Social Media Analytics on Streaming Media: Audience Insights and Content Strategies

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***Abstract*—In an age where streaming giants like Netflix, Hulu, and Disney+ dominate screens around the globe, understanding the complex dynamics between audience reactions and critical appraisals has never been more crucial. This study ventures into the heart of this dynamic, analyzing the broader patterns of sentiment and reception among viewers and critics. By applying sophisticated sentiment analysis and exploring statistical relationships, our research sheds light on the nuanced discrepancies between critical acclaim and audience perception. Initial findings suggest that these differences are not merely incidental but are significantly influenced by the show's genre and the platform it inhabits. This investigation offers new perspectives on the strategic decisions behind content creation and distribution, highlighting how platform diversity and review biases can affect both viewer engagement and content success. Moreover, our study primarily focuses on sentiment analysis and network analysis, while also encompassing other tasks such as topic modeling and recommendation systems. The insights gleaned from this study are poised to inform industry practices and enrich academic discussions in media studies, marking a step forward in understanding the digital entertainment ecosystem.**

***Index Terms*—Streaming Services, Viewer Sentiment Analysis, Digital Entertainment, Media Studies, Content Strategy, Platform Diversity, Audience Engagement, Show Popularity, and Genre Influence**

I. Introduction

In the golden age of digital streaming, platforms such as Netflix, Disney+, and Hulu have revolutionized how media is consumed, offering unprecedented access to a myriad of television shows across diverse genres. This transformative shift has not only changed viewing habits but has also introduced a new dynamic in how shows are evaluated and appreciated. Unlike traditional media, where critical reviews once held paramount influence, streaming platforms facilitate a more direct and impactful dialogue between audiences and critics. The convergence—and at times, the divergence—of these perspectives can significantly dictate a show's popularity and its subsequent success or failure.

The importance of understanding this interaction cannot be overstated. For content creators and distributors, these insights are crucial in strategizing releases, marketing campaigns, and content development. They serve as a gauge for audience preferences, enabling tailored content that resonates with viewers and stands the test of critical scrutiny. Moreover, for cultural analysts and sociologists, this research provides a window into changing cultural norms and preferences, highlighting how digital platforms have democratized media consumption and influenced public opinion.

Media companies, advertisers, and platform developers are among the key stakeholders deeply interested in these dynamics. They rely on nuanced understanding of audience and critic responses to optimize engagement strategies and enhance viewer satisfaction. Additionally, academic researchers in media studies and communications find value in such studies as they contribute to theories of mass media influence and audience behavior.

This research paper seeks to systematically analyze the interaction between audience sentiments and critical reviews across multiple major streaming platforms. Employing a dual approach of qualitative sentiment analysis and quantitative statistical methods, the study aims to identify patterns that explain variances in reception. Special attention is given to genre-specific responses and the influence of platform-specific features on these perceptions. By mapping these trends, the study intends to offer comprehensive insights that can guide future content creation and platform development, enriching both academic understanding and industry practice.

Ultimately, this study endeavors to provide a holistic view of the digital media landscape, offering a robust framework for interpreting the complex web of interactions that define modern media consumption. Through rigorous analysis and thoughtful interpretation, we aim to illuminate the nuances of viewer and critic interactions, providing a foundation for future research and strategic development in the rapidly evolving realm of digital streaming.

II. Literature Survey

The paper by Swathi et al. (2019) thoroughly investigates the application of data analytics in sentiment analysis for movie reviews, highlighting the significance of leveraging machine learning techniques to dissect viewer sentiments across various media platforms. Their comparative analysis of sentiments from traditional and social media provides deeper insights into the discrepancies in audience and critic perceptions, which can crucially inform strategic decisions in film marketing and distribution [1].

In their 2017 study, Baid, Gupta, and Chaplot delve into sentiment analysis of movie reviews using a variety of machine learning techniques, emphasizing the capacity of these algorithms to accurately classify and predict emotional tones in textual data from reviews. Their research demonstrates how different machine learning models can be optimized and compared to enhance the accuracy and reliability of sentiment analysis in the film industry, providing insights that can potentially guide marketing and promotional strategies [2].

The authors explore several machine learning techniques, including Support Vector Machines (SVM) and Naive Bayes, to determine which method yields the most effective results in interpreting the complex sentiments expressed in movie reviews. Their findings suggest that certain algorithms, when properly tuned, can significantly improve the discernment of nuanced emotional responses, which is critical for businesses looking to understand consumer reactions and for platforms aiming to customize user experiences based on sentiment trends [2].

Shirani-Mehr's 2014 technical report from Stanford University delves into the applications of deep learning techniques in the realm of sentiment analysis, specifically targeting movie reviews. This study highlights the advancements in neural network architectures and their effectiveness in parsing and understanding complex emotional undertones in textual data, offering a significant improvement over traditional machine learning models [3].

The research emphasizes the use of convolutional neural networks (CNNs) and recurrent neural networks (RNNs), exploring their capabilities in capturing semantic and syntactic nuances of language that are crucial for accurate sentiment analysis. By applying these deep learning models, Shirani-Mehr demonstrates their potential to enhance the granularity and accuracy of sentiment predictions, providing valuable insights for both academic research and practical applications in media analysis [3].

