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Machine learning in Dynamic Adaptive Streaming over HTTP (DASH)

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ABSTRACT

Recently machine learning has been introduced into the area of adaptive video streaming. This paper explores a novel taxonomy that includes six state of the art techniques of machine learning that have been applied to Dynamic Adaptive Streaming over HTTP (DASH): (1) Q-learning, (2) Reinforcement learning, (3) Regression, (4) Classification, (5) Decision Tree learning, and (6) Neural networks.

Keywords—**Machine learning; DASH; Q-learning; Reinforcement learning; Regression; Classification; Decision Tree learning; Neural networks**

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I. INTRODUCTION

The growing trend of the usage of video services demands the availability of efficient and reliable video quality assessment and transmission techniques. In a HAS design, video content is stored on a server as segments of fixed duration at different quality levels. Each client can request the segment at the most appropriate quality level on the basis of the local perceived bandwidth or its internal buffer level. In this way, video playback dynamically changes according to the available resources, resulting in a smoother video streaming.

Typical goals that measure the goodness of a streaming session take into account average quality levels displayed to the user, fluctuations in quality levels, and rebuffering events [21]. Unfortunately, there is no single agreed upon measurement of streaming quality. The ultimate standard of goodness might involve conducting comprehensive user surveys under different network conditions and devices [37]. Hence, the ability to optimize with respect to a wide variety of objective functions that take these events into account is of utmost importance.

Q-learning can also be viewed as a method of asynchronous dynamic programming (DP). It provides agents with the capability of learning to act optimally in Markovian domains by experiencing the consequences of actions, without requiring them to build maps of the domains [35]. In Q-learning, if each subagent uses the conventional Q-learning algorithm [39], global optimality is not achieved. Instead, each subagent learns the Q_j values that would result if that subagent were to make all future decisions for the agent. This "illusion of control" means that the subagents converge to "selfish" estimates that overestimate the true values of their own rewards with respect to a globally optimal policy [24].

In adaptive streaming environments the concept of reinforcement learning (RL) is at client side. The client is able learn the most appropriate parameter configuration under different network conditions. RL is a machine learning technique, in which an agent can learn about its environment by performing a number of actions. Every time an action is taken, the agent perceives feedback through a numerical reward from the environment [30]. The agent's goal is to learn which action should be taken in a given environmental state, in order to maximize the cumulative numerical reward.

Regression is a simple, yet powerful technique for identifying trends in datasets and predicting properties of new data points. The output can be a continuous value, a discrete value (e.g. a boolean), or a vector of such values. The input is a vector, and can also be either discrete or continuous. The individual properties of one data row are called features. For discrete problems, threshold value(s) is/are chosen between the various "levels" of output. The phase-space surface defined by these levels is called the decision boundary [14]. The prediction is done via a hypothesis function. The "learning" is driven by a set of examples.

Classification is the procedure of placing a new observation into a set of categories (sub-categories), on the basis of a training set of data, which contains observations (or instances) whose category membership is known [18]. The classification model can be developed on the complete case data for a given feature. This model treats the feature as the outcome and uses the other features as predictors. Feature subset selection is the process of identifying and removing as many irrelevant and redundant features as possible [12]. This reduces the dimensionality of the data and enables data mining algorithms to operate faster and more effectively.

The decision tree is defined as a supervised learning model that hierarchically maps a data domain onto a response set. It divides a data domain (node) recursively into two sub domains such that the subdomains have a higher information gain than the node that was split. The goal of supervised learning is the classification of the data, and therefore, the information gain means the ease of classification in the subdomains created by a split. Finding

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the best split that gives the maximum information gain (i.e., the ease of classification) is the goal of the optimization algorithm in the decision tree-based supervised learning [29].

