Machine Learning Approaches to Detect Spoiler Reviews

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Git Repo: https://github.com/im-daniel-wang/Spoiler_Detection

Abstract

Spoilers are important plot information of books/movies that can ruin user experience on review websites when they are looking for plot summary or user reviews/ratings. This project aims to predict sentence-level spoiler probability based on machine learning models and compare performance metrics among different models including Support Vector Machine (SVM), Logistic Regression, and Convolutional Neural Networks (CNN).

1 Introduction

Book content and reviews websites such as *goodreads.com* provide users with ratings and reviews. The reviews on the website can sometimes contain 'spoilers', which are review or summary texts that reveal elements of the plots and thus have the potential to kill the joy of audience who have not seen the book. Major movie/book content websites have put out guidelines that discourage spoiler contents, but more work can be done to 'mask' the content that have a high probability of containing spoilers, such that users can have a more confident browsing experience on the website. This project is designed to predict spoiler content using machine learning models in order to achieve this goal.

2 Related Work

There have been numerous approaches to text classification using machine learning and deep learning models. These models have been used extensively for sentiment analysis, classifying news stories into categories, etc.

Support Vector Machine (SVM) was introduced by V. Vapnik et al., and in 1998 was recognized by Joachims to be especially suited for text categorization tasks for its ability to deal with high dimensional input space and sparse document vectors. It was also pointed out that most text categorization tasks are linearly separable, and SVM performs well in these tasks since its idea is to find such linear separators between the classes.

Neural network approaches including CNN-based (Kim, 2014) and RNN-based (Yang, 2016) have also achieved success on sentence classification.

Although text classification has seen substantial progress throughout the years, spoiler detection is still rather unexplored. Only a few labeled datasets containing sentence-level label for spoilers are publicly available online. Previous attempts include leveraging user/item spoiler bias to create additional features, using different models to account for different sentence semantics across genre contexts for better generalizations. Hierarchical attention network (HAN) was recently applied on the task to account for the dependency among the sentences in a review, since human pay different attention to different parts of a review (Wan, et al., 2019)

3 Dataset

The dataset used is from UCSD Book Graph's Goodreads Datasets which were collected in late 2017's from *goodreads.com*. This project uses the spoiler subset where each book/user has at least one associated spoiler review. The corpus contains 1,378,033 review documents and 17,672,655 sentences, out of which 3.1% are sentences that have spoilers. For each review, information on the user identifier, time of review, each sentence in the review along with the label, and the book identifier is provided. The labels for each sentence in each review are the response variable used in this project.

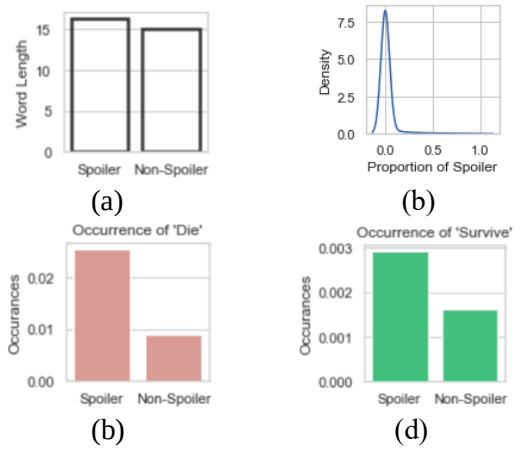


Figure 1: (a) Average number of words per review sentence for spoiler/non-spoiler reviews (b) Density plot of proportion of spoiler sentences in a review (c) Proportion of occurrences of "die" in spoiler and non-spoiler review corpus (d) Proportion of occurrences of "survive" in spoiler and non-spoiler review corpus

From the visualizations (a) to (d) it can be seen that spoiler reviews tend to have more slightly more sentences than non-spoiler reviews. The two classes of texts have drastically different characteristics in terms of the occurrences of words such as "die" and "survive" that are closely related to the plot information. It is then worthwhile to discover manually extracted signals of metadata from the sentences.

