Leveraging Viewer Feedback

Enhancing Content Creation through Comprehensive Review Analysis

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Project Overview:
This project aims to refine Netflix's content analysis pipeline by integrating viewer review summaries with existing metadata, tags, and expert insights for improved identification of similar titles and more accurate audience size estimations for new content. It also examines the impact of a show's production region on viewer perception, introducing a novel approach to leverage both viewer feedback and expert analysis in a comprehensive strategy that enhances content personalization and decision-making. This initiative is expected to lead to more precise content recommendations, bolster viewer retention, and contribute to higher subscription growth. Additionally, the introduction of a summarizer feature aims to provide studio production, marketing, and content executives with direct insights into viewer reactions and preferences, further enabling them to tailor content, marketing strategies, and production decisions to meet viewer demands more effectively. The expected outcomes extend beyond improved resource allocation within Netflix to broader economic and societal impacts, such as fostering innovation in content production and promoting cultural diversity. This multifaceted approach not only addresses the challenge of catering to diverse viewer preferences in a saturated market but also marks a significant step towards creating a more dynamic, responsive, and inclusive entertainment ecosystem, driving greater user satisfaction and engagement.

Problem Statement:
Netflix's use of expert-based "learned embeddings" for recommendations may not fully align with viewer preferences, risking content mismatches and affecting satisfaction. Not using viewer reviews, which offer valuable insights into content, misses a chance to align with viewer trends. Integrating these reviews could significantly improve recommendation accuracy and viewer loyalty in the competitive streaming market.

Dataset(s):
Our study originally aimed to refine Netflix's content analysis models by analyzing user reviews with a focus on regional impacts, hypothesizing that cultural differences influence viewer feedback. Thus, we began by analyzing 500 user reviews from IMDb and Rotten Tomatoes for each of 10 globally popular Netflix shows from North America and East Asia, covering a variety of genres and ratings.These were sourced using an IMDb scraping script and MiniRPA data scraping tool. This resulted in the creation of four versions of the dataset: one with region labels, one without, one with only North American reviews, and one with only East Asian reviews to assess differences in classification accuracies. This approach sought to understand if incorporating regional embeddings enhances models' accuracy and aids in the prediction of ratings. The outcome of this approach indicated only minor differences in classification accuracies across the four datasets, implying that the region plays a negligible role. Thus the final dataset used moving forward was the one without any regional labels.

Analytical Approach and Results:
We began by exploring the impact of textual features and region on the performance of various machine learning models. We created four datasets, one with region and one without, and two with different types of regions (North America and East Asia) to analyze viewer reviews and ratings of Netflix content, focusing on how region may influence the classification accuracies of the different models. We tested both CountVectorizer and TfidfVectorizer to transform the text data, experimenting with different n-gram ranges and training our own Word2Vec model for deeper semantic embeddings. We also employed encoders such as OneHotEncoder and Label Encoder to handle the categorical variables. Due to the natural class

imbalance as a reflection of the show being a hit, we integrated SMOTE to address this effectively. Our analysis spanned several models, including Multinomial Logistic Regression, Linear SVC, Multinomial Naive Bayes, Random Forest, Gradient Boosting, and Multiclass XGBoost, with Logistic Regression consistently showing promise. Following the testing of these various models, we chose the best-performing model (Multinomial Logistic Regression) and compared the datasets with and without a region column, noting a minimal accuracy difference, the largest being only 3%. Additionally, we examined the coefficients of the Logistic Regression model to assess if the region was a significant influencer, finding that, despite its presence, the region did not dramatically affect the model's predictive accuracy, underscoring the nuanced role of regional preferences in content reception analysis.

This experiment formed the basis of our preprocessing and model prediction pipeline as we moved forward with the dataset without regional consideration. In addition to classification, the project introduces a Review Analysis Pipeline designed to generate concise summaries from viewer reviews, categorized by rating levels to provide actionable insights. This summarization process leverages TF-IDF vectorization and cosine similarity, combined with Latent Semantic Analysis (LSA), to distill key sentiments and feedback from a broad spectrum of viewer reviews. This summarization technique, while not traditional, is highly effective and precise, making it ideal for settings where detailed understanding of complex text is key. Tailored for various roles within the content creation and distribution process, such as studio production, content creators, and marketing executives, this approach aims to capture and utilize viewer feedback more effectively. By focusing on both the quantitative classification of content ratings and qualitative analysis of text reviews, the project seeks to enhance Netflix's ability to align content offerings with viewer preferences, thereby improving viewer engagement and overall content strategy.

Expected Outcomes & Business Implications:

Incorporating viewer reviews into Netflix's content analysis pipeline offers numerous benefits, including broadening the understanding of content through diverse audience reactions, enhancing personalization and recommendation accuracy by tapping into actual viewer preferences and discovering niche content. It provides cultural and demographic insights by highlighting preferences across different groups, essential for a global platform. The large volume of feedback and qualitative insights from viewer reviews can create a more comprehensive feedback loop, enriching quantitative data with nuanced viewer experiences. This approach aids in content strategy development by identifying themes and suggestions for new content and mitigating potential issues highlighted by viewers. Additionally, it offers competitive insights by comparing Netflix content with competitors and spotting emerging market trends, thereby positioning Netflix to better meet viewer demands and stay ahead in a competitive landscape.

Introducing role-based summaries filtered by high, medium, and low ratings as a separate feature for studio production, content creators, and marketing executives offers a strategic advantage beyond the general content analysis pipeline, facilitating nuanced content development and strategic marketing. High ratings highlight content strengths for replication, medium ratings reveal areas for refinement, and low ratings identify critical issues for correction. This approach enables precise promotional strategies such as dubbing/subtitles and responsive content adjustments, enhancing viewer engagement and optimizing Netflix's competitive positioning with focused, actionable feedback.

Appendix

Appendix 1. Future Strategic Steps & Directions for Netflix

Model scalability: To enhance model scalability, future efforts will focus on optimizing algorithms and infrastructure to efficiently process increasingly large and complex datasets. This involves employing distributed computing techniques and exploring more sophisticated machine learning frameworks capable of handling vast amounts of data across multiple dimensions. Additionally, expanding our analysis to include more regional markets and languages will necessitate advanced natural language processing capabilities to accurately interpret and analyze diverse linguistic data. Implementing these enhancements will enable our models to deliver more nuanced and globally relevant insights, making our recommendations for Netflix even more precise and impactful.

Other methodologies: Future exploration will consider deep learning for enhanced sentiment analysis and trend prediction, utilizing architectures like recurrent neural networks (RNNs) and convolutional neural networks (CNNs) for richer, context-aware analyses. This shift aims to capture subtleties in viewer sentiment and emerging trends more effectively, leveraging large-scale data to train models that can better predict viewer preferences and reactions. Incorporating these advanced methodologies could significantly refine our predictive capabilities, offering deeper insights into viewer behavior and preferences for Netflix.

Appendix 2. Streamlit Application

As part of the demonstration, we aim to showcase our project and its integration and impact within Netflix's models, through a Streamlit Application, which can be viewed here: https://text-analytics-kp5kbyhyuwblheynlr6vuh.streamlit.app/

References

Netflix. (2021, October 4). Supporting Content Decision Makers with Machine Learning. Netflix TechBlog. https://netflixtechblog.com/supporting-content-decision-makers-with-machine-learning-995b7b76006f