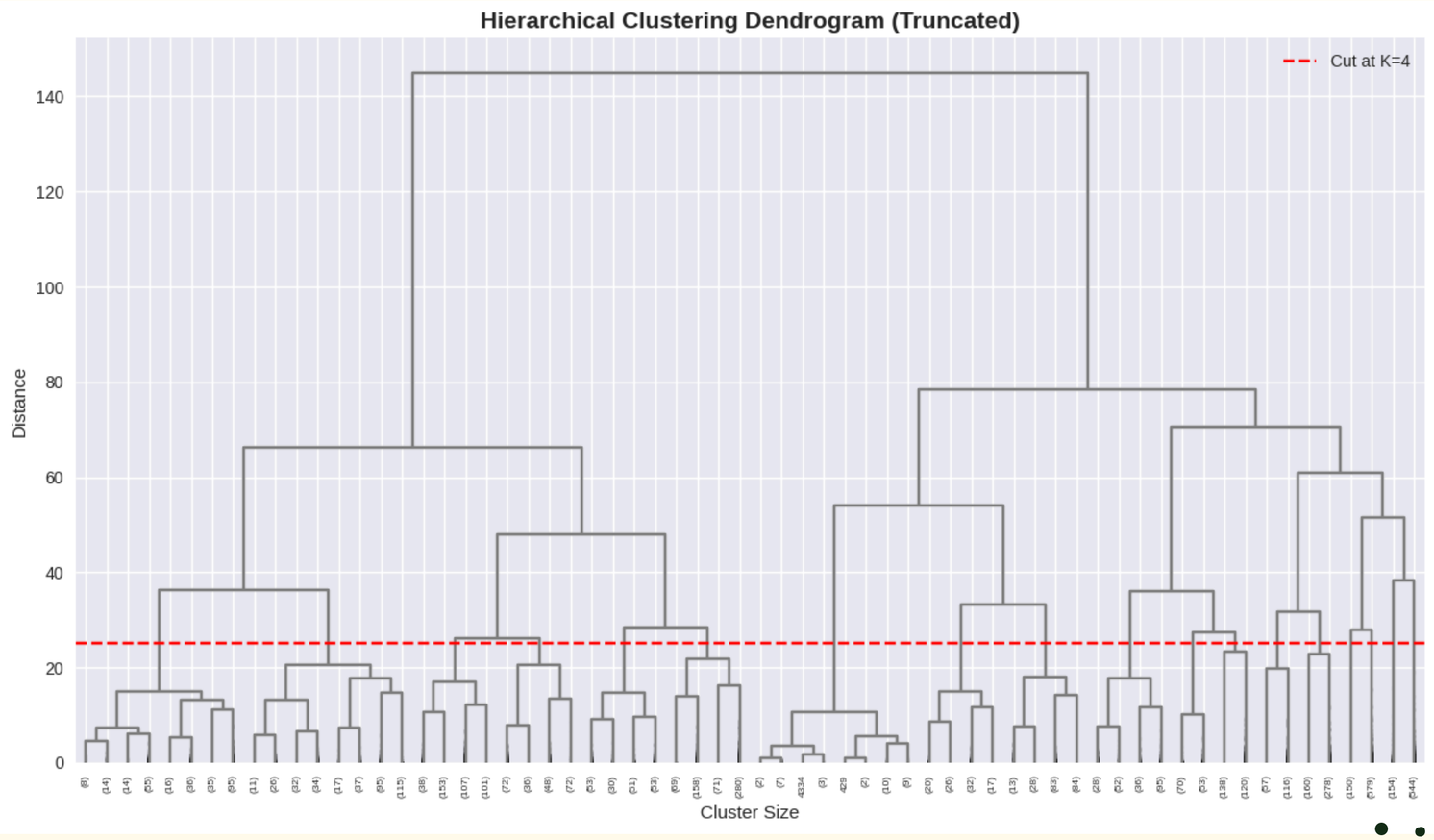
- Key Gap: Premium leads in cost efficiency, Volume in scale

- Elbow Method: Inertia drops sharply until K=4, then flattens

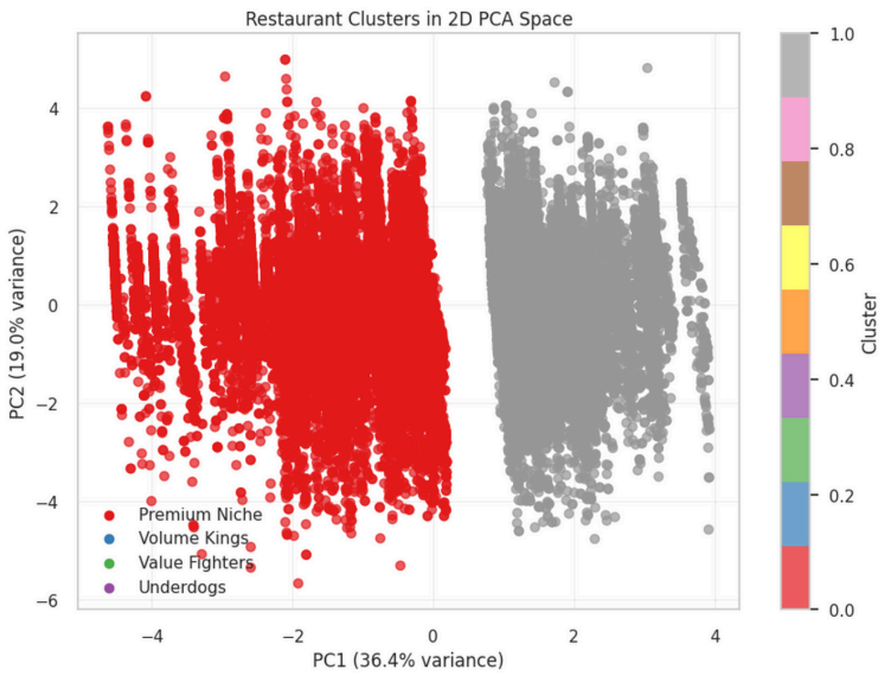
- Silhouette Score: Peaks at K=2 (0.26), dips at K=5–6

