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Enhancing Linear TV Channel Surfing:

A Real-time Personalized Ranking and Recommendation System with Dual Dynamic Queues

By Ning Xu, Ph.D., and Tao Chen, Ph.D.

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Abstract
The proliferation of linear TV channels complicates content discovery, necessitating more efficient methods for viewers. This paper presents a real-time personalized ranking and recommendation system designed to enhance viewer satisfaction and interaction through dynamic channel surfing. Our approach uses a dual dynamic queue system, comprising Dynamic History Channel Queue (DHCQ) and Dynamic Future Channel Queue (DFCQ), to manage the viewer's interaction effectively. Leveraging advanced deep learning models, we generate "global" and "local" content embeddings and "user" embeddings to ensure real-time updates tailored to content and user time-sensitivities. A 'look-ahead' feature further enriches personalization by considering upcoming content on each channel. Preliminary user feedback indicates a strong preference for this system over traditional channel navigation methods, highlighting its potential to transform how viewers engage with linear TV. This paper underscores the system's significant contribution to improving linear TV content discovery and its implications for enhancing viewer satisfaction.

In an era of digital transformation, traditional linear television is undergoing rapid changes, including the surge in the number of channels available to viewers. According to a report by Nielsen in 2016, the average American adult had access to more than 200 TV channels,[1] a significant increase from the past. This explosion of channels often leads viewers to grapple with an overwhelming amount of content, finding it increasingly challenging to navigate through it and discover programming that caters to their preferences. Traditional browsing methods, such as manual channel flipping and program guide scanning, often lead to a suboptimal viewer experience due to their time-consuming and inefficient nature. Moreover, the increased demand for personalized content has rendered these methods insufficient. Thus, there is an urgent need to rethink how viewers interact with linear TV and enhance their channel-surfing experience.

Over the past decade, the media landscape has witnessed the rise of short-video platforms and streaming services that have successfully adopted personalized ranking and recommendation systems. These systems thoroughly analyze user behavior, preferences, consumption patterns, and interactions with diverse content by utilizing collaborative filtering, content-based filtering, and advanced deep-learning techniques. This analysis not only formulates a dynamic, personalized ranking of recommendations but also ensures users receive real-time adjustments, greatly enhancing user engagement and satisfaction. This personalization has contributed significantly to the success of these platforms. However, translating such systems to the real-time, continuously broadcasted world of linear television presents unique challenges and opportunities.

This paper introduces a new, real-time system that personalizes channel recommendations for viewers as they surf through linear television channels. Our system relies on two dynamic queues—the Dynamic History Channel Queue (DHCQ) and the Dynamic Future Channel Queue (DFCQ)—alongside advanced deep learning models. The DHCQ keeps track of the channels a viewer has recently browsed where the content is still playing. At the same time, the DFCQ organizes and continually updates the order of all other channels based on real-time changes in their personalized ranking scores.

Furthermore, our system calculates personalized scores using "global" and "local" embeddings from the video content and "user" embeddings derived from viewers' past interactions and preferences. A special "look-ahead" feature is also incorporated, which considers not just the current content but also what's coming up next. This way, viewers get a peek into future programs, adding an extra touch of personalization.

The remainder of this paper is organized as follows: Initially, we explain how our proposed channel surfing method interacts with dynamic queues. Following that, we delve into the dynamic mechanisms of the DHCQ and DFCQ, elucidating the core features of our proposed system, including the application of deep learning models. Subsequently, we introduce the personalized ranking and recommendation algorithm employed in our system, explaining how personalized ranking scores are computed. Afterward, we discuss the incorporation of 'look-ahead' features in linear TV channel surfing. Finally, we present survey results, discussing the potential impact of our system on viewer engagement and its implications for personalized content delivery strategies across various media platforms, and conclude our findings with a discussion on the implications and potential future developments of our proposed system.

