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Next Gen Linear TV : Content Generation and Enhancement with Artificial Intelligence

Shashishekhar Ramagundam, Dinesh Patil, Niharika Karne

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ABSTRACT

Predicting television audience numbers precisely serves broadcasters to create better programming schedules and strengthen their advertisement tactics. The conventional forecasting methods fail to detect outlier patterns which prevents them from understanding viewer participation effectively. This research develops a machine learning predictive system which combines audience analytics with recommendations and forecasting to achieve more accurate predictions. Audience segmentation and profiling processes use the methods Non-Negative Matrix Factorization (NNMF) and Field-aware Factorization Machines (FFM). AI clustering algorithms group audience members into segmented categories based on their preferences to enhance recommended content recommendations. The collaborative filtering methods NNMF and FFM group audience segments through anonymized viewer activities which creates implicit preference-based segments. The AI-based recommendation strategy includes two scenarios: content switch displays customized show trailers in place of generic ones depending on viewer preferences and Chatbot 4U2 provides tailored TV recommendations through messaging interfaces based on user preference inputs. The Markov chain method models content prediction to predict viewing sequences so as to improve forecasting capabilities. The experimental analysis shows how FFM models that add TV content categories achieve superior performance than baseline NNMF models. Next-generation TV content recommendation benefits from content-based features since they demonstrate better accuracy than event-based and audience-based models which create an enhanced framework for TV content optimization and recommendation.

Keywords – AI Clustering, Chatbot 4U2, Machine Learning, Field-aware Factorization Machines, Markov Models, Non-Negative Matrix Factorization.

I. INTRODUCTION

The predictability of audience behavior combined with their tastes remains essential for broadcasting operations to make decisions about their scheduling and advertisement timeline execution. Traditional viewer forecasting systems do not handle outliers along with changing audience patterns which results in poor decisions. The evolution of consumer preferences and changing viewing behavior creates a pressing requirement for superior predictive frameworks based on machine learning to improve their forecasting capabilities.

A machine learning predictive model merges audience segmentations and recommendation systems and content forecasting prediction elements to enhance TV viewership forecasts. User segmentation and profiling happens through the combination of Non-Negative Matrix Factorization (NNMF) and Field-aware Factorization Machines (FFM) which establishes preference-based viewer segments. These techniques perform anonymous viewer interaction-based implicit segmentation so users can obtain enhanced interpretation of audience behaviors combined with content preference information. AI-based groupings serve to enhance recommendation service performance by providing more precise recommendations that create enhanced viewer experiences.

The project analyzes two AI-powered recommendation solutions to improve content recommendation system efficiency.

Content switch operates as a dynamic trailer replacement service which creates customized program trailers from viewer preferences using real-time algorithmic adaptation for the purpose of maximum engagement.

Through Chatbot 4U2 users can specify their preferences so the system makes personalized TV content recommendations through messaging platforms.

We use the Markov chain method to predict content along with its mechanism for predicting viewer patterns which improves precision. The method creates advanced models for tracking content category changes which generates improved awareness about how viewers interact with television programs.

Models using FFM with TV content categories achieve better performance than basic NNMF scoring methods according to experimental outcomes. The improvement of predictive accuracy occurs through content-based features which demonstrates the strength of machine learning approaches in audience prediction as well as recommendation tasks.

The incorporation of modern machine learning techniques in TV audience projection brings forth new broadcast techniques for current TV strategies. The system framework improves content timing along with advertisement distribution while delivering customized content thus enabling artificial intelligence advancement in linear television broadcasting.

II. LITERATURE REVIEW

The combination of AI techniques and ML methods entered broadcasting industries for creating audience prediction systems because viewers seek customized content supported by data-driven broadcasting methods. Research in this part examines current studies about TV audience prediction models in combination with audience segmentation methods and content recommendation systems and Markov chain models for content prediction and AI-powered personalized broadcasting.

