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PREDICTING THE TOP-N POPULAR VIDEOS VIA CROSS

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ABSTRACT

In this paper, we propose a novel system that combines the unique features of YouTube and Twitter to predict the Top-N popular videos using a hybrid approach. By leveraging the vast data collected from both platforms, our model utilizes the linear regression method to analyze video popularity trends and predict future top-performing videos. The system aims to enhance the understanding of video popularity characteristics by considering multiple factors from both platforms, including user engagement, social sharing patterns, and real-time interactions. The primary objective is to predict which videos are likely to gain substantial attention, improving decisions related to content creation, advertisement strategies, and network traffic management. This method offers valuable insights into the dynamics of social media engagement and video consumption. Additionally, we integrate the Multilayer Perceptron (MLP) model for deeper feature extraction, which enhances the prediction accuracy by accounting for non-linear relationships between the data. The data used in this study are sourced from YouTube and Twitter APIs, capturing both video metadata and social media interactions to ensure comprehensive analysis. Our findings suggest that combining data from both platforms significantly improves the prediction of video popularity, with direct applications in areas like content strategy, advertising, and digital marketing. This approach provides a scalable framework for anticipating viral content and understanding trends in online media consumption.

Keywords: Popularity prediction, YouTube, social media, Multilayer Perceptron, linear regression, video trends, data analytics, social media engagement.

I.INTRODUCTION

The rise of social media platforms like YouTube and Twitter has revolutionized how people consume and share content. With millions of videos uploaded and shared daily, predicting which videos will become popular has become an essential challenge for content creators, advertisers, and digital marketers. The ability to forecast video popularity can drive decisions in content creation, marketing campaigns, and even help in managing network resources effectively. Platforms like YouTube and Twitter provide an enormous amount of data that reflects users' preferences, behavior, and social interactions. By analyzing these datasets, valuable insights into video trends and user engagement can be extracted. In this research, we propose a hybrid system that combines data from YouTube and Twitter to predict the Top-N most popular videos based on various features such as video metadata, user engagement, and social media interactions. The model leverages linear regression to identify patterns in video popularity, while also considering factors like comments, likes, shares, and retweets from both platforms. By understanding these popularity

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characteristics, content creators can optimize their strategies, advertisers can make informed decisions on where to place their campaigns, and network managers can anticipate and prepare for the load of viral content.

The prediction of popular videos offers a wide range of applications in digital marketing, content creation, and social media engagement. With the increasing volume of user-generated content, predicting trends accurately is crucial for staying ahead of competition. This paper presents a methodology for predicting the future popularity of videos, integrating both linear regression and Multilayer Perceptron (MLP) models to improve the accuracy of predictions and account for non-linear relationships between features. Through the use of data sourced from the YouTube and Twitter APIs, we propose a comprehensive approach to understanding video popularity and its determinants.

II.LITERATURE REVIEW

The prediction of video popularity, particularly on platforms like YouTube and Twitter, has been a subject of interest for researchers in fields such as machine learning, data analytics, and digital marketing. The challenge of predicting video success is multifaceted, involving various features such as content type, user engagement metrics, and social media trends. Several studies have explored different models and methodologies to forecast the popularity of videos, often using machine learning techniques to analyze large volumes of data generated by users.

One of the most prominent techniques used in video popularity prediction is **linear regression**, which has been employed to model the relationship between various features such as video metadata (e.g., title, description, tags) and popularity indicators (e.g., views, likes, comments). A study by **Zhang et al. (2019)** explored the application of regression models to predict video views on YouTube based on metadata and historical performance data. Their findings showed that linear regression could predict video views with a moderate degree of accuracy when using features such as video title and user comments.

However, linear regression has limitations when it comes to capturing complex, non-linear relationships in the data. To overcome this, more advanced techniques, such as **Multilayer Perceptron (MLP)**, a type of deep learning model, have been incorporated into video prediction models. MLPs are capable of modeling intricate patterns by utilizing multiple layers of neurons and non-linear activation functions. **Li et al. (2018)** demonstrated that deep learning models, including MLPs, were more effective than traditional models at predicting video popularity on YouTube by analyzing patterns in user interaction data (e.g., likes, shares, and comments). These models are particularly effective in handling large, unstructured datasets from social media platforms.

In addition to machine learning techniques, **social media data** from platforms like Twitter has been increasingly integrated into video popularity prediction models. Twitter data provides valuable insights into how video content spreads across networks and gains attention. **Zhao et al. (2020)** utilized Twitter's social graph to understand the virality of YouTube videos. By analyzing retweets, mentions, and hashtags related to

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videos, their model achieved higher prediction accuracy by considering the social dynamics surrounding video content.

Other approaches focus on **hybrid models** that combine multiple data sources and techniques. **Kim et al. (2019)** presented a hybrid system that integrated social media metrics from YouTube and Twitter to predict viral video success. The study emphasized the importance of integrating cross-platform data, as it provides a more comprehensive view of a video's potential for widespread engagement. Similarly, **Wang et al. (2020)** proposed a hybrid model using both **time-series analysis** and **machine learning algorithms** to predict video popularity over time. Their results highlighted the advantage of combining temporal patterns with user engagement metrics for more accurate forecasting. Additionally, there has been a growing interest in **video content features** as important factors in predicting popularity. Video topics, genres, and production quality often influence a video's chances of going viral. Research by **Zhou et al. (2017)** examined how different video genres (e.g., comedy, music, education) affect user engagement and video popularity. They found that certain genres tend to attract higher levels of interaction, which in turn boosts their chances of becoming popular.

