

# Analysis of relation between Stars rating vs. most relevant Attributes and n-grams (words) in Reviews filtered by State and Business Category.

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## Introduction

In order to get top rate as business in a city is analyzed where have to be established my business, which services I need to offer, what positive review words I need to be associated to my business and what negative review words I need to avoid

To do that analysis is used as input Business Category and State. As output: Top Rate, Location-Neighborhood, Services, Top-5 positive words to promote, Top-5 negative words to avoid.

For example, If I want to open a business for category “dentist” in Arizona, I need to know where is the best place to open the business, services that I need to offer to my customers, like “credit card accepted”, and identify most relevant positive review words that I need to get from my customers and negative review words for my business category in Arizona.

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## Methods and Data

### Steps:

#### 1.ETL -> 1.Get\_Data.R

1.1.Download data from [https://d396qusza40orc.cloudfront.net/dsscapstone/dataset/yelp\\_dataset\\_challenge\\_academic\\_dataset.zip](https://d396qusza40orc.cloudfront.net/dsscapstone/dataset/yelp_dataset_challenge_academic_dataset.zip) and unzip it.

1.2.Extract json information from files “business”, “checkin”, “tip”, “review” (Excluded “user”, not relevant for my analysis)

1.3.Store it into RDS file. Review is divided into files with 100.000 lines/file in order to make affordable the calculation for my computer. For review processing are obtained 16 files.

1.4.Identify business per state.

1.5.Filter files per business\_id per State, create RDS files “checkin”, “tip”, “review” per State.

#### 2.Process -> 2.Proces Data.R

## Obtain auxiliar dataset

2.1. Use as input State and Business Category.

### List of States:

[1] “AZ, BW, CA, EDH, ELN, FIF, HAM, IL, KHL, MA, MLN, MN, NC, NTH, NV, NW, ON, OR, PA, QC, RP, SC, SCB, WA, WI, XGL”

### List of Categories:

[1] “(Other), Accessories, Active Life, American (New), American (Traditional), Apartments, Arts & Crafts, Arts & Entertainment, Asian Fusion, Auto Repair, Automotive, Bakeries, Barbeque, Bars, Beauty & Spas, Beer, Wine & Spirits, Books, Mags, Music & Video, Breakfast & Brunch, Burgers, Cafes, Caterers, Chicken Wings, Chinese, Coffee & Tea, Convenience Stores, Cosmetics & Beauty Supply, Day Spas, Delis, Dentists, Department Stores, Desserts, Diners, Doctors, Drugstores, Dry Cleaning & Laundry, Electronics, Event Planning & Services, Fashion, Fast Food, Fitness & Instruction, Flowers & Gifts, Food, Food Trucks, Furniture Stores, Greek, Grocery, Gyms, Hair Removal, Hair Salons, Health & Medical, Home & Garden, Home Decor, Home Services, Hotels, Hotels & Travel, Ice Cream & Frozen Yogurt, Indian, Italian, Japanese, Jewelry, Latin American, Local Services, Lounges, Massage, Mediterranean, Men’s Clothing, Mexican, NA’s, Nail Salons, Nightlife, Oil Change Stations, Parks, Pet Boarding/Pet Sitting, Pet Groomers, Pet Services, Pet Stores, Pets, Pizza, Professional Services, Public Services & Government, Pubs, Real Estate, Restaurants, Salad, Sandwiches, Seafood, Shoe Stores, Shopping, Southern, Specialty Food, Sporting Goods, Sports Bars, Steakhouses, Sushi Bars, Tex-Mex, Tires, Venues & Event Spaces, Veterinarians, Wine Bars, Women’s Clothing”

2.2. Intermediate Output to support analysis and define model

2.3. Relation Attributes-Stars

2.4. Count words.

## Get output

2.5. Attributes to have, top-5 positive words ( $\geq 4$  stars comments), top-5 negatives words ( $< 3$  stars comments).

2.6. Map of top rated business.

2.7. Random forest model fitted for a Business Category and State and analysis to verify that all those attributes and words can predict star rates.

## Results

Used as State “NC” and “Food” as category.

