What Factors Influence Restaurant Ratings?

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Introduction

Online review platforms like Yelp have become a crucial part of how customers discover and evaluate local businesses, particularly restaurants. With millions of user-generated reviews, ratings, and metadata, Yelp provides a rich data source for analyzing patterns in customer preferences and business performance.

This article explores various attributes of Yelp-listed restaurants to determine which features are associated with higher star ratings. While star ratings offer a simplified summary of customer satisfaction, they can be influenced by a wide range of factors.

This analysis will focus on the following characteristics:

1. Location
2. Type of Cuisine
3. Price Level
4. Take-Out Option
5. Parking Availability
6. Reservation Policy
7. Check-In Frequency

Data Sharing and Administration

One of the first challenges in our project was to get everyone to use the same dataset. Some members experienced technical difficulties such as crashes from large files. For some there were variations in the amounts of observations after cleaning the data from slight differences in packages and unknown reasons. In order to centralize the data, we had one member download the original CSV, clean the data, then upload this clean CSV to their AWS RDS MySQL instance. The upload was performed using the DBI and RMySQL packages in R, with credentials managed through environment variables to maintain security. The rest of the team was then provided with these read-only credentials to add to their own environmental variables. This allowed all collaborators to connect to the database and retrieve the dataset using a single SQL query. Hosting the data in a shared cloud environment ensured that all team members worked with a consistent dataset, avoided redundant local storage of large files, and enabled reproducible analysis through R.

Overview of the Data

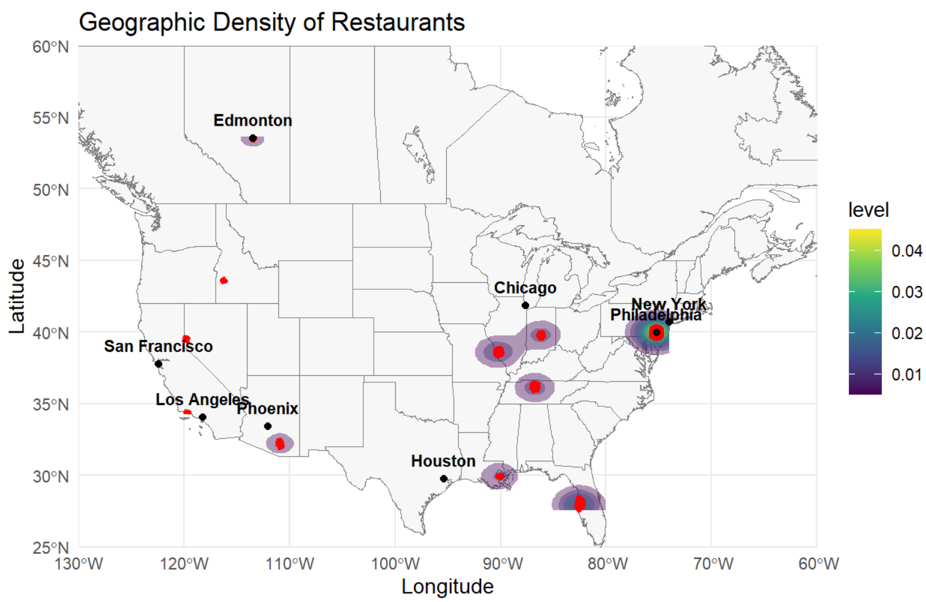
The Yelp Open Dataset [1] provides real-world business data, which we utilized to explore restaurant-related information. Specifically, we worked with two of the provided JSON files: `business.json` and `checkin.json`. Each file was converted to a data frame, then merged using `business_id` as the primary key. After merging, we filtered the combined dataset to include only entries categorized as restaurants.

The resulting restaurant dataset contains 44,018 rows, with each row representing a unique restaurant. Each entry includes a variety of attributes, such as the name of the restaurant, city location, star rating, number of reviews, check-in activity, and service features like take-out availability, parking availability, and reservation policy. These variables form the foundation of our analysis as we investigate what factors are most associated with higher Yelp ratings.

The table below presents the summary statistics for the relevant numeric variables in the dataset.

Table 1: Summary Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
Latitude	36.905	5.998	27.564	53.650
Longitude	−87.818	13.693	−120.084	−74.664
Stars	3.543	0.817	1.000	5.000
Review Count	99.709	202.889	5	7,568
Check-In Count	168.416	285.158	1	1,561



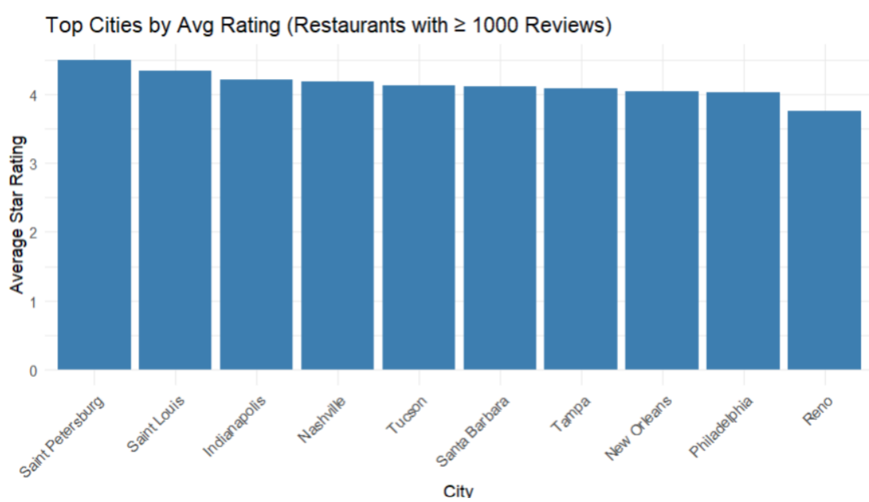
The map above illustrates the geographic density of restaurants, with individual locations represented by red dots. The majority of restaurants are concentrated in the United States, with a small number located outside the country, notably in Edmonton, Canada. Within the U.S., restaurant clusters are clearly visible in major metropolitan areas, such as New York and Philadelphia. Additional dense clusters can also be seen in smaller cities including Santa Barbara, South Pasadena, and Madison, among others.

1 Where Are the Highest-Rated Restaurants Located?

This section explores the geographic distribution of restaurant quality by analyzing Yelp ratings. We focus on two key metrics: average restaurant rating and the number of 5-star restaurants in each location. By examining both city-level and state-level patterns, we aim to identify areas that consistently deliver top-tier dining experiences. These findings offer practical value to restaurant investors, food critics, travelers, and consumers seeking high-quality dining across different regions.

