Rating YouTube Videos: An Improvised and Effective Approach

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Abstract. YouTube is one of the best sources of video information on the Internet. While it serves as the best media for creators to communicate to a broad audience, it has become less user-friendly over the past few years. Some official changes to the YouTube app have triggered many global audiences. One significant change that took place in the past year was the removal of the dislike count from every YouTube video. Without a dislike count, the current YouTube rating system has become ineffective. The proposed work recommends more user-friendly methods over the current inadequate rating system.

Some previous researchers like Alhujaili and Rawan Fahad (Alhujaili, R.F., Yafooz, W.M.: Sentiment analysis for youtube videos with user comments. In: 2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS)) have already given insights on how sentiment analysis can be used on video comments to know the fairness of the video. So, the authors try to create a robust rating system that primarily uses sentiment analysis to provide fair ratings to every video depending on comment sentiment and would be easier to embed in the official YouTube app as a plugin. This rating system even helps to detect clickbait videos to a certain extent, making it much better than the previous systems.

Keywords: Youtube · Machine learning · Sentiment analysis · Comment analysis · Video rating

1 Introduction

With YouTube removing the dislike count, it has now become challenging for users to predict a video's fairness accurately. As a result, users are forced to watch the entire video without knowing whether it will be helpful to them. So authors try to tackle this challenge with a new lightweight rating system that can accurately predict a video's fairness. In doing so, the authors considered three main properties that define every YouTube video.

1. Video thumbnail: This is one of the most common ways creators try to falsify their content.

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2. Video description: Creators try to spam their descriptions with all popular/unwanted tags to rank their videos and improve their search engine optimization (SEO) score.
3. User Comments: This is the essential feature used for the proposed research.

User comments contain users' sentiments about a particular video. It is one of the most actual data available for each video, as the video creators cannot tamper with this data. So these comments can give insights into the fairness of a video.

Since the goal of the proposed work is to design a rating system, the user comment becomes the essential feature for the proposed analysis.

2 Previous Work

Now that YouTube does not show the number of dislikes, every user has to scan through the comments to get a quick summary regarding the fairness of a video. The user comments can have any words ranging from positive to negative. Alhujaili and Rawan Fahad [1] have given some insights on different methods one can use to detect these comment sentiments. Even Chen and Yen-Liang [19] showed us how user opinions could be efficiently predicted using sentiment analysis on video comments. These comment sentiments have many practical applications, like detecting clickbait videos or identifying popular video trends.

While enough research has been done on how sentiment analysis helps to identify user opinions, there is very little to no information available on how a rating system can be developed with the help of comment analysis.

3 Implementation

The authors collected 1000 videos of all categories for proposed analysis and labeled them as Fair or False (clickbait videos). The proposed model predicts the required output for any video on YouTube. Due to the fact that there was no publicly accessible dataset for our application, we had to manually create our dataset, which is why it is modest in size.

3.1 Comment Collection and Preprocessing

In this section, the authors tried to collect all the comments associated with a selected YouTube video using Youtube data API. Youtube Data API is an official API provided by Youtube that gives access to all the public properties of a video, like Title, Description, and Comments. The Youtube data api limits queries to only 20,000 comments per day for non premium users and there is a high possibility that we may end up fetching 20,000 comments from just one video which also significantly reduced our ability to create larger datasets. Also, the extracted comments need to be preprocessed as they were heterogeneous regarding the users' use of different symbols and languages. Therefore, the authors carried out some data cleaning and preprocessing on these comments to make them more compatible with the proposed model.

The following preprocessing is applied to the comments:

- Eliminate any phrasing or punctuation marks like (“.“,"-”,”,”,”;“).
- Tokenization of comments.
- Apply PorterStemmer on each comment word to obtain the root word.

Another challenge is choosing the subset of comments that can represent the video in the best way possible. This subset is chosen so that it is not biased, and this subset of the comments can judge the video. Also, the size of this subset is kept small so that the proposed model performs faster. However, this challenge could be handled by accessing the number of likes associated with each user comment and sorting them in decreasing order, then choosing the first k comments such that the model performs the best depending on the value of k. From experiments the size of subset(k) was calculated to be

$$k = min(157,\ len(TotalCommentSet))$$

Sorting also ensures that spam comments get filtered from entering our model, as spam comments end up getting no to very low number of likes.

