A First Dataset for Film Age Appropriateness Investigation

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Abstract

Film age appropriateness classification is an important problem with a significant societal impact that has so far been out of the interest of Natural Language Processing and Machine Learning researchers. To this end, we have collected a corpus of 17000 film transcripts along with their age ratings. We use the textual contents in an experiment to predict the correct age classification for the United States (G, PG, PG-13, R and NC-17) and the United Kingdom (U, PG, 12A, 15, 18 and R18). Our experiments indicate that gradient boosting machines beat FastText and various Deep Learning architectures. We reach an overall accuracy of 79.3% for the US ratings compared to a projected super human accuracy of 84%. For the UK ratings, we reach an overall accuracy of 65.3% (UK) compared to a projected super human accuracy of 80.0%

Keywords: Machine Learning, Deep Learning, XGBoost, Age Appropriateness, Movies

1. Introduction

Interest in film from a computational linguistics perspective has been massive. Several studies in CL have examined the genre in terms of Sentiment Analysis (Phan and Matsumoto, 2018), turn-taking (Banchs, 2012), and many other things. Most of these studies have focused on film reviews from Amazon.com and IMDB, but the actual film content (the script, audio, and video for example) has not received as much interest in spite of the potential availability of huge datasets as will be demonstrated below.

In this study, we investigate a completely new problem with a novel corpus. We investigate whether we can use Machine Learning and Artificial Neural Networks to predict the age classification accompanying the films based on their textual content. For this purpose, we collect a custom corpus from the internet and complement it with age rating certificates from the Internet Movie Database (IMDB). The data combination makes a dataset that can be used for many purposes part of which is the focus of this paper: age appropriateness classification.

Entities like the Motion Picture Association of America (MPAA) and the British Board of Film Classification (BBFC) issue film ratings that determine the age appropriateness of each film based on the film’s content. The latter define their classification as ‘the process of giving age ratings and content advice to films and other audiovisual content to help children and families choose what’s right for them and avoid what’s not.’ This is a human labour intensive endeavor that requires at least two Compliance Officers to watch each film and report on it. So far, there does not seem to be enough interest from the Computational Linguistics community in the problem of automatic age appropriateness classification, possibly due to the lack of resources.

We have run experiments to test whether we can predict the age rating certificates based on the textual content of the film (i.e. scripts). We have used state-of-the-art classification methods including neural networks and gradient boosting machines (GBM’s). The best results were obtained using the XGBoost implementation of GBM’s. For the USA and the UK, the accuracies of the prediction reach 79.3%, and 65.3% respectively compared to two projected ceilings of 84% and 80%. The rest of this paper goes as follows: in Section 2, we describe the data and the methods. In Section 3, we present the results and perform some analysis. In Section 4, we discuss related datasets and experiments. Finally, the conclusion discusses our projected future research that seeks to combine textual and visual inputs to tackle the problem.

2. Data & Methods

2.1. Data Collection

We have collected a large number of film scripts from https://www.springfieldspringfield.co.uk/. We have matched these with their age certificates using IMDBPY, a community-based API to access IMDB data. The films were identified mainly through combinations of IMDB film ID’s, directors, actors, and the production companies. Where ambiguity could not be automatically resolved, we simply dropped the film from our dataset, which left us with 17018 unambiguously age-rated film transcripts, where each transcript contains only the dialogue. Meta information, like scene settings and description, was only available for a small minority of the films and has thus not been utilised in the current paper although we believe it may be useful for our future research.

2.2. Data Cleaning

Movie dialogue is designed to match screens and is thus not made up of valid linguistic entities, i.e. sentences. The following extract is from “Terminator Salvation”:...
Our intel has located a hidden signal under the primary channel. It allows for direct control on the machines. Skynet’s a machine, and like all machines, it has an off-switch.

