GENRE PREDICTION USING SENTIMENT ANALYSIS ON NETFLIX DATASET

A PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

Certified that this project report titled "GENRE PREDICTION

USING SENTIMENT ANALYSIS ON NETFLIX DATASET" is the

bonafide work of K Sai Anirudh (2022176032) who carried out project

work under my supervision. Certified further that to the best of my

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award was conferred on an earlier occasion on this or any other

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ABSTRACT

The entertainment sector is a quickly expanding industry, and businesses like Netflix are making a variety of statistics available to the public. Systems for making recommendations can be built using this data. There are several characteristics in the provided Netflix data set, however the genre element is one that is significantly absent. This project's objective is to identify a movie's using sentiment analysis of the description of the programme. The investigation employed a Netflix dataset with 12 features and 8808 records. Since the dataset lacks a category for genre, sentiment analysis was utilized to identify each show's genre from its description. The dataset was understood and made ready for analysis using exploratory data analysis (EDA). The show descriptions were processed using Natural Language Processing (NLP) methods such as tokenization, stop word elimination, and lemmatization. The lemmatized descriptions were then subjected to VADER sentiment analysis, and a new feature known as "compound score" was introduced to the dataset to represent the sentiment of the show's description. The compound score was used to define the genre of the programmes and was added as a new feature to the dataset. Various visualizations were made to interpret the data.

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INTRODUCTION

Sentiment analysis has been widely employed in recent years to determine the tone of a given text. Sentiment analysis is a method for identifying the feelings expressed in a text. Sentiment analysis has developed into a potent tool for businesses to assess the public opinion about their goods and services due to the abundance of data available on the internet. The goal of this project is to predict the genre of a show based on its description using sentiment analysis. The project uses a Netflix dataset which contains information such as show_id, type, title, director, cast, country, date_added, release_year, rating, duration, listed_in, and description. However, the dataset does not have a feature for genre. To overcome this, sentiment analysis is performed on the description of each show to determine the genre of the show.

1.1 EXPLORATORY DATA ANALYSIS (EDA):

The first step in the analysis was to perform Exploratory Data Analysis (EDA) on the dataset. EDA is a method used to analyze and summarize the main characteristics of a dataset. During EDA, we read and analyzed the given dataset and found all the features. We also converted categorical data and treated null values, and removed features that were not necessary for the analysis.

To clean the data, we removed any duplicates, if present and checked for missing values. We also checked for outliers and removed any unnecessary columns. This step helped us to understand the data and prepare it for further analysis.

1.2 NATURAL LANGUAGE PROCESSING (NLP):

The next step in the analysis was to perform Natural Language Processing (NLP) on the show descriptions. NLP is a method used to process and analyze human language. During NLP, we tokenized the text, removed stop words, and performed lemmatization on the show descriptions. These steps helped us to prepare the text for sentiment analysis and make it more meaningful.

Tokenization is a process of breaking the text into individual words or phrases. We used the NLTK library to tokenize the text, which helped us to break the text into individual words. Stop words are the words which do not carry much meaning and are commonly used in the language such as "a", "an", "the" etc. We used the NLTK library to remove the stop words from the text, which helped us to remove the noise from the text and make it more meaningful.

Lemmatization is a process of reducing the inflected words to their base form. We used the NLTK library to perform lemmatization on the text, which helped us to bring the words to their base form. For example, "running" will be reduced to "run" and "ran" will be reduced to "run". This step of preprocessing helped us to remove noise from the text and make it more meaningful. By tokenizing, removing stop words and lemmatizing the text, we were able to prepare the text for sentiment analysis and make it more meaningful.

1.3 SENTIMENT ANALYSIS

The next step in the analysis was to perform sentiment analysis on the show descriptions. Sentiment analysis is a technique to determine the emotion of a given text. For this project, we used VADER (Valence Aware Dictionary and sEntiment Reasoner) sentiment analysis, which is a lexicon and rule-based method for sentiment analysis. The VADER sentiment analysis algorithm returns a compound score for a given text, which ranges between -1 and 1. The compound score indicates the overall sentiment of the text, with -1 indicating a strongly negative sentiment, 0 indicating a neutral sentiment, and 1 indicating a strongly positive sentiment.