3.2 Sentiment Measure

In this section, the authors try to develop a model that can accurately determine the sentiment score of a word and thus can classify the complete sentence as Fair or False with their appropriate confidence levels. To do this Alhujaili and Rawan Fahad [1] has performed a survey on how different methods can be used to classify a video, based on comments rating. Authors make use of similar NLP techniques to develop the proposed model and tuned it to give the best results possible.

To perform the classification process, authors have used average word vector with TF-IDF to vectorize the comments and then tested the model using various algorithms like svm, logistic regression and xgboost. The analysis showed that the model achieved the best results when authors used Logistic Regression and unigrams with TF-IDF.

3.3 Word Cloud

With proper data cleaning and feature extraction techniques, authors came up with word clouds for both fair and falsified/clickbait videos which gave us some great insights on how frequently a word occurs depending upon its category.

As shown in Fig. 1, bad words like “fake”, “shit”, “fight”, “kill”, etc. occur more frequently in false contents, whereas fair videos generally have positive words like “love”, “good”, “amazing”, “beautiful”, etc. and make use of these words to rate the video and provide a Fairness label(Fair or Falsified/clickbait).

Fig. 1. Word cloud of Fair and False videos

3.4 Video Rating

In this section, the authors try to determine the quality of the video with the help of comments ratings. First, authors merge the k topmost comments into one large corpus and use this corpus to get the required predictions using NLP model. The predictions are such that it can classify the video as Fair or Falsified. However, a rating system can be created from these predictions by knowing the confidence levels of both classes (fair and falsified/clickbait).

Using these confidence score model provide every YouTube video with a rating that is fairly based on comments' sentiment. This rating system provides users with what other people are thinking of that video, unlike the existing rating system (as shown in Fig. 4) in which one can view only the number of likes associated with that video, and in such cases, users have no idea about the negative reviews at all.

Table 1 represents the ratings obtained depending on the different models like Support vector machines, Logistic regression and XgBoost.

Now to chose the best model we calculate the standard deviation(SD) of the predicted rating and the actual rating.

$$SD = \sqrt{\frac{\sum (x - y)^2}{N}}$$

where x, y are predicted and actual ratings respectively.

Table 1. A brief comparison between actual and predicted ratings

Video ID	Support Vector Machine	Logistic Regression	XG Boost	Actual Rating	Flagged as
2W-oMj8Ddo	90% (Fair)	77% (Fair)	25%(Clickbait)	81%	Fair
vJtISoZagb4	67% (Fair)	68% (Fair)	60% (Fair)	71%	Fair

(*continued*)

Table 1. (*continued*)

Video ID	Support Vector Machine	Logistic Regression	XG Boost	Actual Rating	Flagged as
zIB4c9rCn9k	87% (Fair)	71% (Fair)	83% (Fair)	76%	Fair
B0BROZCNRic	85% (Fair)	77% (Fair)	86% (Fair)	89%	Fair
6IU0ZXjdUVs	97% (Fair)	88% (Fair)	89% (Fair)	91%	Fair
ba08lxJx4kI	98% (Fair)	85% (Fair)	88% (Fair)	91%	Fair
n9oBKqpcZsc	98% (Fair)	86% (Fair)	60% (Fair)	90%	Fair
H0fr7AwqxnA	99% (Fair)	87% (Fair)	84% (Fair)	93%	Fair
ztpnM1XwCxw	69% (Fair)	53% (Clickbait)	77% (Fair)	60%	Clickbait
uy4mOlYwZbA	91% (Fair)	78% (Fair)	87% (Fair)	74%	Fair
Mquits0Ob2U	89% (Fair)	78% (Fair)	90% (Fair)	77%	Fair
aCHnFnBcRpc	85% (Fair)	78% (Fair)	76% (Fair)	78%	Fair