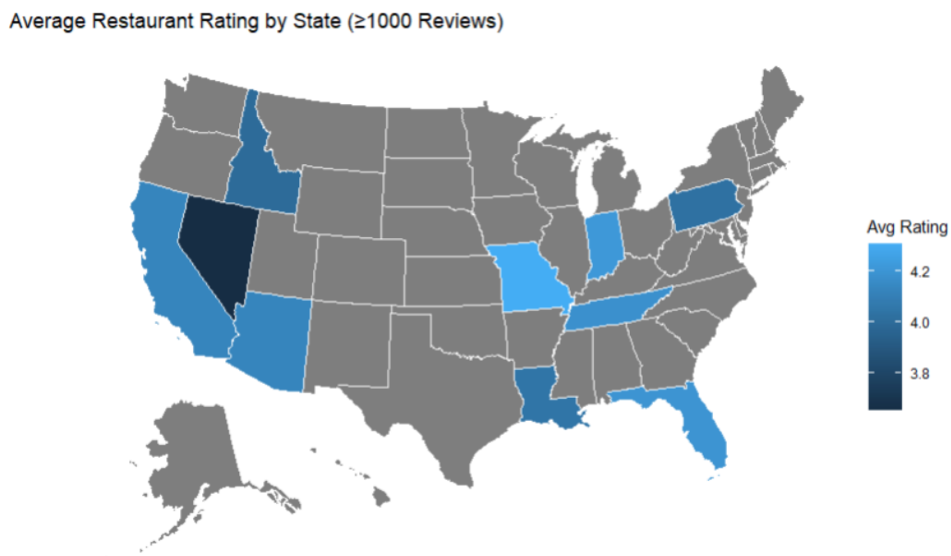
Which Cities Have the Highest Average Restaurant Ratings?

To better assess consistency and quality, we filtered the dataset to include only restaurants with at least 1000 reviews. This ensures that cities with a high average rating are supported by a meaningful volume of customer feedback. The bar chart below displays the top 10 cities by average restaurant rating, led by Saint Petersburg and Saint Louis. These cities maintain high scores across multiple well-reviewed restaurants, indicating consistently positive dining experiences.



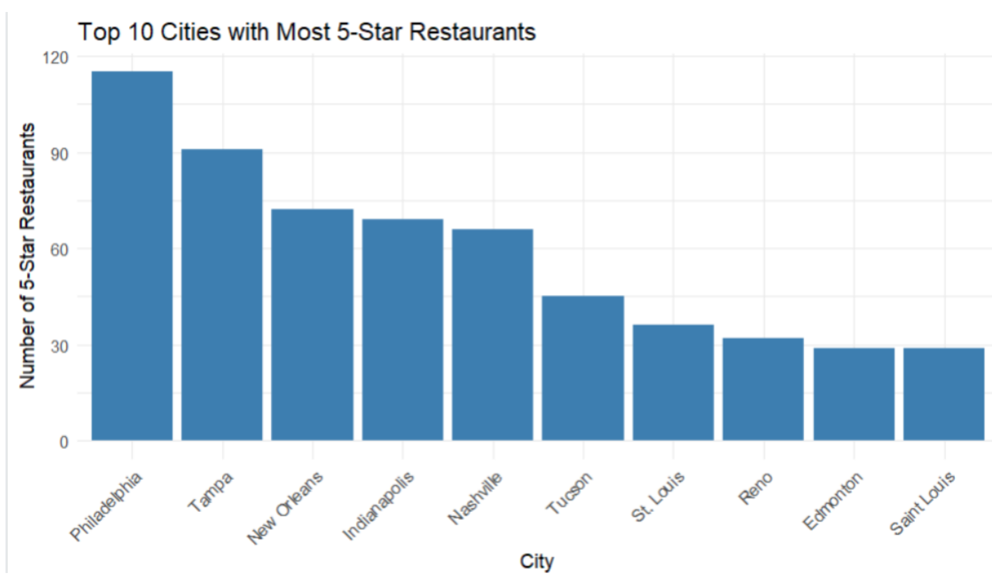
Which U.S. States Have the Highest Average Restaurant Ratings?

To explore broader regional patterns, we also aggregated average ratings at the state level and displayed them on the map below. States like California, Louisiana, and Florida exhibited some of the highest average ratings.

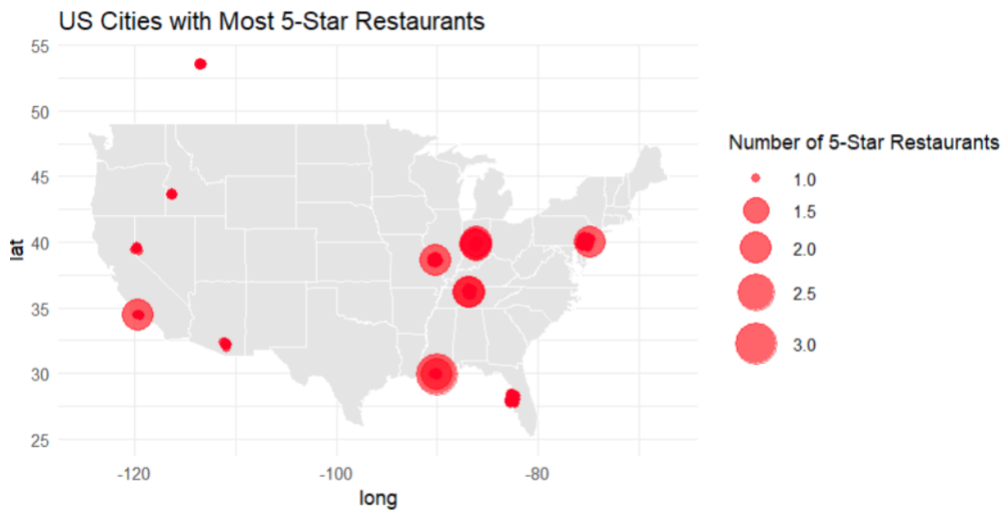


Which Cities Have the Most 5-Star Restaurants?

In addition to identifying the cities and states with the highest average ratings, we also examine which locations have the most 5-star restaurants. The top cities include Philadelphia, Tampa, and New Orleans, which stand out as culinary hubs with dense clusters of highly rated establishments.



To better visualize the geographic distribution of these restaurants, we plotted a bubble map using latitude and longitude data. Larger red circles represent cities with more 5-star restaurants, revealing regional clusters on the East Coast, Midwest, and parts of California.



This analysis reveals key patterns in the distribution and quality of 5-star restaurants across the United States. While cities like Philadelphia lead in the total number of 5-star restaurants, others such as Saint Petersburg and Saint Louis stand out for their consistently high average ratings, when filtered by review volume. By combining count-based and quality-based perspectives, and visualizing results geographically, these results highlight regional strengths in the American dining landscape and offers actionable insights for both consumers and industry stakeholders.

2 Does Type of Cuisine Affect Rating?

To examine whether certain cuisines tend to receive higher Yelp ratings, we began by refining the dataset. Initially, we filtered the Yelp dataset to include only restaurant-related entries, where each row's `categories` column included the word `"Restaurant."` However, each restaurant was associated with multiple categories. For example, Sonic's `categories` entry was recorded as `Restaurants, Fast Food, Ice Cream`.

The first step was to identify and group cuisines in a way that best captured the variety in the data. We split the `categories` column by commas and recorded the frequency of each individual category, focusing on the top 20 most common.

From these, we excluded general or ambiguous categories, like Restaurants, Food, Nightlife, Bars, and Event Planning, as they do not reflect specific cuisines. We also excluded Cafes, due to its overlap with other food categories. This left us with 14 specific cuisine types. Any restaurant that did not fall within these 14 categories was labeled as `"Other"` and was removed from this part of the analysis.