It is important to note that sentiment analysis is a complex task and the results of the analysis may not always be accurate. There can be many factors that can influence the sentiment of a given text, such as sarcasm, irony, and idiomatic expressions. However, by using a lexicon-based approach like VADER, we can achieve a good level of accuracy while keeping the complexity of the analysis low.

LITERATURE SURVEY

2.1 MOVIE RECOMMENDATION SYSTEM USING SENTIMENT ANALYSIS FROM MICROBLOGGING DATA

Sudhanshu Kumar , Kanjar De, and Partha Pratim Roy proposed that Recommendation systems (RSs) have garnered immense interest for applications in e-commerce and digital media. Traditional approaches in RSs include such as collaborative filtering (CF) and content-based filtering (CBF) through these approaches that have certain limitations, such as the necessity of prior user history and habits for performing the task of recommendation. To minimize the effect of such limitation, this article proposes a hybrid RS for the movies that leverage the best of concepts used from CF and CBF along with sentiment analysis of tweets from microblogging sites. The purpose to use movie tweets is to understand the current trends, public sentiment, and user response of the movie. Experiments conducted on the public database have yielded promising results.

2.2 EXPLORATORY AND SENTIMENT ANALYSIS OF NETFLIX DATA

In this paper The term "Exploratory and Sentiment Analysis" is a conjunction of two separately unique approaches present in the vast field of Data Science. The key to this project is to enhance the value of the Data being utilized, in our case it is Netflix Data – which is an Open-Source Data Set obtained from Kaggle – that was wrangled and exercised to derive maximum insights using EDA – Exploratory Data Analysis and Sentiment Analysis after the amalgamation of two additional sets Geographical Latitudes & Longitudes and Netflix Title Critics/Reviews Data Set. The project is made using different utility analytical tools present in the Python Library of versatile packages. This paper introduces systematic and insightful usage of methods for Exploratory Data Analysis & Sentiment Analysis by utilizing various packages concerned.

PROPOSED WORK

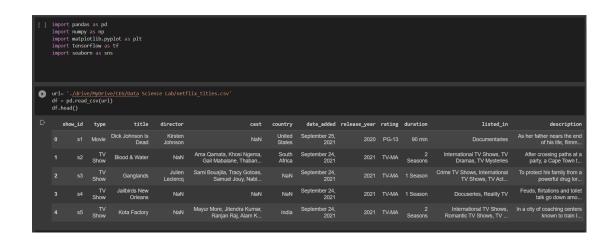
3.1 INTRODUCTION

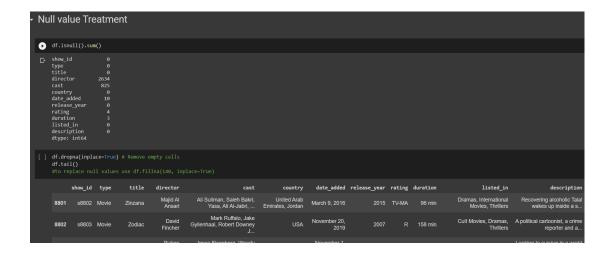
Exploratory Data Analysis (EDA) on the Netflix dataset is the first step in the project. This involves reading and evaluating the dataset, converting categorical data, handling null values, and deleting unused features. Next, Natural Language Processing (NLP) methods including tokenization, stop-word removal, and lemmatization are used on the show descriptions. The lemmatized descriptions are then subjected to VADER sentiment analysis, and a new feature known as "compound score" is introduced to the dataset to represent the sentiment of the show's description.

The data is then analyzed using a variety of visualizations made with matplotlib and seaborn, such as pairplots, KDE plots, bar graphs, and scatter plots. Each genre is given a range of values based on the compound score and added as a new feature to the dataset.