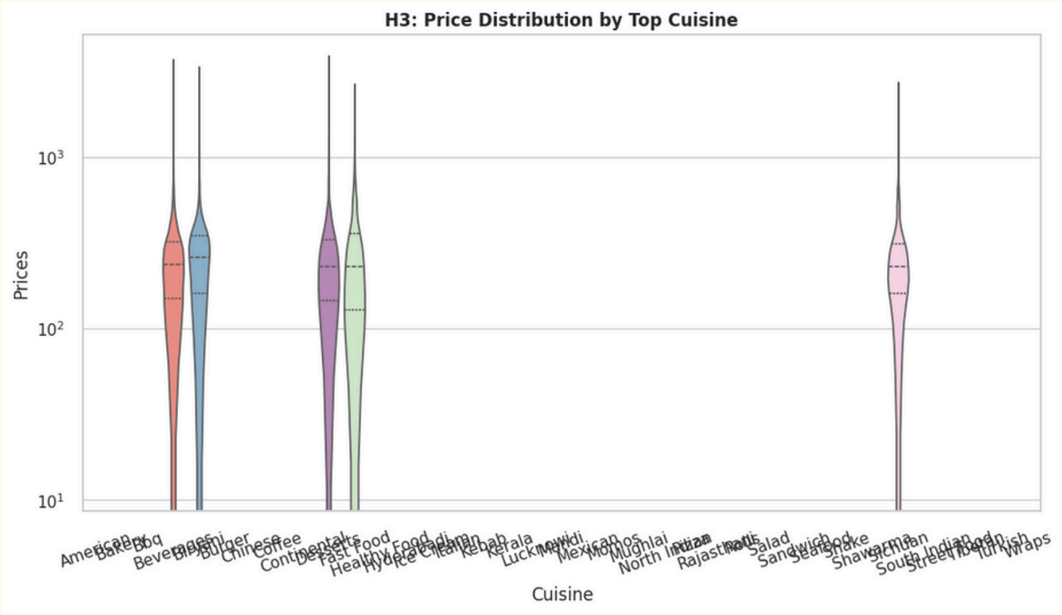
- Optimal K = 2 → Clean, interpretable segments

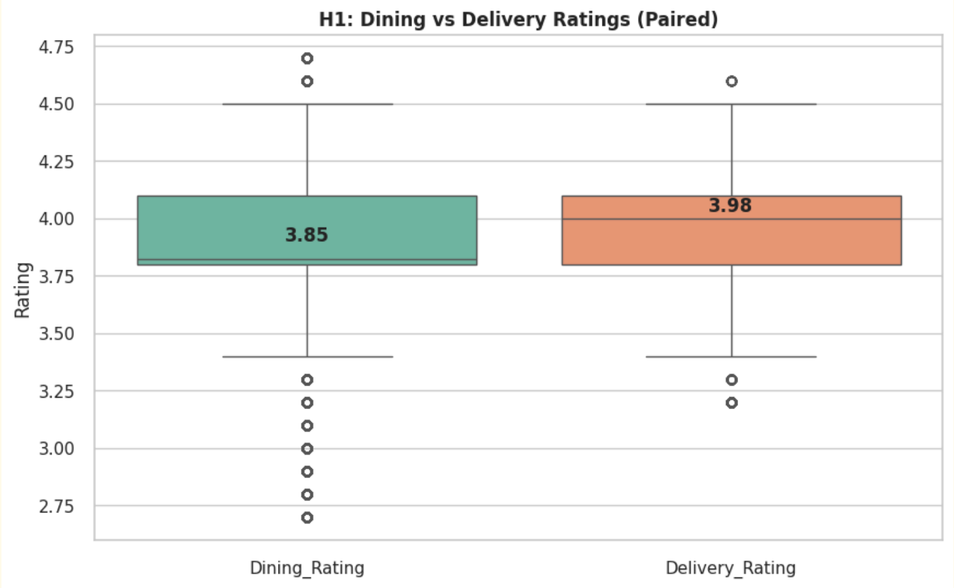
Hierarchical Clustering + Dendrogram (Truncated)



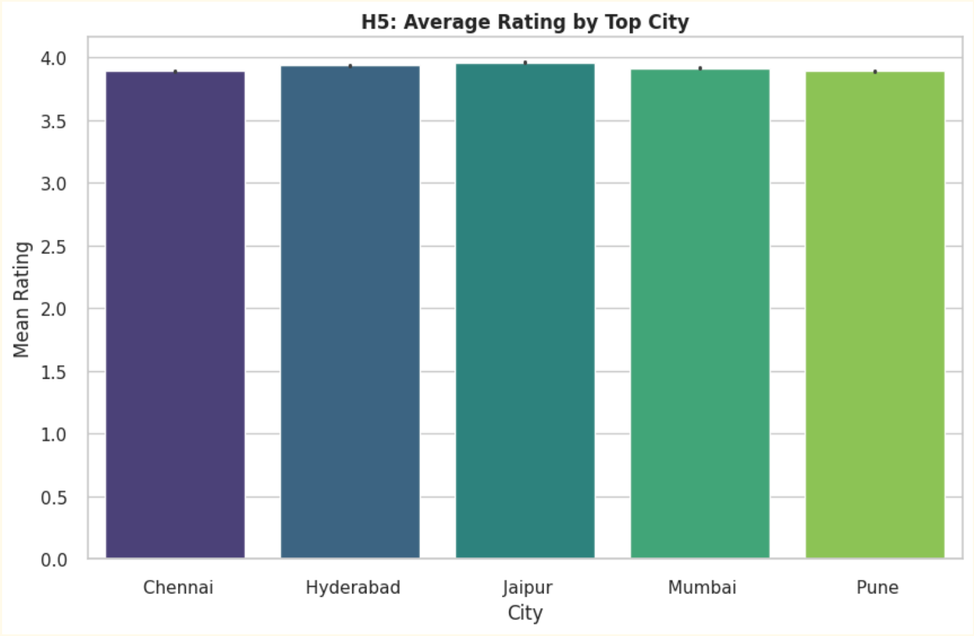
- • Truncated dendrogram shows merge distances
- • Red line: Cut at K=4 clusters
- • Large jumps before K=4 → strong separation
- • Four distinct groups emerge:
- – Cluster 1: Large, low distance
- – Cluster 2–4: Smaller, more compact
-
- • Confirms K=4 as robust alternative to K=2