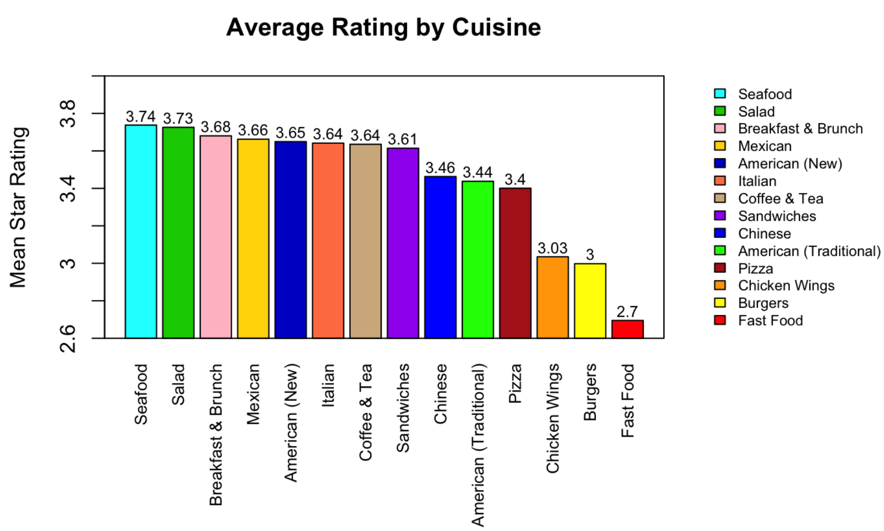
Table 2: Top 20 Restaurant Categories

Category	Count
Restaurants	44,018
Food	13,522
Nightlife	8,002
Bars	7,687
Sandwiches	7,533
American (Traditional)	7,375
Fast Food	5,902
Pizza	5,867
Breakfast and Brunch	5,836
American (New)	5,474
Burgers	5,150
Italian	4,074
Mexican	3,825
Coffee and Tea	3,790
Seafood	3,172
Salad	2,911
Event Planning and Services	2,698
Chicken Wings	2,698
Cafes	2,507
Chinese	2,482

The table below summarizes the number of businesses and the average star rating for each cuisine.

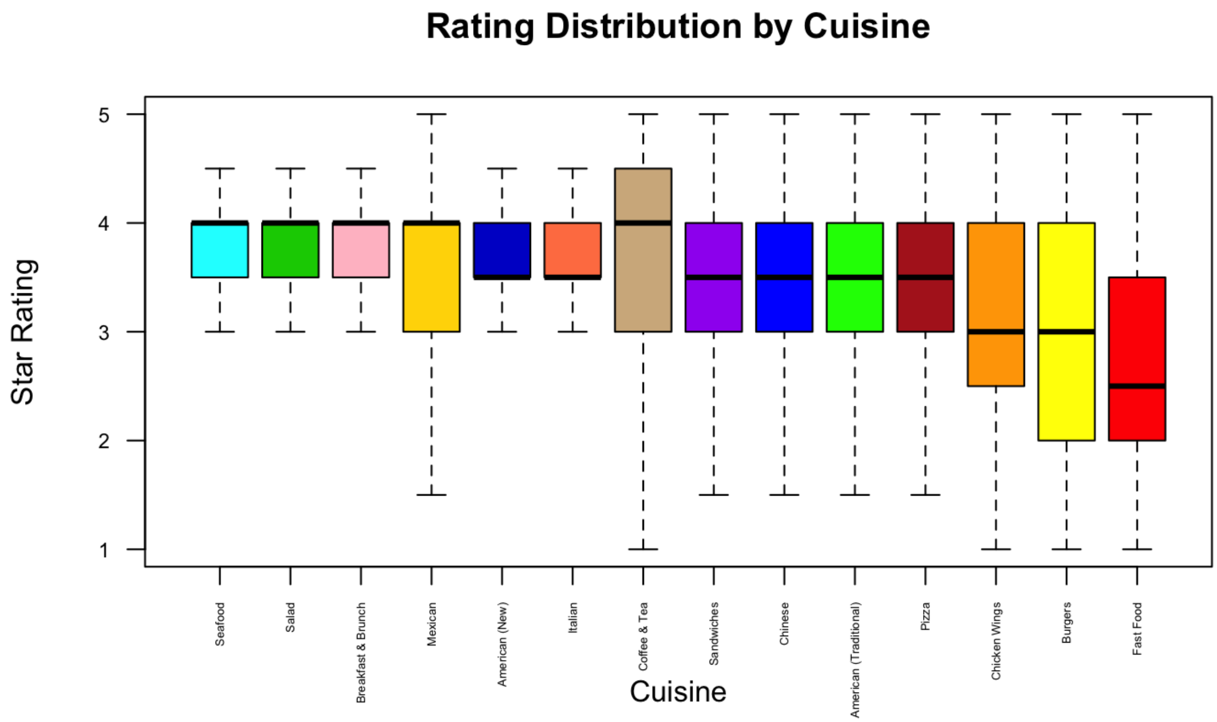
Table 3: Number of Businesses & Average Star Rating by Cuisine

Rank	Cuisine	Count	Mean Rating
1	Seafood	1907	3.74
2	Salad	1169	3.73
3	Breakfast & Brunch	2739	3.68
4	Mexican	2853	3.66
5	American (New)	3106	3.65
6	Italian	2088	3.64
7	Coffee & Tea	2172	3.64
8	Sandwiches	3743	3.61
9	Chinese	2178	3.46
10	American (Traditional)	4085	3.44
11	Pizza	3438	3.40
12	Chicken Wings	1103	3.03
13	Burgers	2177	3.00
14	Fast Food	2607	2.70



From this figure, we observe that certain cuisines tend to receive higher ratings. For example, Seafood and Salad restaurants have average ratings above 3.7 stars, whereas Fast Food and Burgers are closer to 3.0.

To further explore the variability in rating across cuisines, we visualized the full distribution using boxplots.



These visualizations help us understand both the central tendencies and the spread of ratings for each cuisine. While average ratings tell part of the story, variability gives additional insight into customer satisfaction and and consistency within each category.

One-Way ANOVA Test

To statistically test whether mean ratings differ across cuisine types, we conducted a One-Way ANOVA (Analysis of Variance). ANOVA is an extension of the two-sample t-test that compares the means of multiple independent groups, while controlling for the Type I error rate.

We set up the hypothesis as follows:

- **Null Hypothesis (H_0):** The mean star ratings are equal across all cuisine types.
- **Alternative Hypothesis (H_a):** At least one cuisine has a mean rating that differs from the others.

Table 4: One-Way ANOVA: Effect of Cuisine on Star Rating

Source	df	Sum Sq	Mean Sq	F value	Pr(>F)
Cuisine	13	3,018.0	232.2	378.76	< 2.2e-16
Residuals	35,351	21,670.0	0.61		

With 35,351 observations across 14 cuisine groups, the ANOVA returned an F-value of 378.76 and a p-value of 2.2×10^{-16}. This extremely low p-value provides strong evidence to reject the null hypothesis, suggesting that at least one cuisine has a significantly different average rating.

Tukey Test

Given the significant ANOVA result, we conducted a Tukey Honest Significant Difference (HSD) test to determine which specific cuisine pairs differ significantly in their mean ratings. This post-hoc analysis controls for multiple comparisons, while identifying meaningful differences.

