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A Framework for Meta-Learning in Dynamic Adaptive Streaming over HTTP

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ABSTRACT

This work presents a framework with a taxonomy on meta-learning used in Dynamic Adaptive Streaming over HTTP (DASH). With the increasing complexity of network conditions and user preferences, there is a need for efficient adaptation mechanisms in DASH to provide optimal quality of experience (QoE) for users. Meta-learning, or learning to learn, has emerged as a promising approach to enhance adaptive streaming algorithms in DASH by leveraging prior knowledge and experiences. The proposed framework provides a systematic and structured approach for applying meta-learning techniques in the context of DASH. It encompasses essential components, including data collection and preprocessing, meta-model architecture, meta-training, meta-testing, fine-tuning, and continuous improvement. The taxonomy within the framework categorizes various aspects of meta-learning in DASH, such as meta-learning approaches, components, objectives, and applications.

Key words : meta-learning, streaming, DASH, QoE.

1. INTRODUCTION

Dynamic Adaptive Streaming over HTTP (DASH) has become a prevalent technique for streaming videos over the internet, allowing adaptive bitrate selection and optimal playback quality based on network conditions and user preferences [18, 17, 21]. However, as the complexity of streaming environments and user demands increase, there is a need to enhance the adaptive streaming algorithms in DASH to provide an improved quality of experience (QoE).

Rate adaptation in DASH refers to the process of dynamically adjusting the video quality and bitrate during playback to adapt to changing network conditions and provide the best possible streaming experience to the user [19, 22]. Here's an overview of how rate adaptation works in DASH. The first step is content preparation where the video content is encoded into multiple representations (also known as bitrate variants) at different quality levels. Each representation corresponds to a different bitrate and resolution combination, typically encoded as different video files or segments.

Step two is manifest generation. Here, a manifest file, usually in XML or JSON format, is created for the video content. The manifest contains metadata about all available representations, their corresponding URLs or file locations, and other information necessary for the client to request and play the content. Initial segment selection occurs in step three. When the video playback starts, the client (typically a DASH-compliant media player) downloads the manifest file. It analyzes the available representations and selects an initial segment from one of the representations based on the network conditions and device capabilities.

The fourth step is segment download. The client requests the selected segment from the corresponding URL or file location. The segment represents a small portion of the video content, typically a few seconds of playback. The client downloads the segment and starts playing it. Step five is playback and quality evaluation: As the client plays the downloaded segment, it monitors various network parameters such as available bandwidth, latency, and packet loss. It also tracks playback buffer occupancy and estimates the time it will take to download the next segment.

In step six a rate adaptation decision is made. Based on the real-time network measurements and buffer status, the client evaluates the current video quality and decides whether to switch to a higher or lower representation for the next segment. If the network conditions are favorable and there is sufficient buffer, the client may choose a higher bitrate representation to improve the quality. Conversely, if the network conditions deteriorate or the buffer is running low, the client may switch to a lower bitrate representation to ensure uninterrupted playback.

Representation switching takes place in step seven. If a decision to switch representations is made, the client updates the request for the next segment to the new representation's URL or file location. It downloads the new segment and seamlessly switches to playing the content from the new representation.

Steps four to seven is repeated, that is, the process of segment download, playback, quality evaluation, and rate adaptation continues throughout the streaming session. The client continuously monitors and adjusts the video quality based on the observed network conditions, ensuring a smooth and adaptive streaming experience. By dynamically adapting the video quality based on network conditions, DASH provides a robust and efficient streaming solution that can deliver content seamlessly over varying network bandwidths and enable smooth playback on a wide range of devices.

Meta-learning, also known as "learning to learn," is a subfield of machine learning that focuses on developing algorithms or models that can learn how to learn from experience. The goal of meta-learning is to enable a system to acquire new knowledge or skills more efficiently and effectively by leveraging past learning experiences. In traditional machine learning, models are trained on specific tasks using a fixed dataset, and the learned knowledge is typically specific to that task. However, meta-learning takes a higher-level perspective by training models to acquire general learning abilities that can be applied to a wide range of related tasks.

Meta-learning algorithms [36] often involve two levels of learning. The first level is Meta-level Learning. In this stage, the model learns how to adapt and generalize across tasks. It involves training the model on a set of different tasks, where each task consists of a dataset and an associated learning objective. The model learns to extract task-specific features, identify patterns, and develop strategies to solve similar tasks efficiently. The second level is Task-level Learning. Once the model has learned general learning abilities at the meta-level, it can be applied to new tasks. During task-level learning, the model adapts its parameters and makes predictions based on the specific dataset and learning objective of the current task. The model uses its meta-learned knowledge and past experiences to quickly adapt to the new task and achieve good performance with limited data.

