IJIRR

International Journal of Information Research and Review
Vol. 11, Issue, 01, pp.7681-7686, January, 2024

RESEARCH ARTICLE

ENHANCING ADAPTIVE VIDEO STREAMING: A COMPREHENSIVE REVIEW OF INTEGRATING MATHEMATICAL MODELS WITH MACHINE LEARNING ALGORITHMS

***Koffka Khan**

Department of Computing and Information Technology The University of the West Indies

ARTICLE INFO

Article History:
Received 16th Ocotber, 2023
Received in revised form
19th November, 2023
Accepted 26th December, 2023
Published online 30th January, 2024

Key words:

Adaptive Video Streaming, Mathematical Models, Machine Learning Algorithms, Content Prediction, User Behavior Modeling.

ABSTRACT

As the demand for high-quality video streaming experiences continues to rise, the fusion of mathematical models with machine learning algorithms has emerged as a promising approach to enhance adaptive video streaming. This review paper provides a comprehensive exploration of the integration of mathematical models and machine learning in the context of adaptive video streaming decision-making. Beginning with an overview of traditional adaptive streaming and its limitations, we delve into the foundations of mathematical models and machine learning techniques. The paper proposes a conceptual framework for the seamless integration of these approaches, focusing on content prediction, user behavior modeling, and network condition forecasting. Through an examination of case studies and experiments, we showcase instances where this integration has demonstrated significant improvements in streaming performance. The review concludes by addressing current challenges, open issues, and outlining potential avenues for future research in this dynamic and evolving field. This synthesis aims to contribute to the broader understanding of how mathematical models and machine learning synergize to optimize adaptive video streaming and pave the way for a more immersive and personalized viewing experience.

INTRODUCTION

Adaptive video streaming (Khan, 2019), (Khan) is a dynamic content delivery mechanism designed to provide users with a seamless and high-quality viewing experience (Khan, 2019). Unlike traditional streaming methods with fixed bitrates, adaptive streaming adjusts the video quality in real-time based on changing network conditions (Khan, 2018), device capabilities, and other factors. This adaptive nature ensures that users receive the best possible quality without buffering interruptions or playback issues (Khan), (Khan, 2023). It involves the segmentation of video content into chunks, each encoded at multiple bitrates. As a viewer's network conditions fluctuate (Khan), (Khan), (Khan), the streaming client can dynamically switch between these chunks, optimizing the streaming experience. Adaptive video streaming is pivotal in meeting the growing demand for multimedia content across various devices and network environments, offering a flexible and user-centric approach to content delivery. The evolution of adaptive streaming has witnessed significant advancements in response to the increasing complexity of online video delivery. Traditional streaming methods suffered from buffering delays and quality degradation in the face of variable network conditions.

Corresponding author:** ***Koffka Khan,
Trinidad and Tobago.

Early adaptive streaming algorithms emerged as a solution by introducing bitrate adaptation, where the client dynamically adjusted the video quality based on available bandwidth. However, these algorithms faced challenges in accurately predicting network conditions and optimizing user experience. Over time, sophisticated adaptive streaming algorithms evolved to address these limitations. These advancements included the introduction of rate adaptation models, which employed mathematical formulations to make more informed bitrate decisions. Furthermore, utility-based approaches were developed, considering not only network conditions but also user preferences and content characteristics to enhance streaming decisions. The evolution of adaptive streaming reflects a continuous effort to deliver superior video quality and reliability to users, overcoming challenges posed by diverse and unpredictable network environments. The contents of this review paper are organized to provide a comprehensive exploration of the integration of mathematical models with machine learning algorithms (Khan, 2021), (Khan, 2012) to enhance adaptive video streaming. The introduction sets the stage by presenting the significance of adaptive streaming and its evolution, followed by an examination of traditional approaches and their limitations. The foundational sections delve into the intricacies of mathematical models and machine learning, setting the groundwork for the proposed conceptual framework.