Artificial neural networks can be employed to solve a wide spectrum of problems in optimization, parallel computing, matrix algebra and signal processing [6]. There exist many training methods for both feedforward networks (including multilayer and radial basis networks) and recurrent networks. In addition to conjugate gradient and Levenberg-Marquardt variations of the backpropagation algorithm (BA), the Neural Network BAs also covers Bayesian regularization and early stopping, which ensure the generalization ability of trained networks [8]. Practical uses of neural networks includes training for function approximation, pattern recognition, clustering, prediction, and of lately adaptive video streaming.

This work consists of four sections. Section II presents the Taxonomy of Machine Learning-based techniques currently applied to DASH. Section III gives examples of these state of the art techniques that were defined in the taxonomy. Finally, the conclusion is given in Section IV.

II. TAXONOMY OF MACHINE LEARNING-BASED AVS

The Machine Learning-based AVS techniques are categorized into (1) Q-Learning, (2) Reinforcement Learning, (3) Regression, (4) Classification, (5) Decision Tree Learning, and (6) Neural Networks. (cf. Figure 1)

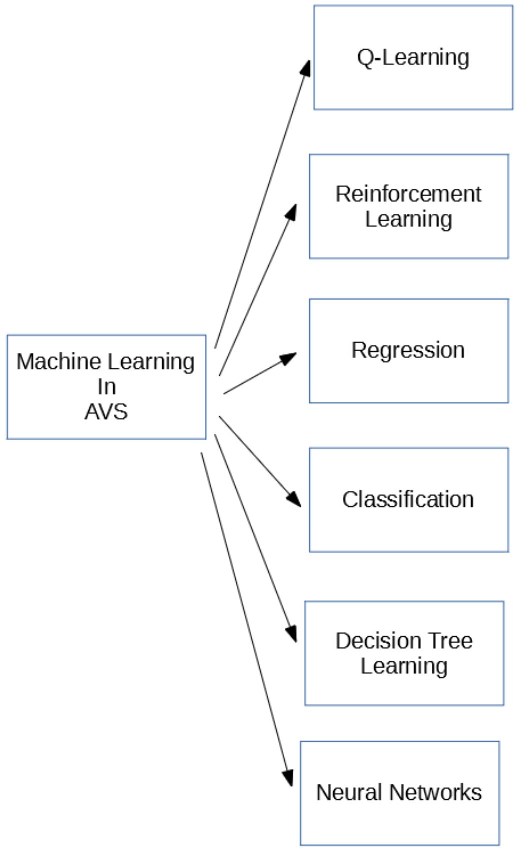

Figure 1: Machine Learning in AVS: a taxonomy.

III. MACHINE-LEARNING IN DASH

A. *Q-Learning*

An adaptive Q-Learning-based HAS client is proposed in [4]. The proposed HAS client dynamically learns the optimal behavior corresponding to the current network environment. This is in contrast to the way current heuristics deal with the AVS problem. It considers (1) multiple aspects of video quality, (2) a tunable reward function which gives the opportunity to focus on different aspects of the Quality of Experience (QoE), and (3) the quality as perceived by the end-user. The proposed HAS client is evaluated by a network-based simulator. It investigates multiple reward configurations and Q-learning specific settings. The proposed client outperforms standard HAS players in the evaluated networking environments.

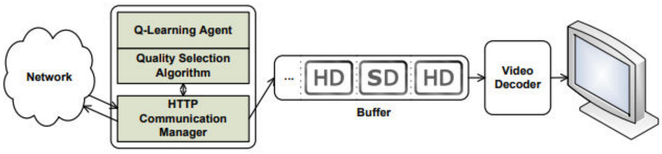

Figure 2: Schematic overview of the Q-learning HAS client design. [4]

Authors in [31] use a novel learning model to determine (a) the optimal time to re-route the traffic flows, and (b) to change the bitrate of the video. To accomplish this task they propose an adaptive video streaming system with a learning-based approach. It runs over a Software Defined Network (SDN) [11], [13]. In the proposed video streaming system the learning model aims to minimize (1) the packet loss rate, (2) quality changes, and (3) controller cost. It concurrently adapts (i) the flow routes and (ii) video quality. The performance of the learning-based approach is tested by comparing it to traditional Internet routing and the greedy approach. The proposed system significantly outperforms the traditional Internet routing approach and the greedy approach in experiments under different network scenarios. The tests covered both Quality of Experience (QoE) and network cost.