Channel Operations with Dynamic Queues

Our real-time personalized ranking and recommendation system for linear TV channel surfing is built on a novel approach involving two dynamic queues, i.e., the Dynamic History Channel Queue (DHCQ) and the Dynamic Future Channel Queue (DFCQ).

The DHCQ is designed to keep track of the viewer's recently browsed channels, enabling the viewer to navigate channels back and forth with ease. Unlike static video surfing histories found in short-video platforms, the DHCQ refreshes every time a new program starts on a channel in the queue. Therefore, the DHCQ is not merely a static list but rather a real-time reflection of the viewer's browsing behavior.

The DFCQ, on the other hand, hosts all other channels. Each channel in this queue is assigned a personalized ranking score calculated using the viewer's profile and preferences. This score determines the channel's position in the queue. Similar to the DHCQ, the DFCQ is also dynamic. It continuously reorders channels based on real-time adjustments in their personalized ranking scores. This ensures a more engaging and personalized viewer experience than static linear TV line-ups.

We first describe the channel change operation, given a fixed DHCQ and DFCQ. **Figure 1** shows when the DHCQ has channels available for channel up or down and how the current channel changes in the DHCQ. In this case, the channel change operates similarly to the regular channel history browsing. **Figure 2** shows when the current channel is the last channel of DHCQ. In this case, there is no additional channel in DHCQ for channel-up operation, so the first channel in DFCQ will be removed from the DFCQ and be appended to the end of DHCQ. The channel-up operation will result in showing this newly appended channel.

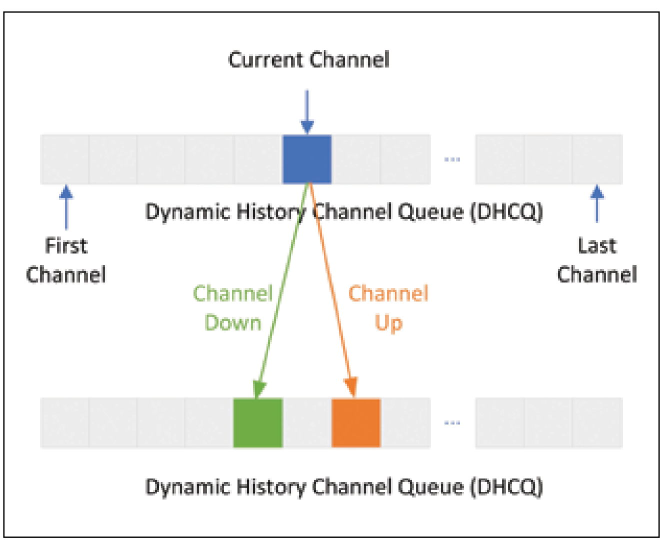

FIGURE 1. Illustration of channel navigation using the Dynamic History Channel Queue (DHCQ). The user can navigate up or down through the previously browsed channels when there are available channels.Channel up moves the current channel to the next channel in the DHCQ, while channel down moves the current channel to the previous channel in the DHCQ.

Dynamic mechanism of the DHCQ and DFCQ:

The following elaborates on the initial setup and the dynamic updating of the Dynamic History Channel Queue (DHCQ) and the Dynamic Future Channel Queue (DFCQ).

Initialization:

We first set the DHCQ as an empty queue to initiate the system. Concurrently, all channels at time t=0 are ranked using an algorithm, which will be elaborated on later. Based on their ranking scores, these channels are then positioned in the DFCQ in descending order. The channel with the highest score is placed at the top of the DFCQ. It is then moved from the DFCQ to the DHCQ, becoming the current channel in the DHCQ. Consequently, the viewer's television experience starts with this channel.