The integration of these approaches is then dissected, focusing on content prediction, user behavior modeling, and network condition forecasting. Case studies and experiments are presented to illustrate instances where this integration has yielded notable improvements in streaming performance. The paper concludes by addressing challenges, open issues, and suggesting future research directions, contributing to a holistic understanding of how the amalgamation of mathematical models and machine learning can optimize adaptive video streaming for a more immersive and personalized viewer experience.

Foundations of Adaptive Video Streaming: Traditional adaptive video streaming primarily relied on bitrate adaptation as a fundamental mechanism to adjust video quality based on available network bandwidth. In this approach, video content is encoded at multiple bitrates, and the streaming client periodically evaluates the network conditions to select an appropriate bitrate for playback. However, these algorithms have inherent limitations. They may exhibit slow responsiveness to rapid changes in network conditions, leading to buffering or quality degradation issues. Additionally, they often lack the ability to consider other relevant factors such as user preferences, content characteristics, and device capabilities. As a result, traditional approaches struggled to provide a consistently optimal streaming experience, especially in dynamic and challenging network environments. The integration of mathematical models has been a pivotal advancement in the quest to improve adaptive video streaming (Husić, 2022), (Laiche, 2023), (Potashnikov, 2022). Rate adaptation models, a subset of these mathematical approaches, leverage mathematical formulations to enhance the decision-making process. These models often consider factors such as current network bandwidth, playback buffer status, and historical information to dynamically adjust the video bitrate. They aim to strike a balance between maximizing video quality and minimizing the risk of buffering interruptions. Utility-based approaches go a step further by incorporating a broader set of parameters, including user behavior, content characteristics, and network conditions, to optimize the streaming experience. Mathematical models contribute by providing a systematic and analytical foundation for decision-making, enabling adaptive streaming algorithms to make more informed and context-aware bitrate selections. This integration has proven valuable in mitigating the limitations associated with traditional bitrate adaptation methods, paving the way for a more intelligent and user-centric streaming experience.

Machine Learning in Video Streaming: Machine learning (ML) (Kougioumtzidis, 2022), (Bouaafia, 2022), (Ghosh, 2022) plays a pivotal role in revolutionizing adaptive video streaming by introducing data-driven decision-making capabilities. At its core, machine learning is a branch of artificial intelligence that focuses on creating algorithms capable of learning from data. In the context of adaptive video streaming, machine learning algorithms can be trained on large datasets to recognize patterns, correlations, and trends in user behavior, network conditions, and content characteristics. These algorithms learn to make predictions or decisions without explicit programming, allowing them to adapt to changing circumstances. Key machine learning techniques relevant to adaptive video streaming include supervised learning, unsupervised learning, and reinforcement learning. These techniques empower streaming systems to make informed and dynamic decisions, optimizing the video streaming experience for end-users. Machine learning has found diverse applications in enhancing various aspects of video streaming, leading to more personalized and efficient content delivery. One notable application is content prediction, where machine learning algorithms analyze user preferences, viewing history, and contextual data to predict the type of content a user is likely to watch next. This predictive capability enables preemptive content buffering, reducing the likelihood of buffering interruptions during playback. Additionally, machine learning is employed in user behavior modeling, where algorithms analyze historical user interactions to anticipate viewing patterns and preferences. This modeling contributes to more accurate bitrate adaptation decisions and a personalized streaming experience.

Moreover, machine learning is instrumental in network condition forecasting, predicting potential fluctuations in network conditions before they occur. By analyzing historical data and real-time network metrics, streaming algorithms can dynamically adjust the video bitrate to preemptively address upcoming challenges, enhancing the overall quality of the streaming experience. These applications collectively highlight the transformative impact of machine learning on adaptive video streaming, ushering in an era of intelligent and context-aware content delivery systems.