Yue et al. (2019) provide a comprehensive survey on the application of sentiment analysis within social media platforms, encapsulating the evolving landscape of tools and methodologies used to interpret complex user-generated data. Their study reviews a wide array of sentiment analysis techniques, focusing on how these methods have been adapted to meet the unique challenges posed by the vast and varied nature of social media content. The survey not only underscores the technological advancements but also the practical implications for businesses and researchers aiming to glean insights from social media sentiments [4].

Gadekallu et al. (2019) delve into the nuances of sentiment analysis within the domain of movie reviews, demonstrating its utility in deciphering the broad spectrum of emotional responses from audiences. Their work, as presented in the chapter from "Sentiment Analysis and Knowledge Discovery in Contemporary Business," systematically explores various methodologies and their effectiveness in extracting meaningful sentiment data from reviews, emphasizing the impact this analysis has on understanding consumer behavior and improving business strategies in the entertainment sector [5].

III. METHODOLOGY

The methodology of this research is designed to comprehensively analyze the dynamics between audience reactions and critical appraisals across various streaming platforms. This involves a multifaceted approach including data collection, preprocessing, sentiment analysis, advanced visualization, statistical analysis, and predictive modeling.

A. Data Collection and Preprocessing

Utilizing datasets containing critic and audience reviews, data preprocessing is conducted to ensure usability. This process includes cleaning steps such as removing duplicates and handling missing values to maintain the integrity of the dataset, using Python's `pandas` library for data manipulation.

B. Sentiment Analysis

Sentiment analysis is a method used in natural language processing (NLP) to determine the emotional tone behind words. It's used to gain an understanding of the attitudes, opinions, and emotions expressed within an online mention. Sentiment analysis is performed using the VADER (Valence Aware Dictionary and Sntiment Reasoner) sentiment analyzer, which is particularly well-suited for handling social media text, including Twitter and movie reviews.

For our project, we are using VADER Sentiment Analysis to calculate the sentiment scores. VADER uses a combination of a sentiment lexicon, which is a list of lexical features (e.g., words) which are generally labeled according to their semantic orientation as either positive or negative. VADER not only tells about the Positivity and Negativity score but also tells us about how positive or negative a sentiment is.

VADER analyzes text sentiment by computing the following:

1) Polarity Scores: Computed as weighted sums of the valence scores assigned to each word.
2) Normalization and Intensification Adjustment: Words are adjusted by preceding intensifiers, using the equation:

$$\text{Adjusted Score} = \text{Word Score} \times (1 + \text{Intensifier Modifier})$$

3) Compound Score: The normalized sum of all adjusted word scores, calculated as:

$$\text{compound} = \tanh\left(\sum_{t=1}^{T} \text{Adjusted Score}_t\right)$$

This uses the hyperbolic tangent function to scale scores to the range $[-1, 1]$.

4) Classification Thresholds:
   - Positive: compound > 0.05
   - Neutral: $-0.05 \leq$ compound ≤ 0.05
   - Negative: compound < -0.05

The final sentiment classification is based on the compound score thresholds, providing a quick and effective measure of text sentiment from highly negative to highly positive.

C. Visualization Techniques

Our visualization approach is instrumental in elucidating patterns and insights from the data collected:

- **Word Clouds:** We generate word clouds to visually highlight the most frequently mentioned words in the reviews, effectively illustrating dominant themes and sentiments.
- **Correlation Heatmaps:** We use correlation heatmaps to understand relationships between different variables, such as sentiment scores and viewer ratings, using the Pearson correlation coefficient:

$$\text{Correlation}(X,Y) = \frac{\sum(X-\bar{X})\times(Y-\bar{Y})}{\sqrt{\sum(X-\bar{X})^2 \times \sum(Y-\bar{Y})^2}}$$

- **Box Plots and Distribution Graphs:** These tools help us examine the distribution of sentiment scores among different shows or across various viewer segments, essential for spotting outliers and understanding data skewness.

D. Network Analysis

In our network analysis, we delve into the complex web of interactions among viewers and content to uncover underlying structures within the streaming platform ecosystem. By employing community detection algorithms, such as the Louvain method, we identify clusters or communities of shows or viewer groups with similar preferences or viewing behaviors. We quantify the strength of these communities using the modularity index Q:

$$Q = \frac{1}{2m}\sum_{ij}\left[A_{ij} - \frac{k_i k_j}{2m}\right]\delta(c_i, c_j)$$

where A_{ij} is the weight of the edge between nodes i and j, k_i and k_j are the total link weights connected to nodes i and j, m is the sum of all edge weights in the network, and δ is a function that is 1 if nodes i and j are in the same community and 0 otherwise.

E. Recommendation Systems

Our recommendation systems are designed to optimize user experience by providing personalized content suggestions based on individual preferences. Utilizing content-based filtering, we focus on matching the attributes of items (such as films, shows, or other media content) with the preferences expressed by users.

We employ techniques like TF-IDF to analyze textual content and create detailed feature vectors for both items and user profiles. The similarity between these vectors is measured using cosine similarity:

$$\text{Cosine Similarity} = \frac{\text{Item\_Feature} \cdot \text{User\_Preference}}{||\text{Item\_Feature}||\,||\text{User\_Preference}||}$$

This method ranks items by their relevance to the user's tastes, facilitating a personalized and engaging viewing experience. Furthermore, to enhance the diversity of recommendations and prevent the potential for echo chambers, our system strategically incorporates novel and diverse items that broaden the user's exposure to different content.