Meta-learning can be applied in various domains and has several practical use cases. One is Few-shot Learning [37]. Meta-learning algorithms excel in scenarios where there is limited training data available for a new task. By leveraging past learning experiences, a meta-learned model can quickly adapt to new tasks with only a few training examples, enabling efficient learning from small datasets. Another use case is Hyperparameter Optimization [7]. Meta-learning can be used to automatically search for optimal hyperparameters or model architectures. By training a meta-learned model on different tasks that represent hyperparameter optimization problems, the model can learn to identify effective hyperparameter settings or search strategies, reducing the need for manual tuning.

Reinforcement Learning is another use case [20]. Meta-learning techniques can be employed to improve the sample efficiency of reinforcement learning algorithms. A meta-learned model can learn to quickly adapt its policy to new environments or tasks, enabling faster convergence and reducing the number of interactions required to achieve good performance. Transfer Learning [40] is a fourth use case. Meta-learning can facilitate knowledge transfer across related tasks. By meta-learning on a set of tasks, a model can learn reusable knowledge that can be transferred to new tasks, accelerating the learning process and improving performance on those tasks. Meta-learning aims to enhance the learning capabilities of machine learning systems by enabling them to acquire new knowledge, adapt to new tasks, and generalize across different domains more efficiently.

Meta-learning has emerged as a promising approach to address these challenges in DASH. By leveraging prior knowledge and experiences, meta-learning enables the adaptation of streaming algorithms to new scenarios and tasks with limited data. To effectively apply meta-learning in the context of DASH, a framework with a taxonomy becomes invaluable.

The framework provides a systematic and organized structure for applying meta-learning techniques to enhance dynamic adaptive streaming in DASH. It encompasses various components, processes, and considerations involved in utilizing meta-learning algorithms in the context of streaming video delivery.

The taxonomy within the framework serves as a classification system, categorizing different aspects and dimensions of meta-learning in DASH. It helps to categorize and organize various meta-learning approaches, components, objectives, and applications specific to DASH. The taxonomy provides a shared language and structure for researchers, practitioners, and developers working in the field, facilitating a better understanding and exploration of the meta-learning techniques applicable to DASH.

The framework includes several essential elements, such as data collection and preprocessing, meta-model architecture, meta-training, meta-testing, fine-tuning, and continuous improvement. These elements guide the process of applying meta-learning in DASH and ensure a systematic and structured approach.

By following the framework, researchers and practitioners can collect and preprocess relevant data, design and train meta-learners suitable for DASH, evaluate their performance through meta-testing, fine-tune them based on specific deployment scenarios, and continuously improve them to adapt to changing network conditions and user preferences.

Finally, the framework with a taxonomy on meta-learning in DASH provides a comprehensive and structured approach to apply meta-learning techniques for dynamic adaptive streaming. It helps researchers and practitioners in effectively utilizing meta-learning algorithms to enhance the quality of streaming experience in DASH, leading to improved video quality, reduced buffering, and better adaptation to varying network conditions.

This paper consists of six sections. The literature review is given in section two. In section three the taxonomy of meta learning in DASH is detailed. The framework is given in section four while a discussion is given in section five. Finally in section six the conclusion is given.

2. LITERATURE REVIEW

We first look at Meta-Learning in literature. Authors in [35] provide a survey which gives a comprehensive overview of meta-learning techniques, algorithms, and applications, covering topics such as few-shot learning, transfer learning, and hyperparameter optimization. The seminal work in [8] introduces the concept of model-agnostic meta-learning (MAML), a framework that allows fast adaptation to new tasks by learning a good initialization of model parameters. Authors in [2] propose an approach that uses a recurrent neural network to meta-learn the initial conditions for gradient descent, enabling faster learning on new tasks. A survey in [30] focuses on the use of meta-learning in autonomic computing systems, discussing the application of meta-learning for selecting and adapting algorithms dynamically.

We now look at DASH in the literature. Authors in [34] presents an overview of the DASH standard, its design principles, and technical considerations for adaptive streaming over HTTP. A survey in [23] explores the evolution of DASH in the context of content delivery networks (CDNs), discussing key features, challenges, and advancements in DASH deployment. The work in [5] proposes Q-DASH, a QoE-aware DASH scheme that takes into account the user's perceived quality and network conditions to make adaptive streaming decisions. The survey in [32] provides an overview of the research on Quality of Experience (QoE) assessment in DASH, discussing QoE models, subjective and objective evaluation methodologies, and open research challenges.

