IMDB SENTIMENT ANALYSIS

LUO, ROBIN (260851506), ROUSSEAU, MARC-ANDRE (260089646), AND XU BIDE, (260711367)

Abstract. We investigated the predictive power of several well known algorithms to perform sentiment analysis on imdb movie reviews. Using a linear support vector machine model trained on a dataset of 25000 movies reviews, we were successful in processing the text of a review and predicting whether the review was positive or negative with an accuracy of 91.786 percent on a dataset of 25000 reviews with the true sentiments withheld. After extensive analysis of various models, we concluded that support vector machine slightly outperformed linear regression which significantly outperformed the Naive Bayes implementation. The predictive power of a simple support vector machine model including tf-idf, minimal text preprocessing and tetragrams performed extremely well which made it very difficult to determine other features which may have significantly improved predictive power in a less parametrized model.

1. Introduction

The ubiquity of social networks is no longer a budding phenomenon and is part of the reality in which we now find ourselves. Many popular sites have included ways for users to share their opinions on a variety of topics and therefore the ability to mine through these posts and determine how users feel about the things being discussed is extremely useful for businesses. Knowing that a user or group of users desire something or find it appealing creates a market of opportunity for companies in search of low risk opportunities to expand their business operations. This is one of the most alluring aspects of machine learning. While the discovery of many of the mathematical underpinnings of machine learning have been discovered for quite some time, it is the rise in computing power which has given us the ability to use these techniques in otherwise intractable situations. For example gradient descent was invented by the prolific mathematician Augustin-Louis Cauchy in 1847. For our project, we were given 12500 positive and 12500 negative reviews to train our algorithm and another 25000 to test our code and submit our best guess as to the correct labeling of the test reviews as either positive or negative. Our best model which used a linear SVM (0.918 accuracy), was much better than Naive Bayes (0.83).

2. Related Work

Machine learning and sentiment analysis are hot topics of research with many machine learning conferences having several talks on the topic. For example, Twitter has been releasing datasets to be mined for things like whether a piece of task is positive, negative or neutral. Recently, a group of researchers extended this problem to five classification categories and added arabic language content (Rosenthal, 2017). Many teams submitted ML proposals to classify the twitter posts and the top performing groups used deep neural networks (DNNs) (Rosenthal, 2017). In addition, out of the top 10 submissions, the second most successful approach to DNNs involved the use of SVMs which is consistent with our best performing model for this project. A more directly related work involved taking into account sentence negations (Das, 2018). In this paper, the authors have decided to use a shortcut for negation by negating the word immediately following a negation. One example of this method would be to take the sentence "I am not happy" which gets converted to "I am not_happy". The benefit of this is that by changing only one word, they are able to change the meaning of the entire sentence (Das, 2018). Our team implemented this feature but it did not have a significant impact on the score as checked by the cross-validation.

3. Dataset and Setup

Our training dataset consisted of a list of 25000 reviews properly marked as positive or negative for us to train. We also had another 25000 data points to test out our model. The data consist of the content of the reviews and both the training and test sets needed to have their data preprocessed to be able to be consumed by the python libraries. For the purpose of training and validation, we separated our data into 80% training and 20% validation.

Date: February 22, 2019.

4. Proposed Approach

4.1. **Preprocessing.** For the preprocessing, we considered several models including a raw text input model, a model where the text was cleaned to only include letter characters (LC), a model where the text was processed through a normalization library and the words were separated from the punctuation symbols (SWP), a model with lemmatization (LZ) and a model with next word negation (NWN) from the previously mentioned paper. For the model where the text input was cleaned and normalized, we also converted the text to lowercase. Following the initial preprocessing, the data was subsequently tokenized. For the normalization model, we removed any characters for which the normalization library could not process. This was usually due to unicode characters which could not be mapped to equivalent ascii characters.

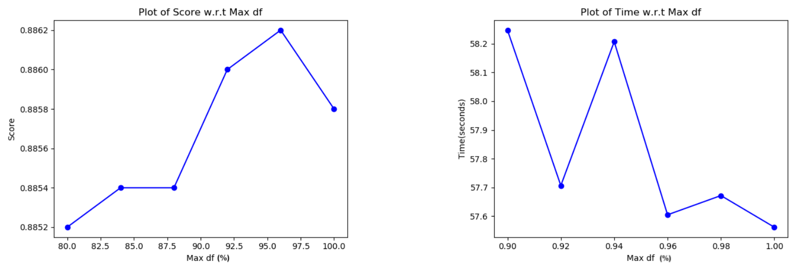
4.2. **Feature, hyperparamter and model selection.** In addition to the features generated by the preprocessing, we used tf-idf and bag of words (BOW) in our pipelines for feature selection. While we eventually submitted an SVM model as our final model, we also implemented Laplace-smoothed Bernoulli Naive Bayes (NB) and logistic regression (LR) models. To determine the hyperparameters and for regularization as well as the feature selection, we used a grid-based search algorithm with a cross-validation parameter of 5. For our BOW feature, we tested out many different values for possible n-gram size and settled with 1-4 after testing out several different options. For the SVM model, we tried values for the penalty parameter "c" and decided to use the default value of 1. In addition to this, once our model was able to associate good or bad to a particular set of words, we used these word to sentiment mappings to analyse subsentences separated by punctuation. For each bad or good word found, we added 1 or -1 to a counter and then classified the value for the overall text to the sum of all the individual good/bad words found in the text. In addition to this, we used a normalization library to standardize the feature vectors so that they had unit length. In terms of the theoretical underpinnings of the model selection, we used a data-driven approach rather than a conceptual one and so there was little discussion about which model was more appropriate and instead we opted to go with the model that had the best predictive power.