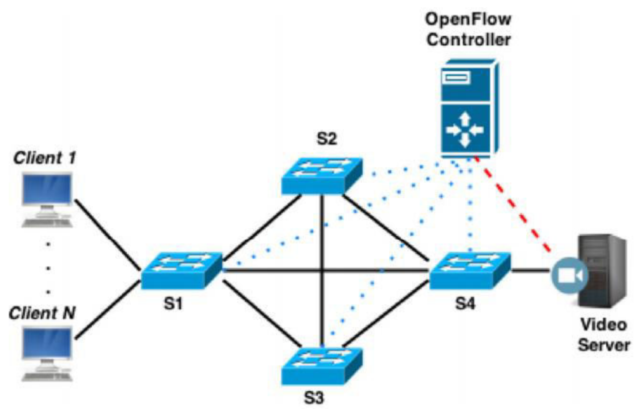

Figure 3: Network topology used in the simulations. There are six clients, one server and one controller in the network. The blue dotted lines indicate the OpenFlow protocol and the red dashed line represents the communication between the server and the controller. [31]

A (frequency adjusted) Q-learning HAS client is proposed in [5]. The proposed HAS client dynamically learns the optimal behaviour in terms of the Quality of Experience (QoE) corresponding to the current network environment. Thus, the client has been optimised both in terms of (1) global performance and (2) convergence speed. In a wide range of network configurations, thorough evaluations show that the proposed client can outperform deterministic algorithms by 11–18% in terms of mean opinion score [28], [36] (MOS).

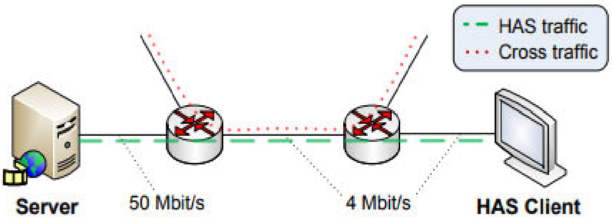

Figure 4: Overview of the simulated topology. [5]

Authors in [17] propose a Q-Learning-based algorithm for an HTTP Adaptive Streaming (HAS). It maximizes the perceived user quality. Account is taken into the relationships amongst (a) the estimated bandwidth, (2) the qualities, and (3) penalizing the freezes. Results show that it produces an optimal control as observed with other approaches do, but in addition it keeps the adaptiveness.

B. *Reinforcement Learning*

Authors in [22] propose a Reinforcement Learning-based quality selection algorithm. It is able to achieve fairness in a multi-client setting. A coordination proxy in charge of facilitating the coordination among clients is a key element of their approach. There are three advantages to this approach: (1) the algorithm is able to learn and adapt its policy depending on network conditions. This is unlike recently developed HAS heuristics. (2) fairness is achieved without explicit communication among agents. Thus there is no significant overhead introduced into the network. (3) There are no modifications to the standard HAS architecture. This novel approach is evaluated through simulations using (a) mutable network conditions, and (b) in several multi-client scenarios. The proposed approach improves fairness by up to 60% compared to current HAS heuristics.