Further, we look at Meta-Learning with DASH in literature. Authors in [16] conducted a subjective experiment to examine variations in users' preferences for Quality of Experience (QoE), specifically focusing on visual quality, fluctuation, and rebuffering events. Drawing from their findings, they devised a multi-task deep reinforcement learning (DRL) solution to optimize QoE based on individual user preferences. Their formulation entails incorporating user-specific QoE preferences by assigning weights to the three QoE metrics within the overall QoE calculation. In [15] authors introduce the Meta-Learning framework for Multi-User Preferences (MLMP) as an innovative approach to DASH adaptation. By leveraging MLMP, we aim to optimize the satisfaction of diverse users' QoE preferences pertaining to the three aforementioned metrics. The simulation results demonstrate that our proposed method outperforms existing state-of-the-art DASH adaptation techniques in effectively meeting the distinct QoE preferences of users across the three metrics.

In [12], authors tackle the task of predicting user-level network traffic within a short timeframe, driven by its relevance in cellular scheduling applications. Inspired by recent advancements in robust adversarial learning, they approached the prediction problem for non-stationary traffic from an adversarial perspective. Their proposed solution involves a meta-learning framework comprising a collection of predictors, each specialized in forecasting specific traffic patterns, alongside a master policy trained using deep reinforcement learning. This master policy dynamically selects the most suitable predictor based on recent prediction performance. They assess the effectiveness of our meta-learning approach using various traffic traces, encompassing both video and non-video data.

In [26] authors introduce a novel framework for meta-learning-driven Adaptive Bitrate (ABR) design and explore the challenges associated with deploying learning-based ABR mechanisms in real-world video streaming systems. Their proposed framework serves as the foundation for MetaABR, an innovative adaptive bitrate selection algorithm that leverages meta-reinforcement learning to maximize users' Quality of Experience (QoE). By training multiple learning tasks together using a shared meta-critic, MetaABR acquires transferrable meta-knowledge that enables effective bitrate selection across tasks. Moreover, it exhibits the ability to quickly adapt and learn new tasks in previously unseen environments with minimal trial runs. They implement MetaABR on an emulation platform that interfaces with the Linux network protocol stack through virtual network interfaces. Through extensive experiments conducted with real-world traces and wireless testbeds, we demonstrate that MetaABR consistently outperforms state-of-the-art ABR algorithms, providing the best comprehensive QoE across a range of network environments.

In [27] authors introduce a pioneering framework for personalized 360-degree video streaming based on meta-learning. Their approach efficiently captures the commonalities shared by viewers with diverse viewing patterns and Quality of Experience (QoE) preferences through effective meta-network designs. Specifically, they devise a meta-based Long Short-Term Memory (LSTM) model for viewport prediction and a meta-based reinforcement learning model for bitrate selection. Through extensive experiments conducted on real-world datasets, they demonstrate that their framework surpasses state-of-the-art data-driven approaches with an average improvement of 11% in prediction accuracy and a 27% average enhancement in QoE. Additionally, their framework exhibits swift adaptation to users with new preferences, requiring 67%-88% fewer training epochs on average.

Authors propose in [11] a meta-learning framework and introduce CosAttn, a method for streamer action recognition in live videos. Their method includes the following components: (1) Pretraining the backbone network with training samples similar to the streamer actions to be recognized, thereby enhancing its performance; (2) Extracting video-level features using the R(2+1)D-18 backbone and global average pooling within the meta-learning paradigm; (3) Utilizing CosAttn to generate streamer action category prototypes and recognize the streamer actions by calculating cosine similarity between the video-level features and the prototypes. They validate the effectiveness of our method through extensive experiments conducted on various real-world action recognition datasets.

In their work [3], authors introduce the MELANIE model, which treats events as Markov Decision Processes and applies meta-learning to reinforcement learning tasks. By considering each event as a distinct task, they develop an actor-critic learning approach to determine the optimal policy for estimating viewers' high-bandwidth connections. To facilitate rapid adaptation to changes in connections or viewer dynamics during an event, they incorporate a prioritized replay memory buffer based on the Kullback-Leibler divergence of viewers' connection rewards and throughputs. Additionally, they employ a model-agnostic meta-learning framework to generate a global model based on past events. Since viewers typically participate in limited events, they address the challenge of low structural similarity among different events. To tackle this issue, they propose a graph signature buffer that calculates structural similarities among multiple streaming events and adjusts the training of the global model accordingly. They evaluate their model on the task of link weight prediction using three real-world datasets of live video streaming events. Their experiments validate the effectiveness of our proposed model, achieving an average relative gain of 25% compared to state-of-the-art strategies.

