BSTAT 625 Final Project Report

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Introduction

Background

The integration of the fields of Machine Learning and Natural Language Processing (NLP) has been growing tremendously in the modern era. Powerful and flexible computers have allowed researchers in the field of NLP to apply statisical methodologies to large, unstructured data in the form of texts to create software applications or draw meaningful insights. Successful NLP applications such as the autocorrect feature on messaging apps, search engine suggestions, and question answering machines (i.e. `Siri`, `Cortana` etc.) have increased the field's popularity. Insight-driven NLP applications such as topic labeling (i.e. classifiying a text to a specific domain), spam and fraud detection, and sentiment analysis (i.e. classifying the tone of the text's author) have also been growning in popularity. As a result, many companies in the industry have started to invest in NLP to analyze the large amounts of textual data which they own at their disposal.

Motivation

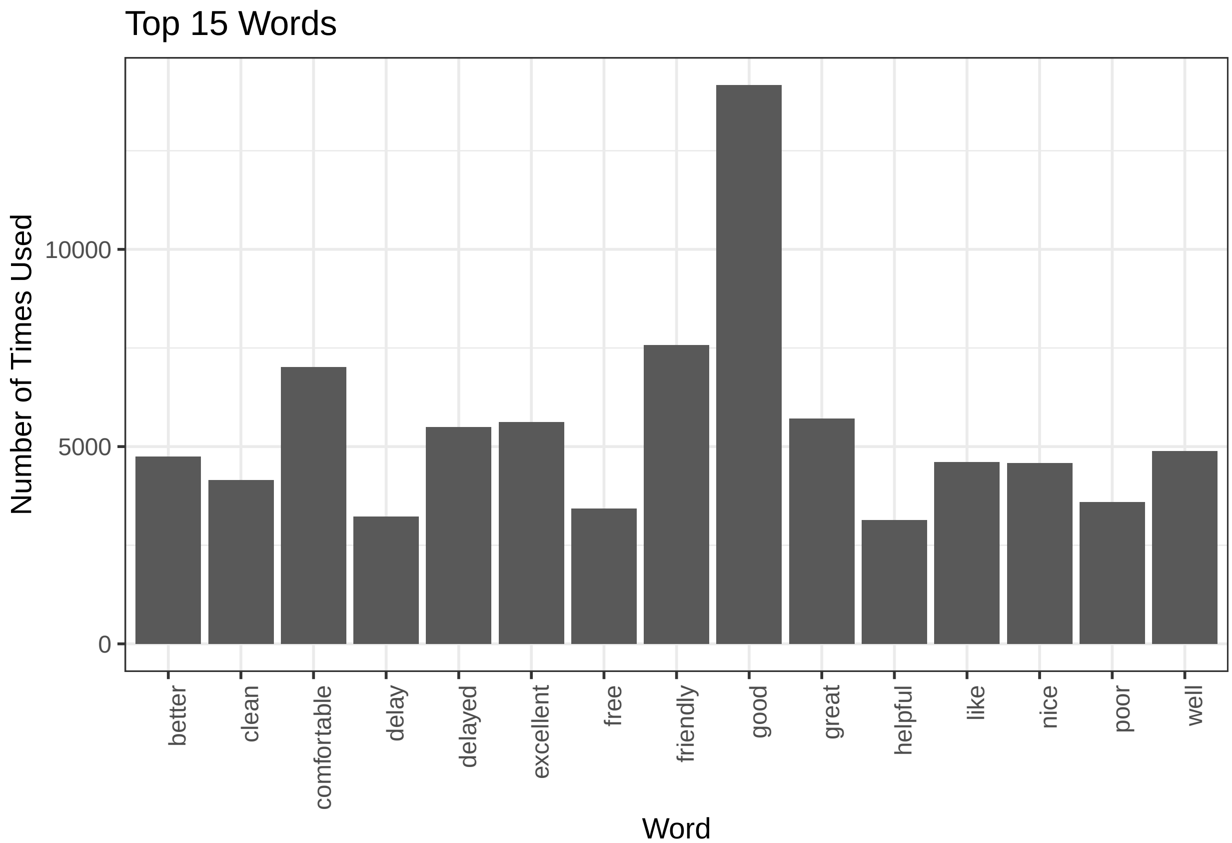
In this project, we spin a scenario where we are data science consultants at a world renowed consultancy firm, **HuiJiang625 LLC**. The primary clients of this consultancy group are airline agencies (i.e. Delta, American Airlines, & JetBlue etc.) who are looking to gather some insights from the flight reviews they receive from their customers daily. The marketing teams at these agencies would like to identify customers who are most likely to recommend their airline to friend(s) or family member(s) based on their review of the flight. This would allow the teams to optimize their marketing strategy by making recommend-friendly customers as their priority when sending out incentive-based offers such as gift cards, sky miles, or vouchers etc. in return for a recommendation. For example, if the marketing team knows that Tom is more likely to recommend the airline than Sarah then the marketing team could reach out to Tom first.

