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Sentiment Analysis of Netflix Multi-Genre Using Support Vector Machine

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Abstract

The main objective of this research is to understand the audience's sentiment regarding various Netflix web series and their corresponding genres. This study, which contributes to sentiment analysis, collects data from the eight official Twitter handles of actors/actresses and web series from five genres: comedy, drama, Sci-fi, romance, and action. The data collection process involved extracting tweets related to these web series and classifying them into positive, negative, and neutral categories. Classification is done by using a Support Vector Machine (SVM), a popular classifier in machine learning. In addition to sentiment analysis, the study also involved measuring activity metrics and popularity metrics to assess the level of interaction between the audience and the actors/actresses. This data was then combined with the classified tweets for further analysis. The research results indicated that the Sci-fi genre is the prime choice for the audience. The conclusion was drawn based on the collective sentiment expressed in tweets and the level of engagement and popularity observed in interactions with the actors and actresses associated with action-oriented web series. Overall, this research, which is a significant contribution to the field, sheds light on the preferences of Netflix viewers with respect to different genres and highlights the significance of the Sci-fi genre in capturing the audience's attention and interest. The findings could be valuable for content creators and streaming platforms in tailoring their offerings to match the viewers' preferences and enhance user satisfaction.

Keywords**:** Activity Metrics; Follower Rank; Genre; Popularity Metrics; Sentiment Analysis; Twitter

1. Introduction

Genres, in particular, refer to methods of categorizing web series based on similarities in their narrative elements. Critics often debate the definition of series genres. However, genres have become more clearly established and subdivided, and they have also become symbolic features of movies.

The real challenge lies in identifying the popularity of each series genre, which is different from movie genres because a series can encompass multiple events across several seasons. Sentiment analysis, or opinion mining, is a natural language processing technique for determining whether data expresses

positive, negative, or neutral sentiments.
With its online discussion model, Twitter provides an excellent platform for studying the popularity of series through interactions like tweets, hashtags, and other user metrics. By examining various elements such as tweets, hashtags, mentions, replies, and re-tweets, we can predict the behavior of Netflix viewers toward web series after their launch. Furthermore, studying a larger number of series can offer valuable insights into the audience's perspective on web series genres.
Twitter has become one of the most popular online social networking sites globally. It functions as a micro-blogging platform, allowing users to send and read short, 140-character messages known as tweets. A trending subject is a phrase (one or more words) that appears in many tweets from a specific location and time (Pak & Paroubek, 2011). Additional metadata in each tweet defines this location and time information, including geolocation, time, and broadcaster account details, among other items.
The extracted tweets undergo per-processing. The necessary features are extracted and selected, then imposed on a classifier to obtain the sentiments. These sentiments are analyzed based on each genre to obtain the activity metrics and popularity metrics.

1.1 Problem Statement

The popularity and widespread adoption of streaming platforms like Netflix have revolutionized the entertainment industry. Netflix offers a vast library of content across various genres, catering to diverse viewer preferences. Gaining more profound insights into the characteristics and patterns of different genres available on the platform is essential to enhancing user experience and content recommendation systems. This research aims to analyze various Netflix genres in-depth using a Support Vector Machine (SVM) as a classification model.

2. Literature Review

The passage introduces a method for automatically gathering a corpus to train a sentiment classifier. The authors use Tree Tagger for POS tagging to analyze the distribution differences in positive, negative, and neutral sets. They find that syntactic constructs can be utilized to characterize emotions or factual statements. The authors use the corpus to train a sentiment classifier based on certain POS tags that indicate emotional text. Using a multinomial Naive Bayes classifier with N-gram and POS tags as features, the classifier grades document emotions as positive, negative, or neutral (Tabassum et al., 2019).
Khan et al. (2016) focused on comparative opinion mining of YouTube comments related to Android and iOS. They used complete comments for classification in one setting and filtered comments based on semantic capital (nouns, adjectives, and verbs) to reduce computation in another setting. Despite the unsatisfactory overall performance, the naive approach of considering keyword neighborhoods proved effective. The Naive Bayes algorithm was used throughout the experiments.