In their research [25], authors introduce GMMP (GCN Meta-learning with Multi-granularity POS), a novel approach that utilizes multi-granularity Part-of-Speech (POS) guidance to train a Graph Convolutional Network (GCN) via meta-learning. Our objective is to generate high-quality captions for videos. GMMP leverages a graph-based representation where frames are treated as nodes, enabling modeling of temporal dependencies. Additionally, it incorporates a multi-granularity POS attention mechanism to capture POS information at the word and phrase levels. To enhance the learning of GCN, we employ meta-learning, which involves simultaneously maximizing the reward of the generated caption in a reinforcement task and the probability of the ground-truth caption in a supervised task. Through comprehensive experiments conducted on several benchmark datasets, we demonstrate the advantages and effectiveness of our GMMP model.

In order to effectively handle concept drifts with limited sample availability, [28] present an approach for online tuning of the Uncertainty Sampling threshold using meta-learning techniques. Their method leverages statistical meta-features extracted from adaptive windows to provide meta-recommendations for selecting an appropriate threshold. This approach enables a fine balance between the number of labeling queries and achieving high accuracy. Through extensive experiments, they demonstrate that their proposed approach achieves the optimal trade-off between accuracy and query reduction by dynamically adjusting the uncertainty threshold using lightweight meta-features.

In their research [9], authors introduce the System-status-aware Adaptive Network (SAN), which takes into account the real-time state of the device to deliver accurate predictions with minimal delay. By incorporating our agent's policy, they enhance the efficiency and robustness of the system, enabling it to handle fluctuations in the system status effectively. On two commonly used video understanding tasks, SAN achieves state-of-the-art performance while consistently maintaining low processing delays. However, training such an agent on diverse hardware configurations poses challenges, as labeled training data may be unavailable or computationally demanding. To tackle this issue, they propose the Meta Self-supervised Adaptation (MSA) method, which allows the agent's policy to adapt to new hardware configurations at test-time. This facilitates easy deployment of the model on unseen hardware platforms, overcoming the limitations of labeled training data and ensuring scalability.

From the literature we observe that Meta-learning is applied to DASH (Dynamic Adaptive Streaming over HTTP) for several reasons. One reason is Adaptation Optimization: DASH aims to dynamically adjust video streaming parameters, such as bitrate, quality, and buffer management, to provide an optimal streaming experience based on network conditions and user preferences. Meta-learning can improve the adaptation algorithm by learning from past experiences and optimizing the decision-making process. By leveraging meta-learning, DASH can adapt more efficiently and effectively to changing network conditions, leading to enhanced Quality of Experience (QoE).

Another reason is Personalization. Different viewers have diverse QoE preferences. Meta-learning can capture and model individual user preferences to personalize the streaming experience. By training on a range of user-specific QoE data, meta-learning algorithms can adapt the streaming parameters to optimize the QoE for each user, considering their unique preferences and viewing habits. Fast Adaptation is another reason: Network conditions can change rapidly, requiring quick adaptation to ensure uninterrupted streaming and high QoE. Meta-learning facilitates fast adaptation by learning from a variety of streaming scenarios and generalizing to new situations. By pre-training a meta-learner on diverse scenarios, it can quickly adapt to new environments without extensive retraining, enabling efficient and seamless streaming experiences.

The last reason we will discuss is Robustness to Uncertainty. Streaming environments often exhibit uncertainty, such as fluctuations in network bandwidth or congestion. Meta-learning can enhance the robustness of DASH algorithms by learning from past experiences and adapting to uncertain conditions. The meta-learner can generalize across various scenarios and make informed decisions, minimizing the impact of uncertainties on the streaming quality. Finally, the application of meta-learning to DASH improves adaptation optimization, enables personalization, facilitates fast adaptation, and enhances robustness to uncertainty. These benefits lead to improved QoE and a more satisfying video streaming experience for users.

3. TAXONOMY

A taxonomy is a classification system that categorizes and organizes the different aspects or types of Meta-Learning techniques used in DASH. It provides a hierarchical structure that groups similar methods together and highlights their unique characteristics. Taxonomies can be valuable when you want to provide an overview of the different types or categories of Meta-Learning techniques in DASH, allowing readers to understand the breadth of approaches available. It helps in presenting a more comprehensive landscape and can be used as a reference for researchers or practitioners. The hierarchy of the taxonomy is shown next.

Meta-Learning Approaches:
|__ Model-Agnostic Meta-Learning (MAML)
|__ Reptile
|__ Memory-Augmented Neural Networks
|__ Learning to Learn

Meta-Learning Components:
|__ Task Representation
|__ Meta-Model Architecture
|__ Optimization Algorithm
|__ Adaptation Strategy

Meta-Learning Objectives:
|__ Fast Adaptation
|__ Few-shot Learning
|__ Generalization

Meta-Learning Applications in DASH:
|__ Quality Adaptation
|__ Network Estimation
|__ Buffer Management

Each level is represented by a vertical bar (|), and subcategories or subtopics are indented with two underscores (__). This representation gives an overview of the taxonomy structure and the relationships between different categories in a hierarchical manner.
The taxonomy on Meta-Learning in Dynamic Adaptive Streaming over HTTP (DASH) is as follows:

Meta-Learning Approaches:
a. Model-Agnostic Meta-Learning (MAML) [6]: This approach focuses on learning a meta-learner that can quickly adapt to new tasks or streaming scenarios by leveraging pre-trained models and updating them based on a few samples from the new task.

b. Reptile [39]: Reptile is another model-agnostic meta-learning algorithm that aims to learn a good initialization of the model parameters. It gradually adapts the model to new tasks through repeated optimization steps on a few samples from each task.
c. Memory-Augmented Neural Networks [31]: These approaches incorporate external memory modules, such as a differentiable key-value store, to store and retrieve knowledge across different tasks or streaming scenarios.
d. Learning to Learn [31]: Learning to Learn methods employ meta-learning algorithms that aim to learn an optimizer that can quickly adapt the model to new tasks or environments.

Meta-Learning Components:
a. Task Representation: Methods differ in how they represent tasks or streaming scenarios. It can be in the form of features, parameters, or distributional representations.
b. Meta-Model Architecture: This refers to the architecture of the meta-learner. It can be a recurrent neural network (RNN) [33], convolutional neural network (CNN) [1], or any other suitable architecture.
c. Optimization Algorithm: The choice of optimization algorithm plays a crucial role in meta-learning. Different approaches use algorithms like gradient descent, stochastic gradient descent (SGD), or variants of SGD.
d. Adaptation Strategy [10]: This refers to how the meta-learner adapts its parameters to new tasks or streaming scenarios. It can involve gradient-based methods, memory-based methods, or other specialized techniques.

Meta-Learning Objectives:
a. Fast Adaptation [4]: Meta-learning aims to enable fast adaptation to new streaming scenarios or tasks by leveraging knowledge acquired from previous experiences.
b. Few-shot Learning [38]: Meta-learning enables effective learning with limited samples or data points. It focuses on generalizing from a small number of training examples to perform well on new tasks or streaming scenarios.
c. Generalization [29]: The meta-learner should be able to generalize across different streaming scenarios or tasks, capturing underlying patterns and knowledge that can be applied to unseen scenarios.

Meta-Learning Applications in DASH:
a. Quality Adaptation [13]: Meta-learning can be applied to improve the quality adaptation algorithms in DASH, enabling more efficient bitrate selection and smooth video playback across different network conditions.
b. Network Estimation [14]: Meta-learning can be used to estimate network conditions (e.g., available bandwidth, packet loss rate) based on previous experiences, allowing more accurate decision-making in adaptive streaming.
c. Buffer Management [24]: Meta-learning can assist in optimizing buffer management strategies, ensuring a balance between buffering latency and quality of experience (QoE)

during video streaming.

The taxonomy provided is a generalized framework for meta-learning in the context of Dynamic Adaptive Streaming over HTTP (DASH). Note that the specific techniques and approaches may evolve over time as research progresses.

4. FRAMEWORK

A framework provides a structured approach or methodology for understanding and implementing Meta-Learning in the context of DASH. It outlines the key components, processes, and interactions involved in leveraging Meta-Learning techniques. By using a framework, you can present a comprehensive and systematic view of how Meta-Learning is applied in DASH. This approach is particularly useful when you want to emphasize the practical implementation aspects and highlight the relationships between different elements of Meta-Learning. In our framework and we use the taxonomy derived in the previous section to categorize the techniques within that framework. The framework for Meta-Learning in Dynamic Adaptive Streaming over HTTP (DASH) is as follows:

Problem Definition:
Define the objective of meta-learning in the context of DASH, such as improving quality adaptation, network estimation, or buffer management. Identify the specific challenges or limitations in the current adaptive streaming algorithms that can be addressed through meta-learning.

Data Collection and Preprocessing:
Collect a diverse dataset of streaming scenarios, including variations in network conditions, video content, and user preferences. Preprocess the dataset to extract relevant features, such as video characteristics (bitrate, resolution), network metrics (bandwidth, latency), and QoE indicators (buffering time, video quality).

Meta-Model Architecture:
Design the architecture of the meta-learner, considering the specific requirements and characteristics of the DASH domain. Determine the suitable model type (e.g., neural network, memory-augmented network) that can capture the underlying patterns and enable efficient adaptation.

Meta-Training:
Split the dataset into meta-training and meta-validation sets. Define a meta-training algorithm that iteratively adapts the meta-learner to different streaming scenarios or tasks. Use an optimization algorithm, such as gradient descent, to update the meta-learner's parameters based on the performance on the meta-validation set. Explore various meta-learning approaches like MAML, Reptile, or memory-augmented networks, and evaluate their effectiveness in improving DASH performance.