To address the problem of imbalanced classes, the spoiler sentences are kept, and the non-spoiler sentences are down sampled to have equal amount of data (both containing 569,724 rows) during model training.

4 Method

Two options are available since we can both choose to predict whether a review will contain at least one spoiler sentence or predict whether a sentence is a spoiler. The latter one was chosen to be more appropriate since sentence-level data contains less noise, and when we deploy the model in production, we ideally want to mask the exact sentences that are spoilers. Some experiments were done on review-level classification, but they yielded very low recall score.

4.1 Data Cleaning and Feature Extraction

Data cleaning is performed prior to model fitting. All texts are preprocessed with tokenization, normalization, stop-words removal and lemmatization.

Features of text are extracted and review sentences are converted to TF-IDF scoring matrices which reflect the importance words in a review given the corpus context. The TF-IDF scores are used as predictors for the classical machine learning models (logistic regression and SVM), and both 1-gram and 2-gram bag-of-words (BOW) are used and their performance metrics compared to see which one gives the highest predictability.

4.2 Logistic Regression

Logistic regression is used as a benchmark model for the text classification problem. It's parametric nature allow easy interpretation of model result and feature importance.

Some hyperparameter tuning is performed to decide the best combination of parameters that gives the best prediction outcome. The cost parameter C, as well as 1-gram vs. 2-gram in TF-IDF vectorization are tuned. C is the inverse of regularization strenght, and smaller values indicate stronger regularization. Using bi-gram in TF-IDF preserves more temporal traits of the review sentence, and it is thus interesting to see whether including more temporal information would improve the prediction performance.

	F1	AUC
bi-gram, C=5, l1	0.6939	0.6888
bi-gram, C=15, l1	0.6795	0.6751
bi-gram, C=5, l2	0.7060	0.6998
bi-gram, C=15, l2	0.6962	0.6909

The experiments show that logistic regression using bi-gram BOW, regularization parameter C=5, l2-regularization performs best with the highest F1 score and AUC score.

4.3 Support Vector Machine (SVM)

Support vector machine (SVM) is then used for its advantages in text classification. More specifically, texts of different classes are often linear separable, and text contains a lot of features. Using linear kernel in SVM is suited for this type of task since it is fast and mapping the data to a higher dimensional space does not really improve performance. Hyperparameter tuning is done to determine the best combination of 1-gram/2-gram

and regularization parameter c. F1 and AUC scores are recorded for each experiment.

	F1	AUC
1-gram, C=1.0	0.7023	0.6936
1-gram, C=15.0	0.6932	0.6881
2-gram, C=1.0	0.7074	0.6999
2-gram, C=15.0	0.6650	0.6615

Using 2-gram BOW with C=1.0 regularization parameter works best for SVM according to the experiments. The performances across different combinations are similar to the ones produced by logistic regression without significant lifts. It seems that using bi-gram features allow the system to discover more temporal structure of the dataset and discover instances of absolute markers like "the end" and "end of" (Jordan et al, 2013).

4.4 Derived Features for Spoiler Detection

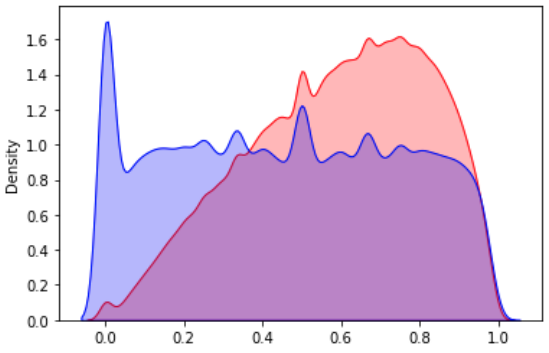
Apart from lexical features generated using TF-IDF, additional metadata of each review sentence can potentially contribute to classifying whether a sentence is a spoiler or not. In this section, we describe features that are useful for this specific classification task.