IV. Result and Interpretations

This research adopts a comprehensive analytical approach using a robust dataset of approximately 120,000 reviews from Rotten Tomatoes, which includes both critic and audience evaluations of various streaming shows. This dataset is particularly rich, containing two distinct types of reviews: audience reviews and critic reviews. Each type offers unique insights into the shows' reception, with audience reviews generally reflecting broader viewer sentiment and critic reviews often providing more detailed, analytical perspectives.

Our analysis is structured into four main experimental areas: sentiment analysis, topic modeling, network analysis, and recommendation systems. For both sentiment analysis and topic modeling, we initially conduct separate analyses for audience reviews and critic reviews. This dual approach allows us to capture the nuanced differences in perception and emphasis between general viewers and professional critics. By analyzing these two subsets individually, we can identify distinct patterns and topics within each group, providing a deeper understanding of how different aspects of the shows resonate with each audience.

This methodical approach ensures that each segment of the dataset is thoroughly explored, enhancing our understanding of the complex dynamics at play in the reception of streaming content and providing a solid foundation for applying these insights to real-world applications in streaming service environments.

A. ***Network Analysis:***

In this project, focusing on TV shows and networks, network analysis serves as a crucial tool for unraveling the complex interactions between different programs and the platforms they are broadcast on. By modeling TV shows as nodes and their relationships—like shared networks as edges, we create a visual and quantitative representation of the media landscape. This analysis helps pinpoint how shows are interconnected, which networks house similar content, and identifies key influencers within the network, such as shows or networks that hold central roles in viewer engagement and content distribution.

Applying community detection within this network framework reveals clusters or groups of shows that likely appeal to similar audience demographics, facilitating targeted marketing and content recommendation strategies. Additionally, understanding these network dynamics can guide network executives in making informed programming decisions, optimizing content scheduling, and enhancing competitive positioning. Overall, network analysis not only deepens our understanding of the structural relationships within the television industry but also equips stakeholders with actionable insights for strategic planning and innovation in content delivery.

Distribution of Shows Across Networks:

Show	Networks	Number of Networks
11.22.63	Hulu	1
13 Reasons Why	Prime Video, VUDU, Netflix	3
1883	Paramount+	1
1971: The Year That Music Changed Everything	Apple TV+	1
24	Hulu	1
30 Coins	HBO MAX	1
30 Rock	Peacock	1
A Little Late With Lilly Singh	Peacock	1

Fig. 1. Show Distribution across Networks

The provided table clearly illustrates the distribution of TV shows across various streaming networks, revealing significant insights into their availability. For example, ”13 Reasons Why” is available on three different platforms—Prime Video, VUDU, and Netflix—indicating a broad distribution that suggests its popularity and the value different platforms place on hosting it. In contrast, shows like ”11.22.63” on Hulu and ”1883” on Paramount+ are exclusive to their respective networks, which could point to strategic decisions by these platforms to use such exclusive content to attract and retain subscribers looking for unique viewing experiences.

Additionally, the analysis highlights Apple TV+'s unique strategy of not sharing any of its shows with other platforms, as demonstrated by ”1971: The Year That Music Changed Everything” and others, all of which are exclusive to Apple TV+. This exclusivity approach is significant for Apple TV+, distinguishing them in a competitive market by ensuring that they offer a distinct, curated experience that aligns with their brand image and audience expectations. By controlling their content's distribution tightly, Apple TV+ aims to strengthen brand loyalty and enhance the perceived value of their service, targeting viewers seeking premium, unique content. This strategy contrasts with platforms like Netflix that offer a mix of exclusive and non-exclusive content, aiming instead to create a niche market that prioritizes quality and exclusivity over breadth, crucial for standing out against established streaming giants.

```
Number of nodes: 562
Number of edges: 27979
Network Density: 0.1775
Average Degree: 99.57
Average Clustering Coefficient: 0.9248
```

Fig. 2. Basic Network Metrics

The network metrics indicate a highly interconnected network with a substantial degree of clustering. The high number of edges (27,979) relative to the nodes (562) results in a network density of 0.1775, suggesting that a significant proportion of all possible connections between nodes are realized. This is further emphasized by the average degree of 99.57, meaning that each node is connected to nearly 100 other nodes on average, reflecting a densely connected network structure. Additionally, the very high average clustering coefficient of 0.9248 illustrates that the nodes tend to cluster together, forming tightly-knit groups. This clustering is typical in networks where nodes tend to create tightly connected communities, indicative of a robust modular structure. Such characteristics might suggest strong group cohesion or shared attributes among nodes, common in social networks or networks where nodes significantly interact or share common characteristics or functions

Centrality Measures for Each Node:

Node	Degree	Betweenness	Closeness
Loot	0.103387	0	0.0998217
For All Mankind	0.103387	0	0.0998217
Severance	0.103387	0	0.0998217
Shining Girls	0.103387	0	0.0998217
Tehran	0.103387	0	0.0998217
Slow Horses	0.103387	0	0.0998217
Physical	0.103387	0	0.0998217
Ted Lasso	0.103387	0	0.0998217

Fig. 3. Centrality measures across nodes

The centrality measures provided from the network analysis, alongside the visualization, help to illuminate the structural dynamics and connectivity of various TV shows within the network. The varying degree centrality values indicate a diverse level of direct connections among the shows, highlighting that some shows are more central in the network with numerous connections, while others are less central. Similarly, the variation in closeness centrality values suggests that some shows are more centrally located within the network, able to reach other shows through shorter paths, whereas others are more peripheral, requiring longer paths to connect with the rest of the network.