Meta-Testing:
Evaluate the trained meta-learner on a separate meta-testing set that represents unseen streaming scenarios or tasks. Measure the performance of the meta-learner in terms of QoE metrics, such as video quality, start-up delay, buffering time, and smoothness of playback. Compare the performance of the meta-learner against traditional adaptive streaming algorithms to assess its effectiveness.

Fine-Tuning and Deployment:
Fine-tune the meta-learner on specific deployment scenarios or user preferences, if required. Integrate the meta-learner into the DASH system architecture, ensuring compatibility with existing components and protocols. Conduct extensive testing and evaluation in real-world scenarios to validate the effectiveness of the meta-learning approach.

Continuous Improvement:
Monitor the performance of the meta-learner in production environments and collect feedback from users. Update the meta-learner periodically using additional data or retraining to adapt to evolving network conditions and user preferences. Stay updated with the latest research in meta-learning and adaptive streaming to incorporate new techniques and advancements.

The framework provided outlines a general procedure for applying meta-learning in the context of DASH. Note that the specific implementation details may vary depending on the chosen meta-learning algorithms, network architectures, and dataset characteristics. In other words, some of the items in the taxonomy will contribute towards the framework implementation.

5. DISCUSSION

Integrating a taxonomy within a framework for meta-learning in DASH can provide a comprehensive and structured approach to understanding and analyzing the different aspects of meta-learning techniques and their applications in the context of Dynamic Adaptive Streaming over HTTP (DASH). Let's discuss the benefits and implications of incorporating a taxonomy within a meta-learning framework in DASH. The first is structured organization. A taxonomy provides a structured organization of concepts, techniques, and applications related to meta-learning in DASH. It helps researchers, practitioners, and industry professionals to navigate the field and gain a clear understanding of the different components and their relationships. By organizing the knowledge in a systematic manner, the taxonomy enables easier comprehension and exploration of the meta-learning landscape in DASH.

A second benefit is conceptual clarity. The taxonomy establishes a common set of terms, definitions, and categories within the meta-learning framework. It clarifies the terminology used in the field and ensures consistent understanding and communication across different research studies. This leads to greater conceptual clarity and minimizes ambiguity when discussing and comparing meta-learning approaches and applications in DASH. A third benefit is identification of research gaps: By providing a taxonomy, researchers can identify the specific sub-areas within meta-learning in DASH that have received significant attention and those that require further exploration. It allows for a systematic analysis of the existing literature, identifying gaps where novel contributions can be made. Researchers can focus their efforts on addressing these gaps and advancing the state-of-the-art in meta-learning for DASH.

A fourth benefit is benchmarking and evaluation. A taxonomy within a meta-learning framework can guide the development of evaluation methodologies, benchmarks, and performance metrics specific to meta-learning in DASH. It helps establish standards for evaluating the effectiveness, efficiency, and real-world impact of meta-learning techniques. Researchers can design experiments and benchmarks that align with the defined taxonomy, enabling fair comparisons and meaningful evaluations of different approaches. A fifth benefit is framework adaptability: The taxonomy can be designed to accommodate the evolving nature of meta-learning in DASH. As new techniques and applications emerge, the taxonomy can be expanded or modified to include these advancements. This adaptability ensures that the framework remains relevant and up-to-date in capturing the latest developments in the field.

Collaboration and knowledge sharing is a sixth benefit. A taxonomy provides a common reference point for researchers, practitioners, and industry professionals working in meta-learning and DASH. It encourages collaboration and knowledge sharing by facilitating discussions, comparisons, and sharing of insights within a common framework. This fosters a community-driven approach to advancing meta-learning in the context of DASH.

Thus, incorporating a taxonomy within a framework for meta-learning in DASH offers several benefits. It brings structure, clarity, and organization to the field, enables the identification of research gaps, facilitates benchmarking and evaluation, allows for adaptability to emerging trends, and promotes collaboration and knowledge sharing. By adopting a taxonomy-driven approach, researchers can effectively explore and advance the integration of meta-learning techniques in the domain of adaptive video streaming.

6. CONCLUSION

In conclusion, the framework with a taxonomy on meta-learning used in Dynamic Adaptive Streaming over HTTP (DASH) provides a structured and systematic approach to enhance adaptive streaming algorithms through meta-learning techniques. By leveraging prior knowledge and experiences, meta-learning enables DASH systems to adapt quickly and effectively to changing network conditions and user preferences, ultimately improving the quality of experience for users.

The framework encompasses essential components, including data collection and preprocessing, meta-model architecture, meta-training, meta-testing, fine-tuning, and continuous improvement. Each component plays a vital role in the successful application of meta-learning in DASH, ensuring efficient adaptation and optimal streaming quality.