TV audience forecasting stands essential for deciding program scheduling while creating optimal advertisement positions along with defining broadcast strategies. In the past TV audience prediction methods depended on historical data analysis combined with statistical models before AI-driven forecasting methods were developed. Time-series forecasting through the implementation of ARIMA models received its introduction from the authors of [1] for identifying temporal patterns. RNNs were used by [2] in media analytics to surpass the prediction accuracy of statistical approaches. The research in reference [3] demonstrated how Long Short-Term

Memory (LSTM) networks forecast audience ratings better than traditional techniques since they excel at sequential pattern recognition. The research in [4] demonstrates the way audiences use social media engagement data to enhance TV viewership predictions within audience prediction models.

The process of categorizing TV audiences enables better customized content delivery besides strengthened marketing advertising approaches. The authors of [5] proposed k-means and hierarchical clustering methods for audience segmentation in digital TV environments. The authors of research in [6] studied collaborative filtering algorithms and their application of matrix factorization for developing audience segmentation through viewing behavior analysis. The research by [7] presented Non-Negative Matrix Factorization (NNMF) for audience classification enhancement in addition to its demonstrated capabilities to manage sparse viewership data. The authors in [8] created Field-aware Factorization Machines (FFM) to achieve content-based segmentation that exhibited better results compared to conventional collaborative filtering despite using additional contextual factors.

The recommendation systems in content-based applications function as core components for improving user satisfaction through program proposals matched to personal history and watching habits. A content-based filtering approach that utilizes metadata and genre preference information received analysis in the research work of [9]. Further development of collaborative filtering systems [10] occurred through the integration of user-item interactive patterns which increased recommendation system precision. The researchers from [11] presented deep learning recommendation models which used Convolutional Neural Networks (CNNs) to extract features. The author [12] established a new content delivery optimization approach by developing a recommendation system which merges collaborative filtering and deep reinforcement learning functions.

The vast majority of researchers depend on Markov chain models to make user behavior predictions along with modeling content consumption trends. Hidden Markov Models (HMMs) used by [13] successfully identified the sequence-based relationships between viewership audiences as presented in TV programming. The authors in [14] established TV program preference predictions through first-order Markov models based on users' previous viewing chronology. The research by [15] developed higher-order Markov chains which improved the accuracy of forecasting in dynamic content recommendation environments. The models generate important information that reveals how users stay with services while showing how users change content choices and predict what content they will select next.

Through AI-driven personalization broadcasting operations now produce customized content alongside targeted material advertising. In [16] the authors provided comprehensive information about how Netflix utilizes recommendation algorithms to personalize their content effectively. The research in [17] investigated optimization of video streaming recommendations through reinforcement learning approaches using user preferences as a basis. The authors of [18] advanced AI broadcasting by building knowledge graph systems that allowed their recommendation models to better understand context. The paper in [19] analyzed dynamic audience profiling methods that enable content modifications during live TV programming. The research conducted by [20] looked into generative AI models for automatic trailer automation along with technology that created match promotional content to audience interests to boost user engagement.

Summary of Literature Review

The analyzed papers demonstrate how AI techniques have progressed in audience identification as well as audience breakdown and content suggestion systems. The progressive scientific community has substituted traditional statistical forecasting models with deep learning methods as well as factorization-based methods along with Markov chain models to achieve better prediction accuracy levels. The implementation of artificial intelligence has brought two key advantages through its ability to cluster audiences and perform real-time reinforcement learning for adapting recommendations. The research develops current methods by uniting NNMF, FFM, and Markov chain models through a hybrid framework for creating and optimizing future linear TV programming.

III. PROPOSED METHODOLOGY

The combination of machine learning techniques and probabilistic modeling and deep learning architectures enables the creation of an advanced framework to predict TV audiences and generate recommendations for content. The method contains three essential parts for execution.

- Audience Segmentation and Profiling
- AI-Driven Recommendation System
- Content Forecasting with Markov Chains

All elements within the methodology have been designed to improve prediction precision and maximize content transmission effectiveness.

