Determining Attributes of Good Restaurants Using Review Text

Analysis for restauranteurs/diners

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Outline

- Business Problem
- Data Understanding
- Classifier Model
- Recommendation System
- Conclusion
- Next Steps

Introduction

Has a restaurant ever not lived up to expectations?

- Service
- Food Quality
- Atmosphere

How do you decide between restaurants when dining out?

- Proximity
- Type of cuisine
- Review based
- Word of mouth

Business Problem

In an industry as sensitive as food service, reviews, whether on a customer level or a professional level can make or break a restaurant. Owners with failing restaurants may be at a loss when trying to find avenues of improvement.

- Investment in new hardware, staffing, or ingredients may be costly and prove to not be worth it.
- Any combination of factors can lead people to leave a review on a business's page, difficult to isolate relevance from noise

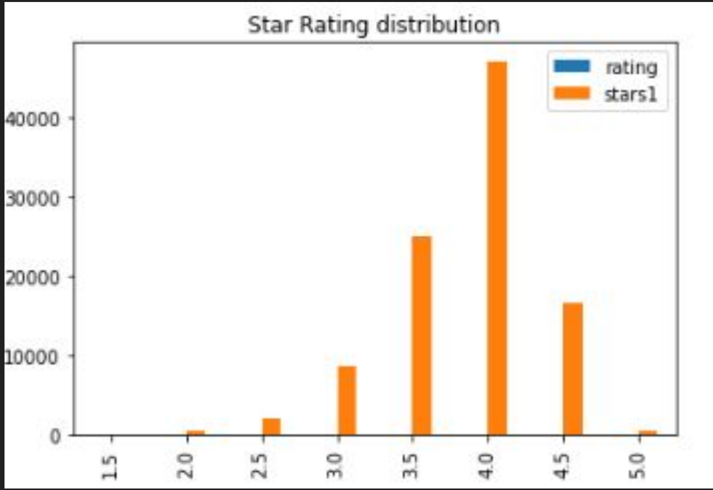
Data Understanding

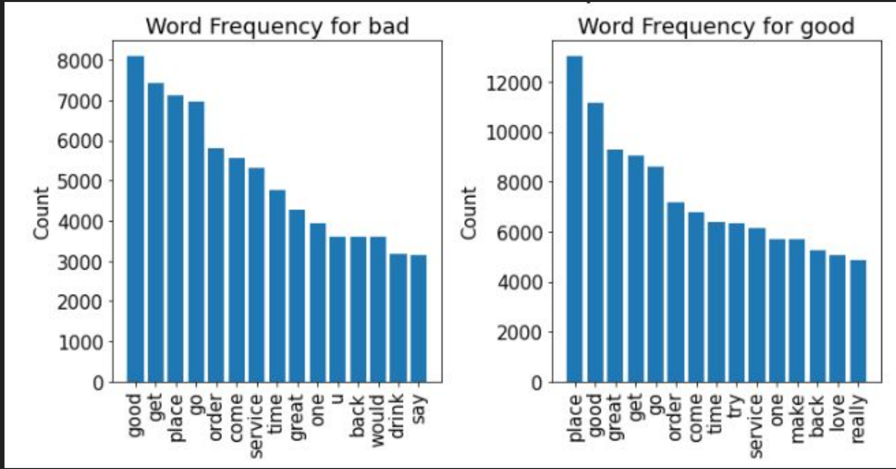
SOURCE: Yelp restaurant review data spanning 2010-2014 (Kaggle)

- Each row in the table represents a unique review written by a user for a specific business, with text stored in a singular string
- **Columns of interest: ‘text’, ‘rating’**

<u>Initial Dataset Review Counts:</u>

- ~700K total reviews before filtering
- ~50K users
- ~3.5K businesses





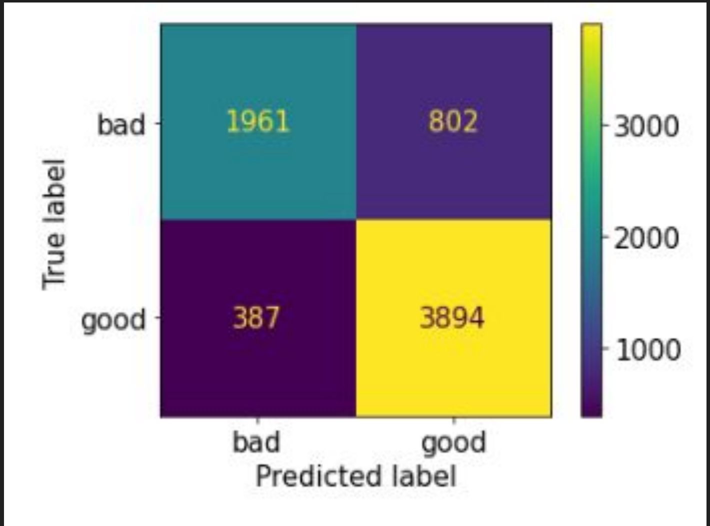
Modeling

An iterative process of classifier model comparison was used to collectively classify a given restaurant review as “good” or “bad”

Final Model: Multinomial Naive Bayes, TF-IDF Vectorizer

Interpretation of Confusion Matrix:

- 3,894 reviews were correctly predicted as Good
- 1,961 reviews were correctly predicted as Bad
- 802 reviews were incorrectly interpreted as Good, when actual review type was Bad
- 387 songs were incorrectly interpreted as Bad, when actual review type was good