Dynamic Updates:

Dynamic updates to the DHCQ and DFCQ are achieved via a set of procedures:

- Periodic Re-ranking: At a pre-set time interval, denoted as , all channels in the current DFCQ are re-evaluated and re-ranked, then sorted in descending order based on their scores.
- DHCQ Refresh: When each channel in the DHCQ (excluding the current channel being watched) is added to the DHCQ, the system records the end time of the current recommended program. When each program reaches its end time, the corresponding channel is removed from the DHCQ. A new ranking score for this channel is then computed, and the channel is placed back in the DFCQ based on this score.
- User Inactivity Management: For every channel in the DHCQ, the last time a viewer visited this channel is recorded. If a channel in the DHCQ is not visited within the period defined by , the system removes this channel from the DHCQ. Subsequently, a new ranking score for this channel is calculated, and the channel is placed back into the DFCQ based on its ranking score.
- Channel Up Navigation: When the viewer is watching the last channel in the DHCQ and presses channel-up, the top-ranked channel in the DFCQ is moved to the DHCQ as the new previous channel, which is also the current channel. If the DFCQ is empty (i.e., all channels are in DHCQ), the system cycles back to the first channel in the DHCQ.
- Channel Down Navigation: Similarly, if the viewer is watching the first channel in the DHCQ and presses channel-down, the top-ranked channel in the DFCQ is inserted as the new first channel in the DHCQ and becomes the current channel. If the DFCQ is empty, the system moves the viewer to the last channel in the DHCQ.

This continuous dynamic management of the two queues ensures a smooth and engaging channel surfing experience for the viewer.

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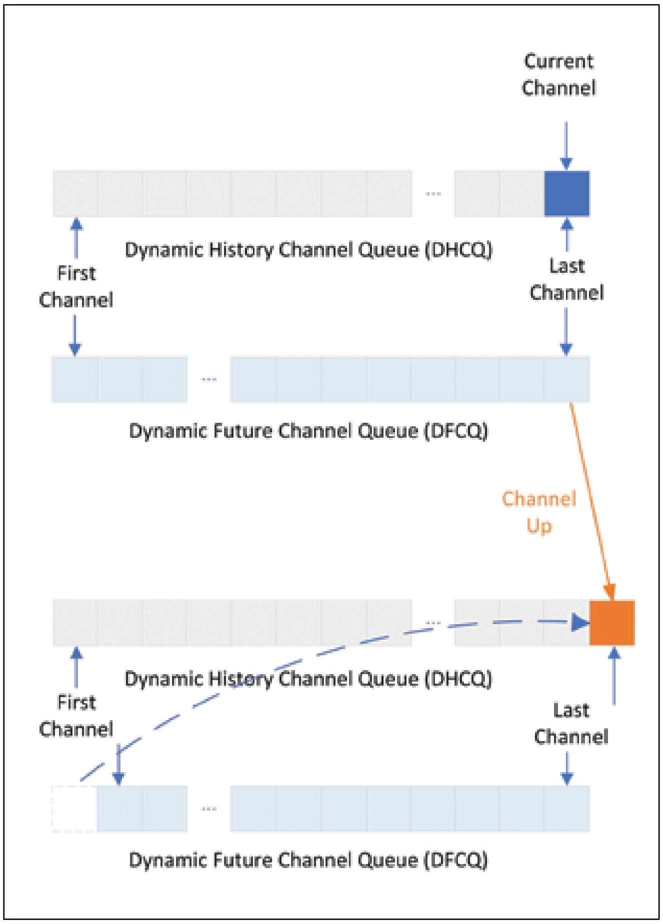

FIGURE 2. Channel-up operation when the current channel is the last one in the Dynamic History Channel Queue (DHCQ). The first channel from the Dynamic Future Channel Queue (DFCQ) is appended to the DHCQ, allowing continuous navigation.