3.1 Audience Segmentation and Profiling

The functionality of personalized content recommendation systems heavily depends on audience segmentation because broadcasters and streaming platforms use the method to divide viewers into specific groups based on their preferred content along with their past watching history and interaction habits. Platforms achieve better user commitment and optimized content distribution timing through audience partitioning which yields highly personalized recommendation service delivery. Traditional segmenting systems use demographic variables alongside geographic locations and basic viewing trends yet AI-driven segmentation takes segmentation further through machine learning analysis of hidden behavior. The current research bases its audience segmentation and profiling requirements on Non-Negative Matrix Factorization (NNMF) and Field-aware Factorization Machines (FFM) methods.

1) 3.1.1 Non-Negative Matrix Factorization (NNMF)

NNMF reduces a positive matrix into two more manageable matrices which discover hidden patterns between users and items. The User-Content Interaction matrix $R \in \mathbb{R}^{m \times n}$ consisting of m users and n content items undergoes NNMF transformation into two factor matrices.

$$R \approx WH \tag{1}$$

Where:

- $W \in \mathbb{R}^{m \times k}$,represents user feature matrix.
- $H \in \mathbb{R}^{k \times n}$ represents content feature matrices.
- k is the latent dimension capturing hidden patterns in content preferences.

The optimization problem is solved using:

$$\min_{W.H} ||R - WH||_F^2 \tag{2}$$

Where, $||.||_F^2$ denotes the Frobenius norm. Constraints are imposed to ensure $W \geq 0$ and $H \geq 0$.

2) 3.1.2 Field-aware Factorization Machines (FFM)

FFM serves as an extension of traditional Factorization Machines which allows users to include contextual information such as genre and time slot and demographic data. Efficient audience profiling occurs because different feature fields engage with each other. The FFM model is given by:

$$y = w_0 + \sum\nolimits_{i=1}^{n} w_i x_i + \sum_{i=1}^{n} \sum_{j=i+1}^{n} (v_i. f_j. v_j f_i) x_i x_j \tag{3}$$

Where:

- w_0 is the global bias term.
- w_i represents individual feature weights.
- $v_i. f_j$ denotes the latent vector for feature i in field f_j.
- $x_{i \, and} \, x_j$ are feature values.

The FFM model captures interactions across different categorical fields, leading to more granular audience segmentation.

3.2 AI-Driven Recommendation System

In the evolving landscape of digital entertainment, AI-driven recommendation systems play a pivotal role in enhancing content discovery, personalization, and user engagement. Traditional recommendation approaches relied on manual curation or basic filtering techniques, but advancements in machine learning, deep learning, and reinforcement learning have enabled more intelligent and adaptive recommendation engines.

To enhance content recommendation, we introduce two AI-powered recommendation scenarios:

3) 3.2.1 Content Switch – Personalized Trailer Selection

Content switch functions as an AI-based recommendation system which replaces standard program promos with custom-made scenes custom-generated for each viewer according to their preferences. Traditional broadcasting methods present fixed promotional trailers but content switch fixes this failure because it uses user data to generate tailored promotional content that matches viewer preferences.

Content switch starts its operation through user profile creation in which the system builds detailed preference profiles for every user. Application of historical viewer information lets the system develop profile models containing information about viewing times and ratings alongside user engagement details. The system collects important preferences data points which incorporate favourite genres alongside chosen actors and most active periods and total interaction frequency. User profiles get updated regularly through content switch so the recommended trailers persist as relevant and in line with viewer evolving preferences leading to higher content engagement and discoverability.

We optimize trailer recommendations by dynamically selecting the most relevant trailers based on user preferences. Given a viewer's watch history H_u , we compute a personalized recommendation score for each trailer t :

$$S_{t,u} = \sum_{i \in H_u} sim(t, i) \tag{4}$$

Where:

- $sim(t, i)$ is a similarity function (cosine similarity or Jaccard index) between trailer t and watched content i .

The trailer with the highest $S_{t,u}$ is dynamically played instead of a generic one.