Confusion Matrix for Final Model

Model was able to classify a good/bad genre with an accuracy of 84%

Model is also relatively accurate in the face of testing data (83%)

Recommendation System

To supplement the classifier, a recommendation system was created that appends self-reported user ratings and generates a list of recommendations based on the other users/ratings available in the dataset

- Inputs: user ID, number of restaurants to review, category

```
                 business_id          name                      categories
29764  15FvoKE2-k6JpGVuhH9YVA  Sushi Catcher  Sushi Bars;Japanese;Restaurants
How do you rate this restaurant/business on a scale of 1-5, press n if you have not been :
2
                 business_id                   name  \
92481  SPBZxmt8_nT30rNVnKHYKA  Akaihana Sushi & Grill

                           categories
92481  Sushi Bars;Japanese;Restaurants
How do you rate this restaurant/business on a scale of 1-5, press n if you have not been :
1
                 business_id         name                       categories
35796  6syMU43FKGkcbX2957Ga8A  Sekai Sushi  Sushi Bars;Japanese;Restaurants
How do you rate this restaurant/business on a scale of 1-5, press n if you have not been :
2
                 business_id               name  \
87008  V3ruBXjLGWniPNPQOzRhiw  Makino Restaurant

                           categories
87008  Sushi Bars;Japanese;Restaurants
How do you rate this restaurant/business on a scale of 1-5, press n if you have not been :
3
                 business_id         name              categories
86546  08IFR_ruWR96K3Q6sakI_g  Sushi Creek  Sushi Bars;Restaurants
How do you rate this restaurant/business on a scale of 1-5, press n if you have not been :
4
```

Out[45]:

business_id	categories	name	recrating
6X9iyuM2XdoCGT4q9qv5cA	Sushi Bars;Japanese;Restaurants	JJANGA Japanese Restaurant	4.492273
OwBPjUz2o0J5K3DzcHkBtg	Sushi Bars;Japanese;Restaurants	Soho Japanese Restaurant	4.491927
HpaYCM_NCaul72LLXxC6SA	Tapas/Small Plates;Sushi Bars;Japanese;Restaur...	Yonaka Modern Japanese	4.489452
sNBquLTaV3lbUWkzSUITpw	Sushi Bars;Japanese;Restaurants	Sakana	4.489281
Pgp3gbOQaJldyjqC9AOz6g	Sushi Bars;Restaurants	I Love Sushi	4.489053
bpGFetX8muk0GxAT3Oea3Q	Sushi Bars;Japanese;Restaurants	Yummy Grill & Sushi	4.485786
u6EUXOSFnjxvzLIl4D21bA	Sushi Bars;Japanese;Restaurants	Harumi Sushi	4.485590
i5Tq_jzm3osbY_uEJ79N1g	Seafood;Sushi Bars;Japanese;Restaurants	Tokyo Boys	4.480236
QrRNFiSXmCo4pzVLAhA_bw	Steakhouses;Sushi Bars;Japanese;Restaurants	Kanji Steak & Sushi	4.479729
AYbUb5UcAngroJ6uJG7tLQ	Sushi Bars;Japanese;Restaurants	Kabuto	4.475067

Recommendation System and Output

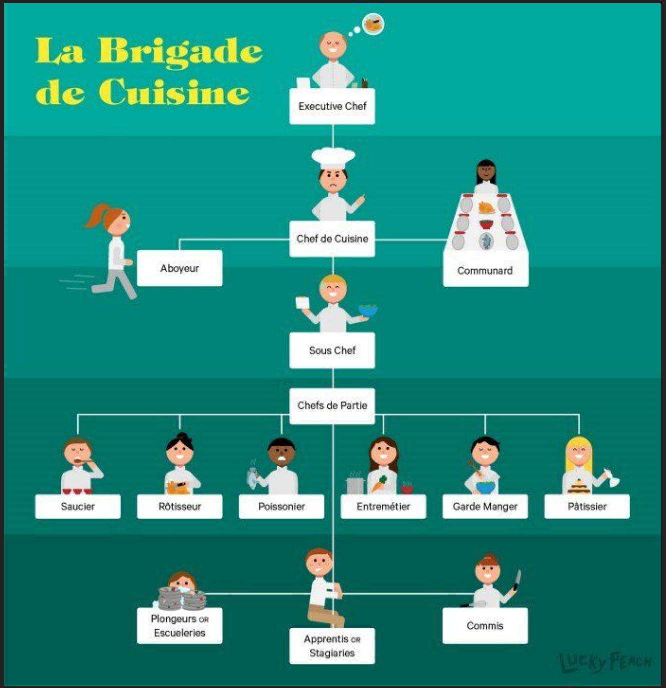
Conclusion/Recommendations

From the model results, it can be seen that rating type (bad/good) can be predicted successfully using review text, with high accuracy in the face of new (test) data. Words/phrases that were most impactful for the performance of the overall classifier identified a restaurant's features and experiences, both good and bad.

- Value perceived by customer
- Service quality
- Food quality
- Time to receive food

Recommendations for Improvement:

- Establish a French brigade system
- Establish a happy working culture and fair front-of-house compensation
- Optimize food spend while maintaining quality



Next Steps

- More nuanced system of rating, similar to metacritic
- Utilize more filtering options in the recommendation system to mimic Yelp filters
- Create word cloud distributions for each restaurant recommendation for more user context
- Provide additional color to potential restaurant improvements, using additional feature flags provided within Yelp's dataset
- Replicate analysis for different restaurant category types; different kinds of restaurants may require different solutions

Thank You!

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