5. Results

The task of deciding on a final model based on the performance is quite easy since we only had to code the model and then pick whichever model worked the best, however a discussion of the relative performance of the models is difficult due to how close the top models performed as well as the sheer quantity of possible adjustments. In general, tf-idf outperformed bag of words, SVM outperformed LR and a model allowing for tetragrams outperformed the trigram models.

5.1. **NB vs LR vs SVM.** The performance of the Naive Bayes was significantly better than a random guess approach but still failed to come close to the performance of the logistic regression or the support vector machine approaches. One of the fundamental differences between our implementation of Naive Bayes and the other two models is that the former does not exclude words whereas the other two had minimum cutoffs for features. This could account for the performance difference seen between the bag of words LR and the Naive Bayes model. Our top performing model on cross-validation was a LR model but this did not extend to kaggle submissions for which the SVM slightly outperformed the LR.

5.2. **Bag of words vs tf-idf.** The performance of SVM and LR using both BOW and TF-IDF were similar with TF-IDF being slightly better than BOW according to the parameters we chose for min-df and max-df. For our model, we used a min_df of 2 and a max_df of 1 meaning that words that appeared in at least 2 of the documents were considered and no constraint was placed on the maximum frequency that a word could occur. In addition to using these models, we had originally also included stop_words but these did not show any additional gains above and beyond tf-idf and therefore it would seem as though the idf aspect of the tf-idf implementation may have already been incorporating the information contained in stop_words by essentially removing those words which were used too frequently by lowering the respective weights. Looking at the values in Table 1, we can see that for models where BOW and TF-IDF were used, the latter usually performed slightly better. A strict comparison of these features is difficult due to the many possible parametrizations of the BOW implementation. Figure 1 shows how the max_df affects the score and the difference in the score between the BOW and tf-idf be partially due to the inclusion of those common words which appear in almost every paragraph of english ("in","the", etc...).



(A) score vs max_df

(B) total runtime vs max_df

FIGURE 1. **Performance analysis of the max_df parameter** In A, we can see the best prediction is obtained just shy of the 100 percent mark which might account for why our BOW model did slightly worse than the tf_idf model which would automatically account for the high frequency words. In (B), we see that above the 90 percent mark, there is little effect on the runtime which coud simply be due to the fact that there are few words which appear extremely frequently and therefore there is no discernable effect on runtime

5.3. **N-grams.** We considered many different possibilities for n-grams but ultimately we settled on using (1-4)-grams even though the gain in performance was quite small between limiting ourselves to trigrams and including tetragrams. The logistic regression model with td-idf showed that the value in increasing above tetragrams was nonexistent. While the increase in score between the trigram and tetragram models was under 1 percent for most models, the increase seemed consistent across almost all models considered and was therefore included. The additional value added in considering fourth level n-grams is probably due to common four-word expressions in the english language which convey sentiment. The low increase in performance is quite simply due to the low frequency of occurrence of these expressions overall for the amount of data we had.

5.4. **Text processing.** The effect of processing and preparing the text was a contributor to performance as can be seen by comparing the values in Table 1. We can see that by limiting ourselves to letters exclusively, we actually lose some information and the score for the LC models suffered as a result. As an example, the model using LR, tf-idf and (1-4)-grams had a performance score of 0.895 for the letter character model, a score of 0.913 for the raw text and 0.915 for the model where the text was normalized and converted to lowercase. The increase in performance between the raw and cleaned data was not universally consistent which could be due to the cleaning removing some information that would otherwise have been useful. One of the most interesting results is that some of the numbers actually ranked quite high in the tf-idf

5.5. **Lemmatization.** The lemmatization seemed to perform consistently better than a non-lemmatized model but the extension to the kaggle dataset suggested that there was in fact a gain in performance in using the lemmatized model. Lemmatization is a feature which reduces the information rather than increases it and therefore it is not surprising to see some drop in perfomance. Despite this, the idea behind lemmatization is that there are many words for which only the root of the word conveys information and therefore this should help reduce noise and regularize so as to better extend our model to unseen data.