### List of top attributes and Top-5 positive and negative words for 1-gram

List filtered, % of positive and negative over total must be over 2.5%, difference between positive and negative must be over 0.15 stars to be relevant.

| Attribute                       | positives | pos_avg | negatives | neg_avg | diff_avg | pos%  | neg%  |
|---------------------------------|-----------|---------|-----------|---------|----------|-------|-------|
| attributes.Parking.street       | 72        | 4.07    | 600       | 3.71    | 0.36     | 10.71 | 89.29 |
| attributes.Accepts Credit Cards | 639       | 3.76    | 33        | 3.50    | 0.26     | 95.09 | 4.91  |
| attributes.Price Range          | 647       | 3.76    | 25        | 3.58    | 0.18     | 96.28 | 3.72  |
| attributes.Parking.garage       | 61        | 3.90    | 611       | 3.73    | 0.17     | 9.08  | 90.92 |
| attributes.Good For.breakfast   | 20        | 3.90    | 652       | 3.74    | 0.16     | 2.98  | 97.02 |
| attributes.Caters               | 76        | 3.88    | 596       | 3.73    | 0.15     | 11.31 | 88.69 |

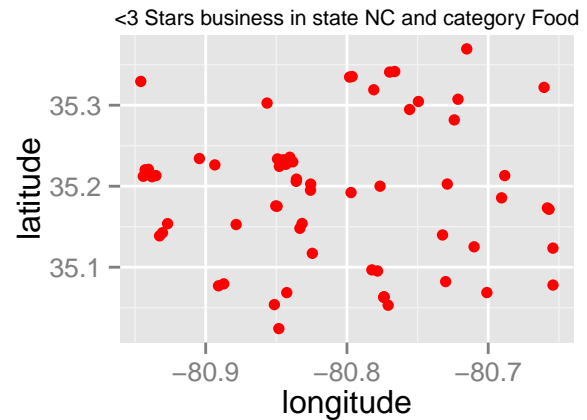
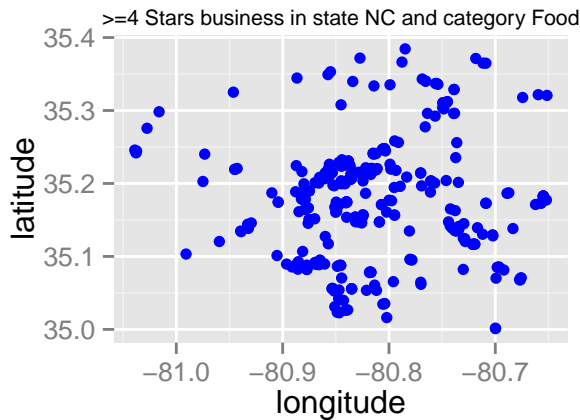
|   | word    | accumulate |
|---|---------|------------|
| 1 | good    | 38.00      |
| 2 | range   | 23.00      |
| 3 | food    | 20.00      |
| 4 | place   | 18.00      |
| 5 | service | 15.00      |

Table 1: Top-5 positive words

|   | word  | accumulate |
|---|-------|------------|
| 1 | food  | 21.00      |
| 2 | time  | 14.00      |
| 3 | good  | 12.00      |
| 4 | place | 12.00      |
| 5 | no    | 11.00      |

Table 2: Top-5 negative words

### Map of Business Stars Rates



## Random Forest Model

### Formula

stars ~ attributes.Parking.validated + attributes.Ambience.hipster + attributes.Parking.street + attributes.Accepts.Credit.Cards + attributes.Music.live + attributes.Price.Range + attributes.Parking.garage + attributes.Good.For.breakfast + attributes.Takes.Reservations + attributes.Caters + attributes.Good.For.Groups + attributes.Has.TV + attributes.Wheelchair.Accessible + attributes.Ambience.casual + attributes.Good.for.Kids + attributes.Parking.lot + attributes.Good.For.dinner + latitude + longitude

### Confusion Matrix Table

|     | 1.5 | 2 | 2.5 | 3  | 3.5 | 4  | 4.5 | 5 |
|-----|-----|---|-----|----|-----|----|-----|---|
| 1.5 | 0   | 0 | 0   | 0  | 0   | 0  | 0   | 0 |
| 2   | 0   | 0 | 0   | 0  | 0   | 0  | 0   | 0 |
| 2.5 | 0   | 0 | 0   | 0  | 0   | 0  | 0   | 0 |
| 3   | 0   | 0 | 0   | 0  | 0   | 0  | 1   | 0 |
| 3.5 | 0   | 0 | 1   | 0  | 2   | 2  | 0   | 0 |
| 4   | 1   | 2 | 4   | 16 | 25  | 27 | 18  | 6 |
| 4.5 | 0   | 0 | 3   | 2  | 4   | 7  | 8   | 2 |
| 5   | 0   | 0 | 0   | 0  | 0   | 0  | 0   | 0 |