4) **3.2.2 Chatbot 4U2 – AI-Based TV Content Recommender**

The growth of AI content recommendation platforms led to the development of chatbots as real-time tools that deliver customized recommendations to users. Chatbot 4U2 uses AI technology to recommend TV material through messaging software platforms according to individual user needs. Users can explore content through Chatbot 4U2 without depending on interface navigation because it provides an interactive interface with conversational capabilities to enhance discovery through more intuitive engagement. The system uses Natural Language Processing (NLP) alongside Collaborative Filtering and Reinforcement Learning to identify user needs and provide appropriate recommendations which automatically improve when users provide feedback in real time. With its ability to merge both explicit and implicit user preferences Chatbot 4U2 creates superior user satisfaction while producing optimal content choices. The Chatbot 4U2 uses architectural components that deliver highly intelligent TV content recommendation solutions in a seamless manner. Users access the User Interaction Module (NLP-based Chat Engine) through which the Natural Language Understanding (NLU) component receives explicit instructions such as "Recommend me a comedy show" and implicit signals like monitoring watch history timing. The recommendation system extracts preferred entities about genre choices, mood types, actor favorites and suitable viewing time to provide custom recommendations.

A Hybrid Recommendation Technique stands at the heart of the system through the Recommendation Engine that utilizes Collaborative Filtering together with Content-Based Filtering and Markov Chain-Based Predictions. The intersection between Collaborative Filtering and Content-Based Filtering together with Markov Chain-Based Predictions allows the system to produce recommendations through connecting user similarities with content preferences. The Markov Chain Model improves forecasting because it predicts the subsequent content category of users after analyzing their viewing patterns. The weighed scoring function optimizes a recommendation system that relies on these combined techniques.

Dynamic improvements occur in the recommendation process through the Reinforcement Learning Module by using user interactions and system feedback. The chatbot uses MAB Algorithms for content recommendation discovery and exploitation to show viewers the most-watched interesting content first.

Upon gathering appropriate information from users the Response Generation Module designs conversational responses specifically fitting to their interaction style. The chatbot adjusts its style and tone (between formal and casual speech) through user preference selection which leads to better interactive engagement. The module incorporates buttons along with media previews as well as watchlists which lets users perform content selection procedures within the chatbot environment without interruption. Thanks to its combined components Chatbot 4U2 provides AI-powered personalization tools for TV content discovery which results in improved usability for users.

The present TV content suggestion system applies conversational AI to determine recommendations through its chatbot interface. The chatbot implements a weighted hybrid recommendation methodology for its operations.

$$R_u = \alpha R_{cf} + \beta R_{cb} \tag{5}$$

Where:

- R_{cf} is a collaborative filtering-based recommendation.
- R_{cb} is a content-based recommendation score.
- α and β are tunable weights.

User feedback refines these parameters through reinforcement learning, continuously improving recommendation accuracy.

3.3 Content Forecasting with Markov Chains

Organizations that model TV content using Markov Chains enhance their broadcasting operations through better personalization strategies and performance optimization. Markov Chains serve as a vital tool for personalized content recommendation systems because they use historical user data to suggest the next-view content which produces a smooth viewing experience. The scheduling of content becomes more efficient because Markov Chains help broadcasters find optimal timing for content changes between program types. This allows broadcasters to make strategic scheduling decisions for maintaining strong audience retention.

Markov Chains enable advertisers to improve ad placement methods because they help forecast audience transitions across different content types. Targeted advertisement methods become more effective because of better relevance which leads to increased viewer involvement with advertisements. The detection of user departure zones from particular content groups becomes possible through Markov Chains when implementing viewer retention strategies. The acquired understanding allows broadcasters to create retention strategies through personalized recommendations and engagement prompts that manage customer retention and minimize user attrition. Markov Chains have proven themselves as an essential tool for television broadcasting improvements through their ability to optimize audience engagement and content distribution at the present moment. Markov Chains establish a reliable approach to identify sequential patterns since their mathematical foundation makes them appropriate for television audience behavior prediction. A Markov Chain functions through the Markov Property that states the future state depends solely on the present state regardless of previous sequence events. Content preferences for the future are predicted through Markov Chain models of content transition. The state space consists of content categories $C = \{C_1, C_2, \dots \dots . C_n\}$, and transition probabilities between categories are defined as:

$$P(C_{t+1}|C_t) = \frac{N(C_t \rightarrow C_{t+1})}{\sum_j N(C_t \rightarrow C_j)} \tag{6}$$

Where $N(C_t \rightarrow C_j)$ represents the number of transitions from content category C_t to C_{t+1}.