With this objective in mind, our team is tasked with building a NLP-driven statistical model that takes in input of a customer's textual review (in English) and outputs whether or not that customer will recommend the airline. A secondary objective of this project is to provide an user-friendly application that allows the user (i.e. marketing team) to input a customer's review and immediately receive the answer of whether or not they will recommend the airline. The purpose of this app is to eliminate the need for statistical knowledge in the user as well as mask the mathematical mechanisms of the models behind an attractive dashboard.

Dataset

Raw Data

The dataset for this project is provided by Skytrax, a United Kingdom based consulting group that specializes in airline and airport reviews. This dataset consists of 41,396 observations with attributes such as customer's textual review regarding their flight, customer's country of origin, customer's ratings (i.e. overall, seat comfort, cabin staff rating etc.), customer's seat type (i.e. Business, Economy etc.) and finally a variable that represents whether or not a customer had recommended the airline after their review. The customer recommendation (variable name : `recommended`) is a binary variable and is the primary outcome of interest in this project. As discussed earlier, the objective of this goal is to create a model that can predict whether a customer will or will not recommend an airline. Therefore, the attribute that represents the customer's textual review is the main independent variable in our analysis plan (variable name : `content`).



Data Processing

Data processing for this project required two steps. The first was to assess whether or not we should include attributes other than the textual review in our statistical model as covariates. Essentially, we wanted to identify some adjusting covariates that may be associated with the outcome variable. This exploratory data anlysis (EDA) would allow us to better understand how to process the non-textual parts of the dataset to apply to our modeling schema. To perform this EDA, we performed a logistic regression to assess the assocations between a set of certain covariates and the recommendation. We decided to exclude all *rating* type variables (i.e. overall rating. wi-fi rating, food rating) since we deemed them to be more like a target variable rather than an adjustment. So, we focused on country of traveller, type of traveller, and the traveller's flight class for our exploration. Based on the EDA, we found that solo travellers were more likely to recommend the airline. However, there were about 39,000 missing values for this covariate, so we dropped the attribute from our analysis plan. We also found that a person from the United States (US), as opposed to someone not from the US, is much less likely to recommend an airline. Furthermore, we found that if a person was flying First class or Business class, they were more likely to recommend the airline compared to someone flying Economy. Therefore, we decided to include these attributes in our analysis plan as adjusting covariates. The variables were coded as: (i) a binary indicator of whether a passenger was from the US or not and (ii) a binary indicator of whether they were in First/Business class or not.

The second aspect of our data processing involved the data engineering of our textual data. Essentially, we wanted to identify a feature engineering approach to represent the textual data in numeric format so that we could input the data into our statistical models. We decided to use the document-term matrix (DTM) representation [1] which describes the frequency of words that show up in a set of documents. In our case, the reviews are the documents. We performed the feature engineering using the `tidytext` package in `R`. We tokenized the reviews into unigrams or single words and converted them to lowerclass characters. Then, we removed fillers words that were not associated with sentiments using the **bing** list of words as reference (`tidytext::get_sentiments('bing')`) and finally constructured the DTM. A simple example of a DTM is illustrated below using two hypothetical reviews: "The flight was great!" and "The flight was terrible." Our DTM consisted of 41,117 rows (reviews) and 3,513 columns (unique words), which used up roughly 1.1 GB of memory. We then merged the two adjusting covariates onto the DTM to create our design matrix. We saved this matrix as a `RDS` file. As illustration, we also show the frequencies of the top 15 words on the previous page.

Review ID	the	flight	was	great	terrible
R1	1	1	1	1	0
R2	1	1	1	0	1

Methodology

The dataset provides both the input of the model as well as the output, therefore, we consider four **supervised** learning algorithms to create our classification model: (i) Naive Bayes Classifier, (ii) Logistic Regression, (iii) Support Vector Machines, and (iv) Random Forest. The Naive Bayes Classifier is the most easy-to-use algorithm when it comes to textual data classification [1]. It is a probabilistic classifier based on the Bayes Theorem and we use this as our baseline classifier. Logistic Regression is a regression-based model that allows us to model the probability of a customer's recommendation [1, 2]. For the Logistic Regression, we consider a Lasso Logistic Regression without an intercept and one with an intercept. By applying the lasso shrinkage, we get to shrink the effects of low-importance words in our regression model to exactly zero. Support Vector Machine (SVM) is a discriminative classifier that uses hyperplanes in Euclidean spaces to separate datapoints into separate classes [2]. For our SVM, we used a linear kernel and allowed for shrinkage. Random Forest is an ensemble tree-based learning method that constructes multiple decision trees which can collectively used for classification tasks [2]. For all four of the models, we added two adjusting variables: US Citizen (1 = yes, 0 = no) and Flight Class (1 =First, Business, 0 = Economy). The discussion of how these algorithms work from a mathematical perspective is beyond the scope of this project report, however, we provide references at the end of this document. To assess and compare these models, we take a training-testing approach with recall, precision, specificty, and F1 scores as our evaluation metrics. The statistical computing was performed using `R` (packages: `caret`, `e1071`, `randomForest`, `glmnet`). We also compared the run time for each of the models' training using the `system.time()` functionality. As for the interactive dashboard, we used the `shiny` package in `R` to develop a Shiny application.