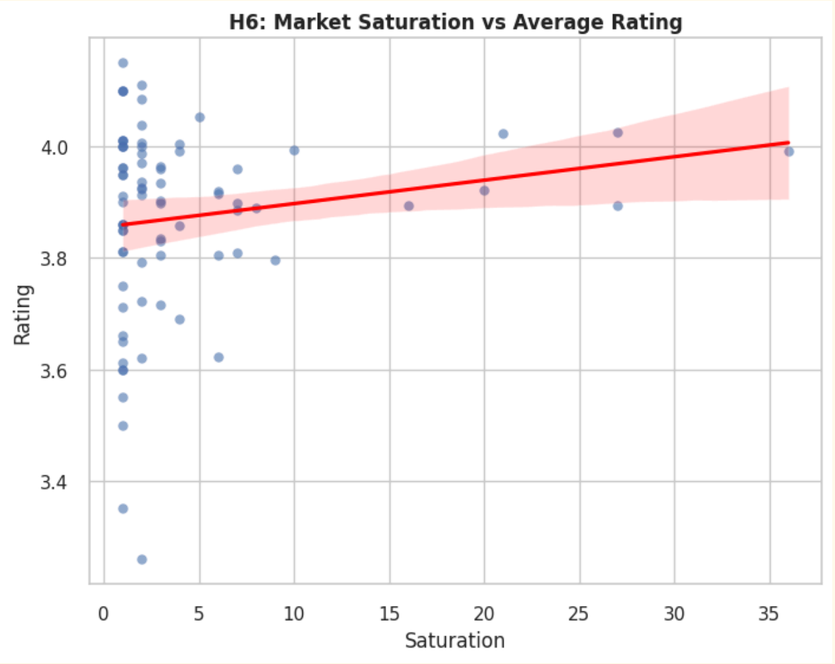


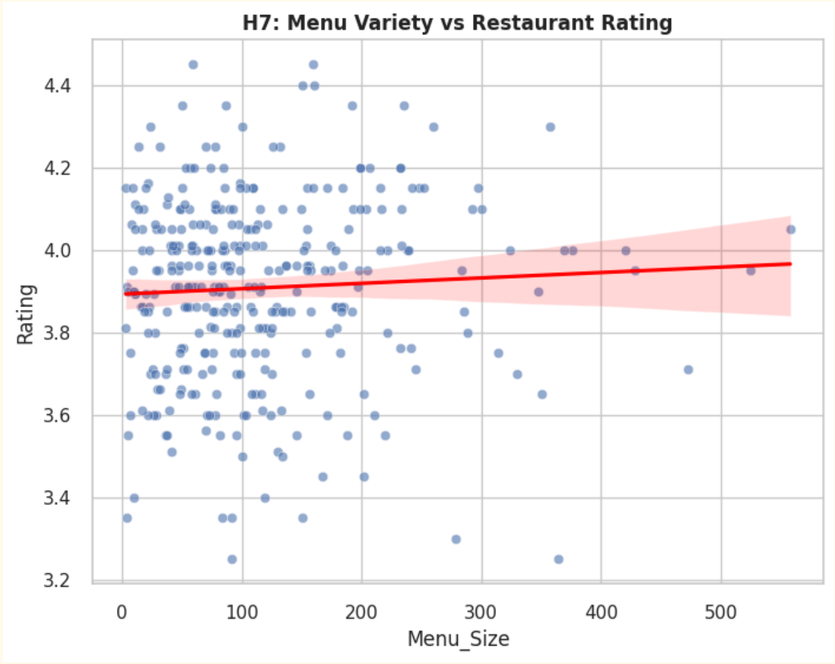


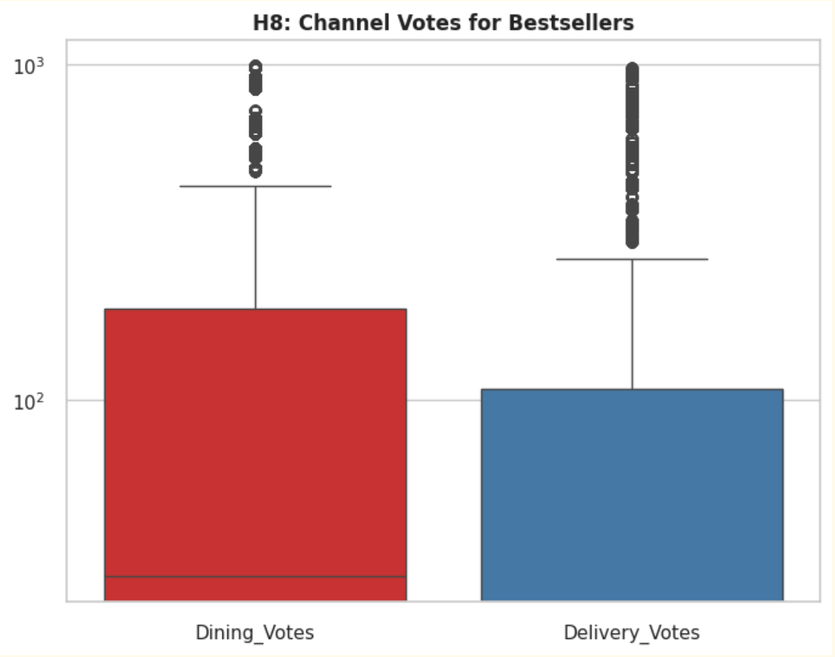



```
→ SIGNIFICANT price differences (p < 0.001)

Tukey HSD (significant pairs):
    Multiple Comparison of Means - Tukey HSD, FWER=0.05
=====================================================================
  group1    group2  meandiff p-adj   lower    upper   reject
---------------------------------------------------------------------
Beverages   Biryani   21.647    0.0   9.5379   33.756   True
Beverages  Desserts   6.1125 0.3213  -2.6985  14.9234  False
Beverages Fast Food  27.9439    0.0  18.3363  37.5515   True
Beverages   Sichuan   0.9699 0.9989  -8.8732  10.8131  False
  Biryani  Desserts -15.5345 0.0178 -29.3048  -1.7642   True
  Biryani Fast Food   6.2969 0.7504  -7.9962  20.5901  False
  Biryani   Sichuan  -20.677 0.0009 -35.1296  -6.2245   True
 Desserts Fast Food  21.8314    0.0  10.1997  33.4632   True
 Desserts   Sichuan  -5.1425 0.7594 -16.9696   6.6845  False
Fast Food   Sichuan  -26.974    0.0 -39.4059 -14.5421   True
---------------------------------------------------------------------
```