Table 5: Significant Tukey Comparisons of Mean Yelp Ratings by Cuisine

Comparison	diff	lwr	upr	p adj
Chicken Wings-Seafood	-0.70	-0.80	-0.60	< 0.001
Burgers-Seafood	-0.74	-0.82	-0.66	< 0.001
Fast Food-Seafood	-1.04	-1.12	-0.96	< 0.001
Chicken Wings-Salad	-0.69	-0.80	-0.58	< 0.001
Burgers-Salad	-0.73	-0.82	-0.63	< 0.001
Fast Food-Salad	-1.03	-1.12	-0.94	< 0.001
Chicken Wings-Breakfast & Brunch	-0.65	-0.74	-0.55	< 0.001
Burgers-Breakfast & Brunch	-0.68	-0.76	-0.61	< 0.001
Fast Food-Breakfast & Brunch	-0.99	-1.06	-0.91	< 0.001
Chicken Wings-Mexican	-0.63	-0.72	-0.53	< 0.001
Burgers-Mexican	-0.66	-0.74	-0.59	< 0.001
Fast Food-Mexican	-0.97	-1.04	-0.90	< 0.001
Chicken Wings-American (New)	-0.61	-0.71	-0.52	< 0.001
Burgers-American (New)	-0.65	-0.73	-0.58	< 0.001
Fast Food-American (New)	-0.95	-1.02	-0.88	< 0.001
Chicken Wings-Italian	-0.61	-0.70	-0.51	< 0.001
Burgers-Italian	-0.64	-0.72	-0.56	< 0.001
Fast Food-Italian	-0.95	-1.02	-0.87	< 0.001
Chicken Wings-Coffee & Tea	-0.60	-0.70	-0.50	< 0.001
Burgers-Coffee & Tea	-0.64	-0.72	-0.56	< 0.001
Fast Food-Coffee & Tea	-0.94	-1.02	-0.86	< 0.001
Chicken Wings-Sandwiches	-0.58	-0.67	-0.49	< 0.001
Burgers-Sandwiches	-0.62	-0.69	-0.55	< 0.001
Fast Food-Sandwiches	-0.92	-0.99	-0.85	< 0.001
Fast Food-Chinese	-0.77	-0.84	-0.69	< 0.001
Fast Food-American (Traditional)	-0.74	-0.81	-0.68	< 0.001
Fast Food-Pizza	-0.71	-0.77	-0.64	< 0.001

Based on these results, we can identify a clear three-tier hierarchy in Yelp star ratings by cuisine type.

Top Tier: Seafood and Salad lead the rankings with average ratings over 3.7 stars. There is no significant difference between these two cuisines, hence their comparison does not appear in the table, but both significantly outperform the lowest-rated cuisines by at least 0.69 stars. While their differences from the middle-tier cuisines are small and not statistically significant, they consistently lead the pack in average rating.

Middle Tier: This tier includes Breakfast & Brunch, Mexican, American (New), Italian, Coffee & Tea, Sandwiches, Chinese, American (Traditional), and Pizza, with average ratings ranging from

3.4 to 3.68. These cuisines are not significantly different from the top tier, nor from each other in most comparisons. However, they are significantly higher rated than the bottom tier by 0.61 to 0.97 stars, indicating a cohesive and substantially better-performing group than the lowest-rated cuisines.

Bottom Tier: Chicken Wings, Burgers, and Fast Food comprise the lowest tier, with average ratings between 2.7 and 3.03 stars. These cuisines are consistently and significantly lower in rating than both the middle and top tiers. Fast Food, in particular, underperforms all other categories by a substantial margin of over 1 full star compared to the top tier.

Overall, the results highlight a meaningful pattern: cuisine type is a strong predictor of Yelp star ratings, with healthier or more niche options tending to receive higher ratings, while fast-food-style offerings lag significantly behind.

3 Do More Expensive Restaurants Receive Better Ratings?

Next, we investigated whether restaurant price range significantly influences Yelp star ratings.

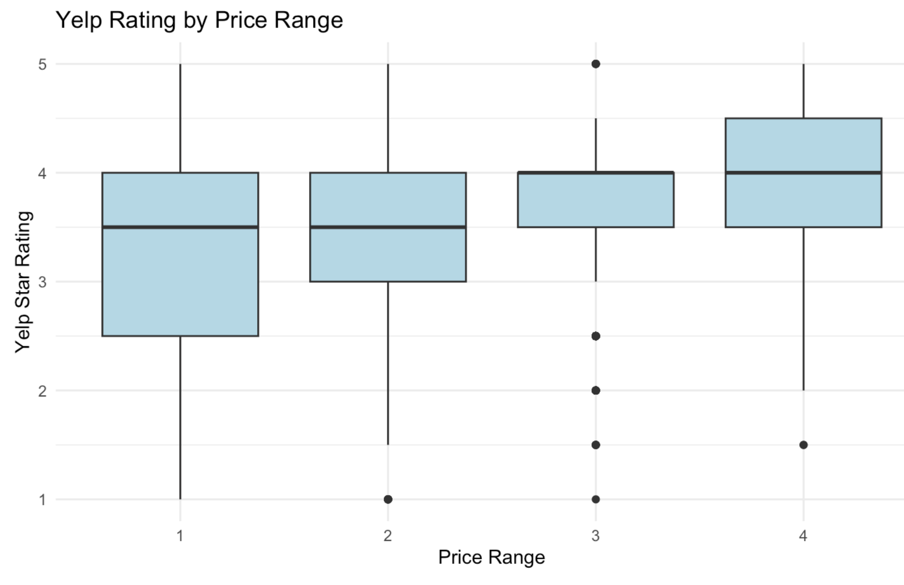
After cleaning the 44,018 restaurants from our filtered Yelp dataset, we retained 38,270 restaurants with valid price and rating data. According to Yelp's official definitions, the `RestaurantsPriceRange2` field represents the following categories:

- `$`: average meal price under $10
- `$$`: average meal price between $11–$30
- `$$$`: average meal price between $31–$60
- `$$$$`: average meal price over $61

Table 6: Restaurant Count by Price Range

Price Range	**Total Restaurants**
$	16,327
$$	20,417
$$$	1,382
$$$$	144

To visualize the relationship between restaurant price range and Yelp ratings, we constructed a box plot comparing the distribution of ratings across different price categories. This visualization helps illustrate the central variability within each price group.



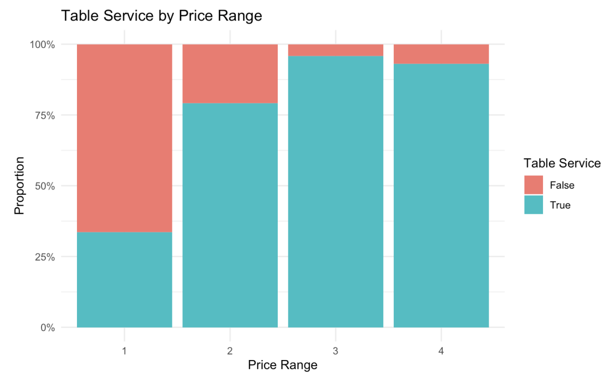
The box plot shows that Yelp ratings tend to increase with price range. The median rating is about 3.3 for the lowest price range (1), and progressively increases to around 3.8 for the highest price range (4) Additionally, higher price ranges display more concentrated rating distributions, suggesting greater consistency in quality among expensive restaurants.