The taxonomy within the framework categorizes different aspects of meta-learning in DASH, such as meta-learning approaches, components, objectives, and applications. This taxonomy provides a shared language and structure for researchers, practitioners, and developers to discuss and explore the application of meta-learning techniques in the context of DASH. It helps in organizing and understanding the various dimensions and components of meta-learning, facilitating further research and development in this field.

By following the proposed framework, researchers and practitioners can collect and preprocess relevant data, design and train meta-learners suitable for DASH, evaluate their performance, and continuously improve them based on specific deployment scenarios. The framework provides a systematic guide to applying meta-learning techniques, enabling the enhancement of adaptive streaming algorithms and improving the overall quality of experience for DASH users.

As the field of DASH and meta-learning continues to evolve, the framework and taxonomy offer a foundation for further exploration, experimentation, and innovation. By incorporating the latest advancements in meta-learning and adaptive streaming, researchers and practitioners can continue to enhance DASH systems, ensuring seamless and high-quality video streaming experiences for users in dynamic network environments.

REFERENCES

1. Albawi S, Mohammed TA, Al-Zawi S. **Understanding of a convolutional neural network.** In2017 international conference on engineering and technology (ICET) 2017 Aug 21 (pp. 1-6). Ieee.
2. Andrychowicz M, Denil M, Gomez S, Hoffman MW, Pfau D, Schaul T, Shillingford B, De Freitas N. **Learning to learn by gradient descent by gradient descent.** Advances in neural information processing systems. 2016;29.
3. Antaris S, Rafailidis D, Girdzijauskas S. **Meta-reinforcement learning via buffering graph signatures for live video streaming events.** InProceedings of the 2021 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2021 Nov 8 (pp. 385-392).
4. Caccia M, Rodriguez P, Ostapenko O, Normandin F, Lin M, Page-Caccia L, Laradji IH, Rish I, Lacoste A,

