Restaurant Success Predictor

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Problem Statement

The main objective of this analysis is to understand and predict the success of local restaurants in America. We apply Machine Learning techniques to help investors/lenders as well as restaurant owners to make data-driven decisions. This project analyzes restaurant's data and its consumers' reviews to predict the feasibility and sustainability of the business

Motivation

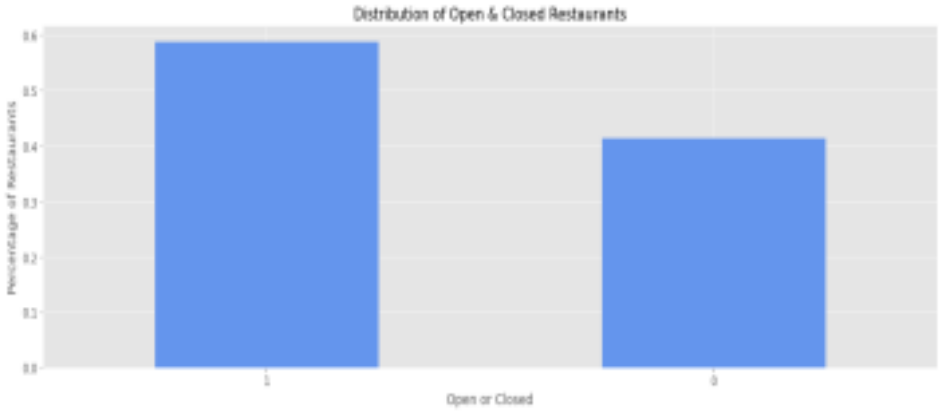
The United States restaurant industry was projected at $899 billion in sales for 2021 by the National Restaurant Association, accounting for about 5 percent of the country's gross domestic product. An estimated 99% of companies in the industry are family-owned small businesses with fewer than 50 employees.The industry as a whole as of February 2022 employed more than 15 million people, representing 10% of the workforce directly. Given the significance of this industry, its size and employment numbers, I decided to create a model that could help business owners and investors determine the essential features that predict a restaurant's success or failure. Based on this analysis, investors can decide whether they should invest in a particular business based on the likelihood that it is going to run out of business in the future or not; existing businesses could intervene and improve upon those parameters whereas new businesses could analyze the potential before entering the market.

Data Source and Preprocessing

In this project, I used the yelp dataset[2] which is publicly available for educational and academic purposes. This dataset contains information about 160,585 businesses across 8 Metropolitan areas for the year 2005 to 2021. The whole dataset shared is 11 GB in size with 5 .json files about business, reviews, users, check-in and tips data. For this project, I have focused on restaurants business in Tampa, FL. After filtering the data, I had 3,009 restaurants and 322,251 reviews related to these restaurants. Restaurant data has 14 features which have details about location, name, categories, attributes, hours of operation, review counts, stars and whether it is open or closed. Review dataset has 9 features with specific details about the review text, stars given by the user, reactions received to review, and date of review. To map this dataset to business and user dataset, the common field available was business id and user id.

Feature engineering and EDA

Distribution of target variable (is_open) is 59% for open restaurants and 41% for closed restaurants.



Combined dataset had 22 features, but predictive ability using only original features was very low and may not have provided meaningful insights. Therefore, new features were added in the dataset. Some of the new features added were:

1. **Chain Restaurant:** During EDA of the 'name' field, it was noted that there were 956 restaurants which were a part of 282 chains. Therefore, 'name' field was further analyzed and it was noted that 28% of chain restaurants were closed whereas 45% of independent restaurants were closed since 2005.
2. **Number of Attributes:** There are a total of 35 unique attributes that can be listed for a restaurant and every restaurant has listed a different number of attributes.
3. **Top Attributes:** I had also extracted the top 7 attributes that were listed by the majority of restaurants.
4. **Top categories:** Top 25 categories of restaurants (e.g., Japanese, cafes, etc.) were also extracted to check if any category has any impact on business success
5. **Repeat users:** 'User_id' field was used for users writing multiple reviews as repeat customers play a major role in a business' revenue generation.
6. **Age:** This field is extracted from reviews dataset using review date.
7. **Sentiment Score:** I used Vader's Sentiment Analysis compound score to study the sentiment behind reviews. I used a compound score for this which is a combination of positive (1), negative (-1) and neutral score (0).
8. **Review Length:** Negative reviews tend to be largely worded and therefore, this feature was used to determine if it helps in predicting a restaurant's future.
9. **Density of restaurants:** Using Haversine formula and latitude/ longitude details, the total of restaurants within 1 km radius were calculated for each restaurant. I also calculated the number of restaurants falling within the same category in its vicinity to further analyze if this impacts a restaurant's success.
10. **Relative fields:** Relative values of different fields were extracted using z-score to see the position of a restaurant compared to mean performance of restaurants within its 1 km radius.

Modeling Summary

I evaluated 4 different supervised machine learning models on this dataset: Logistic Regression, Decision Tree, Random Forest and Gradient Boosting. Based on their test scores, precision, recall score and AUC, I found Logistic Regression and Gradient Boosting performed better than Decision Tree and Random Forest model. In order to select the better model between these two, I used GridSearchCV for hyperparameter tuning.