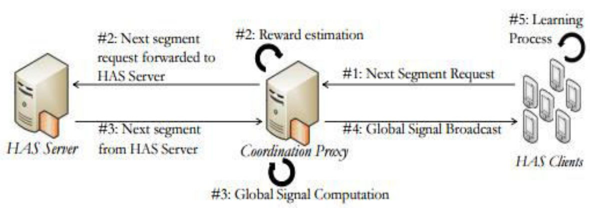

Figure 5: Logical work-flow of the proposed solution. [22]

An adaptive method that combines video encoding and the video transmission control system is presented in [2]. The study was implemented over heterogeneous networks. The method includes the following steps: (1) collect and standardize the real-time information describing the network and the video, (2) assess the video quality, (3) calculate the video coding rate based on the standardized information, (4) process the encoded compression of the video according to the calculated coding rate, and (5) transfer the compressed video. It was shown by experiments that there is a significant improvement for the quality of real-time videos transmission. This is achieved without changing the existing network. The advantages of the solution are (1) it is easy to deploy. (2) easy to implement quickly, and (3) may help to extensively ensure video quality for normal users.

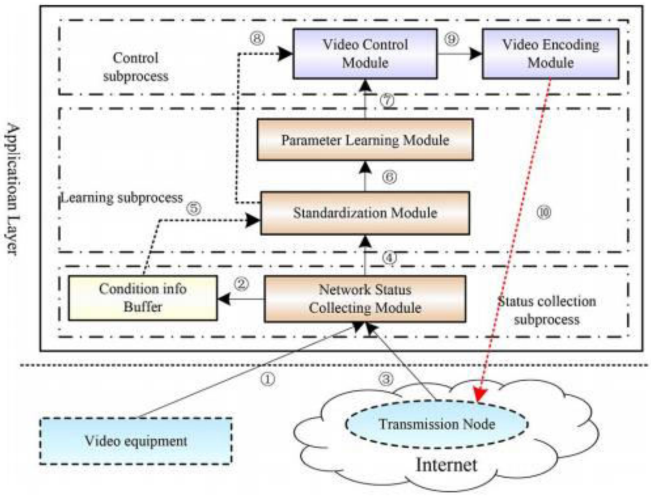

Figure 6: Proposed system framework. [2]

A reinforcement learning approach that uses only the buffer state information to choose the segment quality during playback is proposed in [44]. This approach optimizes for a measure of user-perceived streaming quality. Results are simulated and show that the proposed approach achieves better QoE than rate-based, buffer-based, and reinforcement learning-based approaches.

The concept of reinforcement learning is introduced at client side in [32]. It allows the player to adaptively change the parameter configuration for existing rate adaptation heuristics. Characteristics that are taken into account in the decision process are bandwidth-based. This allows the player to improve its bandwidth-awareness. The goals of the model are (1) to actively reduce the average buffer filling, and (2) to evaluate the results for two well-known heuristics: (a) the Microsoft IIS Smooth Streaming heuristic [43], and (2) the QoE-driven Rate Adaptation Heuristic for Adaptive video Streaming [22]. The average buffer filling can be reduced by 8.3% compared to state of the art by using the proposed learning-based approach. This reduction is achieved while achieving a comparable level of QoE.

Authors in [16] develop Pensieve. Pensieve is a system that generates ABR algorithms. It only uses Reinforcement Learning (RL) techniques. Pensieve uses RL to train a neural network model. The model selects bitrates for future video chunks. This selection is based on observations collected by client video players. Pensieve does not rely upon pre-programmed models or assumptions about the environment, which makes it different from other approaches. Instead, it learns to make ABR decisions solely through observations. These observations are as a result of the performance of past decisions made by the controller. Consequently, Pensieve can automatically allow ABR algorithms that adapt to (1)

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a wide range of environmental conditions, and (2) QoE metrics. Pensieve is compared to state-of-the-art ABR algorithms. Pensive uses (a) trace-driven experiments, (b) real world experiments ((a) and (b) span a wide variety of network conditions), (c) QoE metrics, and (d) video properties. Pensieve outperforms the best state of the art scheme in all considered scenarios. It obtains improvements in average QoE of 13.1%-25.0%. Pensieve's policies generalize well. It outperforms existing schemes. This is so even on networks on which it was not trained.