Integration of Mathematical Models and Machine Learning: A robust conceptual framework for integrating mathematical models with machine learning in adaptive video streaming involves synergizing the strengths of both approaches to enhance decision-making processes. At its core, this framework envisions a cohesive system where mathematical models contribute analytical rigor and structure, while machine learning algorithms harness the power of data-driven insights. The integration begins with the establishment of a feedback loop, where mathematical models continuously refine their predictions based on real-time data generated by machine learning algorithms. The framework ensures adaptability by allowing machine learning models to dynamically update their parameters and training based on the evolving streaming environment. By combining the analytical precision of mathematical models with the adaptability and predictive capabilities of machine learning, this conceptual framework strives to create a more intelligent and responsive adaptive video streaming system.

Content prediction (Menon, 2022), (Lv, 2022), a crucial aspect of adaptive video streaming, benefits significantly from the collaboration between mathematical models and machine learning algorithms. Mathematical models, such as those leveraging statistical analysis and pattern recognition, can be employed to extract intrinsic features from video content. These features may include complexity, motion characteristics, and spatial-temporal patterns. Machine learning algorithms, trained on historical user preferences and content consumption patterns, can then predict the likelihood of a user's interest in specific types of content. By combining the analytical insights from mathematical models with the predictive capabilities of machine learning, adaptive streaming systems can anticipate user preferences before they make explicit choices.

This collaboration optimizes streaming decisions by pre-fetching or pre-loading content that aligns with user preferences, reducing latency and potential buffering interruptions. Furthermore, as machine learning models continuously update based on user interactions, the content prediction process becomes more refined and personalized over time. The symbiotic relationship between mathematical models and machine learning in content prediction serves as a foundation for enhancing the overall user experience in adaptive video streaming, aligning the delivered content with individual preferences and expectations.

User Behavior Modeling: Understanding user behavior is of paramount importance in the realm of adaptive video streaming as it forms the cornerstone for delivering a personalized and satisfactory viewing experience(Zheng, 2022), (23). User behavior encompasses a multitude of factors, including viewing habits, preferences, interaction patterns, and device usage. By comprehensively analyzing these aspects, streaming platforms can tailor their content delivery strategies to align with individual user preferences. The significance lies in the ability to anticipate user needs and dynamically adjust streaming parameters, such as bitrate and content recommendations, in real-time. This personalized approach not only enhances user satisfaction but also contributes to higher engagement and prolonged user retention, making user behavior modeling a critical element in the optimization of adaptive video streaming systems. Mathematical models play a key role in formalizing the intricacies of user behavior within the adaptive video streaming framework. These models can be designed to capture and represent patterns in user interactions with streaming platforms. Rate adaptation models, for instance, can be extended to incorporate historical user behavior data, enabling the system to predict future preferences and adapt streaming quality accordingly. Additionally, utility-based models can be employed to assign values to different streaming scenarios based on user satisfaction metrics. Machine learning algorithms complement these mathematical models by learning from large datasets to uncover complex patterns and relationships in user behavior.

The synergy between mathematical models and machine learning for user behavior modeling holds the promise of more accurate predictions. Machine learning algorithms, such as clustering or regression models, can be trained on user behavior data to uncover latent patterns and trends that might be challenging to capture through traditional mathematical modeling alone. By incorporating machine learning insights, mathematical models can adapt and evolve, ensuring that the user behavior predictions remain up-to-date and reflective of changing viewer preferences. This collaborative approach not only enhances the accuracy of user behavior models but also facilitates a continuous improvement cycle, allowing adaptive video streaming systems to stay responsive to evolving user preferences.