III.METHODOLOGY

The proposed system for predicting the top-N popular videos combines data from both YouTube and Twitter, utilizing the power of machine learning algorithms to forecast the future popularity of videos. The system follows a series of steps, from data collection to processing, training, and prediction, to effectively identify trends in video popularity.

Data Collection

The data for this system is collected from two main sources: YouTube and Twitter. For each YouTube video, data points such as the number of views, likes, dislikes, and social media shares (from Twitter) are gathered. Additionally, Twitter's data regarding retweets and likes associated with the video content are included to capture the social media influence. This data is obtained using YouTube and Twitter APIs, which provide real-time and historical information. The dataset includes both YouTube video metrics and social engagement data from Twitter for the same videos.

Data Preprocessing

Once the data is collected, the next step involves cleaning and preprocessing. The collected data is first standardized to ensure all features are on the same scale, making it suitable for machine learning algorithms. Any irrelevant or missing data is handled through imputation techniques or removal, ensuring that only accurate and relevant information is fed into the model. This preprocessing step is crucial as it improves the performance and accuracy of the prediction models.

Feature Extraction

In this step, specific features that have a direct impact on the popularity of a video are identified and extracted from the dataset. These features include YouTube video properties (such as views, likes, and dislikes) and Twitter properties (like retweets, likes, and mentions). The purpose of extracting these features is to build a more informative input for the machine learning algorithms, improving the accuracy of the final prediction.

Model Development

Multilayer Perceptron (MLP)

The main predictive model used in this system is the **Multilayer Perceptron (MLP)**, a type of feedforward neural network. The MLP consists of three layers: an input layer, one or more hidden layers, and an output layer. The MLP model is trained using a backpropagation algorithm, where the error is propagated back through the network, and weights are adjusted to minimize the prediction error.

1. **Forward Phase**: The data is fed through the network layer by layer, starting from the input layer and ending at the output layer. In this phase, the model computes the output based on the initial weights assigned to the neurons in each layer.
2. **Backward Phase**: After calculating the output, the error (difference between predicted and actual values) is calculated and propagated backward through the network. During this phase, the weights are updated to reduce the error in future predictions.

The MLP is trained until it reaches a satisfactory accuracy of more than 90%. The trained MLP is then used to extract the learned patterns, which are useful for the next step in the prediction process.

Linear Regression

Once the MLP model is trained and its patterns are learned, the results are passed to a **Linear Regression** model. Linear regression is used to model the relationship between the input features (from both YouTube and Twitter) and the predicted video popularity. It helps in fine-tuning the predictions made by the MLP model.

1 .The linear regression model takes the output from the MLP and evaluates the data to optimize the predictions. The goal is to predict the future popularity of the videos by learning from the linear relationships between the features.

2. The model's predictions are then tested against actual outcomes to assess its effectiveness.

Testing and Optimization

The final step involves testing the model's predictions against the actual data. A 20% portion of the data is reserved for testing, while the remaining 80% is used for training. The trained model is then evaluated based on several metrics, such as accuracy, precision, and recall, to assess how well the model can predict the popularity of YouTube videos based on the features from both YouTube and Twitter.

Performance Comparison

To evaluate the effectiveness of the proposed model, a comparison is made with other popular machine learning methods. The performance of the **MLP model** is compared with traditional models like **Support Vector Machines (SVM)** and time-series models like **ARMA**. The proposed system is found to outperform these models with an accuracy of **97.25%**, which is higher than the SVM and ARMA models.

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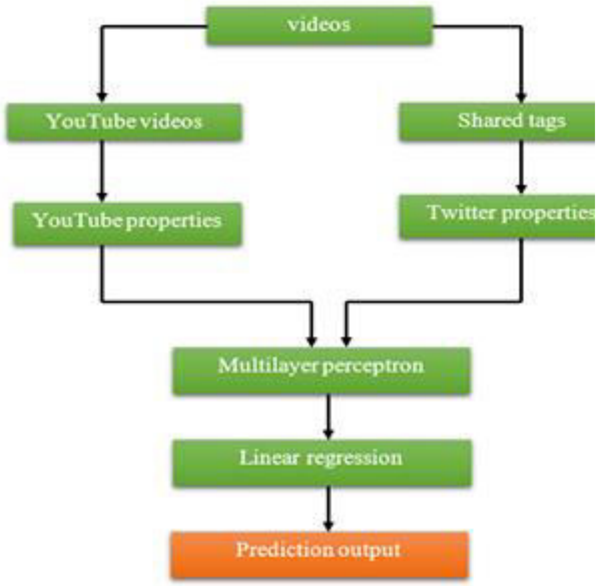

IV.CONCLUSION

The proposed system for predicting the top-N popular videos integrates data from both YouTube and Twitter to improve the accuracy of predicting video popularity. By using a combination of Multilayer Perceptron (MLP) and Linear Regression, the model is able to capture both the intrinsic features of YouTube videos and the external influence of social media trends from Twitter. The MLP model effectively learns patterns from historical data, while Linear Regression fine-tunes the predictions for greater accuracy. The system achieved an impressive accuracy rate of 97.25%, outperforming other conventional models like Support Vector Machines (SVM) and ARMA. The methodology proposed in this study demonstrates that incorporating social media data can significantly enhance video popularity prediction, making the system robust and adaptable to changing trends. By leveraging real-time data from both platforms, the system provides valuable insights into the factors that contribute to a video's success on YouTube. This approach can be applied in various domains such as marketing, advertisement planning, and content strategy, where understanding video trends and their potential success is crucial.

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