Sensitivity Analysis using Regression Models: To Determine the Impact of Meta-level Features on the Youtube Views

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Abstract: The popularity of social media has led to a shift in paradigm with YouTube emerging as a ubiquitous platform for networking and content sharing. YouTube, with over a million content creators, has become the most preferred destination for watching videos online. The meta-level features like the title, tags, number of views, likes, dislikes, etc. are significant to determine the sensitivity of the videos. This study aims to determine how these meta-level features can better be utilized to increase the popularity of the videos. The study specifically analyzes how the number of likes, dislikes and comment count have an impact on the number of views. The number of likes, dislikes and the comment count are the independent variables, while the view count is a dependent variable. The dataset used for this research is the daily Trending YouTube Video Statistics for the years 2017-2019 from Kaggle, that spans across the US region with over forty-thousand videos from sixty plus channels released by YouTube for public use. In this paper, we use the Ordinary Least Square Regression Algorithm and Stochastic Gradient Descent Algorithm to perform Sensitivity Analysis. The analysis is performed on two categories: Media and Sports. The accuracy of both the models are compared by evaluating the mean absolute error (MAE) and the relative absolute error (RAE) taken from the results of the experiment. The results showed a significant impact of meta-level features on the popularity of the videos along with their percentage dependency.

1 INTRODUCTION

The YouTube social media platform ranks as the second most used application around the globe. YouTube has emerged as a ubiquitous platform for networking and content sharing. It has over 2 billion users and counting as of 2021. Over millions of videos are uploaded, viewed, liked, disliked, commented on, and shared every minute. This study is specific to two domains within the Entertainment Category: Media and Sports. The user engagement hits the chart for every entertainment-based video with the top categories being Media and Sports. The database collected from YouTube is mainly based on the key matrices: view count, likes, dislikes and comments. The popularity of the videos is greatly affected by the meta-level features. The aim of the study is to determine how the meta-level features are utilized to analyze the sensitivity of the videos. This study is performed on the dataset collected in the US region in the years 2017-2019. Sensitivity analysis is applied to the dataset to learn and analyze how the key matrices are interdependent. As a result, this study helps to conclude how the total reactions of the audience in terms of likes and dislike have an impact on the number of views.

To extract and discover patterns from the dataset of Media and Sports, data mining was applied. Data mining is the process of analyzing a large sets of data to recognize trends and patterns using different statistics and machine learning techniques. Sensitivity analysis determines the rate of change in the output of a model with respect to the changes in the model inputs (Yao, 2003). Regression is one of the most basic algorithms in data mining that has been used on this dataset. These matrices are an important source to extract implicit knowledge about users, videos, categories and community knowledge (Devika Harikumar, Dolly Kapoor, & Prof. Swapnil Waghmare, 2019).

The aim of this paper is to determine the sensitivity of the views of the YouTube videos with

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respect to the likes and dislikes. In particular, the paper intends to show that by applying sensitivity analysis to the dataset, it is possible to identify the factors that play important roles to the popularity of the video (Aprem & Anup, 2017). The following is the outline of the paper. The following section is about of discusses the Literature Review concerning Sensitivity Analysis of YouTube videos. The third section discusses the Methodology used to find the results. The fourth section introduces the dataset and its details. The fifth section gives detailed information on the results and the analysis of the algorithms used. The conclusion follows.

2 LITERATURE REVIEW

Data mining has been extensively examined in YouTube, which is one of the most popular places for user-generated content. Sensitivity and Sentiment Analysis are two of the most popular peer-study topics on YouTube. Despite its importance, trending video analysis on YouTube has yet to be properly examined. Many people have looked at the YouTube recommendation system, but trending video analysis still has a lot of room for improvement. Studies on the popularity of videos have mainly focused on the viewcount as a single metric (Zeni, Miorandi, & De Pellegrini, 2016). But recently, other metrics have rose to significant importance:

(a) According to studies, the YouTube recommender uses the watchtime as a metric for understanding how a video is popular (Zeni, Miorandi, & De Pellegrini, 2016).
(b) The various meta-level attributes can be used to build a conversion funnel to characterize the impact of advertisement campaigns. (Zeni, Miorandi, & De Pellegrini, 2016; Abdulhadi Shoufan, 2019)

YouTube has become the most popular place to watch videos online. Given the diversity of viewers and content providers, it is difficult to determine the popularity of the videos on the basis of the meta-level attributes. Viral videos play an important role in business marketing to reach target audience in a short time-span (Gohar Feroz Khan & Sokha Vong, 2014). Content creators can monetize their successful videos through YouTube's Partner program and enhance their video popularity with the most sensitive meta-level attributes like title, tag, thumbnail, etc. YouTube uses a combination of measures to analyze and provide a framework of understanding at different levels.

Viewcount is an important popularity metric in YouTube (Niyati Aggrawal, Anuja Arora, & Adarsh Anand, 2018; Jussara M. Almeida, Flavio Figueiredo, & Fabrício Benevenuto, 2011). Studies have established that in the social dynamics setting, there exists a causal relationship between the views and the number of subscribers (William Hoiles, Anup Aprem, & Vikram Krishnamurthy, 2017; Yan Duan & Vikram Krishnamurthy, 2017). The Ordinary Least Square Regression algorithm, which assesses the relationship between one or more independent factors and a dependent variable by minimizing the sum of squares in the difference between the observed and predicted values of the dependent variable defined as a straight line, and the Stochastic Gradient Descent Algorithm have been used.

3 METHODOLOGY

The main goal of this study is to determine how the independent attributes affect the dependent attribute. Likes and dislikes are the independent attributes that have an impact on the dependent variable – view count. To achieve this, two regression algorithms – Ordinary Least Descent and Stochastic Gradient Descent were used, and a model and a prediction model is built (Quyu Kong, Marian-Andrei Rizoiu, Siqi Wu, & Lexing Xie, 2018). The algorithms determined the sensitivity of the view count against the likes and dislikes and were then compared for accuracy (Lau Tian Rui, Zehan Afizah Afif, & R. D. Rohmat Saed, 2019).

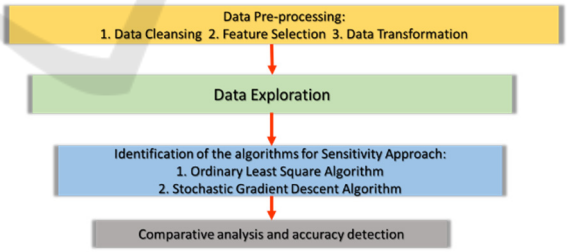
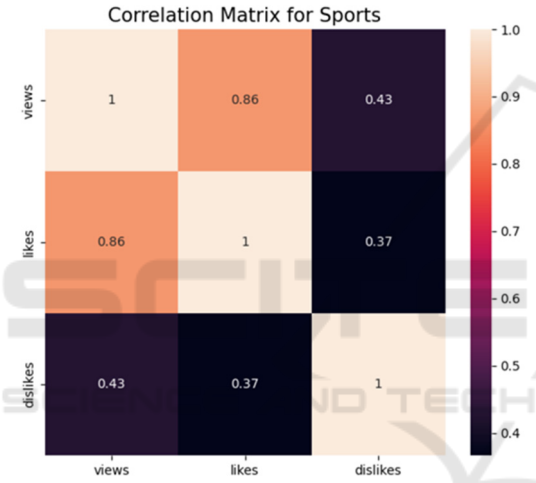


Figure 1: Representation of Methodology.

The data was pre-processed, and the raw data was transformed into efficient and usable data. The first step for pre-processing was data cleaning. In this step, all the inconsistent and incomplete data was removed. The dataset which consisted of various categories, was cleaned of every category except for Sports and Media. In the second step, feature selection was performed. For this research, only 4 attributes were required – Category id, views, likes and dislikes. In a predictive model, feature selection is the process of

reducing the number of input variables to improve the performance of the model.