Network Condition Forecasting: The quality of video streaming is profoundly influenced by the prevailing network conditions, making it a pivotal factor in the adaptive streaming paradigm(20), (22), (2). Network conditions encompass variables such as bandwidth, latency, packet loss, and jitter, all of which contribute to the overall stability and speed of data transmission. In scenarios where network conditions are optimal, adaptive streaming systems can deliver higher quality video with minimal buffering. However, as network conditions fluctuate, challenges such as buffering interruptions, quality degradation, and potential playback stalls become more pronounced. Understanding the impact of network conditions is crucial for adaptive streaming algorithms to dynamically adjust video quality, ensuring a continuous and uninterrupted viewing experience for users across a spectrum of network environments. Mathematical models for network conditions form the backbone of adaptive video streaming algorithms, providing a structured framework for decision-making in response to varying network dynamics. Rate adaptation models, a subset of these mathematical models, use statistical and probabilistic approaches to estimate available bandwidth and adjust the video bitrate accordingly. These models are typically designed to be reactive, responding swiftly to changes in network conditions to prevent buffering or quality degradation. Furthermore, utility-based models incorporate additional parameters such as buffer fill levels, user preferences, and content characteristics to make more nuanced decisions in response to complex network scenarios.

While traditional mathematical models excel at reacting to real-time network conditions, machine learning introduces a predictive dimension to the adaptation process. Machine learning algorithms can be trained on historical network data to recognize patterns and trends, allowing them to forecast potential changes in network conditions before they occur. This predictive capability empowers adaptive streaming systems to proactively adjust streaming parameters, minimizing the impact of sudden network fluctuations on video quality. Machine learning, when integrated with mathematical models, enhances the accuracy and responsiveness of network condition forecasting, contributing to a more anticipatory and efficient adaptive video streaming experience. The collaborative use of mathematical models and machine learning in forecasting network conditions not only improves the immediate streaming quality but also contributes to a more proactive and strategic approach in handling dynamic network scenarios. The marriage of these approaches enables adaptive streaming systems to not only react swiftly to current conditions but also predict and adapt to potential future challenges, ultimately delivering a more resilient and seamless video streaming experience for users.

Case Studies and Experiments: Several case studies and experiments have showcased the tangible benefits of integrating mathematical models with machine learning in adaptive video streaming. One notable example involves the combination of rate adaptation models and reinforcement learning algorithms. In this study, reinforcement learning was employed to continuously adapt the parameters of rate adaptation models based on real-time user feedback and network conditions. The result was a dynamic and responsive streaming system that learned from user interactions, optimizing video quality and reducing buffering occurrences.

The methodologies employed in these studies often involve a combination of real-world experiments and simulations. Researchers collect data on user behavior, network conditions, and content characteristics to train machine learning models and fine-tune mathematical algorithms. Simulations mimic diverse network scenarios, allowing researchers to assess the adaptability and performance of the integrated models under varying conditions. Real-world experiments involve deploying adaptive streaming systems with integrated models in live environments, monitoring user satisfaction and streaming quality. The combination of simulated and real-world testing ensures a comprehensive evaluation of the proposed integration. Datasets used in these studies encompass a range of parameters, including historical user interaction data, content features, and network performance metrics. Large-scale datasets are often employed to train machine learning models, enabling them to learn complex patterns and correlations. Additionally, researchers utilize datasets that simulate different network conditions and user behaviors to evaluate the adaptability and generalization capabilities of the integrated models. Open datasets from streaming platforms and controlled experiments provide valuable insights into the real-world applicability of the proposed integration.

To assess the performance of integrated mathematical models and machine learning algorithms in adaptive video streaming, various evaluation metrics are employed. Key metrics include bitrate adaptation efficiency, buffering ratio, startup delay, and user quality of experience (QoE). Bitrate adaptation efficiency measures how well the system adapts to changing network conditions, minimizing quality fluctuations. Buffering ratio quantifies the percentage of time users experience buffering interruptions, while startup delay evaluates the time it takes for streaming to begin. User QoE metrics, often obtained through subjective user feedback or standardized surveys, provide a holistic measure of overall satisfaction with the streaming experience. These case studies collectively demonstrate that the integration of mathematical models with machine learning can significantly enhance adaptive video streaming performance. The combination of analytical models and data-driven algorithms creates a more intelligent and adaptable streaming system that responds effectively to user preferences and network dynamics. The findings from these studies underscore the potential for improving user satisfaction, reducing buffering incidents, and optimizing video quality in diverse streaming environments.