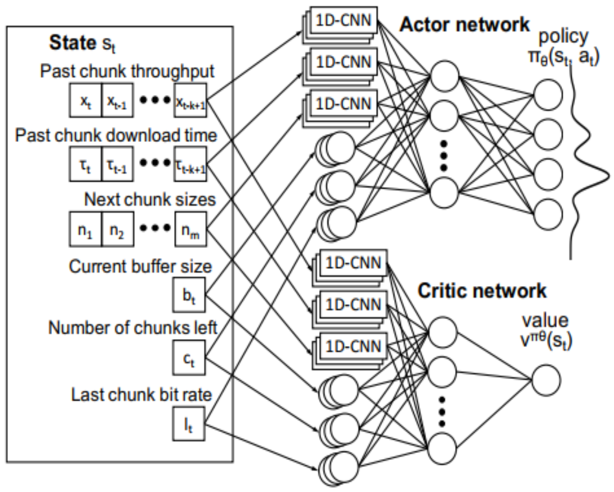

Figure 7: The Actor-Critic algorithm that Pensieve uses to generate
ABR policies. [16]

Authors in [41] discuss the use of reinforcement-learning (RL) to learn the optimal request strategy at the HAS client. It progressively maximizing a pre-defined Quality of Experience (QoE)-related reward function. The most influential factors for the request strategy are investigated under a RL framework. The strategy uses a forward variable selection algorithm. The performance of the RL-based HAS client is evaluated. It is done on a Video-on-Demand (VOD) simulation system. Results are gathered from experiments. The RL-based HAS client is able to optimize the quantitative QoE given the QoE-related reward function. The RL-based HAS client is more robust and flexible compared to a conventional HAS system, even under versatile network conditions.

C. Regression

In is shown in [15] that static users and adaptive streaming users have less starvation events than mobile users. Also researchers observed that with mobile users it is more difficult to predict their video starvation. It was shown that (1) channel conditions, and (2) number of active users are two important features which contribute to better prediction performance. The two features prediction strategy provides sufficient accuracy for static users. However, but not sufficient for mobile users. We also demonstrate that the two information, number of users served in a cell and the number of users experiencing video starvation, provide similar prediction accuracy.

In the proposed method [19], authors use the QoS parameters for the video streaming. These parameters are determined based on a machine learning algorithm. It uses regression analysis. The parameters used for the model are (a) according to the user requirements, (b) computational/network resources, and (c) service provisioning environments. The design and implementation of a prototype shows the method is experimentally valid and feasible.

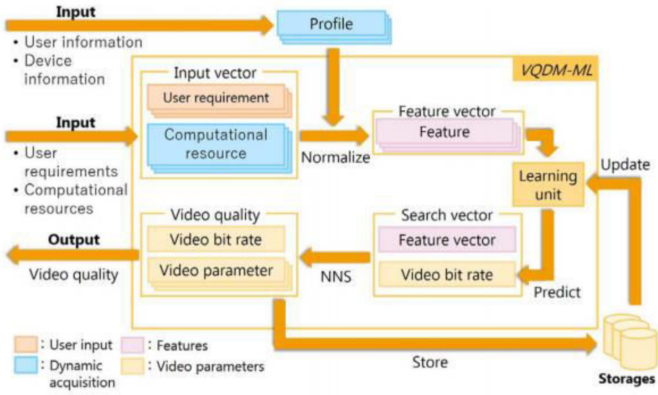

Figure 8: The Video quality determining mechanism with machine learning. [19]

Authors in [27] investigate quality prediction models for videos. They use (1) well-known image metrics, (2) information about the bitrate levels, and (3) a relatively simple machine learning method. Even though quality assessment of ABR videos is a hard problem, the research shows that initial results are promising. A Spearman rank order correlation of 0.88 is obtained using content-independent cross-validation.

