Predicting Rating Based on Yelp Tips Using LASSO

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I Introduction

The tips on the Yelp website is the insider information provided by the Yelp's users or reviewers. The tip text contains the sentiments of the users of how they would (or would not) recommend the other users the service or product they are going to buy from a particular business. The tips can be positive or negative and should be consistent with a review, if any, posted by the same user. In this study, I am going to find the correlation between a business rating and its tips by developing a predictive model using the words (or terms) in the tips text as the independent variables (or features) and rating as the dependent variable.

II Methods and Data

To create and train a predictive model for business ratings, I use two datasets, namely "yelp_academic_dataset_business.json" and "yelp_academic_dataset_tips.json" from the Yelp Dataset Challenge (Rounds 5 and 6).

Both files are in JSON format. The files will be read, merged and cleaned up before they are used to develop the model.

Exploratory Analysis

Here is the summary of the tips dataset:

No. of Tips	Avg. Tip Length	No. of Bus. in Tips	No. of Users Provided Tips	Tips Covered Period
495,107	58.73 chars	42,111	80,836	4/15/2009 - 1/22/2015

Machine Learning Algorithm

The algorithm used to develop the predictive model is called LASSO (Least Absolute Shrinkage and Selection Operator) which was developed by Dr. Robert Tibshirani in 1996. The LASSO is derived from the multiple linear regression and is similar to Ridge Regression which penalizes the coefficients in order to minimize the overfitting. The LASSO has an advantage over Ridge Regression though is that it not only shrinks the coefficients but also forces some of the coefficients to be exactly zero when the regularization parameter λ is selected properly.

Here is the model: $rating = \beta_0 + \beta_1 T_1 + \beta_1 T_2 + \ldots + \beta_p T_p + \varepsilon$

Where the T_p is the frequency of a word or term appears in a tip and ε is a mean-zero random error term. The goal of the LASSO is to find a set of coefficients that can minimize the quantity below:

$$\sum_{i=1}^{n}(rating_i - \beta_0 - \sum_{j=1}^{p} \beta_j T_{ij})^2 + \lambda \sum_{j=1}^{p} |\beta_j| = RSS + \lambda \sum_{j=1}^{p} |\beta_j|$$

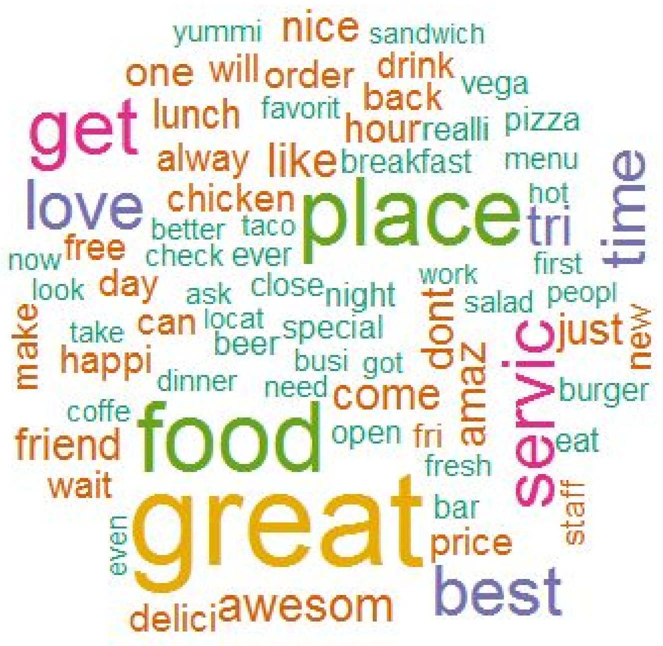
To get the frequency of the most popular words, $T_p s$ from the tips, text mining technique is used. There are more than 80,000 words found in the tips text but many of them are not frequently used in all the tips (high sparsity). So those terms will be filtered out when their sparsity are more than 99%. As a result, there are about 290 terms are left for the model development.

The study first estimates the predictive rating and mean square errors (MSE) from a naive model for comparison. Then we train and validate a LASSO model using *unigrams* (single word in each term) and *bigrams* (two adjacent words in each term) to see which one works better. The code is as follow:

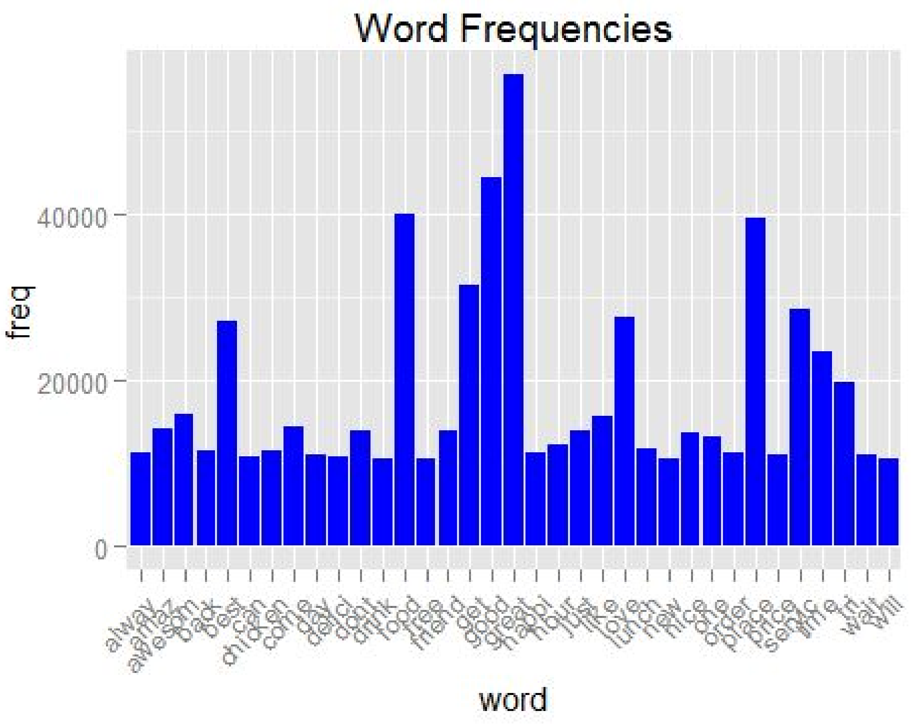
```
## Loading libraries
lapply(c("jsonlite","NLP","tm","SnowballC","wordcloud","glmnet","ggplot2"),
       require, character.only = TRUE)

## Read data from the files assuming they reside in the working directory
bus <- stream_in(file("yelp_academic_dataset_business.json"))
tips <- stream_in(file("yelp_academic_dataset_tip.json"))

## user defined functions
PlotWordCloud <- function (docTermMatrix, maxwords) {
  ## Find frequent terms
  freq <- colSums(docTermMatrix)
  freq <- sort(freq, decreasing=TRUE)
  ## make word cloud
  word <- names(freq)
  wordcloud(word, freq, max.words=maxwords, colors=brewer.pal(6,"Dark2"), rot.per=.15)
  wf <- data.frame(word=word, freq=freq)
  return(wf)
}

GetModelingData <- function (docTermMatrix) {
  ## add the business ID column to the term matrix
  dtm_tips <- cbind(business_id=tips$business_id, as.data.frame(docTermMatrix))
  ## merge the business ratings with tip terms dataframe
  bustips <- merge(bus[,c("business_id","stars")], dtm_tips, by="business_id")
  ## business ID column is no longer needed
  bustips$business_id <- NULL
  ## prepare the training and test data
  x <- model.matrix(stars~., bustips)[,-1]
  y <- bustips$stars
  ## create a list of lambdas for regularization
  lambdas <- 10^seq(10,-2, length=100)
  set.seed(1)
  ## randomly get 70% of the data for training, 30% for validation
  train<-sample (1: nrow(x), nrow(x) * 0.7)
  return(list(x=x, y=y, train=train, lambdas=lambdas))
}

LassoRegression <- function (params) {
  train <- params$train
  test <- (-train)
  ## for Lasso, parameter alpha needs to be 1
  lasso.mod <- glmnet(params$x[train,], params$y[train], alpha=1, lambda=params$lambdas)
  set.seed(2)
  ## perform cross validation
  cv.out <- cv.glmnet(params$x[train,], params$y[train], alpha=1)
  ## get the best lamdba from the validation result
  bestlamda <- cv.out$lambda.min
  ## predict the ratings using the test data
  lasso.pred  <- predict(lasso.mod, s=bestlamda, newx=params$x[test,])
  ## calcuate the mean squre errors on the test predictions
  mse <- mean((lasso.pred - params$y[test])^2)
  ## use the full dataset to re-train the model and get the coeffients from it
  out <- glmnet (params$x, params$y, alpha=1, lambda=params$lambdas)
  lasso.pred.coef <- predict(out, type="coefficients", s=bestlamda)
  ## get the vector of coefficients
  lasso.coef <- lasso.pred.coef[1:dim(lasso.pred.coef)[1],]
  return(list(mod=lasso.mod, bestlamda=bestlamda, mse=mse, coef=lasso.coef))
}

## text mining on the tip texts. Set the tip texts as the source
vsource <- VectorSource(tips$text)
tiptexts <- Corpus(vsource)
## data cleaning
tiptexts <- tm_map(tiptexts, content_transformer(tolower))
tiptexts <- tm_map(tiptexts, removeNumbers)
tiptexts <- tm_map(tiptexts, removePunctuation)
tiptexts <- tm_map(tiptexts, stripWhitespace)

## Naive model. The predicted rating is simply the average of the ratings in the training data
naive.pred <- mean(bus$stars)
## Mean square errors (MSE) of the naive model
naive.mse <- mean((naive.pred - bus$stars)^2)
```