Personalized Ranking and Recommendation Algorithm

To implement personalized ranking and recommendations for linear TV channels, various techniques can be incorporated into the system, for example:

- Collaborative Filtering[2] relies on historical user interactions (likes, views, etc.) to recommend videos to similar users.
- Content-based Filtering[3] leverages the attributes of videos (titles, tags, descriptions, etc.) and the user's past interactions to offer relevant suggestions.
- Hybrid Recommender Systems[4] combines collaborative and content-based filtering techniques. These systems make more accurate recommendations by considering both video attributes and the user's past interactions.
- Deep-learning Based Methods[5,6] employ deep-learning models to detect patterns in user behavior and video data, subsequently making recommendations based on these learned patterns.

This paper uses deep learning models to compute the embeddings of both the content and the viewers. The proposed system combines the progression of time, the details of the content, and the viewer's preferences to recommend the most suitable content on linear TV at any given moment.

Global and Local Timestamps

Linear TV's dynamic nature means that the content changes over time. Therefore, a successful recommendation system must accurately consider time as a critical parameter. In our model, we've utilized two types of timestamps to address this.

The global timestamp T_g is a universal clock, marking the current time across all channels. For each TV channel, denoted by n, specific content is being broadcasted, which we denote as $V(T_g,n)$. However, we use the local timestamp, $T_l(n)$ to measure how far a video content has progressed on a particular channel. Essentially, $T_l(n)$ is calculated by subtracting the content's start time, denoted by global timestamp, from the current global timestamp T_g.

Segmentation of Video Content

For long videos, like movies, if they are longer than a set time T_s, we split them into smaller segments, each not exceeding T_s. This ensures that each segment remains within the set duration. A straightforward way to do this is by cutting the video into segments where all segments have a duration of T_s, except the last one, which may be shorter. More advanced algorithms can also be applied; for example, scene change detection can be used to cut the video into scenes and then aggregate them to obtain segments. Here's how it works: first, identify scene changes in the video. Then, from the beginning of the video, combine the scenes until the combined duration is close to T_s, but does not exceed it. Each segment will consist of these combined scenes. If a single scene is longer than T_s, cut that scene into shorter pieces, each not exceeding T_s, as in the simple method aforementioned. This way, we ensure that all segments are within the specified duration and the segmentation aligns with natural breaks in the content.

Feature Embedding via Deep Learning

Deep learning models are crucial for video and user understanding. In our system, two key video embeddings are created for every channel's content: the Global Embedding E_g and the Local Embedding E_l.

1. Global Embedding:
   The Global Embedding E_g is a vector representation of features extracted from the entire video content of $V(T_g,n)$. It considers attributes like titles, tags, descriptions, and other pertinent metadata. This embedding provides a broad overview of the content, enabling the system to understand the general themes and topics covered in the video.
2. Local Embedding:
   On the other hand, the Local Embedding E_l is more detailed, focusing on specific segments of $V(T_g,n)$. Beyond the broader attributes, E_l further delves into nuances like video frames or subtleties derived from audio or captions of that segment. This allows the system to gain deeper insights into moment-specific aspects of the content, ensuring a more precise recommendation.
   This dual embedding mechanism ensures a balance between general content themes and moment-specific insights, enhancing the system's ability to personalize recommendations effectively.

2. User Embedding:
   In parallel, to cater to the user-centric facet of the recommendation system, a User Embedding E_u is generated. This User Embedding captures a spectrum of user behaviors and preferences, consolidating historical interactions and explicitly declared preferences. The system can tailor recommendations to individual viewing habits and interests by analyzing this comprehensive user profile.

Sensitivity Analysis

Beyond content and user preferences, the system recognizes the importance of the sensitivity associated with the video content and the user's viewing habits. The Video Sensitivity S_v is mainly influenced by the genre of the content. A live event, for instance, might evoke a different viewing urgency compared to a recurring documentary.

Complementing this is the User Sensitivity S_u, which is primarily user-specific. Users can adjust this sensitivity based on their viewing preferences. For example, a lower sensitivity might suggest a user's willingness to join a program midway, whereas a high sensitivity would indicate a preference for starting content from the beginning.