While the box plot shows a clear trend of increasing star rating with higher price ranges, we next perform a linear regression to quantitatively assess the relationship between price range and Yelp ratings. This model allows us to estimate the expected change in rating associate with each incremental increase in price level.

Table 7: Linear Regression Coefficients for Yelp Rating vs. Price Range

Term	**Estimate**	**Std. Error**	**t value**	**p-value**
Intercept	3.032725	0.012018	252.35	$<$ 2e-16
price_range	0.284191	0.007002	40.59	$<$ 2e-16

We found a significant positive association between restaurant price range and Yelp ratings. On average, each increase in price level corresponds to a 0.28 point increase in rating. Although this effect is statistically significant, price alone explains only a small portion of the variation in ratings, as our R^2 is only 0.041, suggesting that other factors such as service quality, food quality, and additional attributes also influence user ratings.



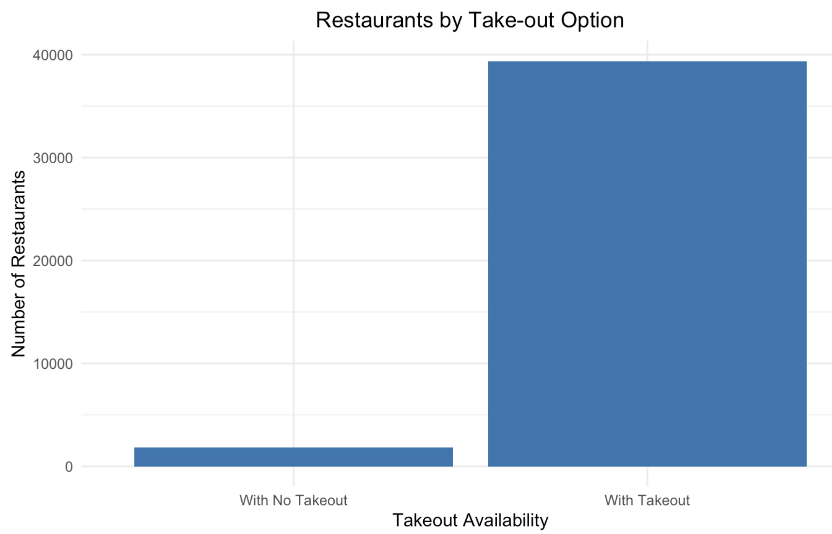
In addition to the observed positive relationship between price range and Yelp ratings, we further examined several service attributes that may contribute to this trend. Two plots display the distribution of alcohol offerings and table service availability across different price levels.

The figure above shows a clear shift toward more comprehensive alcohol offerings in higher price ranges. While low-price restaurants (Price Range 1) predominantly do not offer alcohol, the proportion of restaurants with full bar service increases substantially in Price Ranges 3 and 4. Similarly, as illustrated in *Figure 6*, higher price range restaurants are more likely to provide table service. While only around 30% of Price Range 1 restaurants offer table service, this figure rises above 90% for restaurants in Price Ranges 3 and 4. These findings suggest that part of the reason why higher-priced restaurants receive higher Yelp ratings may be related to enhanced dining experiences associated with premium services such as full bar availability and formal table service.

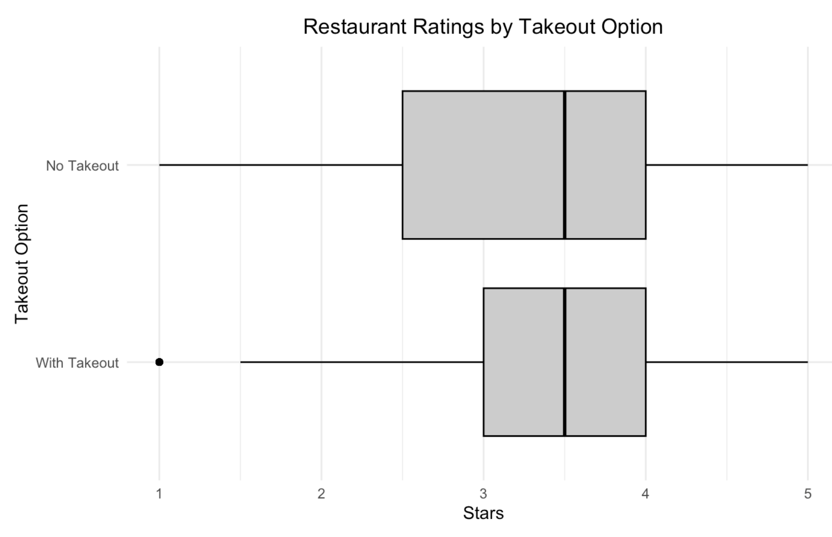
Our analysis demonstrates that restaurant price range is positively associated with Yelp ratings. Higher-priced restaurants not only tend to receive higher average ratings, but also offer enhanced service features such as full bar availability and formal table service, which may contribute to improved customer experiences and satisfaction. The linear regression model confirms that each increase in price level is associated with a significant increase in Yelp ratings ($R^2 = 0.041$, $p < 0.001$), though price alone explains only a small portion of the overall variance. These findings suggest that while price may influence customer perceptions — perhaps due to higher-quality ingredients — other factors like service and ambiance also play important roles in shaping restaurant ratings.

4 Does Offering a Take-Out Option Affect Ratings?

Our analysis also considers whether offering a take-out option affects how customers rate restaurants. As shown in the plot below, take-out availability appears to be nearly universal among the restaurants in the dataset, with over 95% offering a take-out option. Only a small portion (less than 5%) of restaurants do not. On average, restaurants that provide takeout have a higher star rating of 3.54, compared to an average of 3.28 for those that do not.



The box plot below illustrates this difference in the star ratings more clearly, showing a wider spread of lower ratings among restaurants without take-out.



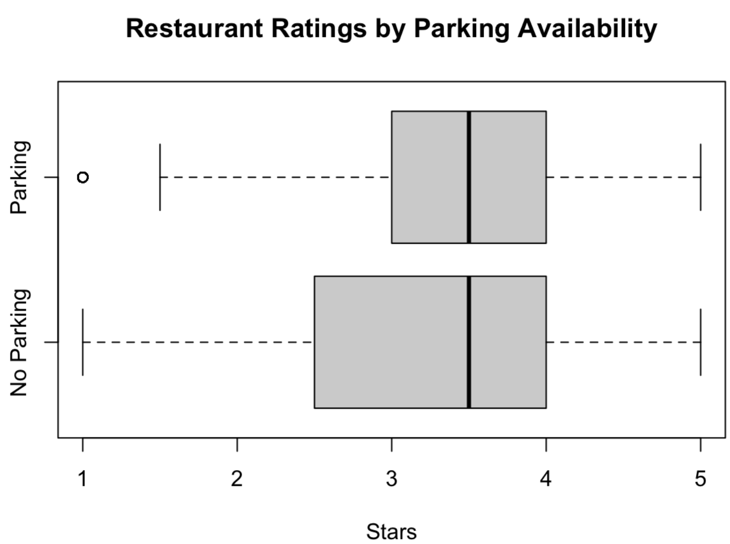
To evaluate whether this difference in ratings is statistically significant, a Welch Two Sample t-test was performed. The results showed a t-value of about 11.2 and a p-value less than 2.2×10^{-16}, indicating a strong and significant difference between the two groups. The 95% confidence interval for the difference in means ranges from 0.214 to 0.305. Overall, the data suggests that offering takeout is associated with higher customer satisfaction.

