PREDICT TRIPADVISOR HOTEL RATINGS BASED ON REVIEWS

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Introduction

The goal of that project is to predict rating of a hotel on TripAdvisor based on their reviews.

Data collection

The data is collected by scraping reviews and ratings from TripAdvisor webpage. In this particular project, I only collect data from New York city. The source page can be found here: https://www.tripadvisor.com/Hotels-g60763-New_York_City_New_York-Hotels.html

I only collect a small sample for academic purpose and got permission from TripAdvisor. To ensure that the data is unbiased even though I only collect a sample, I write my code to go to random review pages for each hotel.

I use Python for web-scraping and initial data pre-processing. As for web-scraping, I use the BeautifulSoup library with a small implementation of multi-threading for faster code. Scrapy can be a more efficient tool, but I use BeautifulSoup for the purpose of learning web-scraping. The multi-threading implementation is not fully correct, but it serves the purpose of getting a small sample of the data.

In the code, I run loops through hotel and review pages because they follow this pattern:

For each hotel:

The first review page:

Hotel_Review-g60763-d223024-Reviews-Hotel_Chandler-New_York_City_New_York.html#REVIEWS

The second review page:

Hotel_Review-g60763-d223024-Reviews-or10-Hotel_Chandler-New_York_City_New_York.html#REVIEWS

The next page is [text]-or20-[text], and the following pages follow similar patterns.

For code, please refer to the following files: TripAdvisorWebScrape.py and TripAdvisorDataCleaning.py.

Data cleaning and text mining

After the initial data pre-processing, I now have a .csv file that contains ratings, reviews, and review headers for each review. Review header is the header before each review, as one can see from the page.

I use the “tm” package in R to convert the reviews and review headers into two Corpuses, from which I perform string processing (convert to lower case, remove punctuation, remove spare terms,… etc) and create two word frequency tables.

The word frequency tables are formatted like the following example:

Review/Word	Rating	bad	good	great
Review 1	5	0	3	3
Review 2	3	1	1	0

In the real dataset, the words are ordered alphabetically. However, the idea is similar. Each column is a word, each row is a review, and the cell values are the frequencies of each word (column) in each review (row).

Then I merge the two tables and weigh the review header frequency three times the review frequency, because I believe the review header summarizes more of the reviewer’s opinion about the hotel.

For the text mining code, please refer to this file: TripAdvisorTextMining.R

Model

I use Naïve Bayes as the model, for the following reasons:

- This is a classification problem; therefore, a linear regression is not appropriate
- There should be no clear linear relationship between frequencies of so many words in a review and its rating, thus the problem is not linearly separable and the logistic regression is not appropriate
- The number of features is too large (compared to the number of observations) to fit a decision tree.

- This leaves us with Naïve Bayes, nearest neighbor, and support vector machine
- Since the training set is small (less than 30,000 observations) and the number of features is large (over 6000 variables), a high-bias, low-variance model like Naïve Bayes is usually a better choice.
- I try the support vector machine and it runs very slowly. Going on forward with this project, I would want to try fitting an SVM using a more efficient way.
- In the literature, Naïve Bayes has always been a good method for text classification

1. Naïve Bayes algorithm:

In the training set:

For each review X:

Find the conditional probability that each word appears in each class: $P(X_j = a_{jz}|c_i)$

X_j: attribute, in the case, users'reviews

a_{jz}: distinct values of attribute X, in this case, word frequency

c_i: class, in this case, users' ratings from 1 to 5

end for

In the testing set:

For each observation X:

Calculate:

$$P = P(X_1 = a_1|c_i) * P(X_2 = a_2|c_i) * P(X_3 = a_3|c_i) * \ldots .* P(X_n = a_n|c_i) * P(c_i)$$

Then find class i that gives the highest value of P

End for

2. Modification of the algorithm:

There are problems with the built-in Naïve Bayes algorithm; therefore, I decide to implement another version of the Naïve Bayes algorithm, using the formulas described in the paper by Karger, Rennie, Shih, and Teevan[1].

a) Find the conditional probability that each word appears in each class:

I use the following formula, which is more suitable for natural language processing:

In each class:

For each word:

$$P(X_j = a_{jz} | c_i) = \frac{Frequency\ of\ that\ word\ in\ the\ class +\ 1}{Frequencies\ of\ all\ the\ words\ in\ the\ class + Vocabulary\ Size} \quad (1)$$

Vocabulary size is the total number of different words in the training set, which is the number of training set columns, in this case.

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b) Using log probability:

When I start predicting, the model involves a lot of multiplication of small probabilities, which brings the result to 0. I fix this problem by using the log of probability, which turns the multiplication into the summation. We can do that because one can prove that if p1 > p2, then log(p1) > log(p2) and vice-versa. Therefore, the class that gives the maximum of log probability also gives the highest probability.

c) Using one-versus-all Naïve Bayes (OVA) to solve the skewed data bias:

I realize that in our data, the majority of the observations are in class 5 and few of them are in class 2. The log probability is negative, the log probability is set to be 0 when a vector does not appear in a given class, and there are two few class 2; therefore, class 2 always have the highest probability for all the testing observations, thus the prediction is incorrect.