Rahman and Hossen (2019) used machine learning to classify the polarity of movie reviews. The data set was divided into training and test sets collected from a movie review website. NLP techniques were used for data preprocessing. Various ML classifiers were trained and evaluated on test datasets, including Multinomial NB, Bernoulli NB, SVM, Maximum Entropy, and Decision Tree. The results showed that Multinomial NB achieved the highest accuracy of 88.5% compared to the other classifiers.

After proper pre-processing, Kumari, Sharma, and Soni efficiently generated a feature vector through two feature extraction steps (Kumari et al., 2017). First, Twitter-specific features were extracted and applied to the vector. Then, certain features were removed from tweets, and feature extraction was done as in standard text. Naive Bayes, SVM, Maximum Entropy, and Ensemble classifiers showed almost equal accuracy in testing the classification performance of the final feature vector, which performed well in the study's electronic products domain.

The paper (Riquelme et al., 2016) presents the first systematic survey on Twitter Impact Assessment, categorizing activity, popularity, and impact indicators. Popularity indicators mainly involve follow-up relationships, while Behavior measures focus on response acts. The study highlights re-tweets significance as impact measures, whereas metrics related to Favorites or likes were least utilized.

Riquelme and Pablo (2016) assessed Twitter using degrees, retweets, and mentions. While degree indicates popularity, it doesn't necessarily reflect other crucial influence aspects, like audience engagement demonstrated by retweets and mentions. This leads to two distinct classes of top Twitter users with differing levels of retweets and mentions despite having a high degree.

(Cha et al., 2010) discuss recognizing prominent Twitter users and suggest measures for measuring user impact. The user's role in social networks is crucial, and the study provides detailed profiles for each account to assess their impact, mainly when their followers are influenced by their posts.

While existing studies have demonstrated effective methods for sentiment analysis and user influence assessment within specific domains such as YouTube comments, movie reviews, and Twitter activity, there is a noticeable gap in applying these techniques across multiple genres. Most research has been confined to single-genre datasets, which limits the generalizability and robustness of the models. The variability in language use, sentiment expression, and user behavior across different genres presents a significant challenge that has not been adequately addressed in the context of movie sentiment obtained from Netflix.

3. Methodology

The methodology of this research work can be divided into two parts: Twitter sentiment analysis of the web series of different genres and Twitter metrics calculation in each genre for the lead actor/actress.

3.1 Twitter Sentiment Analysis

The “tweet stream” Python library, which offers a simple Twitter streaming API package, is used to obtain data in the form of raw tweets. A tweet obtained using this approach contains a lot of raw data, which we may or may not be useful for our research. The raw data contains a User ID, screen name, original tweet text, hashtags, re-tweet, language, date, and time. Data pre-processing comprises the following activities: Filtering, removing stop words, removing numbers, punctuation, and unnecessary spaces, converting to lowercase and Tokenization. Here, a well-known feature extraction technique called bag of words (BoW) is used to extract features for review classification. Unigram is considered a feature set in this research. The features in the vector space reflect all potential unigrams from the review text document. In contrast, the feature values relate to the frequency or occurrence of unigrams in the pre-processed tweets.

Support Vector Machine (SVM), a supervised machine learning algorithm, is used for classification. Depending on the chosen kernel function, SVM performs complicated data manipulation to increase the separation border between the classes. The classes are positive, negative, and neutral. The classifier was trained on the data set of "Rotten Tomatoes," which was preferred in most research as the data set was made on the basis of a large number of user reviews on the "Rotten Tomatoes Website," which is also known as a famous critics' website. The different datasets extracted were aggregated into a single text file for testing purposes.