Predictive rating from naive model: **3.6733051**

```
## Lasso Regression using Unigrams
tiptexts_ugm <- tm_map(tiptexts, removeWords, stopwords("english"))
tiptexts_ugm <- tm_map(tiptexts_ugm, stemDocument)
## create a document-term matrix from the tip texts
dtm <- DocumentTermMatrix(tiptexts_ugm)
## remove the terms with more than 99.6% sparcity from the dtm
dtm <- removeSparseTerms(dtm, 0.996)
## save the dtm as a regular matrix for later processing
dtm2 <- as.matrix(dtm)
## train the model
data <- GetModelingData(dtm2)
out_ugm <- LassoRegression(data)
## plot word cloud and bar chart for most frequent used terms
wf_ugm <- PlotWordCloud(dtm2, 75)
```



```
ggplot(data = subset(wf_ugm, freq>10000), aes(word, freq)) + geom_bar(stat="identity", fill="blue")
+
  ggtitle("Word Frequencies") + theme(axis.text.x=element_text(angle=45, hjust=1))
```



```
## remove the big objects to save memory space
rm(tiptexts_ugm, dtm, dtm2, data)
```

```
## bigrams data (stop words are not removed)
tiptexts_bgm <- tm_map(tiptexts, stemDocument)
BigramTokenizer <- function(x) {unlist(lapply(ngrams(words(x), 2), paste, collapse = " "), use.names
= FALSE)}
dtm <- DocumentTermMatrix(tiptexts_bgm, control = list(tokenize = BigramTokenizer))
dtm <- removeSparseTerms(dtm, 0.998)
dtm2 <- as.matrix(dtm)
data <- GetModelingData(dtm2)
out_bgm <- LassoRegression(data)
rm(tiptexts_bgm, dtm, dtm2, data)
```

III Results

Here are the results from the three different models:

Model	MSE	RMSE	Total No. of Features	No. of Features with non-zero coef.
Naive	0.794237	0.891200	N/A	N/A
Lasso (uni.)	0.352615	0.593814	294	43
Lasso (bi.)	0.359434	0.599528	291	19

Features in unigram model with non-zero coefficients:
(***amaz, awesom, bad, beauti, best, buffet, car, delici, dont, drink, drive, everyth, excel, fantast, favorit, flavor, fresh, friend, great, hotel, hour, line, locat, long, love, minut, must, never, night, owner, pay, recommend, room, server, servic, slow, stay, tri, wine, wing, wonder, yelp***)

IV Discussion

As you can see from the results, the LASSO regression model (unigrams or bigrams) has a much lower mean square error rate (MSE) than the naive model. So the LASSO model is really a better model. Also, for the Lasso unigrams model, the original number of features used for the model training is 294. Now the actual number of features is 43. So the Lasso algorithm not only minimizes the overfitting but also reduces the dimensions of the final model.

Ridge regression (code is not shown here) produces a better error rate which is about 0.3481998 of MSE, but it doesn't force some coefficients to be exactly zero. Principal Component Analysis (PCA) can reduce the dimensions but it is hard to interpret the model because the new features (principal components) are some kinds of transformation from the original features.

The Lasso model using bigrams is also trained here because I think using two adjacent words in a term may have a better sentiment and predicting accuracy, but it doesn't seem to have a much better prediction rate than using the unigrams by looking at the results above. However, it does have a shorter dimensions than the unigrams model.

One interesting finding from the unigrams model is that the top 42 most frequent terms in the tips are not necessarily the features in the Lasso final model:

42 most frequent terms:
(***alway, amaz, awesom, back, best, can, chicken, come, day, delici, dont, drink, eat, food, free, fri, friend, get, good, great, happi, hour, just, like, love, lunch, make, new, nice, night, one, order, pizza, place, price, realli, servic, staff, time, tri, wait, will***)

There are only 13 out of them are in the features of the final model. So in other words, most frequent terms do not necessarily contribute to the rating prediction.

In the Yelp dataset, the reviews contain similar sentiment data to the tips, and each review is also associated with the direct votes for a business rating. So the reviews can also be used to develop a predictive model. And actually there are some people have done the work in this direction.

This study does not try to compare the predictive models using the reviews and the tips, but try to understand if there is a correlation between the ratings and tips; and the results confirm that.

In conclusion, the predicting model based on the Yelp tips using the Lasso regression works pretty well, the error rate 0.352615 is comparable to the ones of the models based on reviews from other studies.

References

1. A. De Catro, A. Du and A. Manicka, "Predicting Ratings Based on Yelp Tips".
2. Yifei Feng and Zhengli Sun, "Yelp User Rating Prediction".
3. Mingming Fan and Maryam Khademi, "Predicting a Business Star in Yelp from Its Reviews Text Alone".