Vázquez D, Charlin L**. Online fast adaptation and knowledge accumulation (osaka): a new approach to continual learning.** Advances in Neural Information Processing Systems. 2020;33:16532-45.
5. Ejembi OO. **Enabling energy-awareness for internet video** (Doctoral dissertation, University of St Andrews).
6. Fallah A, Mokhtari A, Ozdaglar A. **Personalized federated learning with theoretical guarantees: A model-agnostic meta-learning approach.** Advances in Neural Information Processing Systems. 2020;33:3557-68.
7. Feurer M, Hutter F. **Hyperparameter optimization. Automated machine learning: Methods, systems, challenges**. 2019:3-3.
8. Finn C, Abbeel P, Levine S. **Model-agnostic meta-learning for fast adaptation of deep networks.** InInternational conference on machine learning 2017 Jul 17 (pp. 1126-1135). PMLR.
9. Foo LG, Gong J, Fan Z, Liu J. **System-status-aware Adaptive Network for Online Streaming Video Understanding.** InProceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition 2023 (pp. 10514-10523).
10. Gama PH, Oliveira H, dos Santos JA, Cesar Jr RM. **An overview on Meta-learning approaches for Few-shot Weakly-supervised Segmentation.** Computers & Graphics. 2023 May 20.
11. He C, Zhang J, Yao J, Zhuo L, Tian Q. **Meta-Learning Paradigm and CosAttn for Streamer Action Recognition in Live Video.** IEEE Signal Processing Letters. 2022 Apr 19;29:1097-101.
12. He Q, Moayyedi A, Dán G, Koudouridis GP, Tengkvist P. **A meta-learning scheme for adaptive short-term network traffic prediction**. IEEE Journal on Selected Areas in Communications. 2020 Jun 5;38(10):2271-83.
13. Huang T, Zhou C, Zhang RX, Wu C, Sun L. **Learning tailored adaptive bitrate algorithms to heterogeneous network conditions: A domain-specific priors and meta-reinforcement learning approach.** IEEE Journal on Selected Areas in Communications. 2022 Jun 15;40(8):2485-503.
14. Huang T, Zhou C, Zhang RX, Wu C, Sun L**. Learning tailored adaptive bitrate algorithms to heterogeneous network conditions: A domain-specific priors and meta-reinforcement learning approach.** IEEE Journal on Selected Areas in Communications. 2022 Jun 15;40(8):2485-503.
15. Huo L, Wang Z, Xu M, Ding Z, Tao X. **Optimizing QoE of multiple users over DASH: A meta-learning approach.** InICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) 2019 May 12 (pp. 3032-3036). IEEE.
16. Huo L, Wang Z, Xu M, Li Y, Ding Z, Wang H. **A meta-learning framework for learning multi-user preferences in QoE optimization of DASH.** IEEE Transactions on Circuits and Systems for Video Technology. 2019 Sep 3;30(9):3210-25.
17. Khan K, Goodridge W. **Future DASH applications: A survey.** International Journal of Advanced Networking and Applications. 2018 Sep 1;10(2):3758-64.
18. Khan K, Goodridge W. **QoE in DASH.** International Journal of Advanced Networking and Applications. 2018;9(4):3515-22.
19. Khan K, Goodridge W. **Rate oscillation breaks in HTTP on-off distributions: a DASH framework.** International Journal of Autonomous and Adaptive Communications Systems. 2020;13(3):273-96.
20. Khan K, Goodridge W. **Reinforcement Learning in DASH.** International Journal of Advanced Networking and Applications. 2020 Mar 1;11(5):4386-92.
21. Koffka K, Wayne G. **A DASH Survey: the ON-OFF Traffic Problem and Contemporary Solutions.** Computer Sciences and Telecommunications. 2018(1):3-20.
22. Koffka K. **A SURVEY OF APPLICATIONS AND ARCHITECTURES IN SOFTWARE DEFINED NETWORKING (SDN).** Computer Sciences and Telecommunications. 2019(1):13-24.
23. Kua J, Armitage G, Branch P. **A survey of rate adaptation techniques for dynamic adaptive streaming over HTTP.** IEEE Communications Surveys & Tutorials. 2017 Mar 22;19(3):1842-66.
24. Lee R, Venieris SI, Lane ND. **Deep neural network–based enhancement for image and video streaming systems: A survey and future directions**. ACM Computing Surveys (CSUR). 2021 Oct 4;54(8):1-30.
25. Li P, Zhang P, Xu X. **Graph convolutional network meta-learning with multi-granularity POS guidance for video captioning.** Neurocomputing. 2022 Feb 1;472:294-305.
26. Li W, Li X, Xu Y, Yang Y, Lu S. MetaABR: A **Meta-Learning Approach on Adaptative Bitrate Selection for Video Streaming.** IEEE Transactions on Mobile Computing. 2023 Mar 21.
27. Lu Y, Zhu Y, Wang Z. **Personalized 360-Degree Video Streaming: A Meta-Learning Approach.** In Proceedings of the 30th ACM International Conference on Multimedia 2022 Oct 10 (pp. 3143-3151).
28. Martins VE, Cano A, Junior SB. **Meta-learning for dynamic tuning of active learning on stream classification.** Pattern Recognition. 2023 Jun 1;138:109359.
29. Munkhdalai T, Yu H. **Meta networks.** InInternational conference on machine learning 2017 Jul 17 (pp. 2554-2563). PMLR.
30. Peng H. **A comprehensive overview and survey of recent advances in meta-learning.** arXiv preprint arXiv:2004.11149. 2020 Apr 17.
31. Santoro A, Bartunov S, Botvinick M, Wierstra D, Lillicrap T. **Meta-learning with memory-augmented neural networks.** InInternational conference on machine learning 2016 Jun 11 (pp. 1842-1850). PMLR.
32. Seufert M, Egger S, Slanina M, Zinner T, Hoßfeld T, Tran-Gia P. **A survey on quality of experience of HTTP**

adaptive streaming. IEEE Communications Surveys & Tutorials. 2014 Sep 30;17(1):469-92.
33. Sherstinsky A. **Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network.** Physica D: Nonlinear Phenomena. 2020 Mar 1;404:132306.
34. Stockhammer T. **Dynamic adaptive streaming over HTTP-- standards and design principles.** InProceedings of the second annual ACM conference on Multimedia systems 2011 Feb 23 (pp. 133-144).
35. Vanschoren J. **Meta-learning: A survey**. arXiv preprint arXiv:1810.03548. 2018 Oct 8.
36. Vilalta R, Drissi Y. **A perspective view and survey of meta-learning.** Artificial intelligence review. 2002 Jun;18:77-95.
37. Wang Y, Yao Q, Kwok JT, Ni LM. **Generalizing from a few examples: A survey on few-shot learning.** ACM computing surveys (csur). 2020 Jun 12;53(3):1-34.
38. Wang Y, Yao Q, Kwok JT, Ni LM. **Generalizing from a few examples: A survey on few-shot learning.** ACM computing surveys (csur). 2020 Jun 12;53(3):1-34.
39. Yao X, Zhu J, Huo G, Xu N, Liu X, Zhang C. **Model-agnostic multi-stage loss optimization meta learning.** International Journal of Machine Learning and Cybernetics. 2021 Aug;12(8):2349-63.
40. Zhuang F, Qi Z, Duan K, Xi D, Zhu Y, Zhu H, Xiong H, He Q. **A comprehensive survey on transfer learning.** Proceedings of the IEEE. 2020 Jul 7;109(1):43-76.