5.6. **SWP and NWN.** The SWP and NWN models did not seem to provide significant improvements to our model after having already incorporated tf-idf, lemmatize, and a cleaning of the text. While it is true that our best performing model used SWP (Table 1), this result did not extend into the kaggle submission and could be due to random variance in the data. We had expected some gain in performance from the NWN and had also tried other forms of regularization of negation but no clear improvement was seen in our kaggle submissions or our cross-validation.

5.7. **Discussion and Conclusion.** Talking points for discussion:

- preprocessing and the risk of losing information (removing all but the letters or modifying words with negation)
- the difficulty in making improvements once the model is already extremely well tuned (SVM&NWN)
- possible improvements with capitalization features (all caps)
- importance of domain information (specific to the previous point)

6. Division of Work

- **Robin Luo**: Model fitting, analysis of the effect of hyperparameters
- **Marc-Andre Rousseau**: Literature research, TeXing, some minor coding.
- **Peter Xu**: Coding, feature selection and hyperparameter fitting.

7. References

1 Rosenthal, Sara, et al. SemEval-2017 task 4: Sentiment analysis in Twitter Proceedings of the 11th International Workshop on Semantic Evaluations (SemEval-2017), pp. 502518.

2 Das, Bijoyan. Chakraborty, Sarit. "An improved text sentiment classification model using tf-idf and next word negation" June, 2017, eprint arXiv:1806.06407

8. Appendix

Table 1. Runtime and F1 performance analysis of various models

Model	F1-score	#features	Fit runtime (s)	Prediction runtime (s)
Bernoulli NB + BOW	0.84879	67708	1020	5520
LR,LCs, 1-gram	0.88561	27254	10	2
LR, BOW, LCs, (1-4)-gram	0.88961	104211	106	7
LR, tf-idf, LCs, (1-4)-gram	0.89481	104211	95	6
LR, tf-idf, raw, 1-gram	0.88541	27745	29	4
LR, BOW, raw, (1-2)-gram	0.89521	166041	54	9
LR, BOW, raw, (1-3)-gram	0.89601	290118	114	14
LR, BOW, raw, (1-4)-gram	0.89521	342886	230	230
LR, tf-idf, raw, 1-gram	0.89181	27745	20	6
LR, tf-idf, raw, (1-2)-gram	0.90881	166041	55	8
LR, tf-idf, raw, (1-3)-gram	0.91161	290118	110	10
LR, tf-idf, raw, (1-4)-gram	0.91301	342886	199	20
LR, tf-idf, raw, (1-5)-gram	0.91301	358250	211	13
LR, tf-idf, cleanup, (1-3)-gram	0.91381	284493	116	12
LR, tf-idf, cleanup, (1-4)-gram	0.91581	334013	169	18
LR, tf-idf, cleanup, SWP, (1-3)-gram	0.91441	284955	117	10
LR, tf-idf, cleanup, SWP, (1-4)-gram	**0.91561**	**333673**	**166**	**20**
LR, tf-idf, cleanup, lemmatize, (1-3)-gram	0.91161	283063	108	11
LR, tf-idf, cleanup, lemmatize, (1-4)-gram	0.91281	334089	178	12
LR, tf-idf, cleanup, NWN, (1-3)-gram	0.91381	264522	89	9
LR, tf-idf, cleanup, NWN, (1-4)-gram	0.91441	297461	147	11
LR, tf-idf, cleanup, Lemmatize, SWP (1-3)-gram	0.91201	283682	85	8
LR, tf-idf, cleanup, Lemmatize, SWP (1-4)-gram	0.91241	333997	141	11
LR, tf-idf, cleanup, Lemmatize, SWP, NWN, (1-3)-gram	0.91281	263993	90	9
LR, tf-idf, cleanup, Lemmatize, SWP, NWN, (1-4)-gram	0.91261	298356	132	10
SVM, tf-idf, raw, (1-4)-gram	0.91521	1010594	167	13
SVM, tf-idf, cleanup, (1-4)-gram	0.91501	987640	155	15
SVM, tf-idf, cleanup, NWN, (1-4)-gram	0.91401	899187	156	12
SVM, tf-idf, cleanup, Lemmatize, (1-4)-gram	**0.91321**	**987519**	**171**	**12**
SVM, tf-idf, cleanup, SWP, (1-4)-gram	0.91481	988012	161	16
SVM, tf-idf, cleanup, SWP, Lemmatize, NWN, (1-4)-gram	0.91541	901848	164	13

Summary of selected models considered for our final submission. The final model performance was determined via a study of the effect of modifying the parameters on the F1-scores. All runtimes with the exception of the Naive Bayes did not preclude extensive testing. A subset of the models under consideration have been presented. Our best performing model on the cross validation as well as the best performing model on kaggle are in bold.