Challenges

The data processing aspect of this project was very smooth and we were able to do all of it on our local machines (Mac & P.C.). However, we ran into computational issues when it came to training the statistical models. We first attempted to train the models in `R` on our local machines. All of the models were either taking a significant amount of time to run or breaking due to timeout and memory errors. Therefore, we used the `doParallel` package to run our `R` scripts in parallel time. By doing this, we were able to run some of our scripts only on a subset of our full training set (n = 2,000). However, the computational time was still very demanding: SVM and Naive Bayes took more than 20 hours, Logistic Regression never converged, and RandomForest did not finish after running on an 8GB Mac with a 2 GHz i5 Intel Core more over 36 hours.

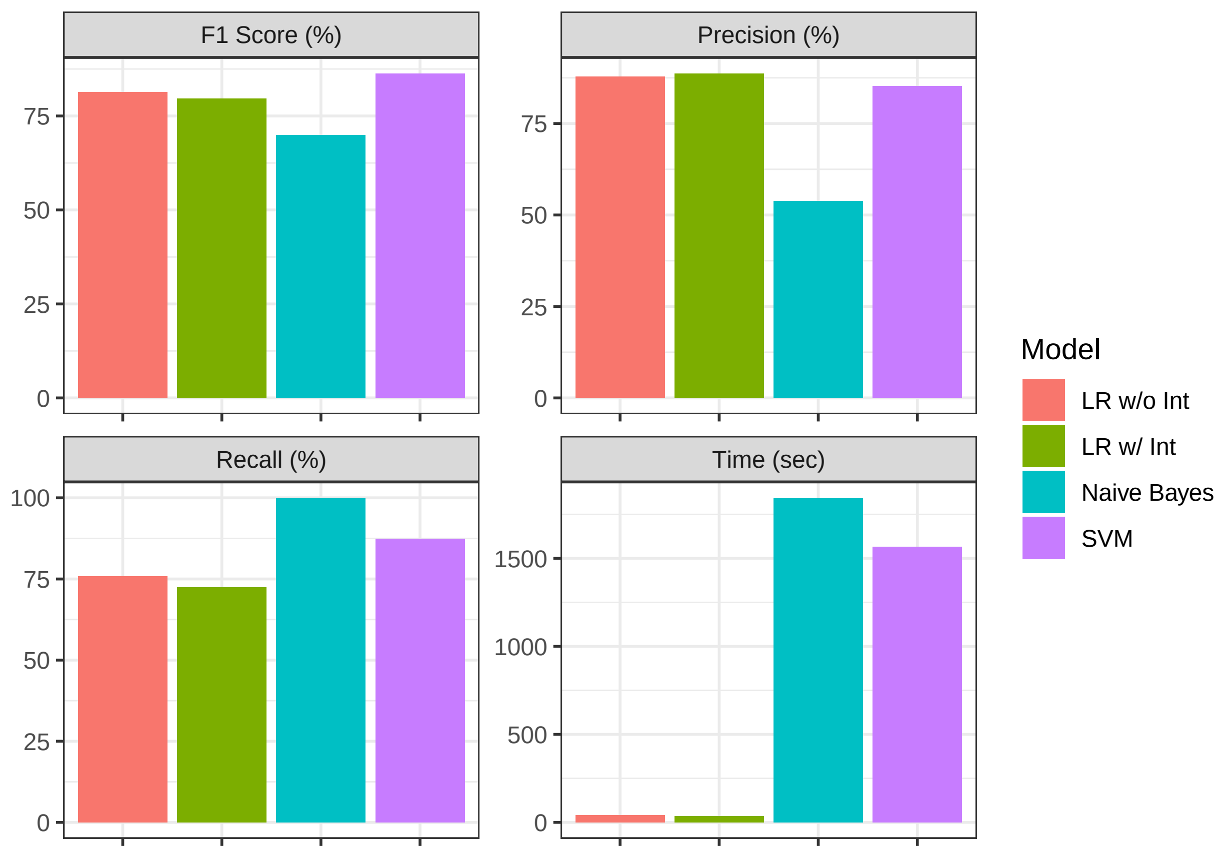
Therefore, we opted to use the University of Michigan Biostatistics Cluster for our model training. For all of the models, we allocated 10 GigaBytes (GB) of data with one core on the cluster. For Logistic Regression, we allocated a total of 45 mins on the cluster and both scripts used about 7 GB of memory (peak usage). For SVM and Naive Bayes, we also allocated 45 mins and found that they used both 10 GB and 8.7 GB respectively. We tried training the Random Forest on the cluster as well with combinations of 10GB, 15 GB, 45 minute, 2 hours, and 12 hour allocations. However, we were unsuccesful in training the model due to timeout or memory errors. Since we were on a time constraint and the other models were showing satisfactory results, we opted to stop training the Random Forest. It is important to mention that the `R` scripts submitted to the clusters incorporated the `doParallel` package's functionality. Each model had its own script which were run individually so that they could be run around the same time on the cluster. The cluster significantly improved our work flow and we were able to achieve satisfactory results.