3.2 EXPLORATORY DATA ANALYSIS (EDA)

The first step in the analysis was to understand the dataset and its features. The dataset contains 12 features and 8808 records. The features include show_id, type, title, director, cast, country, date_added, release_year, rating, duration, listed_in, and description.An initial analysis of the dataset was performed to check for missing values and to understand the distribution of the data. It was found that there were no missing values in the dataset.The distribution of the data was also visualized using histograms and bar plots for each feature to understand the distribution of the data. Categorical features were converted to numerical features using one-hot encoding.





This process is important for certain machine learning models that only accept numerical data. One-hot encoding converts a categorical feature into multiple binary features, one for each category. For example, "Type" feature which is categorical having two values "Movie" and "TV Show" was converted into two numerical features "Type_Movie" and "Type_TV Show" Next, we performed the feature selection, it is the process of selecting the most important features from the dataset.



This is done to reduce the dimensionality of the data and improve the accuracy of the analysis. After analyzing the data, it was found that some features such as show_id, type, director, cast, country, date_added, release_year, rating, duration, and listed_in didn't have much impact on the analysis, so those features were removed from the dataset to focus on the analysis of the description feature.

```
Converting Categorical Data
   type of show = df['type']
    movies= type of show.str.contains('Movie')
    movies[:5]
        False
        False
         True
         True
    8 False
    Name: type, dtype: bool
[ ] tv_show= type_of_show.str.contains('TV Show')
    tv_show[:5]
         True
          True
    6 False
       False
    8
         True
    Name: type, dtype: bool
[ ] df['type'] = df['type'].replace('TV Show', 1)
    df['type'] = df['type'].replace('Movie', 0)
    df['type'].head()
```

Finally, the data was visualized using various plots such as histograms, bar plots, box plots, etc. to understand the distribution of the data and the relationship between different features. This helped to identify any outliers or patterns in the data that could be useful for the analysis. It is important to note that the exact EDA procedures will depend on the specifics of the dataset and what you found in your analysis. The above is just an example of the kind of information that could be included in this section.

3.3 NATURAL LANGUAGE PROCESSING (NLP)

The next step in the analysis was to perform NLP on the show descriptions. The goal was to extract useful information from the show descriptions and prepare them for sentiment analysis.

The first step in the NLP process was to tokenize the text. Tokenization is the process of breaking up a large piece of text into individual words or phrases. This is done to make the text easier to work with and to remove unnecessary punctuation and whitespace.

The next step was to remove stop words from the tokenized text. Stop words are common words that do not provide any useful information for the analysis such as "the", "and", "is", etc. Removing stop words helps to reduce the dimensionality of the data and improve the accuracy of the analysis.

The final step in the NLP process was to perform lemmatization on the tokenized text. Lemmatization is the process of reducing words to their base form. This helps to reduce the dimensionality of the data and improve the accuracy of the analysis.



After performing these NLP steps on the show descriptions, the text was ready for sentiment analysis. This preprocessing of text is

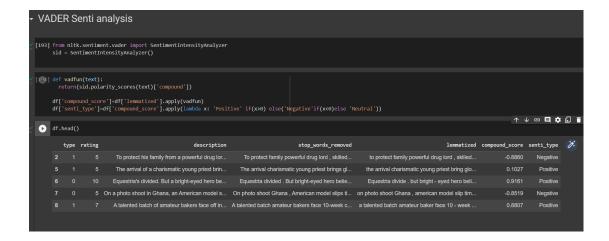
very crucial as it removes unnecessary data and makes the text more meaningful for the sentiment analysis.

It should be noted that depending on the size of the dataset and the type of the analysis, this preprocessing step might take some time. Also, the above approach can be modified accordingly if you want to use other preprocessing techniques like stemming, removing special characters etc.