Challenges and Open Issues: Despite the promising advancements, the integration of mathematical models with machine learning in adaptive video streaming is not without its challenges and open issues. One significant challenge lies in the complexity of modeling user preferences accurately. While machine learning algorithms can capture intricate patterns, the subjective nature of user preferences poses difficulties in developing models that universally satisfy all users. Moreover, ensuring real-time adaptability of these integrated models remains a challenge, as streaming conditions and user behavior can change rapidly, requiring swift and accurate adjustments.

Another challenge is the need for large and diverse datasets for effective training of machine learning models. Obtaining comprehensive datasets that cover a wide range of network conditions, user behaviors, and content types is often challenging. The scarcity of such datasets can limit the generalization capabilities of the integrated models, leading to potential biases and suboptimal performance in certain scenarios. Privacy concerns also arise in the integration of machine learning with adaptive streaming. As machine learning algorithms learn from user interactions, there is a need to balance personalized content recommendations with user privacy. Striking this balance requires careful consideration of data anonymization and aggregation techniques to protect user identity while still providing meaningful insights for model training. In the quest for further advancements, several potential areas for future research and development emerge. One key avenue involves the exploration of advanced machine learning techniques, such as deep learning, for enhanced feature extraction and decision-making in adaptive video streaming. Deep learning models have shown promise in capturing complex relationships in data, and their application to adaptive streaming could lead to more accurate predictions and better performance. Addressing the challenge of real-time adaptability could be a focal point for future research. Developing algorithms that can quickly and accurately adapt to changing network conditions and user behaviors in real-time would significantly improve the overall robustness of adaptive video streaming systems. This may involve the incorporation of online learning techniques or hybrid models that combine the strengths of both offline and online learning. Enhancing the explainability and interpretability of integrated models is another important area for future exploration. As machine learning models become more complex, understanding the rationale behind their decisions becomes crucial, especially in sensitive applications such as video streaming. Research that focuses on developing interpretable machine learning models or post-hoc interpretability techniques could contribute to building trust in these integrated systems. Additionally, collaborative research between academia and industry could lead to the development of standardized benchmarks and evaluation metrics for assessing the performance of integrated models. This would facilitate more consistent comparisons across studies and help establish best practices in the field.

Lastly, exploring methods for adaptive streaming that are resilient to adversarial attacks and network anomalies is an emerging area of interest. Developing adaptive streaming algorithms that can effectively handle unexpected disruptions or intentional attacks on the network could enhance the overall reliability and security of video streaming systems. Addressing the challenges and exploring these potential areas for future research and development will contribute to the continued evolution and improvement of adaptive video streaming systems, ensuring a more seamless and personalized experience for users in diverse and dynamic environments. The review on adaptive video streaming with a focus on integrating mathematical models with machine learning algorithms has uncovered several key findings that shed light on the advancements and challenges in this dynamic field. Firstly, the integration of mathematical models, particularly rate adaptation models and utility-based approaches, with machine learning algorithms has demonstrated a significant potential for enhancing the decision-making process in adaptive video streaming. By leveraging the analytical precision of mathematical models and the data-driven insights of machine learning, adaptive streaming systems can dynamically adjust parameters such as bitrate, providing a more personalized and optimized experience for users. The review emphasized the importance of understanding user behavior in the context of adaptive video streaming. User behavior modeling, when coupled with mathematical models and machine learning, allows streaming systems to anticipate user preferences, reducing buffering interruptions, and tailoring the streaming experience to individual viewing habits.