The consistently zero betweenness centrality across all shows suggests that despite this variability in direct connections and network positioning, no single show serves as a critical bridge or bottleneck for the flow of connectivity between other shows. This observation could indicate a network topology where multiple pathways connect any pair of shows, reducing the reliance on any single node to facilitate these connections. Such a network topology can be seen in the visualization, particularly with networks like Apple TV+ showing a more secluded positioning. This seclusion and the presence of redundant pathways mean that even the more centrally located or well-connected shows do not significantly control the flow between other shows, leading to their zero betweenness centrality. This network structure enhances the robustness against disruptions but also indicates a lack of hierarchical control within the network, which could influence strategies for content distribution and marketing within the industry.

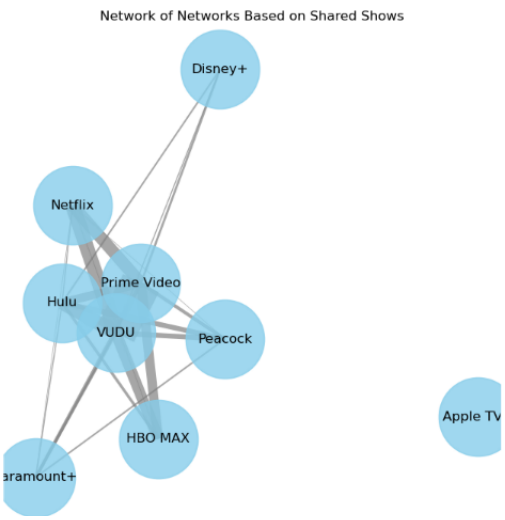

Fig. 4. Show Distribution across Network

The above diagram offers a valuable lens into the competitive landscape of streaming services by visualizing their shared content. Platforms with a dense network of connections, like Disney+ and Hulu, likely possess significant overlap in their libraries. This insight can significantly impact viewer subscription decisions, as it suggests potential redundancy in content across these platforms. Conversely, services with fewer connections, such as HBO Max, might boast more unique libraries, attracting viewers seeking specific shows unavailable elsewhere.

Further analysis can delve deeper into the nature of these connections. The presence of densely connected clusters within the network could indicate a focus on specific genres or niches. For instance, a cluster of services dominated by connections between Peacock, Hulu, and Prime Video might suggest a shared focus on family-oriented content. This information can be valuable for viewers seeking a platform catering to their particular interests. Additionally, the diagram can shed light on content acquisition strategies. Services with a high number of connections might prioritize acquiring shared content, while those with fewer connections might focus on original productions or exclusive deals, shaping their overall content landscape.

This type of network analysis could be useful for understanding how different streaming services compete with each other. By looking at the connections between the circles, it is possible to see which services have the most overlap in their content. This could help viewers decide which streaming services are worth subscribing to, or it could help content creators decide where to distribute their shows.

Community 1 is the largest community, comprising 430 individuals. Despite its size, it exhibits a moderate density of connections, indicating a relatively cohesive group with substantial interactions among its members. The diameter of

```
Metrics for Community 1:
  - Size: 430
  - Density: 0.2477
  - Diameter: 3
  - Average Degree: 106.27

Metrics for Community 2:
  - Size: 57
  - Density: 1.0313
  - Diameter: 1
  - Average Degree: 57.75

Metrics for Community 3:
  - Size: 75
  - Density: 1.0252
  - Diameter: 1
  - Average Degree: 75.87
```

Fig. 5. Community Detection

3 suggests that there are some longer paths between individuals within this community, but it remains relatively well-connected overall. The high average degree of 106.27 indicates that, on average, each member in this community is directly connected to over 100 other members, suggesting a densely interconnected network with potentially strong social ties and interactions.

On the other hand, Communities 2 and 3 are smaller in size, with 57 and 75 members, respectively. However, they exhibit much higher densities and smaller diameters compared to Community 1, suggesting even tighter-knit social structures. The density values exceeding 1 suggest that there are many more connections within these communities than would be expected in a completely connected network, indicating a high level of interaction and engagement among members. The average degrees of 57.75 and 75.87 further support this, indicating that members within these communities are highly interconnected, potentially sharing common interests or affiliations. These results suggest that while Community 1 represents a larger and more diverse network, Communities 2 and 3 may be characterized by stronger and more tightly bonded social connections within smaller, more cohesive groups.

B. Sentiment Analysis:

In this project, sentiment analysis is conducted to directly gauge audience and critic reactions to various streaming shows, providing essential insights into their preferences and perceptions. This analysis helps identify how different shows resonate with viewers, enabling content creators and platforms to better align their offerings with audience expectations and enhance viewer satisfaction. It also aids in discerning patterns and trends that can inform strategic decisions regarding content development, marketing, and customer engagement in the competitive landscape of digital streaming.