Results

Statistical Results

Based on the predictive analysis on the test set (n = 30,882), we found that Naive Bayes performed the best in terms of Recall and Logistic Regression with Intercept performed the best in terms of Precision. However, since F1 Score is the harmonic mean between recall and precision, we use it to identify SVM as our "best" performing model as it had the highest F1 Score. Logitic Regression with and without Intercept had very similar F1 Scores. The Naive Bayes Classifier performed the worst, however, it is our baseline model and we expected it to perform poorly due to its underlying assumptions about independence of its covariates (see [1]). As for computational time, the Logistic Regression models (package : `glmnet`) were trained the fastest whereas Naive Bayes and SVM took a much longer time (package : `e1071`). These times were calculated from the cluster jobs. The results are summarized in the following table and figure.

Model	Time (sec)	Recall (%)	Precision (%)	F1 Score (%)
Naive Bayes	1842.390	99.91	53.79	69.93
Logistic Regression w/ Lasso	34.752	72.41	88.63	79.70
Logistic Reg. w/ Lasso (No. Intercept)	40.403	75.83	87.80	81.38
Support Vector Machines	1565.650	87.34	85.21	86.26



Shiny Application

We built our Shiny application using the SVM model as our classifier embedded behind the dashboard. This means that the dashboard makes predictions using the SVM model. The Shiny application can be viewed by running this command, `shiny::runGitHub('airplanes','benbren', subdir = 'shiny')`, on the `R` console. It is important to note that the `shiny` package must first be installed before this app can be run.

Discussion

There are several ways we could improve our statstical analyses in the future. In this first iteration of the project, we did not attempt hyperparameter tuning for our models. For example, we did not use cross-validation to identify the "best" tuning parameter, λ, that minimizes the loss function for Lasso Logistic Regression. Hyperparameter tuning could potentially improve the prediction scores we see especially for Logistic Regression and Support Vector Machine. We could greatly improve our predictive model by using Deep Learning algorithms such as Feed Forward Neural Networks which are very popular in the field of computational NLP [1]. As for data processing, we only explored the DTM approach when feature engineering our covariates. In the future, we would also like to explore other feature engineering approaches such as TF-IDF (term frequency-inverse document frequency) and Word Embeddings [1]. This project was a challenging project that we formulated and enjoyed it very much. We hope to continue working on it after the course so that we can publish the Shiny application.

Contributions

- Ben Brennan : Helped formulate the research question as well as collect, manipulate and analyze data in both the preprocessing and model development stages. Actively contributed to the writing of the training scripts, as well as the intial attribute modeling. Helped with the writing of the final project report, as well as maintenance of the GitHub repository and associated aspects (READMEs, etc.). Collaborated with teammates through meetings, GitHub collaboration and GroupMe conversations.
- Mandy Meng Ni Ho : Primary development of the RShiny app, along with active contributions to data preprocessing (especially with respect to the DTM matrix) and training model development. Active collaboration with group members via GitHub, GroupMe and in-person team meetings.
- Tahmeed Tureen : Helped formulated the research problem and motivation behind project, identified statistical methodology and evaluation metrics appropriate for text classification, helped find NLP tutorials for `R`, helped write `R` scripts, wrote job scripts (`slurm` files) for the cluster, helped write the final report, and collaborated with teammates via in-person meetings, `GitHub`, and online messeging

Repository

The work directory of this entire project has been published on a `GitHub` repository, which can be accessed via the following link: **click here**

References

1. Jurafsky, Daniel and Martin, James. Speech and Language Processing. Upper Saddle River, NJ, USA: Prentice-Hall Inc., 2009
2. Hastie, Trevor, Tibshirani, Robert and Friedman, Jerome. The Elements of Statistical Learning. New York, NY, USA: Springer New York Inc., 2001