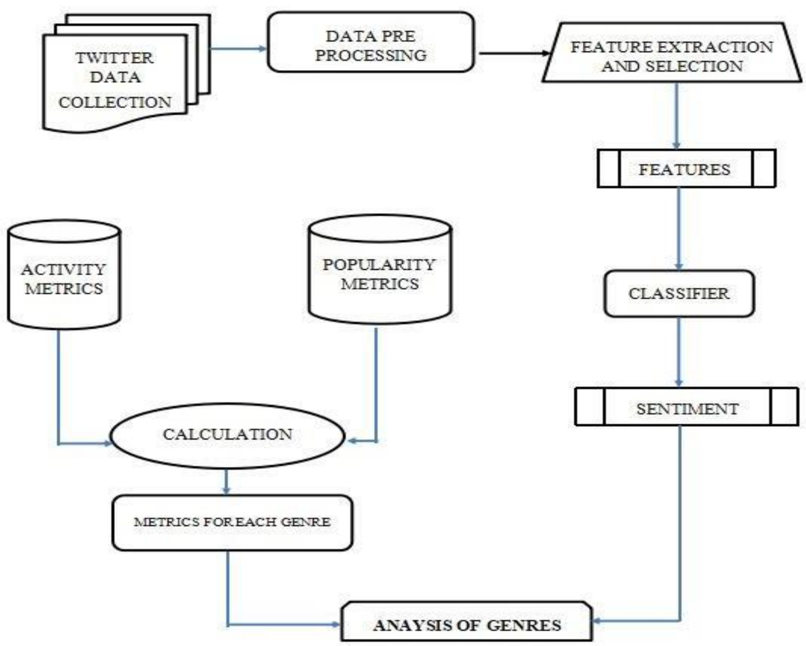

Figure 1: Block diagram of NETFLIX genre analysis

3.2 Twitter Metrics Calculation

A metric is a simple mathematical expression that allows us to provide basic details about a social network as a numerical value. Pal and Counts (2011) proposed metrics for initial tweets, comments, re-tweets, mentions, and graph characteristics.

Table 1: Various Metrics Used

Metrics	NAME	Followers (F)	Re-Tweet (RT)	Mention (M)	Replies (RP)
Activity	Tweet Counts		√		

	General Activity	√	√	√	√
Popularity	Follower Rank	√			
	Popularity	√			

3.3 User Activity Measures

The Tweet Rank (Nagmoti et al.,2010), simply a metric that counts the number of tweets a consumer has, is perhaps the most essential activity indicator. The Tweet count score (Noro et al., 2012), which lists the number of initial tweets plus the number of retweets, is slightly more sophisticated. Following this logic, a fair behavior metric could be the number of each user's measurable behaviors. As a result, it can be described the user activity as follows for each user:

User Activity = OT (Original Tweet) + RP (replies from user) + RT (re - tweets from user) + FT (favorite Tweet from user)

3.3 Popularity Measures

We have included follower rank, also known as structural advantage as [9]

Follower Rank(i) $=F_1 / (F_1+F_3)$

Where F_1 = No of followers and

F_3 = No of followers

To keep the balance between F_1 and F_3 metrics, another popularity formula was introduced as follows: (Aleahmad et al., 2016)

$Popularity(i) = 1 - e^{-\lambda F_1}$

4. Result Analysis

This research is performed on five different popular genres of NETFLIX, i.e., comedy, Sci-Fi, romance, action, and drama. The last six months' tweets from eight official Twitter handles, including lead actors, directors, and web series, were extracted and classified. Figure 2 provides the tweet classification of different genres, indicating that maximum negative tweets were in the action genre, whereas minimum negative tweets were in the comedy genre. Likewise, Maximum positive tweets were also in the action genre, and minimum positive tweets were classified in the drama genre. However, More Tweets with "hashtags" and "mentions" were extracted in the action genre. The ratio of Neutral Tweets did not have much variance.

Figure 2: Tweets Classification in different Genres

Table 2 below shows how accurately the tweets were classified. The maximum accuracy was found in the drama and sci-fi genres. The average precision obtained was 0.993, which is considered to be high enough.