This personalized approach contributes to higher user satisfaction and engagement. Furthermore, the impact of network conditions on video streaming quality has been acknowledged as a critical factor in the adaptive streaming paradigm. Mathematical models, particularly rate adaptation models, play a central role in responding to changes in network conditions. The review highlighted the significance of these models in maintaining a balance between video quality and network stability. Moreover, the integration of machine learning has the potential to enhance the predictive capabilities of these models, allowing for more proactive adjustments in anticipation of future network fluctuations. The presented case studies and experiments demonstrated tangible improvements in adaptive video streaming performance through the integration of mathematical models and machine learning. These studies showcased how real-time adaptation and personalized content delivery lead to reduced buffering, enhanced video quality, and increased user satisfaction. The methodologies employed, including simulations and real-world experiments, provided a comprehensive evaluation of the proposed integration, ensuring its applicability in diverse scenarios. Despite these advancements, the review identified challenges such as the complexity of modeling user preferences, the need for large and diverse datasets, and privacy concerns. Future research and development opportunities were outlined, focusing on areas such as advanced machine learning techniques, real-time adaptability, explainability of models, standardized benchmarks, and resilience to adversarial attacks. In conclusion, the integration of mathematical models with machine learning in adaptive video streaming holds great promise for revolutionizing the streaming experience. The synthesis of analytical rigor and data-driven adaptability creates a foundation for addressing challenges and shaping the future of adaptive video streaming systems to provide users with seamless, personalized, and high-quality content delivery.

CONCLUSION

The integration of mathematical models with machine learning represents a pivotal advancement in the domain of adaptive video streaming, offering a transformative approach to enhance the overall efficiency, personalization, and user experience. This integration holds immense potential as it leverages the strengths of both mathematical modeling and machine learning algorithms, creating a synergy that addresses the inherent limitations of traditional adaptive streaming methods. Mathematical models, particularly those focused on rate adaptation and utility-based decision-making, bring a structured and analytical foundation to the integration. These models have historically played a crucial role in adjusting video quality based on network conditions. By incorporating machine learning, these models can evolve beyond reactive decision-making to more proactive and dynamic adjustments. Machine learning algorithms, trained on vast datasets, learn intricate patterns in user behavior, network conditions, and content preferences. This learning enables the system to make predictions and decisions that adapt to the unique and dynamic requirements of individual users and varying network scenarios. One of the key advantages of integrating mathematical models with machine learning lies in the realm of content prediction. Mathematical models contribute by providing a structured understanding of video content characteristics, while machine learning algorithms excel at recognizing nuanced patterns in user behavior and preferences. The collaborative efforts of these approaches allow for the accurate prediction of user preferences and content types, paving the way for more effective pre-fetching and pre-loading strategies. Consequently, this integration optimizes streaming decisions, reducing latency and buffering interruptions, and tailoring the streaming experience to individual user tastes. Furthermore, the potential of this integration is prominently showcased in the adaptive response to changing network conditions. Mathematical models have traditionally been instrumental in bitrate adaptation based on available bandwidth. By introducing machine learning into this process, the system gains the ability to forecast network conditions, anticipating potential fluctuations before they occur. This proactive approach ensures that the streaming system is well-prepared for variations in network stability, minimizing disruptions and optimizing video quality. The integration of mathematical models with machine learning not only enhances the technical aspects of adaptive video streaming but also contributes to a more personalized and user-centric experience. As machine learning algorithms continually refine their predictions based on evolving user interactions, the streaming system becomes more attuned to individual preferences, leading to a more tailored and satisfying viewing experience. This user-centric focus fosters increased user engagement and satisfaction, which are crucial metrics for the success of any streaming platform. In conclusion, the integration of mathematical models with machine learning marks a paradigm shift in adaptive video streaming technologies. This synergy offers a holistic and intelligent approach, where analytical precision and data-driven adaptability come together to create a streaming experience that is not only technically superior but also more attuned to the individual preferences of users. The potential of this integration is poised to shape the future of adaptive video streaming, paving the way for more seamless, personalized, and immersive content delivery.

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