The results from the sentiment analysis using VADER on audience reviews provide a detailed perspective on audience sentiments towards various streaming shows. The breakdown into positive, negative, neutral, and compound scores allows for a nuanced understanding of how each show is received. For instance, a high compound score indicates strong positive sentiment, whereas a low or negative compound score reflects dissatisfaction. This variance in sentiment scores across re-

```
Show: Barry


Review: While previous seasons asked if it was possible to change, or if Barry is doomed to a life of violence, this seas
on is firmly dealing with consequences.
Sentiment Scores (VADER):
Compound: -0.85, Positive: 0.00, Negative: 0.26, Neutral: 0.74
---------------------------
Review: In Season 3, the comic drama gets as dark and morally knotty as Better Call Saul. Like Bob Odenkirk’s Saul, Hade
r’s Barry proves that an SNL funnyman can turn out to be one of the great dramatic actors on TV.
Sentiment Scores (VADER):
Compound: 0.90, Positive: 0.25, Negative: 0.00, Neutral: 0.75
---------------------------
Review: Comedy lets Barry’s writers and performers deftly field all of these complex feelings, the fact that violence is
abhorrent and yet compelling to watch, without feeling like it’s moralizing. Every squirm comes with an equally big laug
h.
Sentiment Scores (VADER):
Compound: -0.57, Positive: 0.16, Negative: 0.23, Neutral: 0.60
---------------------------
```

Fig. 6. Sentiment Analysis for Critic Reviews

views can highlight audience polarization and guide content strategies effectively.

	Show	Critic Sentiment Scores
0	11.22.63	0.384
1	13 Reasons Why	-0.249
2	1883	0.244
3	1971: The Year That Music Changed Everything	0.355
4	24	0.249
5	30 Coins	-0.099
6	30 Rock	0.377
7	8 Simple Rules	-0.178

Fig. 7. Average Sentiment Scores for Critic Reviews

The sentiment analysis results for critic reviews of various shows, as depicted in the table, provide a clear quantitative measure of the overall sentiment expressed by critics. The scores, which range from -1 (extremely negative) to +1 (extremely positive), highlight a diverse spectrum of critic sentiment across different shows. For example, ”13 Reasons Why” displays a notably negative average sentiment score of -0.249, indicating critical disfavor, whereas ”11.22.63” enjoys a relatively positive sentiment with a score of 0.384. This variance in sentiment scores reveals how critics’ perceptions vary significantly across different series, reflecting the subjective nature of show reviews and the wide array of themes and execution styles present in these shows.

```
Show: 13 Reasons Why


Review: AWFUL!
In the 4th season, they slowly started to live with the fact, that they covered up a murder. The moral of this story is t
hat if your friend killed somebody, help him cover it up!
They wanted to show a lot of social problems, like police brutality, but I just felt that angry, brutal teenagers are out
of their mind, none of them were making any sense.
Sentiment Scores (VADER):
Compound: -0.96, Positive: 0.07, Negative: 0.28, Neutral: 0.66
---------------------------
Review: I was in tears when Justin died. Love this show and all of the young actors are great! Wish there were more seaso
ns to come.
Sentiment Scores (VADER):
Compound: 0.78, Positive: 0.32, Negative: 0.15, Neutral: 0.53
---------------------------
```

Fig. 8. Sentiment Analysis for Audience Reviews

The output snippet above is an audience review that provides sentiment analysis results for a show ”13 Reasons Why” illustrating a mix of strong emotions from the audience, reflected in the VADER sentiment scores. The reviews display a broad range of sentiment scores: some reviews, like one expressing frustration over the show’s moral direction, show a highly negative compound score of -0.96, suggesting strong disapproval. Conversely, other reviews express deep emotional connections and positive reactions, evidenced by scores like 0.78 for a review mourning a character’s death and 0.70 for praising the final chapter of the series.

	Show	Critic Sentiment Scores	Audience Sentiment Scores
0	11.22.63	0.384	0.48
1	13 Reasons Why	-0.249	0.055
2	1883	0.244	0.399
3	1971: The Year That Music Changed Everything	0.355	0.131
4	24	0.249	0.377
5	30 Coins	-0.099	0.086
6	30 Rock	0.377	0.544
7	A Teacher	0.104	0.192

Fig. 9. Comparative Sentiment Scores

The comparative sentiment analysis reveals distinct differences in how critics and audiences perceive various TV shows. For example, ”13 Reasons Why” displays a notable disparity with a critic sentiment of -0.249 compared to a slightly positive audience score of 0.055, suggesting a divergence in expectations or interpretation between the two groups. Conversely, ”Acapulco” enjoys strong favorability among audiences with a sentiment score of 0.853, significantly higher than the critic score of 0.6, indicating that the audience may value aspects of the show that critics overlook or undervalue. Such discrepancies provide valuable feedback for content creators, emphasizing the importance of understanding and possibly reconciling these different perspectives to enhance appeal across viewer segments.