The dataset is reduced to 4 attributes which are used in building the model. In the third step, the data is transformed by removing the noisy data. The incomplete data is filled with null values and the data is then made ready for performing data exploration. In Data Exploration, the data is visualized to get insights into the patterns and trend of the likes and dislikes vs the view count. Correlation matrix determines the correlation coefficient between each variable and the fit is then plotted as scatter plots. The attributes of the data are understood and insights into what each attribute contains are gained. Once the patterns are relationships are established, the dataset is ready for algorithms (Gábor Szabó & Bernardo Huberman, 2008).



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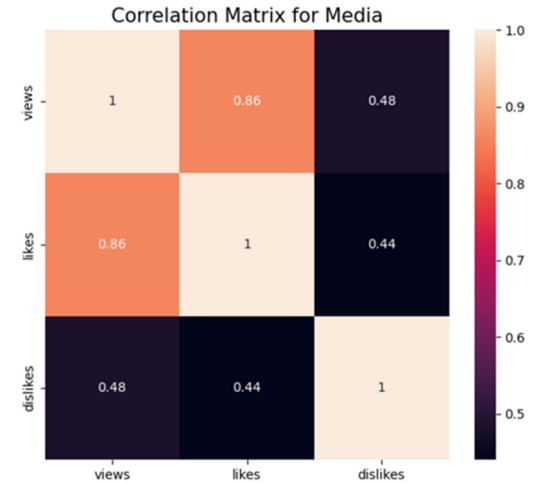


(b)

Figure 2: Correlation Matrix (a) for Sports (b) for Media.

As the aim of this experiment is to determine how the independent variables affect the dependent variables, regression algorithm fits well to draw conclusions. For better accuracy, two regression algorithms are used – Ordinary Least Square Algorithm and Stochastic Gradient Descent Algorithm (Lau Tian Rui, Zehan Afizah Afif, & R. D. Rohmat Saed, 2019). In OLS algorithm, a hyperplane is computed which reduces the sum of squared differences between the true data and the hyperplane. The SGD algorithm is used since the slope of the function, or the gradient measure the degree of change of a variable with respect to change in another variable. In SGD, some samples are randomly selected for every iteration and is less expensive to optimize a learning algorithm.

Once both the algorithms are applied to the dataset, they are compared for their accuracy. The metrics used to test the accuracy are: Mean Absolute Error, Root Mean Squared Error, and the Coefficient of Determination (Lau Tian Rui, Zehan Afizah Afif, & R. D. Rohmat Saed, 2019). The average difference between the estimated and forecasted values is calculated using the Mean Absolute Error. It is calculated as:

RMSE is the standard deviation of the data points from the regression line. It is calculated as:

$$MAE = \frac{1}{N}\sum_{i=1}^{i}|x_i - y_i| \quad (1)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{i}|x_i - yi|} \quad (2)$$

Coefficient of Determination examines how difference in one variable is explained by the difference in another variable. In other words, it determines whether a model fits the dataset. It is calculated as:

The two algorithms are run separately for both the categories – Sports and Media.

$$R^2 = 1 - \frac{Sum\ of\ squares\ of\ residuals}{Total\ sum\ of\ squares} \quad (3)$$

4 DISCUSSION

The Kaggle daily Trending YouTube Video Statistics for the years 2017-2018 were utilized for this study that spans across the US region with over forty-thousand videos from sixty plus channels released by

YouTube for public use. The original dataset consisted of 40949 tuples and 11 attributes.

video_ID	_BcYBFC6zfY
trending_date	18.14.06
title	Ralph Breaks the Internet: Wreck-It Ralph 2 Official Trailer
channel_title	Walt Disney Animation Studios
category_ID	1
publish_time	2018-06-04T16:00:03.000Z
tags	Disney|"Walt Disney Animation Studios"|"Disney Animation"|"Walt Disney"|"Animation"
views	12976087
likes	218467
disliked	13457
comment_count	39393

Figure 3: Original Dataset.