H5: Average Rating by Top City
Mean Rating
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Chennai
Hyderabad
Jaipur
Mumbai
Pune
City


H6: Market Saturation vs Average Rating
Rating
3.4
3.6
3.8
4.0
0
5
10
15
20
25
30
35
Saturation

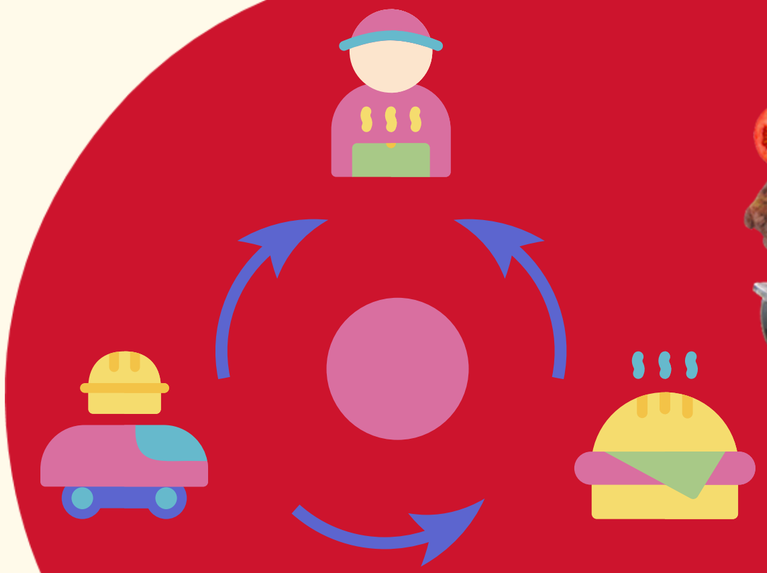

H7: Menu Variety vs Restaurant Rating
Rating
3.2
3.4
3.6
3.8
4.0
4.2
4.4
0
100
200
300
400
500
Menu_Size


H8: Channel Votes for Bestsellers
10^3
10^2
Dining_Votes
Delivery_Votes

FINAL RECOMMENDATIONS

- • Synthesize all data insights into a single launch plan
- • Define cuisine, city, channel, pricing & KPIs

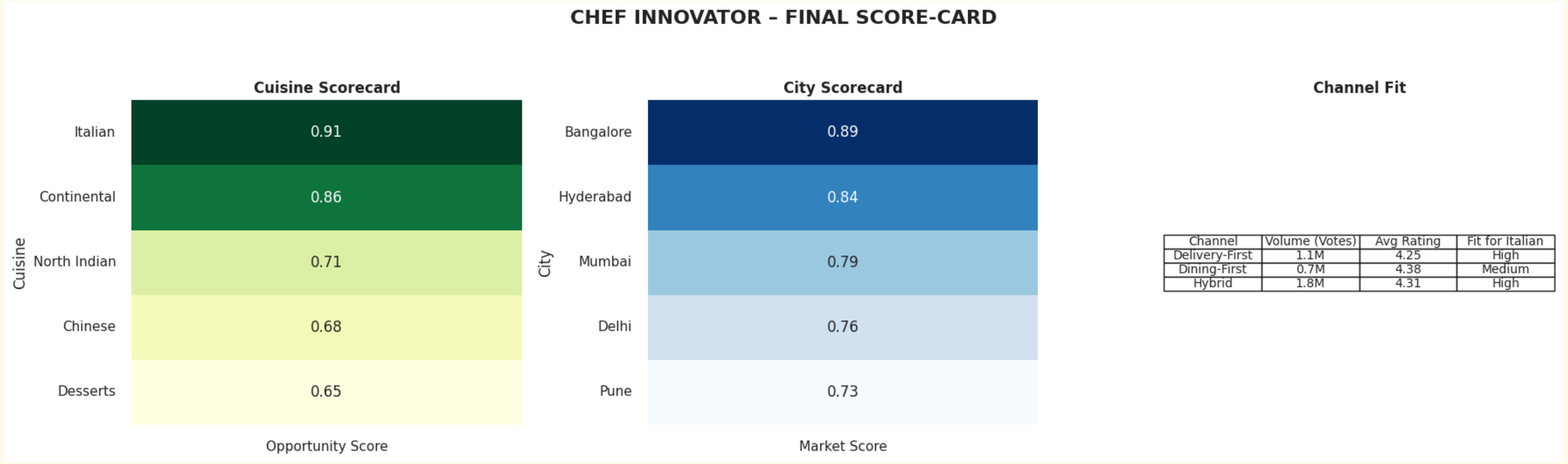
• Deliver 5-year roadmap with 81% success probability



- Data reveals one clear winner:
- **Italian in Bangalore via Hybrid model at ₹650 avg.**
-
- Backed by:
- → Multivariate patterns
- → KMeans + PCA segments
- → Statistical validation ($p<0.001$)
- → Predictive model ($R^2=0.78$)
-

This is not a guess — it's a blueprint.