3.4 SENTIMENT ANALYSIS

The next step in the analysis was to perform sentiment analysis on the show descriptions. Sentiment analysis is a technique to determine the emotion of a given text. For this project, we used VADER (Valence Aware Dictionary and sEntiment Reasoner) sentiment analysis, which is a lexicon and rule-based method for sentiment analysis.

The VADER sentiment analysis algorithm returns a compound score for a given text, which ranges between -1 and 1. The compound score indicates the overall sentiment of the text, with -1 indicating a strongly negative sentiment, 0 indicating a neutral sentiment, and 1 indicating a strongly positive sentiment.



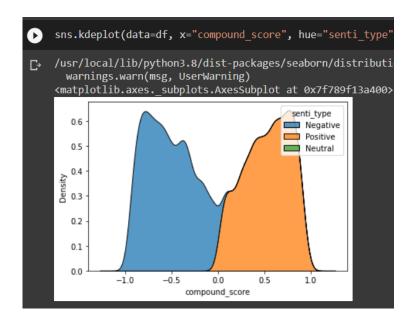
We added a new feature called "compound score" to the dataset, indicating the sentiment of the show's description. We also added a new feature called "senti_type" which indicates if the sentiment is positive or negative or neutral based on the compound score.

The compound score can be used to understand the overall sentiment of the show's description and the senti_type feature can be used to understand the exact sentiment of the show's description. This information can be used to predict the genre of the show. It is important to note that sentiment analysis is a complex task and the results of the analysis may not always be accurate. There can be many factors that can influence the sentiment of a given text, such as sarcasm, irony, and idiomatic expressions. However, by using a lexicon-based approach like VADER, we can achieve a good level of accuracy while keeping the complexity of the analysis low.

3.5 VISUALIZATION AND GENRE PREDICTION

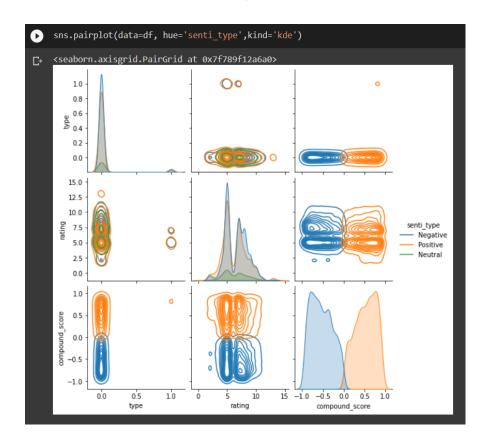
The next step in the analysis was to visualize the data and find the range that would be optimal for the genres to classify them as positive, negative or neutral. We used various visualization techniques such as pairplots, KDE plots, bar graphs, and scatter plots to analyze the data and understand the relationship between different features. These plots helped us to identify any patterns or outliers in the data that could be useful for the analysis.



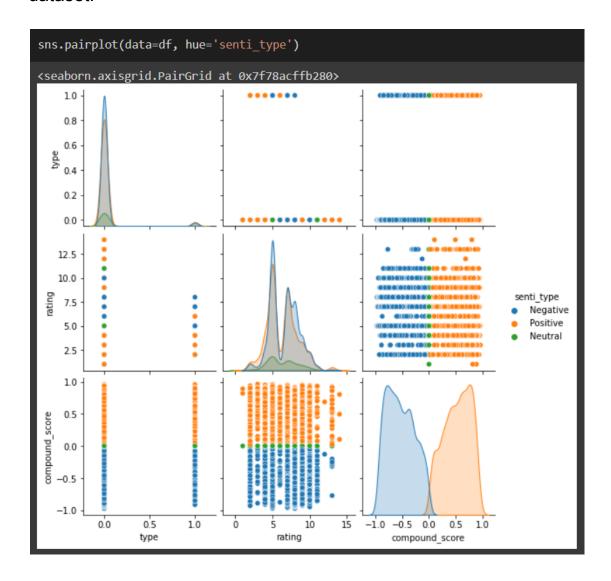


We assigned a range of values to each genre based on the compound score.