After pre-processing the number of rows remained unchanged while the attributes were reduced to four for analysis. Once the attribute construction was performed, the number of attributes increased to 5 for both the categories.

	A	B	C	D	E
1	category_	views	likes	dislikes	total
2	24	2418783	97185	6146	103331
3	23	3191434	146033	5339	151372
4	24	343168	10172	666	10838
5	24	2095731	132235	1989	134224
6	24	2103417	15993	2445	18438
7	1	826059	3543	119	3662
8	24	104578	1576	303	1879
9	10	687582	114188	1333	115521
10	23	295639	8011	638	8649

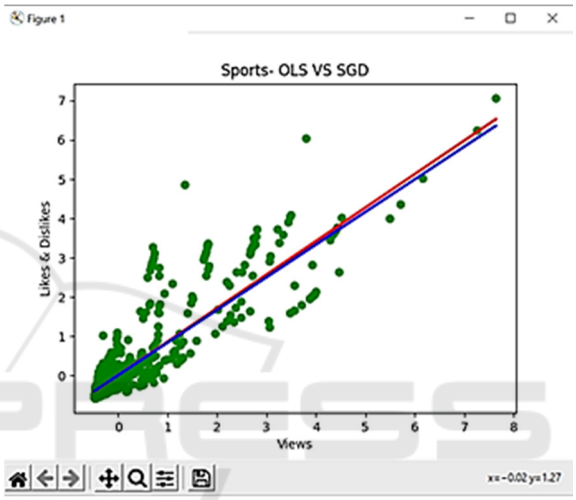
Figure 4: Dataset after pre-processing.

Once the dataset was ready, both the regression models were applied to it. Ordinary Least Square Algorithm works on the principle of minimizing the sum of squares of the differences between the observed dependent variable(views) and the predicted independent variables (likes and dislikes). Stochastic Gradient Descent Algorithm works on the principle of using only one selection from the training set. This makes SGD noisier than other gradient descent algorithms but has a much shorter training time.

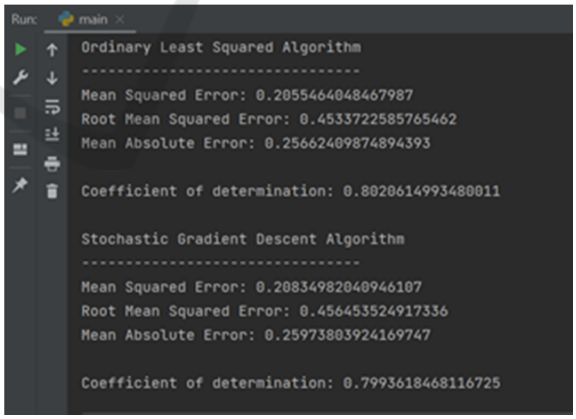
5 RESULTS AND ANALYSIS

This study specifically analyses how the view count is impacted by the number of likes and dislikes. The likes, dislikes and comments count are the independent variables, while the view count is a dependent variable (Lau Tian Rui, Zehan Afizah Afif, & R. D. Rohmat Saed, 2019). Initially, the dataset consisted of 11 attributes, but pertaining to the aim of the study, only 4 attributes were required for the analysis. This was achieved through data cleaning and pre-processing. Attribute construction was performed by data reduction. Data reduction is the technique applied to the dataset to reduce the representation of the data. The data reduction technique used is numerosity reduction using regression.

After the data is pre-processed, the two algorithms, Ordinary Least Square Regression and Stochastic Gradient Descent Algorithm are applied to it.