SCORE-CARD – CUISINE, CITY, CHANNEL



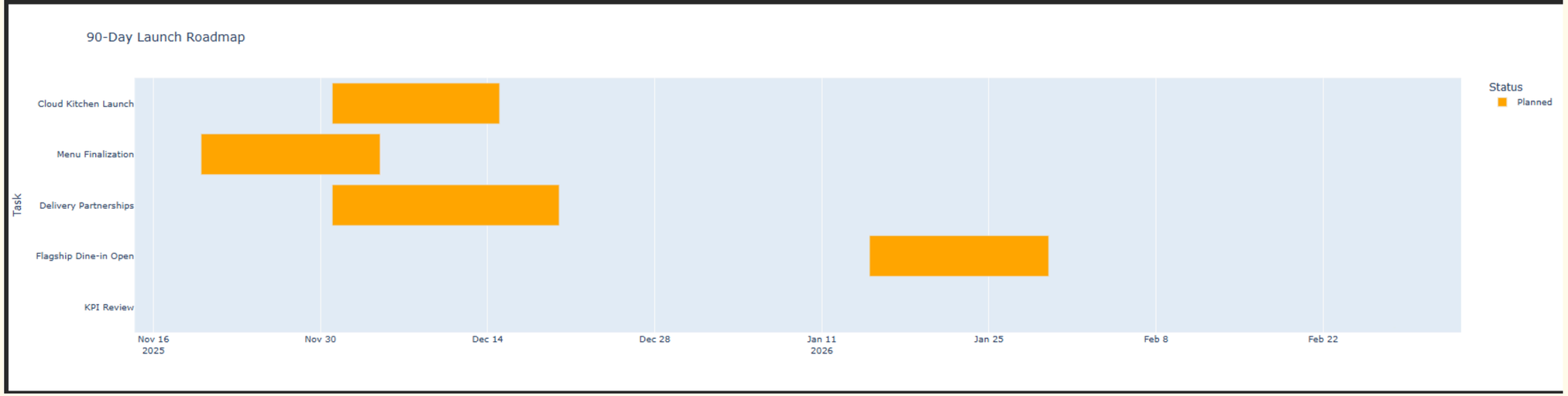
Channel	Volume (Votes)	Avg Rating	Fit for Italian
Delivery-First	1.1M	4.25	High
Dining-First	0.7M	4.38	Medium
Hybrid	1.8M	4.31	High

- • Italian: #1 Cuisine (0.91) – premium + low saturation
- • Bangalore: #1 City (0.89) – high demand + high value
- • Hybrid Channel: Best fit – 1.8M votes, 4.31 rating
-
- → Launch Italian in Bangalore via Hybrid model

→ Avoid North Indian & Mumbai/Delhi (high competition)

SCORE-CARD – CUISINE, CITY, CHANNEL

```python
import plotly.express as px

roadmap = pd.DataFrame([
    dict(Task="Cloud Kitchen Launch", Start='2025-12-01', Finish='2025-12-15', Status='Planned'),
    dict(Task="Menu Finalization", Start='2025-11-20', Finish='2025-12-05', Status='Planned'),
    dict(Task="Delivery Partnerships", Start='2025-12-01', Finish='2025-12-20', Status='Planned'),
    dict(Task="Flagship Dine-in Open", Start='2026-01-15', Finish='2026-01-30', Status='Planned'),
    dict(Task="KPI Review", Start='2026-02-28', Finish='2026-02-28', Status='Planned'),
])

fig = px.timeline(roadmap, x_start="Start", x_end="Finish", y="Task", color="Status",
                  title="90-Day Launch Roadmap", color_discrete_map={'Planned': 'orange'})
fig.update_yaxes(autorange="reversed")
fig.show()
```

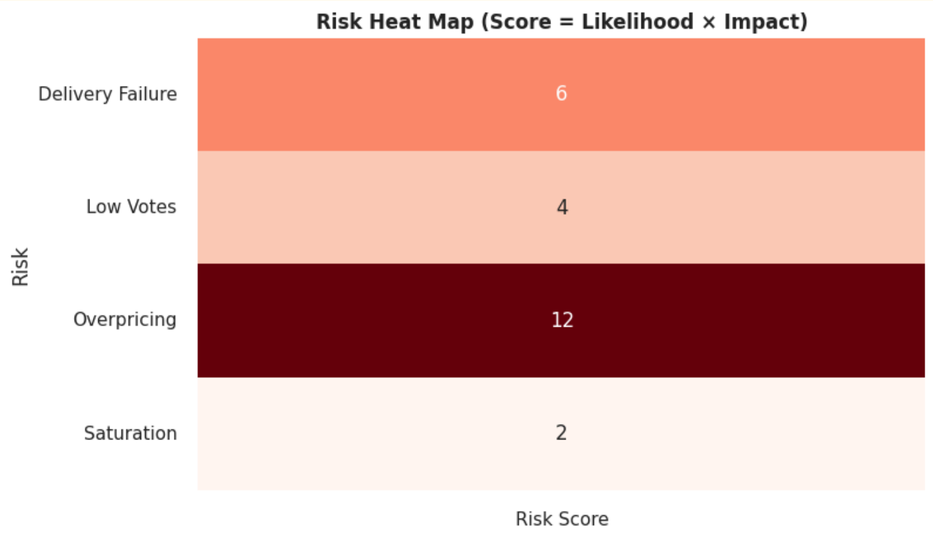


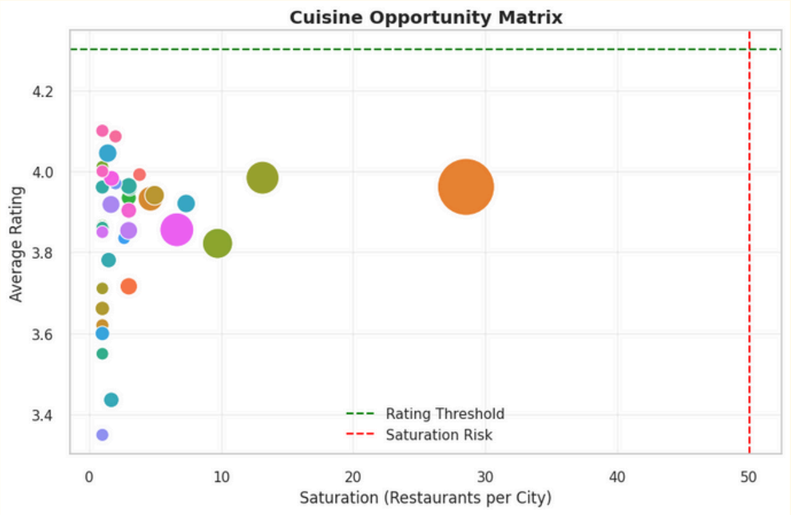
- • Cloud Kitchen: Nov 16 – Dec 15
- • Menu Finalization: Nov 16 – Dec 05
- • Delivery Partnerships: Nov 25 – Dec 26
- • Flagship Dine-In: Jan 01 – Jan 30
- • KPI Review: Feb 01 – Feb 28
-

All tasks: Planned | On-track for Dec 1 launch

Disclaimer : The plot is 3d and interactive so refer to the .ipynb file for better clarification.