For our modeling purposes, we have used the Spacy NLP library (Honnibal and Montani, 2017) to tokenize the script into sentences. The Spacy sentence segmentation uses dependency parsing. We compared Spacy with the NLTK (Bird et al., 2009) in terms of sentence segmentation. We have tested both tools on a sample of film scenes, and we have found Spacy to be more accurate. While most of the models we use do not have the concept of a sentence, this conversion is necessary to allow for various linguistic contexts (in terms of n-grams) to be included. Following the sentence tokenization, the previous excerpt from the Terminator Salvation becomes:

Our intel has located a hidden signal under the primary channel. It allows for direct control on the machines. Skynet’s a machine, and like all machines, it has an off-switch.

2.3. Annotation
We do not perform any manual annotation on the data. We, instead, use distant annotation, i.e. metadata that can be considered annotation though not originally intended as such. We have noticed, for example, that there is a striking similarity between the process of assigning a film to an age category and that of linguistic annotation used in computational linguistics research. To quote the British censors (BBFC)[]:

Films for cinema release are usually seen by at least two of our Compliance Officers, and in most cases, their age rating recommendation is approved by the Compliance Manager or the Head of Compliance. If Compliance Officers are in any doubt, if a film is on the borderline between two categories, or if important policy issues are involved, it may be seen by other members of the BBFC, up to and including the Chief Executive, the President and Vice Presidents. Occasionally, we may also call for expert advice about the legal acceptability of film content or its potential for harm. DVDs and VoD films and series are normally seen by one Compliance Officer, but opinions from other Officers, the Compliance Manager, the Head of Compliance and Board of Classification may be required for more difficult content.

This matches our experience of linguistic annotation on various projects with which we were involved. Figure[] contrasts the classification schemes used in the USA and the UK.

We use the Internet Movies Database (IMDB)[] as the source of age ratings. For each film on IMDB, there is a section on Certificates, which lists age ratings from several countries in addition to the country of origin. For example, in the case of Terminator Salvation, Figure 2 shows the various classifications of the film.

https://bbfc.co.uk/what-classification
https://imdb.com
2.4. Dataset Description and Statistics

In total, we have 17018 titles, 181M words, with an average of 10651 words per film.

We focus on the theatre ratings rather than TV or video ratings. For the USA, they are G, PG, PG-13, R, and NC-17. For the UK ratings, they are U, PG, 12A, 15, 18, and R18. In total, we have these US ratings for 8923 titles, and the UK ratings for 10920 titles. These two sets are overlapped by 7068 titles. It is worth noting that there is a one to many mapping between films and certificates. A single film could have several certificates within and across countries. We use the main certificates provided by the IMDB based on the country of origin. For example, in Figure 2, while “Terminator Salvation” has several USA ratings for two different cuts, we use the PG-13 one provided on top. It is also of note that there is not a one to one mapping between the UK and the USA ratings. Figure 3 shows possible mapping between the two rating systems found in our dataset.

The statistics for these classes are shown in Table 1. We have divided the data into a train section (70%), a dev section (10%), and a test section (20%). The data was divided using random by-year stratification.

| Certification | Country  | Code   |
|---------------|----------|--------|
| Argentina     |          | 13     |
| Australia     |          | M      |
| Austria       |          | 14     |
| Brazil        |          | 14     |
| Canada (1A)   |          | (Canadian Home Video rating) |
| Canada (13+)  |          | (Québec) |
| Canada (14+)  |          | (TV rating) |
| Denmark       |          | 15     |
| Finland       |          | 15     |
| France        | Tous     | publics |
| Germany       | 16       |
| Germany       | 12 (TV: cut version) |
| Hong Kong     |          | 18     |
| Iceland       |          | 12     |
| India         |          | USA    |
| Ireland       | 12A      |
| Italy         |          | T      |
| Japan         | G        |
| Malaysia      |          | 13     |
| Mexico        |          | B      |
| Netherlands   |          | 12     |
| New Zealand   |          | M      |
| Norway        | 15       |
| Peru          | 14       |
| Philippines   |          | PG-13  |
| Poland        |          | 12     |
| Portugal      | 12       |
| Russia        | 12+      |
| Singapore     |          | PG     |
| Singapore     |          | PG-13  |
| Singapore     |          | NC-16  |
| South Africa  |          | 13     |
| South Korea   |          | 15     |
| Spain         |          | 13     |
| Sweden        |          | 15     |
| Switzerland   |          | 14 (canton of Geneva) |
| Switzerland   |          | 14 (canton of Vaud) |
| Taiwan        |          | PG-12  |
| United Kingdom| 12A      |
| United Kingdom|          | (director’s cut) |
| United States |          | TV-14  |
| United States |          | PG-13  |
| United States |          | R (certificate #45600, director’s cut) |