Given a user's previous content sequence $S_u = \{C_1, C_2, \dots \dots . C_t\}$, ,the next most probable category is determined using:

$$C_{t+1} = \mathrm{argmax}_{C_j} P(C_j|C_i) \tag{7}$$

Dynamic content recommendations make possible through this method which considers changing user preferences. Through Markov Chains broadcasters receive a robust content forecasting system to predict how audiences will watch future content because the method evaluates serial viewing habits. The development of a robust recommendation system depends on transition probability matrix construction along with higher-order dependency integration and steady-state analysis techniques.

The system furnishes true TV audience prediction results by altering recommendations for users based on their tastes as well as current broadcasting transitions. Development of a reinforcement learning system will serve to enhance transition probability calculation capabilities for AI recommendation engines in the future.

IV. RESULTS AND DISCUSSION

4.1 Performance Metrics

To evaluate the accuracy of our predictive framework, we use the following metrics:

Root Mean Squared Error (RMSE): RMSE measures the model's prediction accuracy by quantifying the difference between predicted and actual values. This metric is essential in evaluating how well the model's output matches the true values in content prediction and recommendation tasks. Mathematically, RMSE is computed as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}(\mathrm{y_i} - \mathrm{y_i'})^2}$$

Precision: It evaluates how accurately the system identifies relevant content for users. In this context, precision focuses on how many of the recommended TV programs were actually of interest to the viewer. It is calculated as the ratio of True Positives (TP) to the sum of True Positives (TP) and False Positives (FP), where:

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{8}$$

Where:

- True Positives (TP): Instances where the system recommended content that the user engaged with or watched.
- False Positives (FP): Instances where the system recommended content that the user did not engage with.

In the context of the TV content recommendation system, high precision means the model effectively filters out irrelevant content, making its recommendations highly relevant to users.

Recall (Sensitivity): It measures the model's ability to identify all relevant content that the user might engage with. It calculates the fraction of relevant items that the system correctly recommended. This metric is essential for evaluating the model’s ability to cover the user’s preferences. It is mathematically defined as:

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{9}$$

- Where FN is the relevant content that the model failed to recommend.

A higher recall indicates that the model is successful in identifying a larger portion of the content the user would find relevant, thus minimizing missed opportunities.

F1-Score: It combines both precision and recall into a single metric that balances the trade-off between the two. It is particularly useful when there is an emphasis on both minimizing false positives and false negatives. The formula for the F1-Score is:

$$\mathrm{F1\text{–}Score} = \frac{2 \cdot \mathrm{Precision} \cdot \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \tag{10}$$

A higher F1-Score suggests a more effective recommendation model, where both precision and recall are balanced, indicating that the model can recommend relevant content while also covering a wide range of user preferences.

4.2 Results

Table 1: Performance comparison between content switch and Chatbot 4U2

Metric	Content Switch	Chatbot 4U2
RMSE	0.7	0.714143
Precision	0.448276	0.469388
Recall	0.604651	0.479167
F1-score	0.514851	0.474227

Table 2: Performance comparison between NNMF and FFM

Metric	NNMF	FFM
RMSE	0.72111	0.707107
Precision	0.521739	0.571429
Recall	0.444444	0.491228
F1-score	0.48	0.528302