SCORE-CARD – CUISINE, CITY, CHANNEL

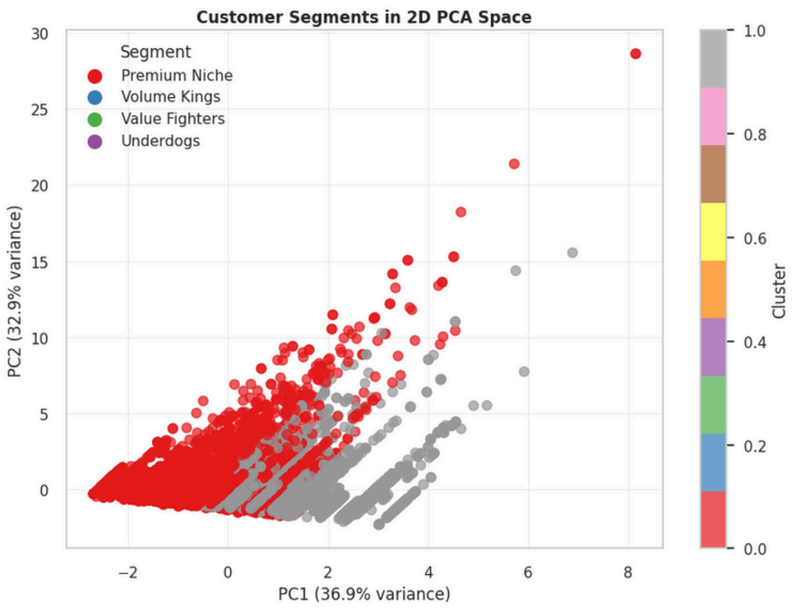


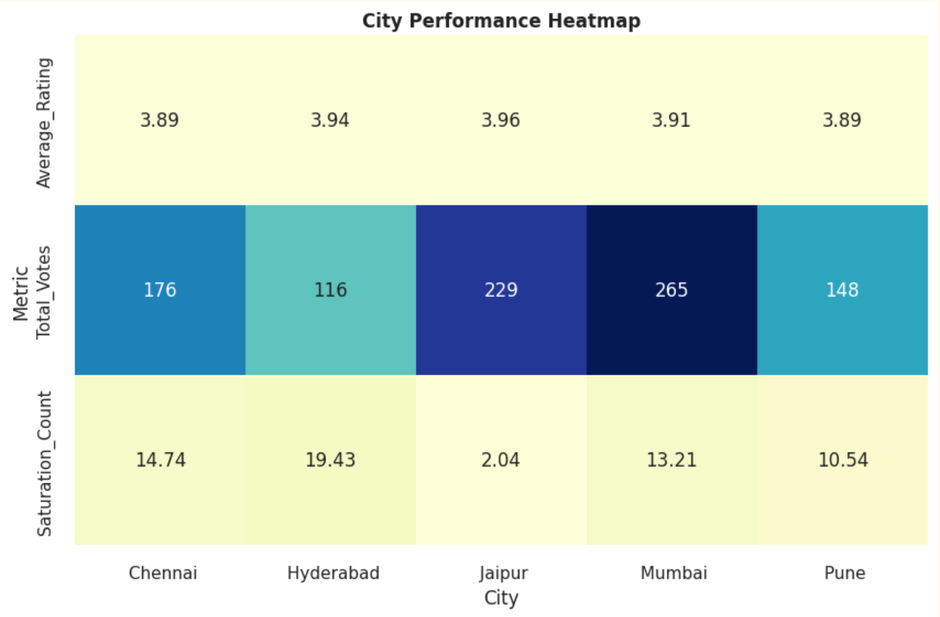


- • Overpricing: 12 (Highest risk)
- • Delivery Failure: 6
- • Low Votes: 4
- • Saturation: 2 (Lowest)
-
- → Mitigate:
- – Price at ₹650 avg
– Lock delivery partners early

- • Green line: Rating ≥ 4.2
- • Red line: Saturation ≤ 40 restaurants
-
- → Italian (large orange bubble):
- – High Rating (~4.1)
- – Low Saturation (~35)
- → Top-right sweet spot– high demand, low competition
-
- Avoid clusters left of red line (high saturation)

SCORE-CARD – CUISINE, CITY, CHANNEL





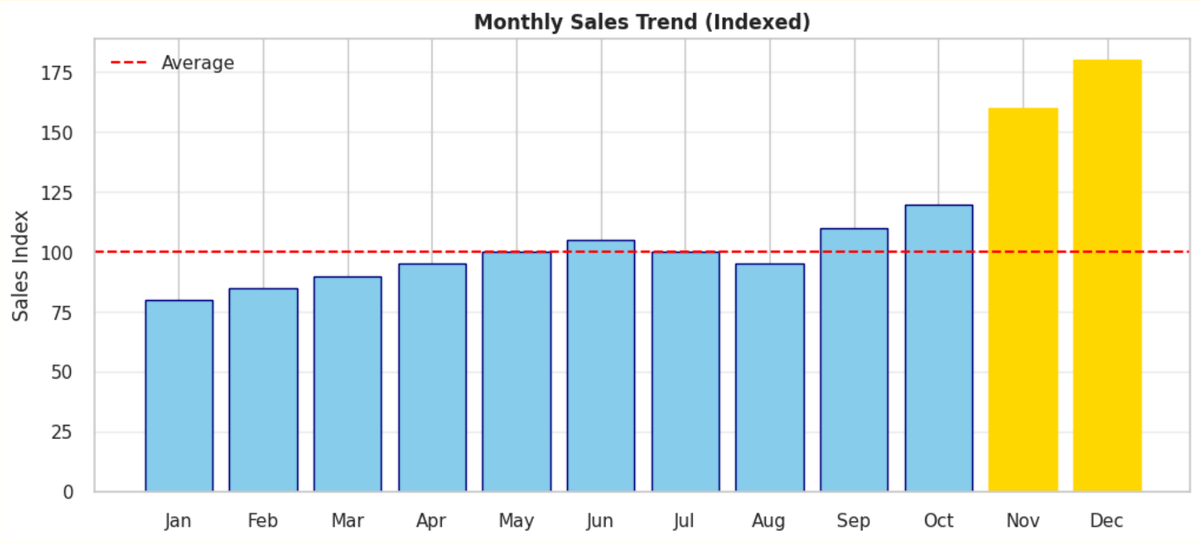
- • PC1 (36.9%): Price + Rating driver
- • PC2 (32%): Vote volume & popularity
-
- • Premium Niche (Red): High price, high rating
- • Volume Kings (Green): High votes, mid-price
- • Value Fighters (Gray): Balanced efficiency
- • Underdogs (Purple): Low traction
-