Ranking Algorithm

With the above foundations established, the core of the system is the ranking algorithm. For every video content $V(T_g,n)$, the system computes a composite score, $Score_v$ with a machine learning model that considers various parameters: the timestamps T_g and $T_l(n)$, video embeddings E_g and E_l, user embedding E_u, and the sensitivity parameters S_v and S_u. This comprehensive scoring mechanism evaluates the relevance of the content on channel n for a specific user at the timestamp T_g.

Consideration of Look-Ahead Features in Linear TV

The system is not limited to the present. It's forward-looking, taking into account what's coming next. If an upcoming program $V_{next}(T_{-g},n)$ is slated to begin shortly, specifically within a duration T_{next}, our system factors it into the recommendation pool. The idea here is to recommend what's currently airing and what will soon be on air, should it align with the viewer's interests.

The look-ahead factor plays a pivotal role in the personalization of linear TV. It's not uncommon for an upcoming movie or program on a channel to yield a significantly higher ranking score than the currently played content on the same channel. For this reason, our system doesn't merely calculate the ranking score of a single program $V(T_g,n)$, but also considers the upcoming video program $V_{next}(T_{-g},n)$. This is particularly true when the upcoming program is scheduled to commence within the period T_{next}. The ranking algorithm will also be used to calculate the ranking score for this upcoming video, and the higher score of the upcoming and current videos will be used as the score of this channel.

Should a channel be chosen as the current channel based on the score of the incoming video, the TV will display this channel. Furthermore, an on-screen notification will provide information about the next-up program and a countdown. This ensures that the user understands why this specific channel is being recommended. If the user is intrigued by the proposed video program, they can either wait on this channel or browse other channels and return later when the recommended program starts.

Survey Results

To understand the acceptance and potential adoption of our proposed channel surfing technique, we surveyed 25 participants from diverse age and gender backgrounds. This diversity was crucial in gauging a comprehensive view of how different users might perceive and value the added functionality.

Preference Over Traditional Channel Surfing

The participants were first introduced to the new channel surfing technique and its intricacies. Upon understanding its nuances, they were asked about their preference between the conventional method and our proposed system. A significant 68% of the respondents indicated their preference for the new system. This inclination towards the proposed approach suggests that most users are open to, or even prefer, our proposed channel surfing methods that cater to their preferences and content consumption habits.

Likelihood of Adoption

To further quantify the acceptance level, participants were asked to rate their likelihood of adopting the proposed method over traditional channel surfing on a scale from 1 (least likely) to 10 (most likely). The average score, calculated from all responses, is 7.48. This score, significantly above the midpoint, further validates the inclination in the preference question and indicates a substantial potential for widespread adoption.

User Feedback and Suggested Improvements

Users appreciated the dynamic and personalized nature of the recommendations, particularly the seamless navigation facilitated by the dual dynamic queue system. However, some feedback highlighted the need for multi-user support, as many households have multiple viewers with varying preferences. Incorporating profiles or a multi-user recognition feature could enhance the system's adaptability in such scenarios. Additionally, users suggested more control over personalization settings, allowing them to fine-tune recommendations based on their viewing habits and preferences.

Discussion

Conclusion

This paper introduced a novel approach to channel surfing in linear television, harnessing the power of advanced deep learning techniques and real-time personalization. The intricate design, which integrates Dynamic History Channel Queue (DHCQ) and Dynamic Future Channel Queue (DFCQ) mechanisms, aims to redefine how users interact with their television sets. This method brings the precision and adaptability of modern streaming recommendation systems to the age-old platform of linear TV.

A critical cornerstone of our system is the personalization algorithm that uses both global and local timestamps. This consideration ensures users are presented with content that's not just aligned with their preferences but also timely and contextually relevant. Subsequent segmentation of longer programs and forward-looking features, such as anticipating upcoming high-interest programs, further enhance user engagement and satisfaction.