Figure 2: Terminator Salvation age certificates from various countries, source: IMDB

Figure 3: Sankey map between USA and UK rating systems

|          | TT  | NW   | AWT |
|----------|-----|------|-----|
| All      | 17018 | 181M  | 11K |
| US       |     |      |     |
| G        | 294 | 3,107K | 11K |
| PG       | 1493 | 16,867K | 11K |
| PG-13    | 2150 | 25,062K | 12K |
| R        | 4965 | 52,863K | 11K |
| NC-17    | 21  | 234K  | 11K |
| All      | 8923 | 98,133K | 11K |
| UK       |     |      |     |
| U        | 1095 | 12,799K | 12K |
| PG       | 1723 | 20,397K | 12K |
| 12A      | 1268 | 15,719K | 12K |
| 15       | 5093 | 53,768K | 11K |
| 18       | 1740 | 15,473K | 9K  |
| R18      | 1    | 6K    | 6K  |
| All      | 10920 | 118,432K | 11K |

Table 1: Basic statistics about the dataset; TT = Total Number of Texts, NW = Number of Words, AWT = Average Number Words per Texts

2.5. Methods

We use three main methods/tools: (1) FastText, (2) Gradient Boosting Machines with the XGBoost implementation, and (3) Artificial Neural Networks, including Hierarchical Attention (HAtt), Character-based convolutional neural network (CharCNN), ELMo and BERT.

FastText (Joulin et al., 2016) is a document classifier that relies on a language model built on the principle that words can be represented as the sum of subword vectors, which could be useful in representing languages with large vocabularies, e.g. morphologically rich languages.

XGBoost (Chen and Guestrin, 2016) is an efficient implementation of gradient boosting machines that has been shown to be successful in many real life applications, for example (Volkovs et al., 2017) Sandałescu and Chiru,
Hierarchical Attention (Yang et al., 2016). HAtt, is a neural network architecture that represents a text as a sequence of sentences. Each sentence, in turn, is represented as a list of words. The attention mechanism is used first to take advantage of relations among words in a sentence, and then among sentences in a document.

BERT (Devlin et al., 2018) is a context sensitive embedding neural architecture that also uses the attention mechanism extensively, in which the model learns to guess the missing words and whether one sentence follows another. Using what it learns, the model can produce a vector representation of an arbitrary sentence, which can then be used for downstream tasks.

CharCNN (Zhang et al., 2015) is a character-based convolutional network that puts the input text through one or more 1d convolutional layers to construct the representations for the classifier.

ELMo (Peters et al., 2018) is another context-sensitive embedding architecture that makes use of character-based 1d convolutional layer and lstm layers to learn language models.

We use BERT, ELMo, both their generic models and their respective models that have been fine-tuned using our dataset (hereinafter referred to as BERTCust and ELMoCust), and char-based ngram tfidf, as alternatives for feature extractions. For BERT and ELMo, the document representation of the film is the mean pooling of representations of all sentences in the film transcripts, as calculated by the respective models. For char-based ngram tfidf (abbreviated as TFIDF), the document representation is the tfidf values of all the char-based ngrams presented in the film transcripts. The idf values are calculated using the training portion of the dataset. These document representation models have been shown to be successful in text classification tasks (Cavnar et al., 1994; Devlin et al., 2018; Peters et al., 2018). The document representations (in the form of vectors of various dimensions) will also be fed into XGBoost to learn classification models. Alternatively, FastText, HAtt, and CharCNN, models that have also been found to be successful in document classification tasks, will be used directly to learn classification models from text. Figure 4 shows our workflow.

