Building a tool to assess business performance based on customer reviews

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Introduction

With the increasing popularity of on-line review databases such as Yelp, both consumers and business owners now have access to a wealth of customer review data that was not possible a decade ago. For the business owner, this data represents a valuable resource, providing insight into customer satisfaction and business performance. While some of the more objective assessments, such as star ratings, may give some idea of customer satisfaction, they do little to provide real insight into exactly how a given business is meeting the expectations of its customers, or as the case may be, falling short.

To fill this gap, customers are encouraged to write reviews that appear as blocks of text. These give the consumer a chance to elaborate on his or her experience with more specific descriptions and offer a wealth of information for the business owner. Yet sifting through customer review texts can be an arduous process; for the business owner wanting to draw general conclusions from hundreds of such documents, the task may be prohibitively time-consuming.

This project is a feasibility study aimed at creating an program that can help streamline this process, making it easier for business owners to gain more insight into the satisfaction of their customers from Yelp reviews. By submitting a query by Yelp business ID, the application will return several pieces of information. The first is a plot of average star ratings (averaged monthly) over time, showing the general trend in the business' customer satisfaction. The second is a text-mining endeavor, aimed at extracting meaningful insight from the written texts of customer reviews. If, for example, a restaurant owner discovers that the word "wait" is often found in the negative reviews, he or she might infer that customers are often critical of how long they must wait for seating or food/drink service. The goal of this project is to determine if such text-mining algorithms can be tuned to provide useful information to the business owner.

Methods and Data

Sourcecode

The R code used for this study can be found in this report's Github repository: https://github.com/jleslie17/CapstoneProject

Loading Data

The data for this study came from the Yelp Dataset Challenge (http://www.yelp.com/dataset_challenge). This dataset includes five JSON files corresponding to several aspects of Yelp review data and should be unzipped in the working directory. For this study, I used only the files pertaining to business IDs and reviews. I loaded the files of interest and saved them as rds files for subsequent analyses.

Subsetting the data into a shortlist

Becuase this is a feasibility study, I used only a subset of the data. This application could easily be expanded to include all businesses in the data set. It should be noted, however, that for businesses with fewer reviews, data describing customer satisfaction (see section below) may become noisy. For this reason, I restricted my feasibility study to a shortlist of businesses consisting of only restaurants and only those restaurants that had 100 or more reviews in the Yelp data set.

Examining changes in performance over time

To examine the change in customer satisfaction over time, I wrote a script that retrieves all review data for a given business (using the business-id number. The program extracts the business_id, review_id, date, stars and text variables from the review data file. Star ratings are gathered by month using the as.yearmon() command of the zoo library and monthly averages are calculated and plotted (Plot 1). The first six lines of an example data frame are shown below.

```
##              business_id  YearMonth AvStarsPerMonth
## 1 2WHP5nhS1rFszfRBKe6fWQ 2014-02-01        4.888889
## 2 2WHP5nhS1rFszfRBKe6fWQ 2014-03-01        4.318182
## 3 2WHP5nhS1rFszfRBKe6fWQ 2014-04-01        4.058824
## 4 2WHP5nhS1rFszfRBKe6fWQ 2014-05-01        4.000000
## 5 2WHP5nhS1rFszfRBKe6fWQ 2014-06-01        4.187500
## 6 2WHP5nhS1rFszfRBKe6fWQ 2014-07-01        4.571429
```

Examining review texts

To perform text-mining I used the tm package. All reviews for a given business are pooled into either a "good" pool or a "bad" pool. This distinction is based on the star rating for each review relative to a threshold star rating supplied by the user. The program generates a corpus for all reviews in each pool (good and bad). The corpora are preprocessed to remove whitespace, transform all words to lowercase, remove stopwords (such as 'the') and stemmed to retrieve word radicals (free of suffixes). Punctuation is also removed. Document-term matrices are generated for each corpus, and mean frequency (how often each term appeared in a corpus) is calculated for each term. The terms are then sorted in order of decreasing frequency and word clouds are generated from the list of the top 50 terms in each group using the wordcloud() package.

Results

Sample business

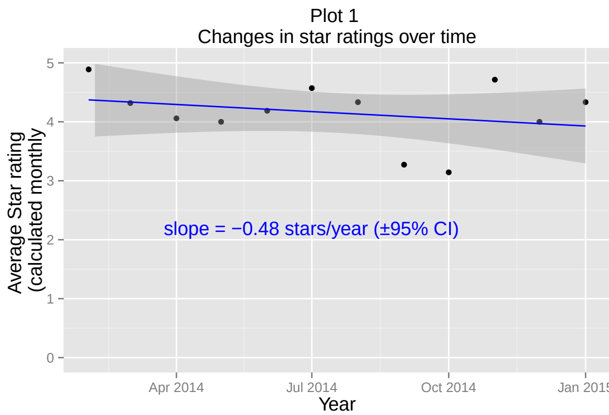
For the remainder of this report, I have shown the data for a single example restaurant with the Yelp business id 2WHP5nhS1rFszfRBKe6fWQ. Because this application is meant to function as a tool for the business owner to investigate performance, I reasoned that in this context, an analysis of an individual business would be more useful than a general analysis of customer tastes accross many businesses. The following sections describe the steps in performing the analysis for this sample business.

Examining changes in performance over time

A central tenant of business is to "know your audience". While a business may have met the demands of its audience well in the past, consumer taste changes quickly, and it can be hard to stay on top of that as a business owner. To assess how well a business is meeting the demands of its public, I wanted to examine ratings over time.