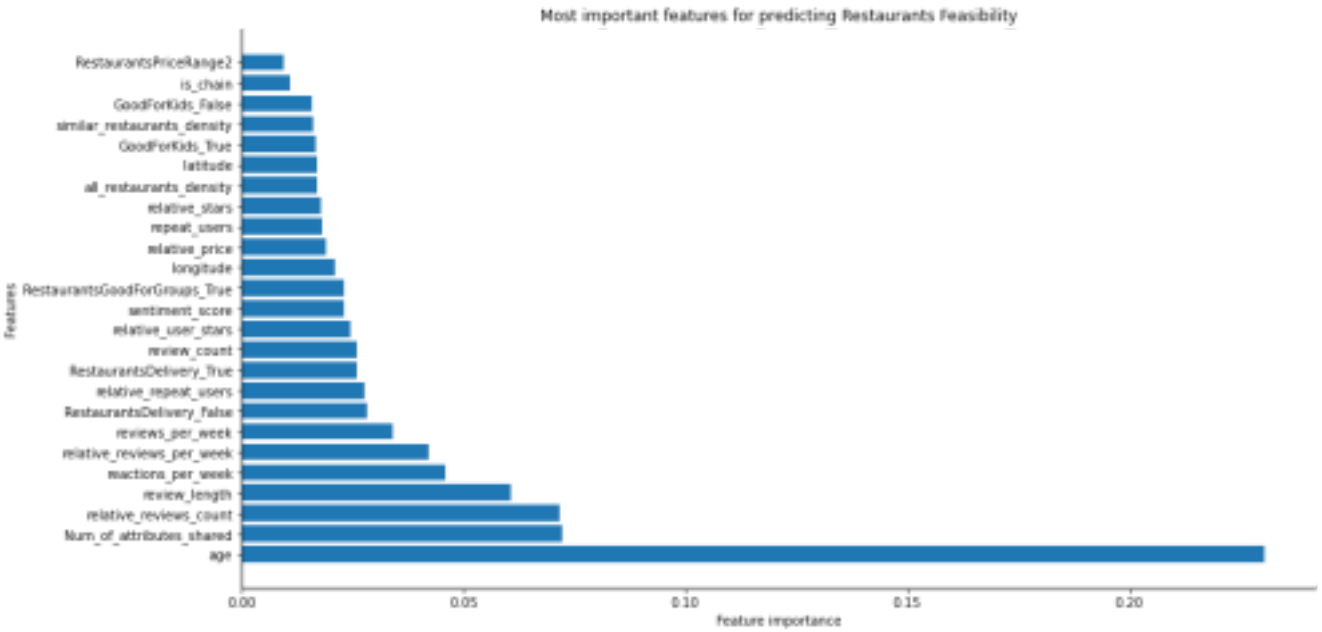
Summary of the results are tabulated below:

Model	Test Score	AUC	Class	Precision Score	Recall Score
Logistic Regression	0.826	0.887	0	0.81	0.76
			1	0.84	0.87
Decision Tree	0.765	0.838	0	0.72	0.70
			1	0.79	0.81
Random Forest	0.813	0.871	0	0.85	0.67

			1	0.80	0.91
Gradient Boosting	0.839	0.913	0	0.84	0.76
			1	0.84	0.90
Gradient Boosting with hyperparameter Optimization	0.853	0.915	0	0.84	0.79
			1	0.86	0.89

Using Gradient Boosting model and optimal values for hyperparameters, test score improved by 1.4% and AUC by 0.2%. This model was able to predict 86% of open restaurants correctly and 84% of closed restaurants. Recall score improved radically by 3% for closed restaurants as compared to initial models.

Summary



Conclusion: Based on our analysis of the given dataset, key features for predicting a restaurant's feasibility are:

1. **Age:** As expected, the age of a restaurant plays a major role in predicting a restaurant's life. Probability of a restaurant getting closed is low if it's been in business a long period of time as compared to new restaurants who are yet to establish their name and place in the market. The older the restaurant, the larger it's customer base would be. More customers in turn generate larger revenues for the business and help the business live longer.
2. **Relative Reviews Count:** Review count is directly proportional to the footfall. This field provides information about how a restaurant is performing as compared to the mean value for restaurants in it's vicinity.
3. **Review Length:** Number of words used in the reviews can help predict the restaurant's feasibility as a customer may write about their exceptional experience or dissatisfaction in a well-written, strongly worded review. Emotions, positive or negative, are generally explained with reasons and hence, this could strongly help in predicting the life/performance of a restaurant.
4. **Number of Attributes Shared:** Most successful restaurants share information about their business' attributes which help customers in making informed decisions about whether to visit that outlet or not based on what they are looking for. Uninformed customer is more likely to get disappointed later if the

customer does not get any particular service/feature they were looking. For example, if a restaurant has specifically provided information about lack of parking facilities at the area, it will significantly help the customer to be prepared for it and use alternate way of transportation or park their vehicle somewhere else.

5. **Relative User Stars:** Stars received by a restaurant relative to places in it's neighborhood is a strong metric. When in the area, a person definitely looks atit's stars rating while deciding on a place to eat. Restaurants with higher ratings are generally preferred and this field can immensely help in measuring a restaurant's performance.
6. **Restaurant Delivery:** Whether a restaurant is providing delivery services or not is essential in today's times. Not everyone is able to dine-in during the weekdays. With the ongoing pandemic, people generally prefer to place an order for home delivery to avoid contact with other people. This also helps reduce the wait and travel time for them. Hence, this attribute is extremely important in predicting a restaurant's life.

Next Steps

As a next step, I would like to analyze the restaurants opened/closed during a shorter duration of say 2 years or 5 years for focused insights as the world is fast paced and always changing.

Also, in the dataset available on Yelp, financial information such as yearly revenue, year-on-year growth and net profit was not available. These metrics could play a substantial role in predicting a restaurant’s feasibility and assist in the decision-making process.

I would also like to study the impact of public transportation and its close-by attraction spots to understand the geographic areas attracting footfall.