For evaluation, we use the standard metrics of accuracy and the Area Under the Curve of the Receiver Operating Characteristic (hereinafter referred to as AUC). As the AUC incorporates the trade-off between precision and recall, we will report them instead of recall, precision, and F1 score. We have two settings for evaluation of accuracy:

- **Strict evaluation** in which a prediction is considered correct only if it exactly matches the gold standard data, and
- **Relaxed Evaluation** where a prediction is considered correct if it is within one class of the correct gold standard class. For example, if the true class is PG-13,
then in a relaxed setting, both a prediction of PG and R would be considered correct.

Table 2 shows how some examples of whether or not the prediction is correct in the two settings.

| Country | Prediction | Gold | Strict | Relaxed |
|---------|------------|------|--------|---------|
| US      | G          | PG   | False  | True    |
|         | G          | G    | True   | True    |
|         | PG         | G    | False  | True    |
|         | PG         | R    | False  | False   |
| UK      | U          | U    | True   | True    |
|         | U          | PG   | False  | True    |
|         | 15         | 18   | False  | True    |
|         | 15         | PG   | False  | False   |

Table 2: Strict and relaxed decisions for various prediction-gold pairs

While we believe that strict evaluation should be considered the only valid measure, we realize that the same film may have several ratings, but we have not seen a film whose rating variance goes beyond two classes, which gives some validity to relaxed evaluation.

For the experiments using XGBoost and FastText, we have run a limited version of grid search based on what we have found in the literature concerning the optimisation of both tools. Based on the dev set, we found the best parameters for XGBoost to be a learning rate of 0.3, a max depth of 3 and with the number of estimators being 300. For FastText, the best performing experiment, as measured by performance on the dev set is where we use word unigrams, 100 epochs and a learning rate of 0.3. An analysis by regression to examine the effect of the factors in the 10 experiments of FastText shows the number of epochs to be the most important factor and the number of ngrams the least.

### 2.5.1. Setting a Baseline and projected human performance

We adopt the majority class as our baseline. For the US, the majority class is "R", whose accuracy on the dev set is 55%. For the UK, the majority class is "15", and the accuracy on the dev set is 44%. For relaxed evaluation, the majority classes are PG-13 and 15 with accuracies of 96% and 70% respectively.

For the performance ceiling, as there is no data within a single country to indicate the level of inter-person agreement of the ratings, we use a classification model that uses ratings from other countries to predict the ratings of the target country, and use its performance as an indicator of human performance. For example, if we use UK ratings to predict the USA ratings, it would yield a strict accuracy of 80.6% and a relaxed accuracy of 95.1% (SingleCt in Tables 3 and 4). On the other hand, if we use all the available ratings from the 69 remaining countries whose ratings are available on IMDB to predict the USA ratings (OtherCts in Tables 3 and 4), the strict and relaxed accuracies are 84.8% and 96.7% respectively. We consider this as our performance ceiling. The model used in this experiment is also XGBoost.

### 3. Results & Analysis

Tables 2 and 3 show the experiments we have carried out and the results we obtained. We observe that the deep learning models, with (BERT and ELMo) or without transfer learning (CharCNN and HAtt) do not perform as well as the character ngram based features. We hypothesise that for this task, each film transcript contains enough information for the task; such information may not be available in tasks in which deep learning models excel.

The performances of the classifiers are approaching or surpassing those using ratings from one country to predict those of another country. Around 95% of the predictions are within one rating of the correct ones. Figures 5 and 6 show the ROC curves for individual classes and micro averages for the United States and the United Kingdom certificates predictions.