The standard deviation of 200 videos for different types of models were calculated to be

$$SD_{LR} = 7\%,\ SD_{SVM} = 13.8\%,\ SD_{XG} = 19.2\%$$

The model with a least SD of 7 comes out to be of logistic regression. It should be noted that YouTube doesn't publicly disclose the actual rating of a video; the dislikes count is not visible to the general audience but is still visible to the video creator. So with the help of a few authentic creators, authors collected the actual video rating by knowing

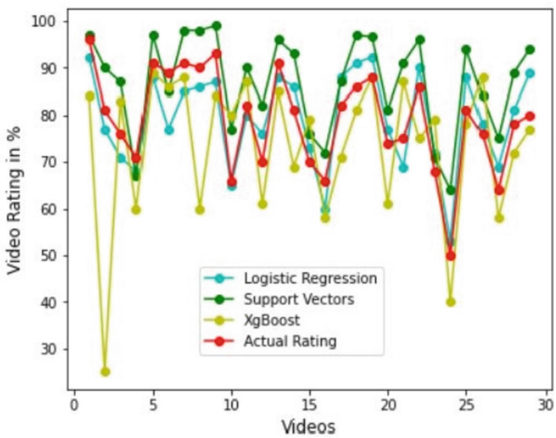

Fig. 2. Comment ratings predicted by different type of models

the count of likes and dislikes. Also, the labels like Fair and clickbait are discussed in Sect. 4.

As shown in Fig. 2, although logistic regression gives the best performance, it gets opposed once it reaches a rating of 90–93%. Even if the video is really good, the rating given by logistic regression will not surpass 93; however other models seem to rate even higher but with a trade-off for overall performance.

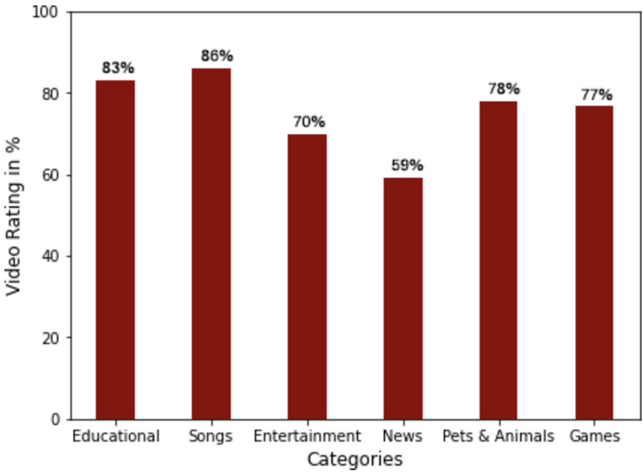

Fig. 3. Average video rating for various categories

Figure 3 depicts the average rating for different types of categories present on YouTube. It can be seen from the graph that categories like songs and educational videos are generally rated higher. In contrast, political videos are rated much lower because of variations in public opinion.

4 Performance Review of Proposed Approach

In this section, the authors discussed the benefits of the proposed rating system over the existing inadequate rating system.

Fig. 4. Current Rating system employed by YouTube

Figure 4 represents the current rating system used by YouTube. Although the number of likes is visible, the dislike count is not publicly available. And in the absence of dislike count the like count becomes ineffective as well, since users don't have access to any negative reviews to compare with. Thus to solve this challenge, the authors created a rating system (as shown in Fig. 5) that uses publicly available data like user comments to calculate the video rating and is visible to everyone on YouTube.

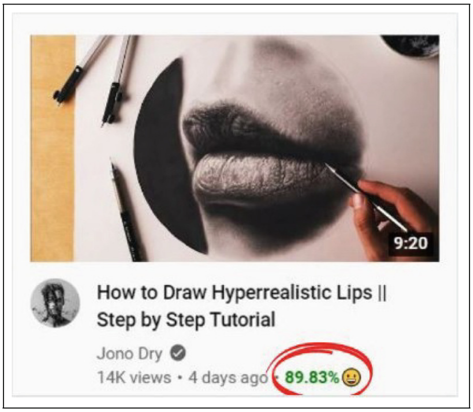

Fig. 5. New rating system based on comments rating

4.1 Major Application: Detection of Clickbait Videos

Fig. 6. Depiction of Clickbait videos

Clickbait is a form of false content that creators purposely design to reach a large audience. The detection of these types of videos becomes so important because often the video content is completely different than what their Title, Thumbnail, and description try to convey. There is a great possibility of users getting misinformed by those types of content.