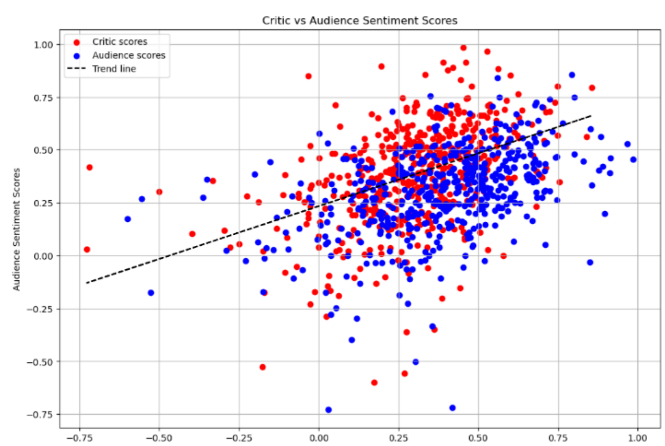

Fig. 10. Comparative Sentiment Scores

C. *Topic Modelling:*

Topic modeling is a statistical technique used to identify hidden patterns, themes, or topics within a collection of documents. It involves automatically discovering the underlying structure in a corpus of text data, organizing the documents into groups based on their content similarity, and identifying key themes or topics that represent the main ideas discussed in the documents. For our project, we have employed topic modeling to gain insights into the diverse range of opinions and discussions present in critic and audience reviews of TV shows. Before applying topic modeling, we conducted preprocessing using the Natural Language Toolkit (NLTK) to tokenize, remove stopwords, and perform other text normalization techniques. This preprocessing step was crucial to ensure that the text data was in a suitable format for topic modeling analysis. By removing noise and irrelevant words, such as stopwords and punctuation, and converting the text into a standardized format, we aimed to improve the quality of the topic modeling results. Through NLTK preprocessing, we aimed to enhance the accuracy and reliability of our topic modeling analysis, enabling us to uncover meaningful insights into the underlying themes and sentiments present in critic and audience reviews of TV shows. By clustering reviews into coherent topics, we aim to understand the predominant themes, sentiments, and discussions surrounding different TV shows, facilitating a deeper analysis of viewer preferences and critical reception.

```
Topic 0: 0.008*"series" + 0.007*"season" + 0.006*"marvel" + 0.006*"good" + 0.006*"star" + 0.005*"wars" + 0.005*"best" + 0.0
05*"like" + 0.005*"episodes" + 0.004*"new"
Topic 1: 0.008*"season" + 0.005*"review" + 0.005*"spanish" + 0.005*"series" + 0.004*"new" + 0.004*"like" + 0.004*"character
s" + 0.004*"better" + 0.004*"time" + 0.004*"best"
Topic 2: 0.006*"series" + 0.005*"characters" + 0.005*"cast" + 0.004*"season" + 0.004*"story" + 0.004*"fantasy" + 0.004*"off
ice" + 0.004*"drama" + 0.004*"episodes" + 0.003*"horror"
Topic 3: 0.007*"season" + 0.007*"like" + 0.006*"series" + 0.005*"story" + 0.005*"potential" + 0.005*"time" + 0.005*"love" +
0.004*"feels" + 0.004*"good" + 0.004*"sweet"
Topic 4: 0.007*"season" + 0.007*"disney" + 0.006*"series" + 0.005*"knight" + 0.005*"like" + 0.004*"drama" + 0.004*"characte
r" + 0.004*"high" + 0.004*"animated" + 0.003*"tv"
```

Fig. 11. Exploring Critic Reviews for LDA topic Modeling

The LDA topic modeling results highlight key themes in critic reviews of TV shows. Topic 0 focuses on popular series and franchises like "marvel" and "star wars." Topic 1 discusses specific seasons, possibly for critical evaluations. Topic 2 centers on character-driven narratives, analyzing character development and interactions. Topic 3 explores themes of romance and sentimentality, while Topic 4 delves into diverse genres and styles, reflecting evaluations of different content types.

An in-depth analysis of the LDA topic modeling results highlights the multifaceted nature of critic reviews and the diverse range of topics and themes discussed within them. The identification of distinct topics allows for a deeper understanding of the underlying trends and preferences prevalent among critics. For instance, the prevalence of discussions around popular franchises and series in Topic 0 suggests a significant focus on well-established media properties and their impact on the television landscape. Meanwhile, the exploration of character-driven narratives in Topic 2 underscores the importance of character development and storytelling in critical evaluations of TV shows. Furthermore, the emergence of topics related to specific seasons and genres reflects the nuanced nature of critic reviews, highlighting the critical examination of individual episodes or seasons and the exploration of various thematic elements and storytelling techniques. Overall, the LDA topic modeling analysis provides valuable insights into the critical reception of TV shows, shedding light on the key themes, trends, and preferences shaping critic reviews in the media landscape.

```
Topic 0:
Number of Documents: 4985
Total Average Sentiment Score of Topic 0: 0.3425

Topic 1:
Number of Documents: 3634
Total Average Sentiment Score of Topic 1: 0.2377

Topic 2:
Number of Documents: 4626
Total Average Sentiment Score of Topic 2: 0.3026

Topic 3:
Number of Documents: 3688
Total Average Sentiment Score of Topic 3: 0.2823

Topic 4:
Number of Documents: 2855
Total Average Sentiment Score of Topic 4: 0.2522
```