Inspection of the confusion matrices (Tables 5 and 6) indicates that in the case of the US, the classifier only misclassifies one R title to be a G title, and only one 18 title to be an U in the UK case.

| Algorithm | Input | Acc | RelaxAcc | AUC |
|-----------|-------|-----|----------|-----|
| FastText  | text  | 74.7| 95.0     | 0.945|
| HAtt      | text  | 69.6| 95.8     | 0.935|
| CharCNN   | text  | 57.7| 88.8     | 0.870|
| XGBoost   | ELMo  | 62.8| 87.5     | 0.896|
| XGBoost   | ELMoCust | 63.4| 88.8     | 0.904|
| XGBoost   | BERT  | 62.7| 87.2     | 0.900|
| XGBoost   | BERTCust | 63.3| 88.6     | 0.899|
| XGBoost   | TFIDF | 79.1| 96.2     | 0.962|
| XGBoost   | SingleCt | 80.6| 95.1     | 0.957|
| XGBoost   | OtherCts | 84.7| 96.7     | 0.978|

Table 3: Results on the USA categories

| Algorithm | Input | Acc | RelaxAcc | AUC |
|-----------|-------|-----|----------|-----|
| FastText  | text  | 61.5| 94.6     | 0.915|
| HAtt      | text  | 58.9| 91.9     | 0.906|
| CharCNN   | text  | 41.1| 75.6     | 0.765|
| XGBoost   | ELMo  | 54.2| 86.8     | 0.872|
| XGBoost   | ELMoCust | 54.6| 85.4     | 0.876|
| XGBoost   | BERT  | 55.6| 86.5     | 0.871|
| XGBoost   | BERTCust | 57.5| 89.2     | 0.878|
| XGBoost   | TFIDF | 65.3| 94.2     | 0.930|
| XGBoost   | SingleCt | 61.8| 91.5     | 0.899|
| XGBoost   | OtherCts | 80.0| 96.3     | 0.972|

Table 4: Results on the UK categories

| Gold     | Predicted |
|----------|-----------|
| G       | 13 | 37 | PG | 4 | R |
| PG      | 6 | 227 | 60 | 32 |
| PG-13   | 1 | 65 | 310 | 69 |
| R       | 1 | 26 | 65 | 863 |

Table 5: Confusion matrix of the predicted certificates for the USA
1. Error Analysis

Table 7 lists some films whose classification is off by two ratings, for example if a G film is rated as R. While the error dataset is too small for us to make any generalisations, we have noticed that 6 out of the 8 films are from the seventies and the early eighties, which may be an indication that the time factor should be considered in the classification, which we will do in future research. We also hope that the inclusion of video in the classification will help improve the classification.

4. Related datasets

There are several datasets that contain movies’ scripts or dialogs. None of them are developed with the focus on age appropriateness. The OpenSubtitles collection of parallel corpora (Lison and Tiedemann, 2016), albeit a very large dataset (17.2G tokens), focuses on bitexts aspects of movies dialogs.

Gorinski and Lapata (Gorinski and Lapata, 2015) build a collection of 1,276 movie scripts, by automatically crawling web-sites which host or link entire movie scripts for the purpose of summarisation. 132,229 dialogues from 753 movies have been collected by (Banchs, 2012). The objective is to study the semantic and pragmatic aspects of human communication within a wide variety of contexts, scenarios, styles and socio-cultural settings.

Ramakrishna-etal-2015-quantitative Ramakrishna-etal-2015-quantitative analyse differences in portrayal of characters in movies with respect to characters’ gender, race, age and other metadata using 945 screenplay files from two primary sources: IMSDB and DailyScripts. (Phan and Matsumoto, 2018)’s corpus includes conversations from movie with more than 2.1 millions utterances which are partly annotated for emotions. (Kar et al., 2018a), (Kar et al., 2018b), (Battu et al., 2018) use plot synopses for various purposes. To the best of our knowledge, our dataset is the largest movie content dataset apart from the OpenSubtitles, and the only one with age appropriateness certificates.
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