Relative Position of Sentence in Review

With some exploratory data analysis, we found that spoilers tend to occur in the latter half of the review text, meaning that the position of the sentence within the review text has a strong implication of whether the sentence contains spoilers. To account for such behavior, for each sentence the position of the sentence in percentile is calculated. For each sentence:

$$Percentile = Sentence\ Index\ /\ \#\ Sentences$$

These two features are incorporated into the modelling process in addition to the TF-IDF scores and performance metrics are compared to see whether they introduce lift. We select the best-performing logistic regression and SVM model to do the comparison. From the below chart, red represent the density of percentile indices for spoiler sentences, while blue represents the same for non-spoiler. The two densities are clearly different and worth investigating.



	TF-IDF		Additional Feature	
	F1	AUC	F1	AUC
LR	0.7023	0.6936	**0.7214**	**0.7149**
SVM	0.7074	0.6999	**0.7243**	**0.7158**

The above chart shows that with the additional feature of index percentile, both SVM and LR model saw significant improvement in F1 and AUC scores. The additional feature does provide additional predictability of spoilers.

4.5 Convolutional Neural Network (CNN)

It was shown by Kim that a simple CNN with little hyperparameter tuning and static vectors achieves excellent results on multiple benchmarks (Kim, 2014). Convolutional neural networks (CNN) utilize layers with convolving filters that are applied to local features (LeCun et al., 1998).

For this project only a subset of 150,000 samples is used to train the neural network. The network is trained in mini batches of 150 and 10 epochs. Convolution filter of size 10*10 is used to generate features from the texts, and dropout layer is used for regularization and reducing overfitting. 10-fold cross-validation is used to compute the F1 and AUC scores. Relu and Sigmoid activations are tried and their respective performance metrics compared.

	F1	AUC
Relu	0.6504	0.8305
Sigmoid	0.6431	0.7849

The experiments show that ReLu activation is more suited for this task with higher F1 score and AUC score. The property of ReLU is better suited for this task possibly due to its mechanism to combat exploding/vanishing gradient. The CNN approach achieves higher AUC score at the expense of lower F1 score. This could imply that the model does well in terms of ranking the data

based on classes, but still has problem of a low recall value, indicating that a lot of the spoiler sentences failed to get recognized.

5 Results

After each experiment for each model specifications, F1 and AUC scores are recorded and compared in the table below.

	F1	AUC
Logistic Regression	0.7023	0.6936
SVM	0.7074	0.6999
CNN	0.6678	0.8312
SVM with Rank Feature	0.7243	0.7158

In terms of F1 score, SVM with added rank feature performs best with F1 = 0.7243. In terms of AUC score, convolutional neural network (CNN) performs best with AUC = 0.7158.

SVM with Rank Feature is selected to be productized for its balanced performance across F1 and AUC score. Since CNN is trained on a small subset of data and may have overfitting, we decided to not use it although it did achieve a higher AUC score. CNN also has a significantly lower F1 score which indicate that the classification threshold might not be well-chosen.

Example Output

```
{
    'reviews':  [
        'He died in the last episode.',
         'I really enjoy this show.'
    ],
     'Class':  [
        'Spoiler',
         'Non-Spoiler'
    ]
}
```

6 Discussion

The CNN approach can be further fine-tuned by adding layers that contain specific lexical information. Due to run-time constraint only a small subset of data is used to train the network for 10 epochs, possibly leading to some overfitting. As a next step, it is interesting to see the performance of a fully trained CNN.

For the classical machine learning models, more feature engineering can be done to extract more metadata from the review sentences. The main tense of a sentence can be hugely important since past tensed sentence have a higher likelihood of containing information from the plot (as an example, “He died.” is more likely to be a spoiler than “I hope he will live.”) The tense detector is computationally expensive and was hence not implemented in this paper but is worth investigating in the future.

References

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