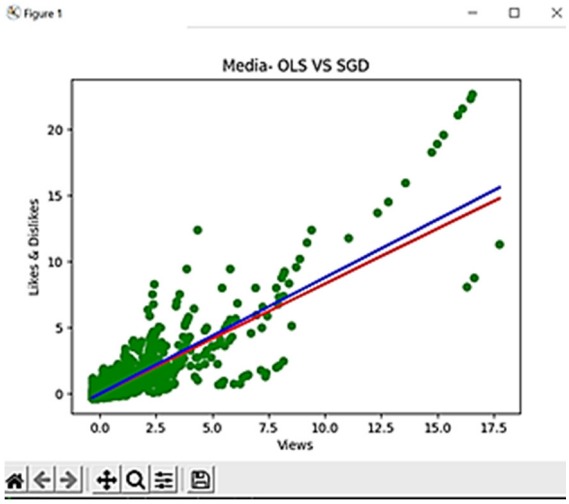


(a)



(b)

Figure 5: (a) A comparative graph of algorithms for Media Category and (b) Findings of Data Analysis and Interpretation.



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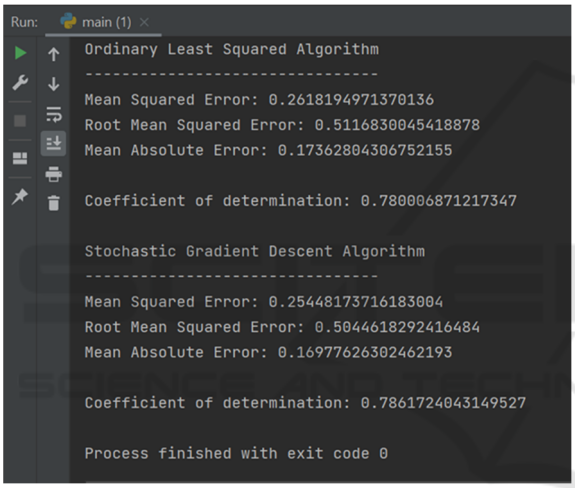

(b)

Figure 6: (a) A comparative graph of algorithms for Media Category and (b) Findings of Data Analysis and Interpretation.

We were able to conclude from the results that in the Media Category, there is a variation of 78% in views concerning the likes and dislikes using the Ordinary Least Square Algorithm and 76.8% for Stochastic Gradient Descent Algorithm. Similarly, in the Sports Category, there is a variation of 80.2% in views against the likes and dislikes using the Ordinary Least Square Algorithm and 79.9% using the Stochastic Gradient Descent Algorithm. SGD algorithm proved to be more accurate as compared to the OLS algorithm and this is tested and verified by comparative analysis and accuracy detection. In conclusion, the Stochastic Gradient Descent Algorithm is more efficient to provide the accurate Sensitivity of the Views for both the Media and Sports Category.

6 CONCLUSIONS

YouTube, a platform that receives millions of views, likes and dislikes each day, provides a strong ground for analysing the performance of videos and the effect of meta-level features on each other. The study was conducted on a dataset for the USA region for two popular categories- Media and Sports for the years 2017-2018.

The analysis showed that in both the categories, view count was highly sensitive to the number of likes and dislikes on the video. This study presented a new dimension to assessing YouTube content, however, it has its limitations. The number of users viewing any content online do not necessarily react to it in terms of likes, dislikes, or comments. This creates ambiguity regarding user reactions and hence imposes a limit on the output of the model. The analysis of any YouTube database can be further explored in terms of viewer emotions by taking into account the comments on the videos. This analysis was conducted only from the perspective of user reactions; however, other attributes can also impact the view count. This study did not consider attributes like watch-time, demographics, subscriber growth, click-through rates and the keywords used, to name a few. By including these factors, this study can be enhanced and made more productive.

The results show that the OLS algorithm can further be used to analyse the effect of other meta-level attributes on the number of views. This can further lead to developing prototypes for increasing the user engagement. This foundational study was carried out to gauge the reaction of the audience and further analysis can be carried out in terms of age bracket, therapy, and social impacts (William R. Casola, et al., 2020; Mike Thelwall, 2018). This study could also lead to more advanced study on how YouTubers can increase their view count with sponsored content (Fulya Acikgoz & Sebnem Burnaz, 2021; Natasha Matson & Elmira Djafarova, 2021) and recommend content to users based on the metrics (James Davidson, Benjamin Liebald, Junning Liu, & Palash Nandy, 2010).

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