5 Does Parking Availability Affect Ratings?

Another key area of focus was parking availability and its potential relationship to customer satisfaction.

As shown in the bar plot above, a large majority (over 90%) of the restaurants in the data set offer parking, while less than 10% do not, indicating that parking is a widely available amenity.

Restaurants with parking have an average rating of 3.56, whereas those without parking have an average of 3.30. The box plots below provide additional context.



Although both groups share the same median of 3.5, the lower quartile among the restaurants without parking indicates a wider spread of lower ratings. To assess whether this difference is statistically significant, a Welch Two Sample t-test was conducted. The test returned a t-value of 13.5 with a p-value less than 2.2×10^{-16}, indicating a highly significant difference. The 95% confidence interval for the difference in mean ratings is between 0.221 and 0.296.

These results suggest a meaningful association between parking availability and higher customer satisfaction.

6 Does a Restaurant's Reservation Policy Affect Ratings?

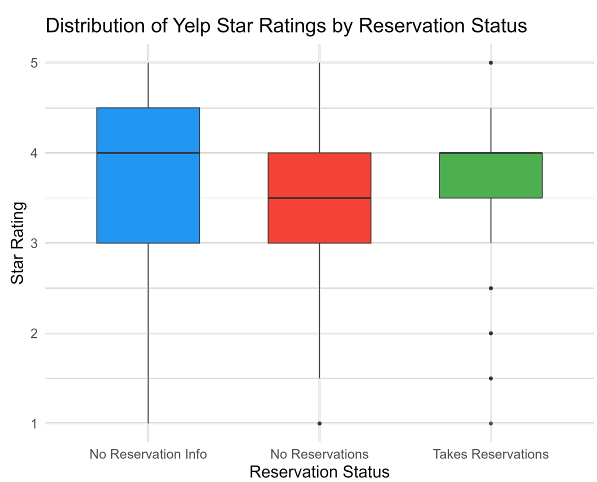
Every restaurant has the option to state on their Yelp page whether they accept reservations or not. Businesses also have the ability to not specify their reservation policy at all. This analysis investigates whether accepting reservations has an impact on the average Yelp rating of a restaurant. We will consider the following three groups of restaurants:

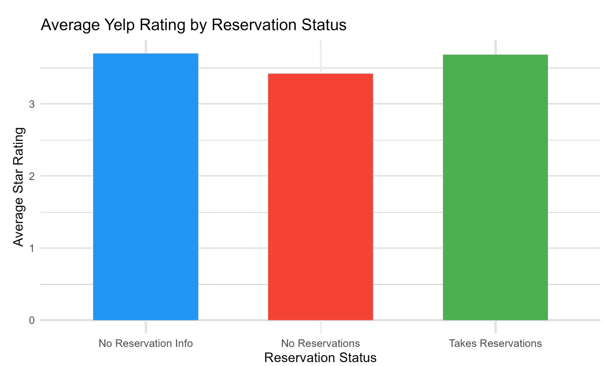
- Restaurants that accept reservations
- Restaurants that do not accept reservations
- Restaurants that do not specify their reservation policy

Below is the frequency distribution of the three reservation categories.

Table 8: Restaurant Counts by Reservation Policy

Group	Count
No Reservations	24286
Takes Reservations	12987
No Reservation Info	6745





The `No Reservation Info` and `Takes Reservations` groups have a very similar mean star rating, while the `No Reservations` group has a lower mean star rating. This suggests that while stating reservations are accepted does not necessarily help rating, specifying that reservations are not accepted can negatively impact rating. Perhaps if a restaurant does not accept reservations, they might be better off not specifying that information at all (though this raises questions about transparency).

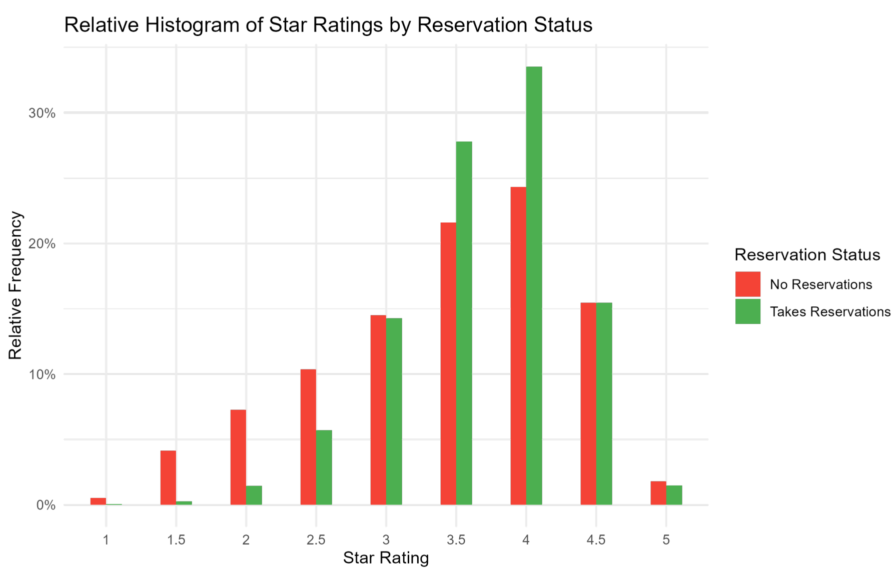
Tukey's Test

Now we will test if these differences are statistically significant. Since we have three groups, we will use Tukey's test to compare the means of the groups.

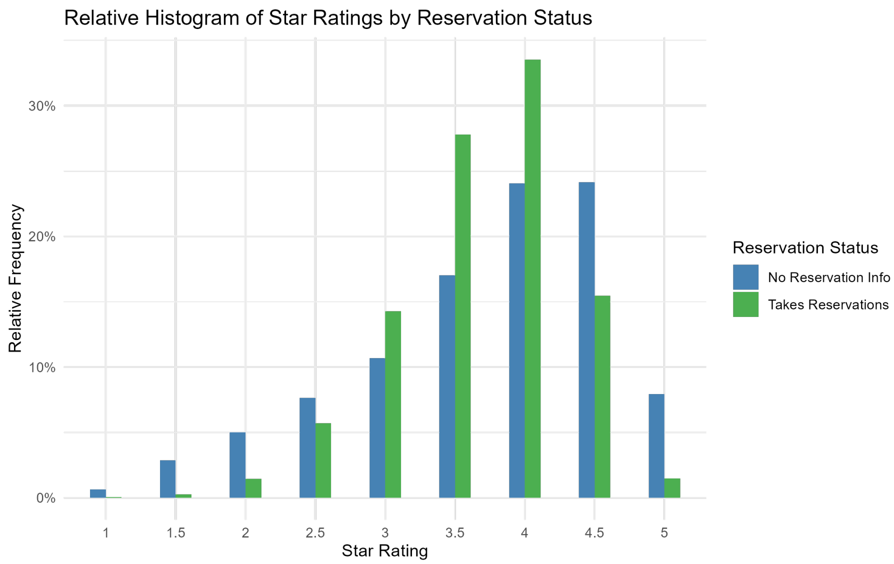
Table 9: Tukey HSD Post-Hoc Test Results