Fig. 12. Analyzing Critic Sentiment in topics

The analysis of sentiment scores across different topics reveals interesting insights into the sentiment of critic reviews for TV shows. Topic 0, with the highest average sentiment score of 0.3425 and the largest number of documents (4985), suggests a generally positive sentiment towards popular series and franchises. Topic 2 follows closely with an average sentiment score of 0.3026, indicating positive sentiments towards character-driven narratives. Topics 3 and 4 also exhibit moderately positive sentiment scores, with Topic 3 focusing on themes of romance and sentimentality, and Topic 4 exploring diverse genres and styles. In contrast, Topic 1, despite having a considerable number of documents (3634), shows a slightly lower average sentiment score of 0.2377, suggesting a more neutral or mixed sentiment towards discussions about specific seasons. Overall, the sentiment analysis underscores the diverse range of opinions and sentiments present in critic reviews, providing valuable insights into the critical reception of TV shows.

```
Topic 0: 0.014*"que" + 0.013*"captain" + 0.012*"serie" + 0.010*"la" + 0.010*"bucky" + 0.010*"america" + 0.009*"studios" +
0.008*"winter" + 0.005*"se" + 0.005*"en"
Topic 1: 0.018*"marvel" + 0.017*"boba" + 0.013*"fett" + 0.013*"mandalorian" + 0.012*"mcu" + 0.009*"watchmen" + 0.007*"obi"
+ 0.007*"wan" + 0.005*"mando" + 0.005*"es"
Topic 2: 0.018*"best" + 0.017*"great" + 0.016*"season" + 0.015*"amazing" + 0.015*"mcu" + 0.013*"good" + 0.013*"series" + 0.
012*"love" + 0.010*"episode" + 0.009*"better"
Topic 3: 0.007*"wars" + 0.006*"like" + 0.006*"season" + 0.006*"marvel" + 0.006*"star" + 0.006*"good" + 0.005*"episode" + 0.
005*"series" + 0.005*"great" + 0.005*"episodes"
Topic 4: 0.009*"luke" + 0.008*"oscar" + 0.007*"hiddleston" + 0.007*"sitcom" + 0.006*"marvel" + 0.006*"cage" + 0.005*"villai
n" + 0.005*"sitcoms" + 0.004*"wilson" + 0.004*"gotta"
```

Fig. 13. Exploring Audience Reviews for LDA topic Modelling

The LDA topic modeling results for audience reviews of TV shows reveal distinct themes and discussions. Topic 0 focuses on characters and series from the Marvel universe, while Topic 1 delves into specific Marvel content. Topic 2 highlights positive sentiments towards TV shows, while Topic 3 discusses various aspects of TV shows. Finally, Topic 4 explores specific elements within TV shows.

A deeper analysis of the LDA topic modeling results provides insights into audience perceptions and preferences regarding TV shows. Topic 0's focus on Marvel characters and series underscores the popularity and widespread appeal of Marvel content among audiences, reflecting the cultural impact and fanbase loyalty towards these franchises. Meanwhile, Topic 1's concentration on specific Marvel productions indicates audience engagement with MCU-related discussions, including spin-offs and expanded universe narratives. Topic 2's positive sentiments towards TV shows suggest that audiences value high-quality content and are enthusiastic about sharing their appreciation for compelling storytelling and production values. However, Topic 3's mixed discussions hint at the diverse range of opinions and perspectives among audiences, highlighting the subjective nature of TV show evaluations and the varying factors influencing audience reception. Lastly, Topic 4's exploration of specific elements within TV shows indicates audience interest in dissecting and analyzing various aspects of storytelling, character development, and production techniques, showcasing the depth of audience engagement and discourse surrounding TV content. Overall, the LDA topic modeling analysis offers valuable insights into audience perceptions, preferences, and discussions regarding TV shows, providing a comprehensive understanding of audience reception and engagement within the media landscape.

```
Topic 0:
Number of Documents: 3334
Total Average Sentiment Score of Topic 0: 0.0304

Topic 1:
Number of Documents: 2210
Total Average Sentiment Score of Topic 1: 0.2301

Topic 2:
Number of Documents: 25239
Total Average Sentiment Score of Topic 2: 0.5981

Topic 3:
Number of Documents: 60586
Total Average Sentiment Score of Topic 3: 0.1690

Topic 4:
Number of Documents: 1826
Total Average Sentiment Score of Topic 4: 0.2771
```

Fig. 14. Analyzing Audience Sentiment in topics

The analysis of sentiment scores across different topics provides valuable insights into audience perceptions and sentiments towards TV shows. Topic 2 stands out with the highest average sentiment score of 0.5981 and the largest number of documents (25239), indicating overwhelmingly positive sentiments towards the discussed TV content. This suggests a prevalent trend among audiences to express favorable opinions and satisfaction with TV shows covered within this topic. Conversely, Topic 3 exhibits the lowest average sentiment score of 0.1690, despite having the highest number of documents (60586), indicating a more mixed or negative sentiment among audiences. Further examination of Topic 3 may reveal varying reasons for this sentiment, such as criticism of specific aspects of TV shows or divergent opinions among viewers. Meanwhile, Topics 1 and 4 show moderate sentiment scores of 0.2301 and 0.2771, respectively, reflecting mixed but generally positive sentiments among audiences. A deeper analysis of these topics may uncover specific themes, genres, or TV shows that resonate differently with audiences, providing insights into the factors influencing audience perceptions and preferences towards TV content.