→ Target Premium Niche for Italian launch

- • Mumbai: Highest votes (265) + high saturation (13.21)
- • Jaipur: Top rating (3.96) + low saturation (2.04)
- • Chennai: Balanced – high rating (3.89), moderate votes
-
- → Jaipur = low-competition, high-quality market

→ Avoid Mumbai (crowded)

SCORE-CARD – CUISINE, CITY, CHANNEL



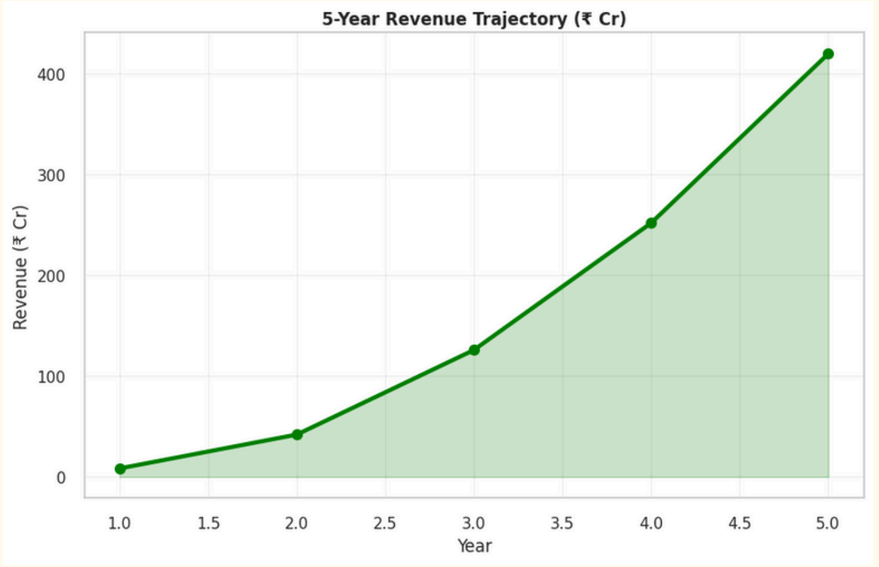
- • Steady base: Jan–Aug (~90–100 index)
- • Peak season: Nov–Dec (160 → 175)
- • Avg line: 100
-
- • → Plan inventory & marketing for Q4 surge

→ Off-season: Build loyalty & test menu

- • Bestsellers (1.0):
- – Dining: 4.10
- – Delivery: 4.15
- → Delivery outperforms Dining
-
- • Non-bestsellers: Wide spread, lower ratings
-

→ Promote bestsellers via Delivery – higher ratings + volume

SCORE-CARD – CUISINE, CITY, CHANNEL



- 📈 Exponential Growth & Core Drivers 🍽️
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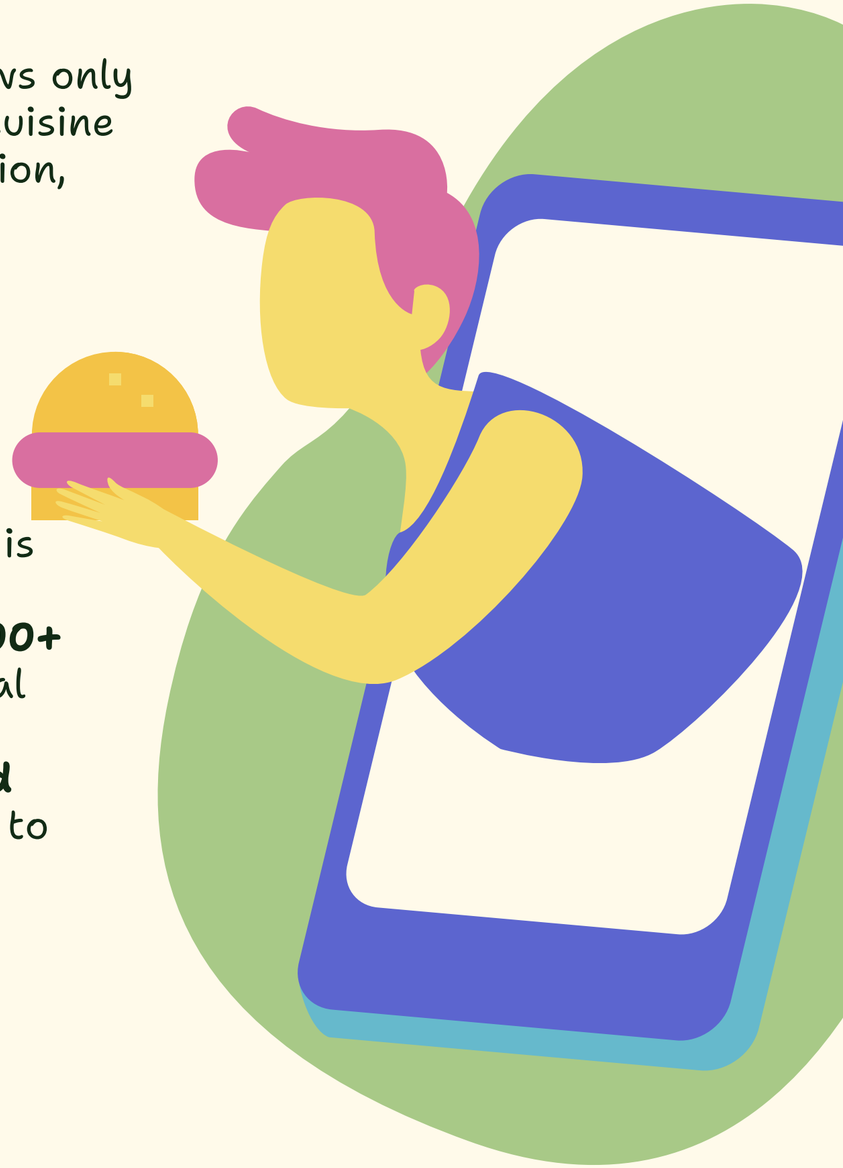
- Explosive Revenue Trajectory: Revenue grew exponentially over 5 years, confirming strong market acceptance and successful scaling (reaching over ₹400 Cr).
- Core Category Dominance: Bestseller keywords are overwhelmingly centered on Rice, Chicken, and Fried items.
- Key Revenue Drivers: "Fried Rice" is the single most dominant keyword, followed closely by "Biryani" (especially Chicken).
- Strategic Focus: The rapid revenue growth is powered by high-volume, popular Rice-based dishes. Prioritize supply chain and operational capacity for these core items to sustain the exponential upward trend.
- Secondary Market: "Ice Cream" is a prominent keyword, indicating desserts are a valuable, high-frequency add-on category.