Comparison	diff	lwr	upr	p adj
No Reservations-No Reservation Info	-0.2802	-0.3062	-0.2542	0.00000
Takes Reservations-No Reservation Info	-0.0150	-0.0434	0.0134	0.42990
Takes Reservations-No Reservations	0.2652	0.2447	0.2858	0.00000

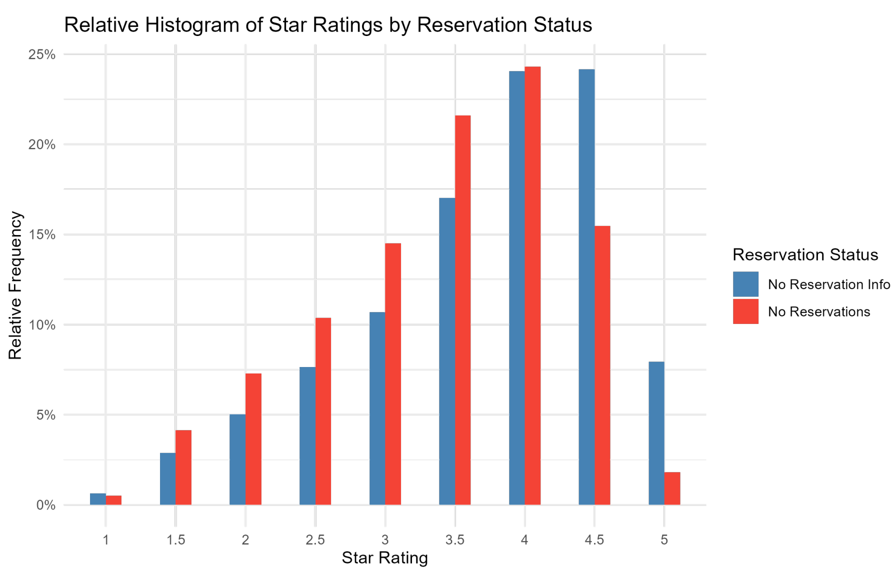
The Tukey test reveals significant differences in mean star ratings between some groups. Specifically, `No Reservations` restaurants have a significantly lower average rating compared to `No Reservation Info` and `Takes Reservations` restaurants. However, there is no significant difference between the `Takes Reservations` group and the `No Reservation Info` group. Again, this suggests that explicitly stating "no reservations" is associated with lower ratings, whereas having reservations shows no benefit compared to not stating reservation information.



As we can see above, the `Takes Reservations` group has a high concentration of medium to medium-high star ratings, with a peak at 4 stars. The `No Reservations` group has a somewhat more balanced distribution of star ratings with significantly more low ratings than the `Takes Reservations` group.



While the mean star ratings of the above groups are similar, the distributions of star ratings are quite different. The `Takes Reservations` group has an extremely high proportion of 3.5 and 4 star ratings, while the `No Reservation Info` group has a more balanced distribution of star ratings in comparison.

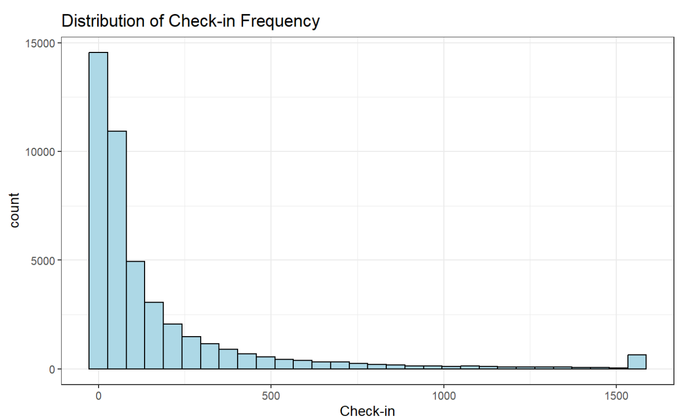


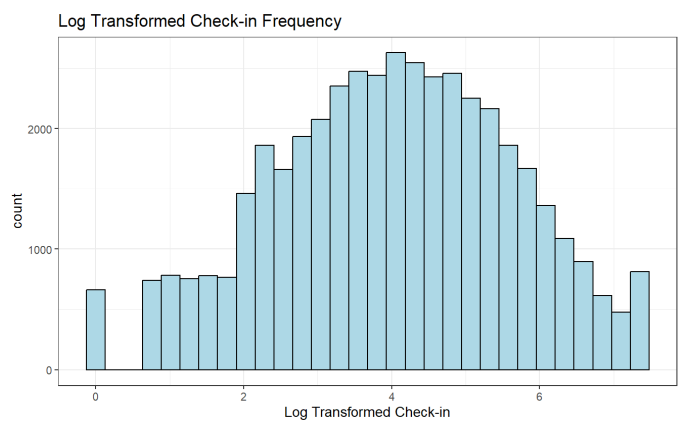
Interestingly, the `No Reservations` and `No Reservation Info` groups have very similar distributions of star ratings, with the main differences being a much higher frequency of 4.5 and 5 star ratings in the `No Reservation Info` group.

Overall, restaurants that accept reservations tend to correlate with *higher* star ratings but do not correlate with the *highest* star ratings. Not accepting reservations is consistently correlated with lower star ratings and not specifying reservation information is the most volatile group with the highest proportion of 5 star ratings, but also a similar number of low rating when compared to the `No Reservation` group.

7 Does Check-In Frequency Affect Ratings?

Yelp's mobile app includes a check-in feature that allows users to log their visits to local businesses and share updates with friends. To encourage participation, Yelp awards badges for check-ins, and some businesses offer discounts to users who check in. In the merged dataset, each restaurant includes a list of check-in timestamps. To simplify analysis, a new column called `checkin_count` was created to represent the total number of check-ins for each restaurant.



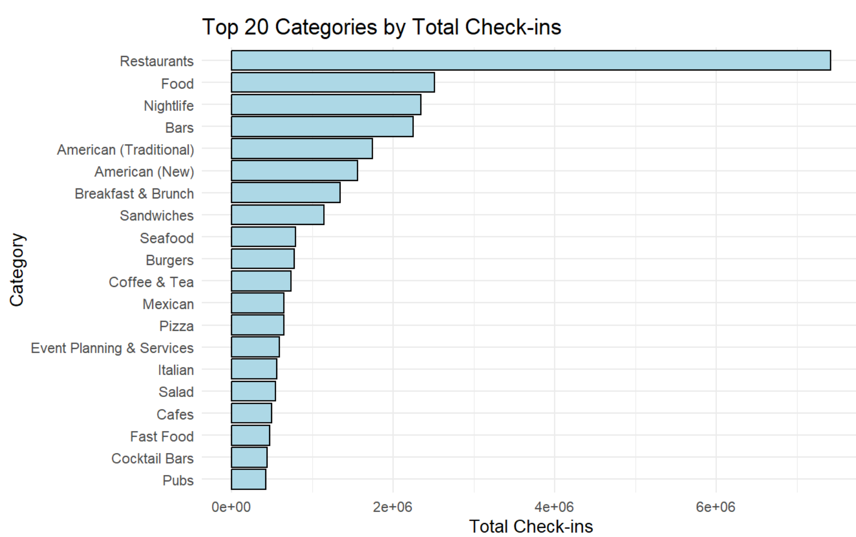


The distribution of check-in frequency among the restaurants is heavily right-skewed. The average number of check-ins is 168.4, while the median is considerably lower at 57, indicating that a small number of restaurants receive disproportionately high numbers of check-ins.