To solve this problem, I use one-versus-all Naïve Bayes. The formula is as follow:

[1] Karger, Rennie, Shih, Teevan: http://people.csail.mit.edu/jrennie/papers/icml03-nb.pdf

$log_{OVA}(P(x\ in\ c_i)$=

$$\left[\log(p(c_i)) + \left(\sum \log(conditional\ probability\ \ (instance\ x = x(1,2,3\ \dots)|class\ i)) - \sum \log(complement\ conditional\ probability\ (instance\ x = x(1,2,3,\dots)|class\ i)\right)\right]$$

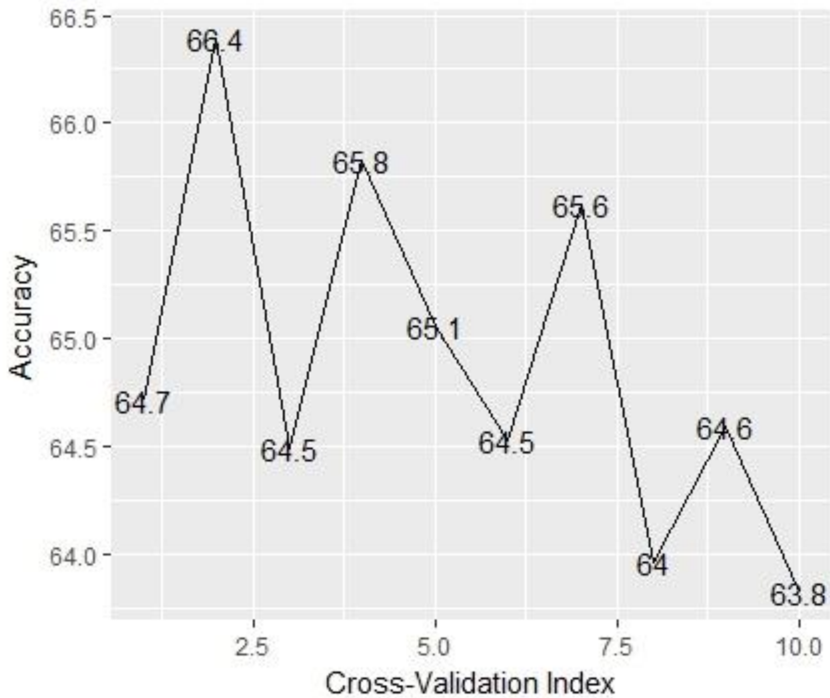
Conditional probability (instance X | class i) are the values that I calculate in part a. Complement conditional probability is calculated as follow:

$$Pcom(X_j = a_{jz}|c_i) = \frac{Frequency\ of\ that\ word\ in\ classes\ other\ than\ c(i) +\ 1}{Frequencies\ of\ all\ the\ words\ in\ classes\ other\ than\ c(i) + Vocabulary\ Size} \quad (3)$$

Results

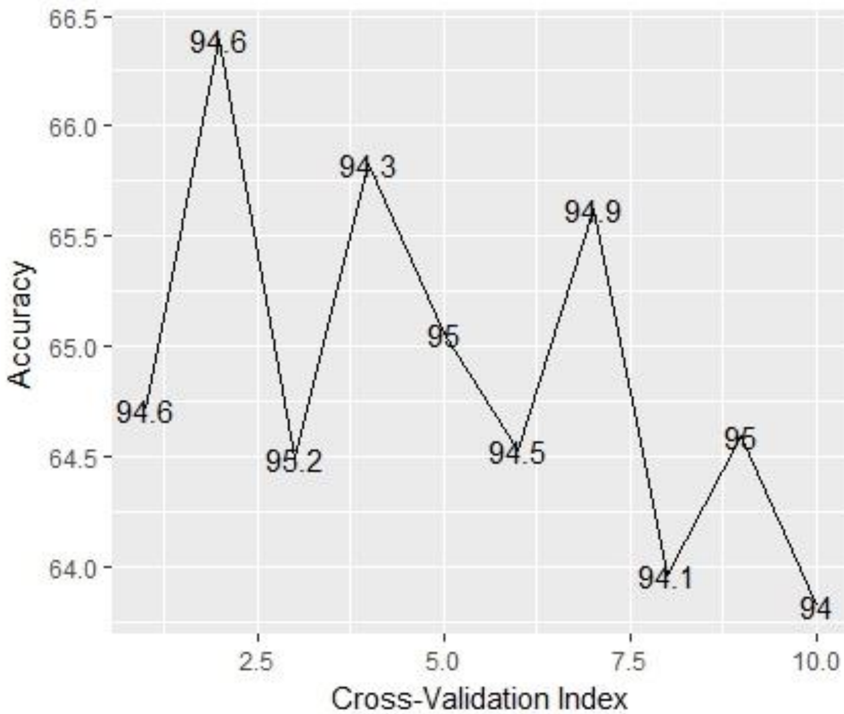
Cross-validation test accuracy:

If we maintain the strict classification accuracy criteria, which means that if the true rating is 4, the predicted rating has to be 4 to be correct, the cross-validation test accuracy are shown below:



The accuracy is around 65%. The base model, which is predicting every rating to be 5, has a 49% accuracy. This model is better than the base model

The performance of this model is better when if I make the classification accuracy criteria a little less strict. In this case, if the predicted rating is one value above or below the actual rating, that prediction is still considered correct. In this case, the cross-validation accuracy is shown below:



The accuracy rate around 95%, which is very high compared to the 79% accuracy of the based model (predicting all ratings to be 5).

For code, please refer to the file TripAdvisorProject-NaiveBayesModel.R

Ways for improvement

There are still many ways to improve this model to be improved. Going forward with this topic, I would like to explore semantic meaning of the words further and see if there are any features (frequencies of particular words) that can be eliminated. I would also like to fit other models and compare their performances, and to find a way to efficiently train a support vector machine model.

References

Karger, Rennie, Shih, Teevan. "Tackling the Poor Assumptions of Naive Bayes Text Classifiers." *Proceedings of the Twentieth International Conference on Machine Learning* (ICML). 2003.