To visualise this trend, the program plots average stars over time. It further fits a linear model to the data and uses this model to draw linear regression line (see code snippet below). The slope of this line can be thought of as the trend in customer satisfaction.

```
fit <- lm(AvStarsPerMonth~YearMonth, data = BIDStarsDatesGrouped)
```



In this example, the change in star rating (stars per year) for business 2WHP5nhS1rFszfRBKe6fWQ is: **-0.48**

As we can see from the plot, the reviews have, on average, gotten worse with time. The owner of this restaurant might want to know why. The next section deals with ways to help answer that question.

Generating word lists for good and bad reviews

To help shed light on factors that might be contributing to customer satisfaction (either for the good or the bad), I wanted to emply text-mining techniques on the texts that accompany each review. I hypothesize that such an analysis might reveal trends associated with customer satisfaction that may be otherwise hidden.

Since each business owner may want to decide what star rating differentiates between a "good" and a "bad" review, I allow this threshold to be set. In this case, it is set with the StarsThresh variable. In this example, StarsThresh is set to 3.5, so reviews receiving 1, 2 or 3 stars will be pooled in the "bad" group, and the rest will be considered "good".

```
StarsThresh <- 3.5
```

The text mining algorithm generates a so-called corpus for each group, with the text from each review within the groups functioning as a disctinct document. The algorithm goes on to apply preprocessing techniques as described in the Methods and Data section above to yeild final corpora used for subsequent analyses.

The good and bad corpora were used to generate document-term matrices, which were further used to produce final lists of frequently used terms. The 20 most commonly-used terms (minus stopwords such as "the" and "an") for each group are listed below:

```
[1] "Keywords associated with good reviews:"

seafood     good    great     food    place lobster     high    fresh     tide
   0.66     0.63     0.62     0.61     0.56     0.48     0.41     0.40     0.36
```

```
   tri    back     bar   happi    nice    love   order    will    best 
  0.36    0.35    0.33    0.31    0.31    0.29    0.29    0.28    0.27 
friend    hour 
  0.27    0.27 
```

```
[1] "Keywords associated with bad reviews:"
```

```
  food   order   place    good  servic    fish    just    high    nice 
  0.94    0.84    0.72    0.56    0.53    0.44    0.44    0.41    0.41 
   one seafood     bar  dinner    menu     pot   steam    tast    went 
  0.41    0.41    0.38    0.38    0.38    0.38    0.38    0.38    0.34 
  back  better 
  0.31    0.31 
```

Word usage visualization

To better visualize word usage, I took advantage of the wordcloud package to produce a wordcloud for each group (good and bad reviews). This process included converting each document-term matrix into a data frame listing words and frequency of use, and employing the wordcloud() function as shown below.

```r
wordcloud(dGood$word, dGood$freq, scale=c(2.5,0.5),
          max.words=50, random.order=FALSE,
          rot.per=0.35, use.r.layout=FALSE,
          colors=brewer.pal(8, 'Dark2'))
title(main = "Words appearing in \nGood reviews")

wordcloud(dBad$word, dBad$freq, scale=c(2.5,0.5),
          max.words=50, random.order=FALSE,
          rot.per=0.35, use.r.layout=FALSE,
          colors=brewer.pal(8, 'Dark2'))
title(main = "Words appearing in \nBad reviews")
```

These word clouds help to give a better visual appreciation for what topics have often been discussed in customer reviews, and may provide useful information to the business owner.

Discussion

The goal of this project is to explore ways in which business owners might be able to make better use of customer review data. Specifically, I was interested in (1) assessing changes in customer satisfaction over time and (2) using text-mining approaches to extract useful information from customer reviews. This report is a feasibility study, aimed at determining if my program achieves these goals.

In the first case, I believe the algorithm was successful. Using linear regression in concert with appropriate grouping and averaging parameters, this program produces a clear picture of trends in average customer satisfaction over time. The robustness of this analysis is dependent on several factors, including the number of reviews gathered, the variation in stars awarded and the period over which reviews are averaged. I restricted this study to only those businesses that had more than 100 reviews, hoping that this would make the algorithm less susceptible to these confounding factors. For businesses having fewer reviews, the period over which star ratings were averaged would probably have to be adjusted in order to smooth out noise. Nonetheless, for this example business (and many others not shown), the algorithm produces an informative visualization of temporal trends in customer satisfaction.

For the second part of the analysis I employed text-mining techniques to extract meaningful keywords from review texts. When analyzing word clouds one must use caution. For instance, in this example, many words are shared between good reviews and bad ones. Words such as "food", "place" and "good" show up in both groups with similar frequencies and therefore don't reveal much about customer satisfaction. Other words are more telling. For example, in the positive reviews, we see that the words "lobster", "fresh", and "seafood" appear with a high frequency. In contrast, the words "order", "servic" and "menu" show strongly in the negative reviews. One might infer, then, that when customers of this business are happy with their experience, the quality of the food is something they notice. When they are unhappy, however, the service seems to be where the business falls short.

In the case of this example, the program worked reasonably well. Text mining is a complicated endeavour, and it is rare that the output gives a black-and-white picture of the trends in term usage. I suspect that this algorithm could be tuned to be more robust, and in a final application, it may be wise to make these tuning parameters variables that can be adjusted by the user. Ultimately, whether or not such text-mining applications are useful to the business owner may largely depend on the individual user.

Nevertheless, it seems that this program may indeed provide a useful tool to allow business owners to make better sense of their customer reviews. I the future, I would like to use this program as the basis for an on-line app in which a merchant can use his or her business ID number to query the dataset and get a comprehensive customer satisfaction report as output.