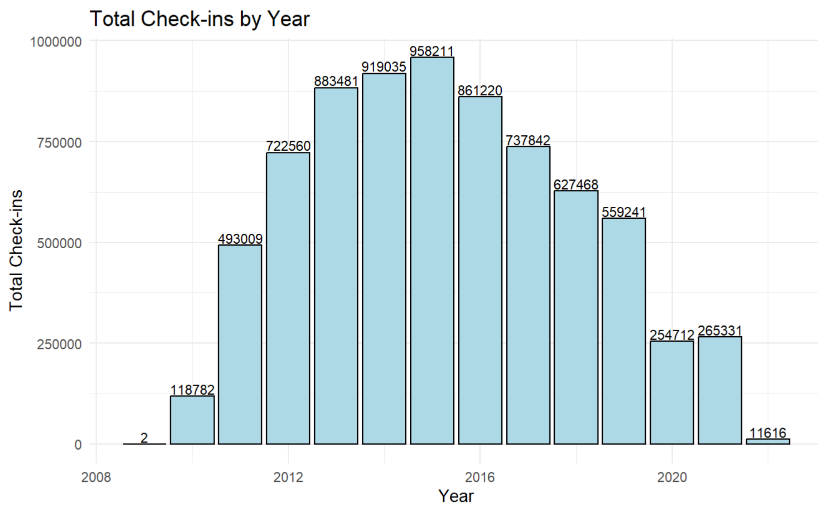
Table 10: Top 10 Restaurants by Total Check-Ins

Restaurant Name	**Total Check-ins**
Wawa	264,606
Panera Bread	218,203
Chick-fil-A	190,410
McDonald's	189,970
Starbucks	183,379
Cracker Barrel Old Country Store	142,075
Buffalo Wild Wings	135,139
Applebee's Grill + Bar	119,579
Olive Garden Italian Restaurant	99,234
Chipotle Mexican Grill	98,964

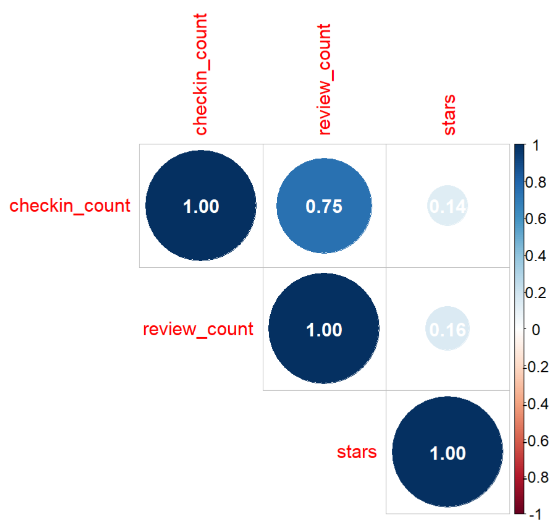
To identify which establishments had the highest overall customer engagement on Yelp, we aggregated the total number of check-ins by restaurant. The results show that national chains dominate the list, with Wawa, Panera Bread, and Chick-fil-A leading in total check-ins. This suggests that large, well-known franchises tend to attract more consistent foot traffic and customer activity compared to smaller, local businesses.



The figure above displays the 20 most popular categories based on total check-ins. Restaurants lead by a significant margin, followed by Food, Nightlife, and Bars. However, it is important to note that there is likely overlap among these categories. For instance, a single business can be categorized as both Restaurant and Food, or even span multiple cuisine types, such as American (Traditional), American (New), Mexican, or Italian.



The total number of check-ins spans from 2009 to 2022. Interestingly, the distribution is approximately bell-shaped, resembling a normal distribution, with a peak around the year 2015. This pattern is somewhat non-intuitive, as one might expect a steady increase over time. However, check-in activity declines sharply after 2015. This trend aligns with external statistics showing a decline in the number of unique mobile Yelp users from 2016 to 2021 [2].



The association between the number of check-ins and the number of reviews for a restaurant is moderately strong and positive ($r = 0.75$), suggesting that more popular restaurants tend to receive more reviews. In contrast, the correlation between the number of check-ins and star rating is very weak ($r = 0.15$), indicating that higher foot traffic does not necessarily correspond to higher customer satisfaction.

Table 11: Linear Regression Results of Check-In Frequency on Restaurant Ratings

	Dependent variable:
	stars
checkin_count	0.0003***
	(0.00001)
Constant	3.491***
	(0.004)
Observations	44,018
R^2	0.016
Adjusted R^2	0.016
Residual Std. Error	0.811 (df = 44016)
F Statistic	721.815*** (df = 1; 44016)
Note:	*p<0.1; **p<0.05; ***p<0.01

A linear regression model was used to test the significance of check-in frequency on restaurant ratings. At a significance level of $\alpha = 0.05$, the model indicates that check-in frequency has a statistically significant effect on restaurant ratings ($p - value = 0.0000$). However, the effect size is minimal, as the model explains only a small portion of the variance in ratings ($R^2 = 0.016$). On average, each additional check-in is associated with a 0.0003-star increase in a restaurant's rating.

Conclusions

Our analysis of Yelp restaurant data reveals that location, cuisine type, price, and service features all contribute to customer ratings. At the city level, Saint Petersburg and Saint Louis had the highest average ratings, while Philadelphia and Tampa stood out for having the most 5-star restaurants. At the state level, California, Louisiana, and Florida consistently ranked highest in overall restaurant quality. Cuisine type also played a significant role; seafood and salad restaurants received the highest ratings, while fast food and burger places were rated lowest. More expensive restaurants generally earned better reviews, likely due to enhanced services like alcohol offerings and table service. Features that improve convenience, such as take-out options, parking availability, and the ability to make reservations, were also associated with higher ratings. While check-in frequency was statistically significant, its actual effect on ratings was minimal. All things considered, while location and service-related factors explain some of the variation in Yelp ratings, subjective experiences like food quality and atmosphere remain influential, yet harder to quantify.

Limitations

Observational & Subjective Data

The Yelp dataset is observational and based on user-generated reviews. As such, it does not allow for causal inference. Ratings reflect subjective customer opinions and can be influenced by factors unrelated to food or service quality, such as individual expectations, mood, or the context of the dining experience (for example, a birthday dinner vs. a quick lunch).

Missing or Incomplete Data

Several restaurants in the dataset lacked complete information on attributes such as reservation policies, parking availability, and/or price range. We excluded incomplete cases in our analyses, which may have introduced selection bias by disproportionately excluding certain types of businesses (for instance, smaller or newer restaurants with fewer listed features).

Limited Scope of Variables

While the dataset includes many useful attributes, it does not directly measure some key drivers of restaurant quality, such as food taste, staff professionalism, or ambiance. These unobserved variables likely play a major role in Yelp ratings and contribute to unexplained variance.

References

[1] Yelp. Yelp Open Dataset. https://business.yelp.com/data/resources/open-dataset/, 2023.

[2] Statista. Unique Mobile Visitors to Yelp from 2013 to 2023. https://www.statista.com/statistics/385440/unique-mobile-visitors-yelp/, 2024.