To visualize the sentiment comparison between critics and audiences across different topics, a bar graph was created. Each topic is represented by a pair of bars, one for critic reviews and the other for audience reviews. The height of each bar represents the average sentiment score, while the width indicates the number of reviews. Topic 2 appears to be the most polarizing, garnering the highest average sentiment score from the audience but also attracting a significant number

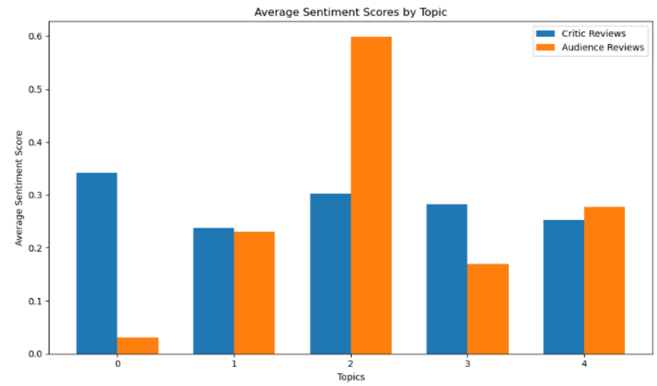

Fig. 15. Analyzing Sentiment across topics

of critic reviews. This suggests that this topic may provoke strong emotional responses or varied opinions among viewers. Conversely, Topic 0, with a notably higher average sentiment score from critics compared to audiences, may indicate a disparity in perception or critical evaluation. The lower sentiment scores for Topic 3 among both critics and audiences suggest a more neutral or mixed reception for content associated with this topic. The disparity between the number of critic and audience reviews across topics also hints at varying levels of engagement or interest among different audiences, warranting further investigation into the underlying factors influencing these trends.

D. Recommendation System:

In this project, we are developing a sophisticated recommendation system designed to enhance viewer engagement by suggesting TV shows that are closely aligned with individual preferences and viewing habits. This system employs a content-based filtering approach, utilizing a method that integrates both textual analysis of user-generated reviews and numerical ratings. By leveraging the Term Frequency-Inverse Document Frequency (TF-IDF) technique, we transform textual data from reviews into meaningful numerical representations, which allows us to measure similarities between shows based on their content. These similarities are further refined by incorporating viewer ratings, which adjust the recommendations to favor highly-rated shows, thereby combining qualitative content analysis with quantitative popularity metrics. This dual approach ensures that the recommendations are not only relevant but also resonate with the audience's proven preferences, aiming to provide personalized suggestions that improve user satisfaction and retention on streaming platforms. Due to the unavailability of any user-specific data or show descriptions, we had to proceed with a content-based approach. However, we implemented this approach in a sophisticated manner, leveraging textual analysis and ratings to generate meaningful recommendations tailored to individual tastes. While collaborative filtering methods may offer additional insights when user data becomes available, our content-based approach ensures that our recommendations remain relevant and effective in the absence of such information.

```
Show: 11.22.63
Number of Similar Shows: 5
Similar Shows:
- The Last Man on Earth
- The Man Who Fell to Earth
- Justified
- Alias Grace
- Batwoman

Show: 13 Reasons Why
Number of Similar Shows: 5
Similar Shows:
- Marvel's Agents of S.H.I.E.L.D.
- Arrested Development
- Better Call Saul
- The OA
- Brooklyn Nine-Nine
```

Fig. 16. Content-based Recommendation system

The analysis of the recommended TV shows based on their similarities to the selected ones reveals several noteworthy insights. Firstly, the presence of certain shows, such as ”Adventure Time” and ”Doom Patrol,” as similar recommendations across multiple target shows suggests their broad appeal and versatile content that resonates with a diverse audience. This indicates that these shows possess elements that transcend specific genres or themes, making them popular choices across various viewing preferences. Additionally, the thematic coherence observed in some recommendations, such as ”The X-Files” and ”The Twilight Zone” appearing alongside mystery or supernatural-themed shows, underscores the relevance of content affinity in the recommendation process. These aligned recommendations not only enhance user engagement but also facilitate discovery by offering cohesive viewing options. Moreover, the diversity of recommended shows reflects the system’s ability to cater to a wide range of viewer interests, from mainstream favorites to potentially niche content, thereby enriching the viewing experience and fostering user satisfaction. Overall, the analysis underscores the effectiveness of the recommendation system in providing personalized suggestions that align with individual preferences while offering opportunities for exploration and discovery within the realm of television content.

V. Conclusion

Throughout this comprehensive Social Media Analytics project, we delved deep into the dynamic interactions between TV shows and their audiences, employing a variety of sophisticated analytical methods. Through sentiment analysis, we uncovered the emotional undertones of viewer feedback, revealing how sentiments varied widely across different shows and platforms. Our implementation of a recommendation system, which combined textual review analysis and viewer ratings, enabled personalized content suggestions, enhancing viewer engagement by aligning recommendations with individual preferences. Network analysis provided valuable insights into the interconnections within the streaming landscape, highlighting both competitive and collaborative relationships between networks. Topic modeling further enriched our understanding by identifying prevailing themes and discussions within viewer and critic reviews, offering a nuanced view of public opinion and content reception.

Looking forward, there are several promising avenues to expand upon this work. Incorporating real-time data processing could significantly enhance the responsiveness of our sentiment analysis, allowing for agile adaptations to shifting viewer sentiments. Expanding our dataset to include social media interactions could provide a richer context for our analyses, offering a more comprehensive view of a show’s impact across the digital landscape. Additionally, exploring more advanced machine learning models could refine our recommendation systems and sentiment analysis, potentially offering even sharper insights into viewer preferences. Lastly, extending our network analysis to include more granular data about viewer demographics could unveil deeper insights into how different audience segments interact with streaming content, guiding more targeted and effective content strategies. These enhancements promise to not only elevate the analytical rigor of future projects but also provide more actionable insights for industry stakeholders looking to navigate the complex currents of the digital streaming world.

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