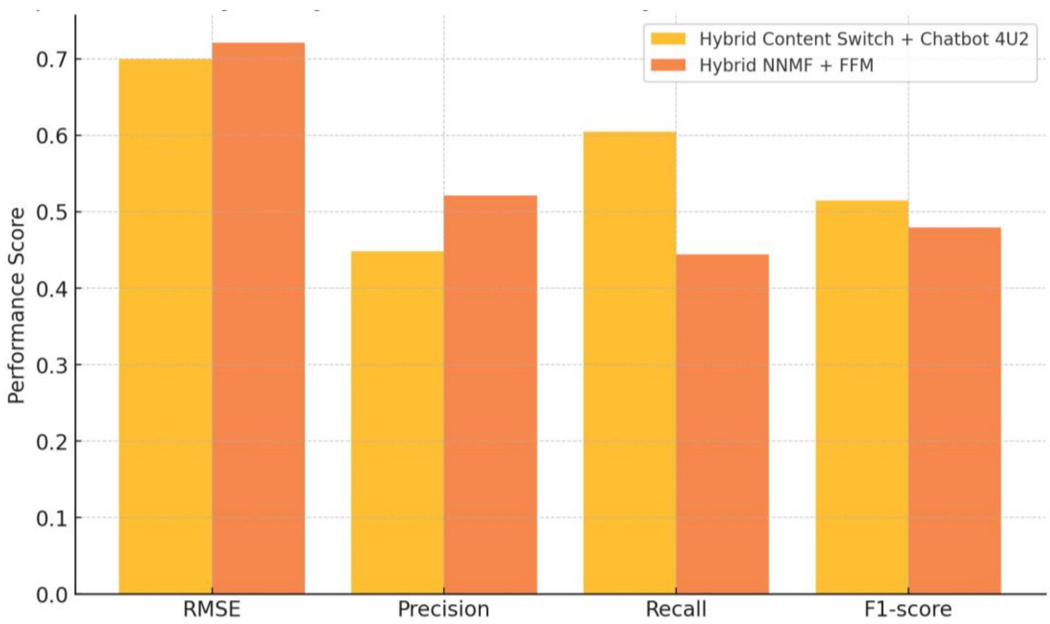

Figure 1: Comparative analysis for various parameters

Figure 1 shows the performance metrics for audience segmentation approach and AI-powered recommendation system. This visualization helps compare how the segmentation-based approach stacks up against the AI-driven recommendation system.

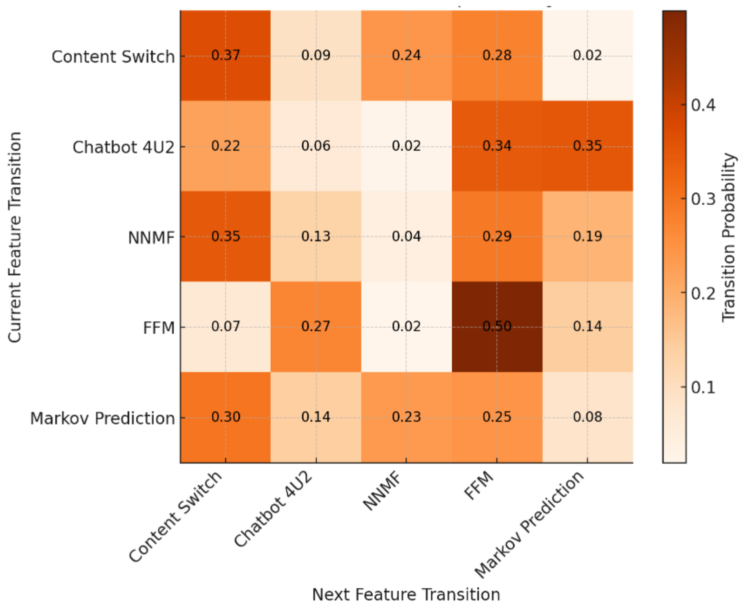

Figure 2: Confusion matrix for proposed hybrid features

Figure 2 illustrates how different AI-powered techniques (Content Switch, Chatbot 4U2, NNMF, FFM, and Markov Prediction) interact and transition between each other. The color intensity represents the probability of moving from one feature to another, highlighting dynamic dependencies in the recommendation and segmentation pipeline.