Authors use the rating model developed in the previous steps, and with the help of a threshold confidence score, authors can accurately classify videos as clickbait or fair.

Authors tested results on 1000 videos and came up with a threshold value that gave us the best precision score of 98.6% for clickbait labels and the best possible threshold value comes out to be 56% i.e. if the video rating is

- <56%: The video will be labelled as a clickbait.
- >=56%: The video will be labelled as fair.

5 Limitations and Loopholes

Authors have used publicly available data for the proposed system, but there are still some limitations:

- Like, YouTube lets the creators disable the comments.
- YouTube also has disabled comments on Videos that are made for kids per the coppa policy.

and in such cases proposed model may not able to fetch any comments at all and thus may not offer the required predictions.

6 Result

This section presents the experimental results of the proposed sentiment analysis approach. To evaluate the proposed model a total of 800 videos were considered for training and 200 for testing.

The actual video ratings were calculated with the help of a manual inspection done by 10 authentic YouTube creators, as these creators have the rights to view their own YouTube video parameters such as "like", "dislike" count and thus the actual rating. A total of 1000 videos were considered from these authentic channels so that the most generalized categories are covered. Among all videos, the highest variation of the developed rating system from the actual system (visible only to video creators and not publicly available) was not more than 15% while the average deviation was observed to be 7% as shown in the logistic regression model.

The authors also found that the proposed model gave the highest video rating at 92.6%, which was based on the educational category. The lowest rating of 33.3% was given to an entertainment video, and it was tagged as clickbait by the model as well as by many numbers of users on YouTube. Some categories in which the model did not perform really well were political, news, etc., as every individual has completely different views on these topics; the content may be exciting for some people but awful for others.

On the same set of 1000 videos, authors tried to analyze our system for clickbait content predictions, and we found that our model gave a precision score of 98.6% for clickbait labels. The clickbait comments are highly volatile and thus the model has high accuracy in predicting those types of content.

Since the model requires a considerable amount of text (comments) to predict required results, authors found that the proposed model worked best when videos with views of more than 1,00,000 were considered, as these videos have enough popular comments required by the model to predict results accurately. However, videos with views in the range of 0-100k have many comments ranging from 0–100, many of which can be noise, spam, etc., and thus these comments add very less value.

7 Conclusion

The proposed model discussed how sentiment analysis can be used to replace YouTube's current rating system (which doesn't consider any negative reviews at all) with better and more efficient ones. Proposed model ratings depict user sentiment for a particular video as these ratings are entirely based on sentiment analysis of comments and reviews. This model offered a robust rating system with a deviation of 7% from actual ratings and with a precision score of 98% in classifying clickbait labels.

8 Future Work

Although authors were successfully able to develop a rating system for YouTube videos there is still a great amount of work and research that needs to be done to make sure this rating system provides accurate and reliable results. Some major scope of improvements are:

- The dataset considered was manually created by authors and was limited as it only contained comments from 1000 videos. The accuracy scores can be increased and tested more efficiently by creating a larger dataset having comments from more than 10k videos flagged as fair or clickbait.
- The vectorizer used was frequency based, however, the precision for clickbait detection can be greatly increased by increasing priority for words like "clickbait", "fake", etc.
- With the help of larger datasets, one can even use neural networks to improve the model performance further
- Most of the YouTube comments have incomplete words or misspelled words, like fak or fek which corresponds to the word Fake, the current model considers these incomplete words as a completely different new word and thus this somewhat reduces the accuracy score. With the help of some libraries like Word complete, etc., these inconsistencies can be removed.

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