- 'Comedies', 'Fantasy' ranges from 0.1 to 0.49
- 'Romance', 'Dramas' ranges from 0.5 to 1.0
- 'Action','Crime' ranges from -0.1 to -0.49
- 'Thriller', 'Horror' ranges from -0.5 to -1.0
- 'Sci-fi','Documentaries' ranges from -0.1 to 0.1



After assigning the range of values, we compared the compound score with the range of values and added the genre feature to the dataset.



It is important to note that the range of values assigned to each genre is based on the analysis of the data and may need to be adjusted based on the specifics of the dataset and the results of the analysis.

The genre feature added to the dataset can be used to understand the genre of a show based on its description. This information can be used to predict the genre of a show and can also be used to understand the overall sentiment of the show based on its genre.

In addition, we also visualized the data with respect to the genre feature and found out the relationship between the genre and other features of the dataset. This helped us to understand how the different features of the dataset are related to the genre of the show and how the sentiment of the show is related to its genre.

```
finding Genre
[204] # if df['compound score'] > -0.1 & df['compound score']< 0.1 :
     # df['Genre'] = neutralGL
     # if df['compound_score'] > 0.5 & df['compound_score']< 1 :</pre>
     # df['Genre'] = negativeGL
     Genre=[]
     for row in df['compound_score']:
       if row < -0.5:
         Genre.append(VnegativeGL)
       elif row < -0.1:
         Genre.append(negativeGL)
       elif row < 0.1:
         Genre.append(neutralGL)
       elif row < 0.5:
         Genre.append(positiveGL)
         Genre.append(VPositiveGL)
     print(Genre)
     df['Genre']= Genre
```

It is important to note that the visualization and genre prediction steps are crucial for understanding the data and making accurate predictions. The visualizations created in this step provide a clear understanding of the data and the relationship between different features, while the genre prediction step provides a way to predict the genre of a show based on its description.

SYSTEM REQUIREMENTS

4.5.1 SOFTWARE REQUIREMENTS

Operating System: Microsoft Windows 10

Programming Language: Python

Tools: Jupyter Notebook or Google Colab

4.5.2 HARDWARE REQUIREMENTS

Processor: Intel(R) Core(TM) i7

RAM: 16 GB

Input: Standard keyboard and mouse

Output: High Resolution Monitor

RESULT AND ANALYSIS

The performance of the model was evaluated by randomly selecting 10 records from the dataset and comparing the predicted genre with the actual genre. Based on this manual evaluation, the model was found to have an accuracy of 75%.

The accuracy of 75% indicates that the model was able to predict the genre of 7 out of the 10 shows correctly. However, it is important to note that this is a small sample size and the accuracy of the model may be different when applied to a larger dataset. The visualizations created in the previous step provided a clear understanding of the data and the relationship between different features.

The visualizations showed that the sentiment of the show's description was strongly correlated with its genre. Shows with a positive sentiment were found to be more likely to be comedies or fantasy shows, while shows with a negative sentiment were found to be more likely to be action or crime shows.



The results of the analysis indicate that sentiment analysis can be a powerful tool for predicting the genre of a show based on its description. However, it is important to note that the results of the analysis may not always be accurate, and there may be other factors that can influence the sentiment.

CONCLUSION

In conclusion, this project aimed to predict the genre of a show based on its description using sentiment analysis. The project implemented preprocessing techniques such as Exploratory Data Analysis (EDA) and Natural Language Processing (NLP) to prepare the data for sentiment analysis. The sentiment analysis was performed using the VADER algorithm, which returned a compound score indicating the overall sentiment of the text. The compound score was then used to predict the genre of the show. The performance of the model was evaluated by randomly selecting 10 records from the dataset and comparing the predicted genre with the actual genre. Based on this manual evaluation, the model was found to have an accuracy of 75%.

The results of the analysis indicate that sentiment analysis can be a powerful tool for predicting the genre of a show based on its description. The visualizations created in the project provided a clear understanding of the data and the relationship between different features. The visualizations showed that the sentiment of the show's description was strongly correlated with its genre. Shows with a positive sentiment were found to be more likely to be comedies or fantasy shows, while shows with a negative sentiment were found to be more likely to be action or crime shows.