The survey results suggest a promising acceptance level for the proposed channel surfing technique among a diverse group of participants. While traditional methods have their foundation and familiarity, there is a notable openness towards methods that use intelligent mechanisms, such as our proposal, to enhance the user experience in linear TV consumption. The likelihood score reinforces this sentiment, presenting an optimistic scenario for the system's real-world adoption and success. The inherent flexibility of our approach, where users can seamlessly toggle between the traditional method and our enhanced technique, further positions it as an attractive and user-friendly proposition.

Comparative Analysis with Existing Systems

Traditional linear TV content discovery methods, such as electronic program guides (EPGs) and manual channel surfing, are often time-consuming and inefficient, providing minimal personalization. Modern streaming platforms, however, have adopted sophisticated recommendation systems using collaborative filtering, content-based filtering, and hybrid methods to enhance the user experience.

Unlike these conventional approaches, our system introduces a dual dynamic queue mechanism—Dynamic History Channel Queue (DHCQ) and Dynamic Future Channel Queue (DFCQ)—to manage and personalize content in real time. This allows continuous updates based on user interactions and content progression, offering a more dynamic and responsive viewing experience. Furthermore, our use of advanced deep learning models to generate 'global' and 'local' content embeddings, along with 'user' embeddings, provides a more granular and accurate personalization than traditional methods. Integrating a 'look-ahead' feature that considers upcoming content adds another layer of novelty, setting our system apart from existing solutions.

Limitations and Challenges

While the proposed approach offers significant enhancements to linear TV content discovery, several limitations and challenges should be addressed for practical implementation. One key limitation is managing personalized recommendations in households with multiple viewers. The system currently tailors content based on individual user preferences, which might not effectively serve scenarios where multiple users with diverse tastes view content together. Incorporating multi-user support, where the system can recognize and balance the preferences of several viewers simultaneously, could be a valuable addition.

Another challenge is the dependency on accurate user data and advanced deep-learning models. The system's effectiveness relies heavily on the quality and granularity of user interaction data and the performance of deep learning algorithms to generate precise embeddings. The recommendations may not be as accurate or engaging in scenarios where data is sparse, or models are less effective. Additionally, ensuring user privacy and data security while collecting and processing this information is important and poses its own challenges.

Finally, integrating this system into existing linear TV infrastructures can be complex and resource-intensive. The dual dynamic queue approach and real-time processing may require local computational power and robust backend support. Despite these challenges, alternative methods like hybrid recommendation systems and simplified algorithms can offer value, providing a spectrum of options based on available resources and implementation feasibility. Addressing these limitations will help drive the widespread adoption and success of the proposed system in enhancing viewer engagement and satisfaction.

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About the Authors

Ning Xu currently serves as Fellow of Advanced R&D at Adeia Inc., pioneering innovations that enhance how we live, work, and play. Before joining Adeia, Xu was the chief scientist of video algorithms at Kuaishou Technology. Prior to that, he held various positions at Amazon, Snap Research, Dolby Laboratories, and Samsung Research America. He earned his Ph.D. in Electrical Engineering from the University of Illinois at Urbana-Champaign (UIUC) in 2005. Xu has co-authored over 200 journal articles, conference papers, patents, and patent applications. His research interests encompass machine learning, computer vision, video technology, and other related areas.

Tao Chen is VP of Advanced R&D, Media Technology at Adeia Inc., leading R&D projects and developing technology roadmaps and research strategies. Formerly, he was senior director of Applied Research at Dolby Labs. He serves as associate editor for the IEEE T-CSVT. In 2021, he was an honoree by the Primetime Engineering Emmy for contributions to Dolby's Philo T. Farnsworth Award. Chen also received an Emmy Engineering Award in 2008 and multiple Silver Awards at the Panasonic Technology Symposium. He was awarded the Most Outstanding PhD thesis by the Computer Science Association of Australia in 2001.

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