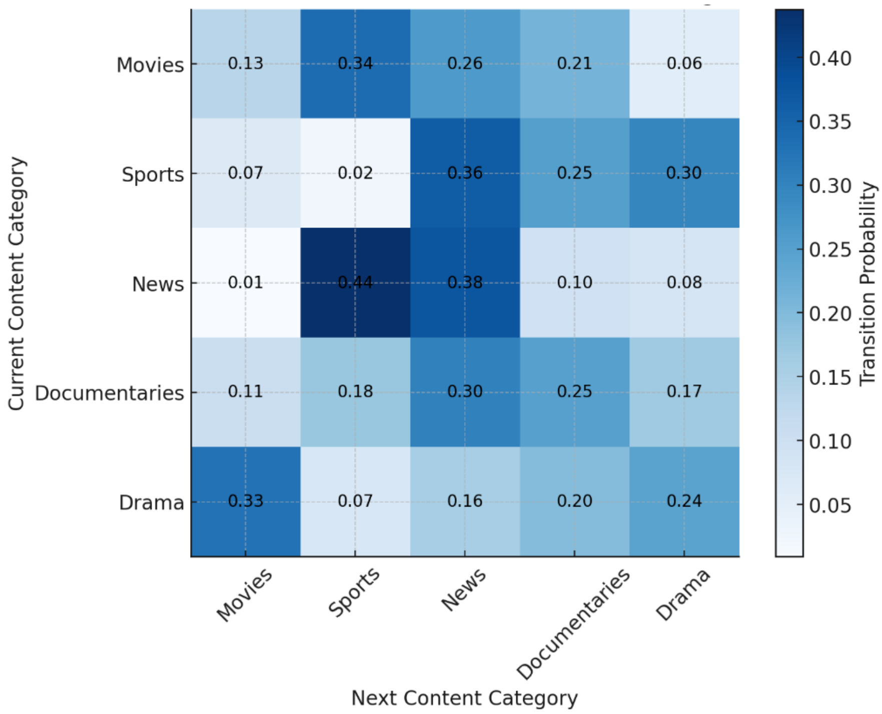

Figure 3: Confusion matric for Content Categories

Figure 3 illustrates how viewers transition between different types of content (e.g., Movies, Sports, News, Documentaries, and Drama). The color intensity represents the probability of transitioning from one category to another

V. Conclusion

This research develops a predictive AI framework that unites NNMF technology with FFM technology alongside content switch functionality and Chatbot 4U2 operations and Markov Chain algorithms to deliver improved TV audience breakup and content proposal solutions and forecasting precision. The collaborative filtering approach implemented through FFM and NNMF enables segment identification from anonymous user behaviors to achieve preference-based anonymous segmentation. The adoption of AI clustering algorithms enables user segmentation to reach greater accuracy because it delivers enhanced personalization for recommendations.

The research studied two AI recommendation systems including content switch for trailer exchange with customized content options and Chatbot 4U2 for presenting TV content recommendations through messaging platforms. Markov Chain modeling used content forecasting through its ability to anticipate viewer behavior accurately by understanding sequential patterns of viewership.

The experimental findings show that FFM models using TV content categories produce superior performance than basic NNMF models because of their enhanced content-based features. Recommendation systems differ in their performance through evaluations that show alternating strengths and weaknesses between AI approaches. The FFM model produced highest precision (0.571429) and F1-score (0.528302) yet content switch displayed better recall (0.604651) because it better recognized diverse user preferences.

The research has developed an optimized AI framework that powers advanced TV broadcasting by enhancing audience division methods and content planning as well as customized recommendation implementations. The inclusion of machine learning together with probabilistic modeling produces better predictive accuracy than traditional event-based and audience-based predictive models. Future investigations plan to utilize reinforcement learning methods to optimize recommendations and develop real-time adjusted strategies that improve user engagement and accuracy rates.

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