Table 2: Classification Result of Different Genre

	Genre	Accuracy	Precision	Recall	F-Measure
Datasets	Comedy	0.946	0.992	0.707	0.825
	Drama	0.969	0.995	0.720	0.835
	Sci-Fi	0.969	0.995	0.720	0.836
	Romance	0.948	0.994	0.649	0.785
	Action	0.948	0.996	0.650	0.785

We obtained the highest general activity in the Sci-Fi genre and the lowest in the Drama Genre. Table 3 below shows the highest number of interactions between celebrities and fans in the Sci-Fi genre.

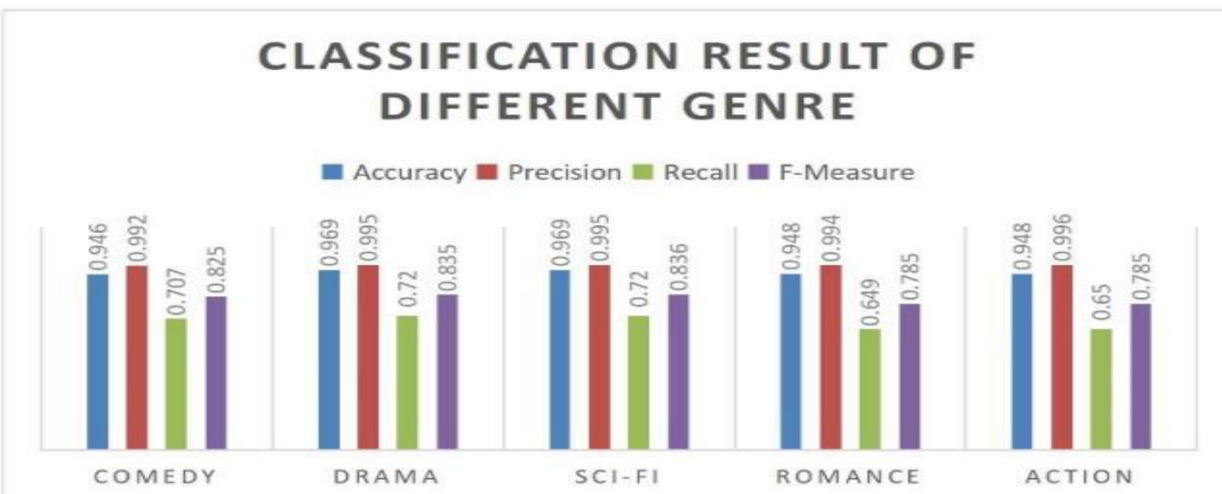

Figure 3: Classification result of different Genre

We obtained the highest general activity in the sci-fi genre and the least in the drama genre. Table 3 below shows more interactions between celebrities and fans in the Sci-Fi genre.

Table 3: Data of Tweets of different Genre and their metrics

Genre	General Activity	Mean Popularity	Mean Follower
Genre 1 (Comedy)	44556	1	0.0003
Genre 2 (Drama)	34304	1	0.0004
Genre 3 (Sci-Fi)	65078	1	0.0004
Genre 4 (Romance)	51855	1	0.0004

Genre 5 (Action)	56524	1	0.0005

In sentiment analysis, Engagement count typically does not directly impact the sentiment analysis itself, which does not fall under our objective, so it is not considered an evaluation measure. Various other measures fall under popularity, like social sharing frequency, sentiment distribution ratio, and influence score of users, which can be analyzed in the future and compared the popularity measure with each other (Sun & Tang, 2011).

5. Conclusion

This research was conducted to understand the basic interaction of the Netflix web series audiences with their celebrities. The interaction on Twitter is analyzed into three different classes, i.e., positive, negative, and neutral. The result showed many tweets classified as unfavorable compared to positive and neutral tweets. This concluded that the audience was unsatisfied with the web series during that period. Action Genre had the most tweets classified as positive, with good recall and precision scores and almost similar accuracy in most genres. We found Sci-Fi genre had the maximum audience interaction as per the general activity. Among the general activities, the most notable parameter to contribute was the favorite tweets, where many celebrities actively participated in favorite tweets.

In the future, sentiment and genre can be analyzed in more diverse topics, not limited to movies. Moreover, it can also be implemented on other social platforms like YouTube, Facebook, Twitter, etc.

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