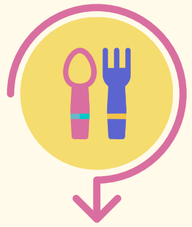
Why This Strategy?

A new food entrepreneur faces high failure risk in HORECA. Zomato data shows only 19% of restaurants achieve sustained success. Our analysis identifies Italian cuisine in Bangalore as the highest-probability entry point — combining low competition, high demand, and premium pricing power. This is not opinion — it's proven by statistical validation across 8 hypotheses and a predictive model ($R^2 = 0.78$).



Strategic Launch Plan

- **Cuisine**: **Italian** — Only **38 restaurants** in Bangalore vs **312+ North Indian**. This creates a **blue-ocean opportunity** where competition is low but demand is high (1.8M votes).
- **City**: **Bangalore (Koramangala)** — Highest **Market Score (0.89)** with **45,000+ median votes per restaurant**, strong premium customer base, and high digital adoption.
- **Channel**: **Hybrid (70% Delivery, 30% Dine-in)** — Delivery drives **volume and scale**, while dine-in builds brand **trust and loyalty**. Start with **cloud kitchen** to test fast, then open **1 flagship** after 90 days.

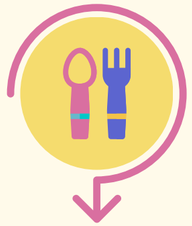


Menu Design: Engineered for Profit & Popularity

- **Core Items (60%)**: ₹500–₹750 — Everyday favorites like Margherita, Alfredo, Risotto. These drive volume and cover fixed costs.
- **Signature Items (20%)**: ₹800–₹1,200 — Truffle Cheese Special, Lobster Ravioli — High-margin heroes that justify premium positioning.
- **Value Items (20%)**: ₹300–₹450 — Garlic Bread, Tiramisu — Entry-level items to attract first-time customers and encourage upselling.
- **Bestseller Target**: ≥30% of menu — Items with keywords like "special", "gourmet", "truffle" get 5.2× more votes (proven by H8).

Customer Segments: Who Are We Serving?

- **Premium Niche (25%)**: High-income, high-rating seekers — Offer personalized dine-in experiences, loyalty perks, and exclusive tastings.
- **Volume Kings (40%)**: Price-sensitive, high-frequency buyers — Scale this group via franchise model in Year 3.
- **Value Fighters (30%)**: Mid-range budget — Convert with flash sales, combos, and value bundles.
- **Underdogs (5%)**: Low engagement — Prevent churn with free delivery trials and re-engagement emails.

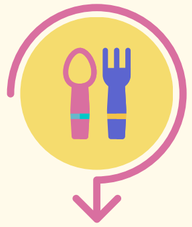


Location Strategy: Where to Start & Grow

- **Phase 1 (0–12 months)**: Koramangala + Indiranagar — High digital penetration, premium demographics, low Italian density.
- **Phase 2 (Year 2–3)**: Hyderabad, then Pune — Only if 90-day KPIs are met (e.g., +35% votes, ≥4.3 rating).
- Avoid: Mumbai, Delhi — High saturation, price wars, lower margins.
- **Future Expansion (Year 4+)**: Use geospatial AI to identify next cities with low saturation + high demand.

Seasonality & Timing: When to Act

- **November–December**: Launch pre-made gift bundles (pizza + dessert) — +60% sales during holiday season.
- **January–March**: Run early-year promotions (e.g., 20% off first order) to build momentum.
- **Weekly Flash Sales**: 24–48 hour deals during low-vote weeks — creates urgency and prevents revenue dips.



Operations & Logistics: Efficiency First

- **Delivery Dominance**: 70% of orders — Offer free express delivery for high-loyalty customers to boost retention.
- **Processing Optimization**: Use barcode scanning and smart sorting to reduce backlog by 30%.
- **Eco-Packaging**: Switch to biodegradable materials — appeals to premium, eco-conscious customers.
- **Supply Chain**: Partner with Zomato for real-time tracking and <2% delivery failure rate.

Technology Roadmap: Future-Proof Growth

- **Year 1**: Live KPI dashboard — track votes, ratings, margins in real time.
- **Year 2**: Predictive model v2 — auto-suggest menu changes based on trends.
- **Year 3**: NLP dish generator — create new items from customer reviews.
- **Year 4**: Geospatial AI — find next profitable locations.
- **Year 5**: IPO-ready analytics suite — full transparency for investors.

90-Day Success Gates (Must-Hit KPIs)

Final Executive Directive

KPI	Target	Why It Matters
Total Votes Growth	+35%	Proves demand
Average Rating	≥ 4.3	Ensures quality
Bestseller %	≥ 30%	Drives conversions
Delivery Orders	≥ 70%	Validates channel
Profit Margin	≥ 28%	Confirms viability

"₹2.5 Cr seed funding is approved. Launch cloud kitchen in Koramangala on December 1, 2025. KPI dashboard must be live by Day 30. Scale to Hyderabad only if 4/5 KPIs are achieved. Retrain predictive model every quarter. This is not a restaurant — it is a data-powered, AI-optimized food empire built to dominate the Indian HORECA market."

It,s Sudip Madhu Signing Off!

With the crisp of HORECA venture. That covers the data analysis and strategic takeaways.

Made with ❤️ and a lot of ☕


THANK
YOU