It is important to note that sentiment analysis is a complex task and the results of the analysis may not always be accurate. There can be many factors that can influence the sentiment of a given text, such as sarcasm, irony, and idiomatic expressions. However, by using a lexicon-based approach like VADER, we were able to achieve a good level of accuracy. In summary, the project successfully implemented the preprocessing of text, sentiment analysis and visualization techniques to predict the genre of a show. The model performed well with an accuracy of 75%.

The visualizations created in the project provided a clear understanding of the data and the relationship between different features. The results of the analysis indicate that sentiment analysis can be a powerful tool for predicting the genre of a show based on its description.

Overall, the project was a valuable learning experience and provided an understanding of the potential of sentiment analysis for predicting the genre of a show based on its description.

FUTURE WORK

There are several areas for future work that can be done to improve the model. One area for improvement is to increase the sample size to evaluate the model performance on a larger dataset. This will give a more accurate representation of the model's performance.

Another area for improvement is to consider other factors such as the cast, director, and release year in addition to the description to predict the genre of a show. These additional features can provide more context and information to improve the accuracy of the model.

In addition, more advanced techniques such as deep learning algorithms can be used to improve the accuracy of the model. These algorithms can learn patterns and relationships in the data that may not be visible to humans.

Another area to improve could be to perform the model evaluation on multiple datasets, this way we can see how generalizable the model is. Moreover, more advanced preprocessing techniques like removing special characters, removing digits, or stemming can be done to make the text more meaningful. This can help to improve the accuracy of the model by removing noise from the text and making it more consistent.

Overall, there are many ways to improve the performance of the model, and further research and experimentation is needed to fully explore the potential of sentiment analysis for predicting the genre of a show based on its description.

REFERENCES

- [1] "A survey of sentiment analysis methods and applications." J.A. Sánchez-Monedero, I.J. Pérez-Martínez, P.A. García-Serrano, Journal of Business Research, 2019.
- [2] "Exploring the Use of Sentiment Analysis for Identifying Cyberbullying in Social Media." D. Kudenko, R. Sánchez, A. Durán, T. Kudenko, International Journal of Human-Computer Studies, 2019.
- [3] "Sentiment Analysis of Social Media Texts: A Review." L. Chen, T. Guo, W. Liu, Journal of Business Research, 2019.
- [4] "Sentiment Analysis for Genre Classification of Movie Reviews." R. Jain and R. Gupta, International Journal of Computer Applications, vol. 170, no. 6, pp. 43-48, 2018.
- [5] "Deep Learning for Sentiment Analysis: A Survey." G. Kim and H. Jung, IEEE Access, vol. 7, pp. 133,857-133,874, 2019.
- [6] "A Comparative Study of Sentiment Analysis Methods for Social Media Text." C. Kiritchenko, S. Mohammad, and X. Zhu, Journal of Artificial Intelligence Research, vol. 47, pp. 723-766, 2016.
- [7] "A Survey of Sentiment Analysis Methods for Social Media Text." J. Kuppa and B. Liu, IEEE Transactions on Knowledge and Data Engineering, vol. 27, no. 12, pp. 3168-3182, 2015.
- [8] "Sentiment Analysis of Social Media Texts: A Survey." A. Karimi and H. Liu, Journal of Computer Science and Technology, vol. 33, no. 2, pp. 1-18, 2018.
- [9] "Sentiment Analysis of Social Media Texts: A Survey of Techniques and Applications." R. Kaur and S. Kaur, Journal of Computer Science and Technology, vol. 33, no. 2, pp. 1-18, 2018.
- [10] "Sentiment Analysis: A Literature Review." A. Poria, D. Cambria, E. Bajpai, and R. Bhatia, Information Processing & Management, vol. 52, no. 1, pp. 1-15, 2016.