Table 3: Confussion Matrix

### Confusion Matrix Overall

| Accuracy  | Kappa     |
|-----------|-----------|
| 0.2824427 | 0.0320704 |

### Confusion Matrix by Class

| ##            |  | Sensitivity       | Specificity    | Pos Pred Value | Neg Pred Value |
|---------------|--|-------------------|----------------|----------------|----------------|
| ## Class: 1.5 |  | 0.00000000        | 1.00000000     | NaN            | 0.9923664      |
| ## Class: 2   |  | 0.00000000        | 1.00000000     | NaN            | 0.9847328      |
| ## Class: 2.5 |  | 0.00000000        | 1.00000000     | NaN            | 0.9389313      |
| ## Class: 3   |  | 0.00000000        | 0.9911504      | 0.0000000      | 0.8615385      |
| ## Class: 3.5 |  | 0.06451613        | 0.9700000      | 0.4000000      | 0.7698413      |
| ## Class: 4   |  | 0.75000000        | 0.2421053      | 0.2727273      | 0.7187500      |
| ## Class: 4.5 |  | 0.29629630        | 0.8269231      | 0.3076923      | 0.8190476      |
| ## Class: 5   |  | 0.00000000        | 1.0000000      | NaN            | 0.9389313      |
| ##            |  | Prevalence        | Detection Rate | Detection      | Prevalence     |
| ## Class: 1.5 |  | 0.007633588       | 0.00000000     |                | 0.00000000     |
| ## Class: 2   |  | 0.015267176       | 0.00000000     |                | 0.00000000     |
| ## Class: 2.5 |  | 0.061068702       | 0.00000000     |                | 0.00000000     |
| ## Class: 3   |  | 0.137404580       | 0.00000000     |                | 0.007633588    |
| ## Class: 3.5 |  | 0.236641221       | 0.01526718     |                | 0.038167939    |
| ## Class: 4   |  | 0.274809160       | 0.20610687     |                | 0.755725191    |
| ## Class: 4.5 |  | 0.206106870       | 0.06106870     |                | 0.198473282    |
| ## Class: 5   |  | 0.061068702       | 0.00000000     |                | 0.00000000     |
| ##            |  | Balanced Accuracy |                |                |                |
| ## Class: 1.5 |  | 0.5000000         |                |                |                |
| ## Class: 2   |  | 0.5000000         |                |                |                |
| ## Class: 2.5 |  | 0.5000000         |                |                |                |
| ## Class: 3   |  | 0.4955752         |                |                |                |

|               |           |
|---------------|-----------|
| ## Class: 3.5 | 0.5172581 |
| ## Class: 4   | 0.4960526 |
| ## Class: 4.5 | 0.5616097 |
| ## Class: 5   | 0.5000000 |

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## Discussion

### Attributes Analysis

At initial analysis are detected attributes that have an impact over  $\pm 0.15 \text{ stars rate}$ . Positive % ( $\text{pos\%} = \frac{\text{positivereviews}}{\text{totalreviews}}$ ) and negative % ( $\text{neg\%} = \frac{\text{negativereviews}}{\text{totalreviews}}$ ) must be  $> 2.5\%$  to avoid to interpret exceptions as true influencers of stars rate.

With this conditions, are identified some attributes with an influence between (0.36, 0.15). This attributes and latitude and longitude are the factors for the model.

### Top-5 positive and negative 1-gram

Top-5 positive and negative 1-gram analysis appears as no useful in this case, because some 1-gram detected as top positive appears also as most frequent into top negative 1-gram, due to this, these are not included into the model. For a small-medium set of reviews is not useful this kind of analysis, is recommended to try use it over greater data set of review or include 2-grams/3-grams to evaluate if are relevant is that scenario.

### Map of business

Map of business shows interesting information, comparing  $\geq 4$  stars (best rated business) vs.  $< 3$  stars (worse rated business) is easy to see the difference between both maps. Moreover, appears an accumulation of best rated business that indicates areas where clients are attracted due to good reviews.

### Random Forest Model

Random Forest Model reveals that hypothesis about influence of attributes alone are not useful to predict rates based on attributes and location. Confusion Matrix Table reveals a poor accuracy into prediction, less than 30%, and appears totally inefficient to classify 1.5, 2, 2.5, 3 and 5 stars, and low accuracy for 3.5, 4 and 4.5.

### Implication for the question

Based on this analysis, in one hand, use of attributes as stars rate predictor and Top-5 positive and negative 1-gram is inefficient, can't be used to recommend to business owner attributes to have or words that have to make arise in reviews. Maybe is possible to recommend some attributes, but is not confirmed their direct influence in stars rate. In the other hand, Map of business can be useful to establish location of business in a specific category.