A no-reference objective quality estimation framework is proposed in [26]. The framework is suitable for any block-based video codec. In the proposed solution, features are extracted from coding units. They are then summarized to form features at frame levels. Stepwise regression is used to select the important feature variables. This reduces the dimensionality of feature vectors. Subsequently, a polynomial regression-based approach is used to model the nonlinear relationship amid (a) the feature vectors and (b) the true objective quality values. Such values are likely for coding units and video frames. The proposed framework is implemented using MPEG-2 and HEVC. The objective quality estimation results are compared against an existing state-of-the-art solution. It is then quantified using the Pearson correlation factor and the root mean square error measure.

D. Classification

Authors in [23] propose a network-based framework. A network controller prioritizes the delivery of particular video segments. This is done to prevent freezes at the clients. This framework is based on OpenFlow. OpenFlow is a widely adopted protocol to implement the software-defined networking (SDN) principle. The main element of the controller is a Machine Learning (ML) engine. This engine is based on the random undersampling boosting algorithm and fuzzy logic. It can detect when a client is close to a freeze and drive the network prioritization to avoid it. This decision is based on measurements collected from the network nodes only. The engine does not have any knowledge on (1) the streamed videos or (2) on the clients' characteristics. The design of the proposed ML-based framework is discussed and illustrated. In addition, its performance with other benchmarking HAS solutions is compared. This is undertaken with various video streaming scenarios. Principally, through extensive experimentation it is shown that the proposed approach can reduce video freezes and freeze time with about 65% and 45% respectively.

A Machine Learning-based Adaptive Streaming over HTTP (MLASH) is presented in [3]. It is an elastic framework and exploits a wide range of useful network-related features to train a rate classification model. MLASH allows its machine learning-based framework to be incorporated with any existing adaptation algorithm and utilize big data characteristics. This would improve a model's prediction accuracy. Trace-based simulations show that machine learning-based adaptation achieves a better performance than traditional adaptation algorithms. Performance is measured in terms of a players target quality of experience (QoE) metrics.

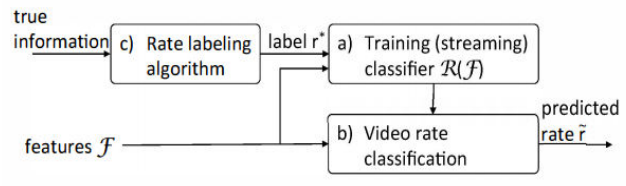

Figure 9: System Architecture ofMLASH. [3]

Authors in [20] present a methodology for the classification of end users' QoE. This is for users watching YouTube videos, and is based only on statistical properties of encrypted network traffic. The developed system is called YouQ. It includes (1) tools for monitoring, (2) analysis of application-level quality indicators, and (3) corresponding traffic traces. Collected data is then used for the development of machine learning models for QoE classification. This is based on computed traffic features per video session. A collected dataset corresponding to 1060 different YouTube videos streamed across 39 different bandwidth scenarios is used to test the YouQ system and methodology. Various classification models are also tested. Classification accuracy was found to be up to 84%. Three QoE classes are used (a) "low", (b) "medium" or (c) "high". Up to 91% classification accuracy is obtained when using binary classification classes (i) "low" and (2) "high". Why and when prediction errors occur are discussed in an attempt to improve the models in the future.

E. Decision Tree Learning

Authors in [1] tackles the problem of QoE monitoring, assessment and prediction in cellular networks, relying on end-user device (i.e., smart-phone) QoS passive traffic measurements and QoE crowdsourced feedback. We conceive different QoE assessment models based on supervised machine learning techniques, which are capable to predict the QoE experienced by the end user of popular smartphone apps (e.g., YouTube and Facebook), using as input the passive in-device measurements. Using a rich QoE dataset derived from field trials in operational cellular networks, we benchmark the performance of multiple machine learning based predictors, and construct a decision-tree based model which is capable to predict the per-user overall experience and service acceptability with a success rate of 91% and 98% respectively To the best of our knowledge, this is the first paper using end-user, in-device passive measurements and machine learning models to predict the QoE of smartphone users in operational cellular networks.

Authors in [7] have used the Institut National de la Recherche Scientifique (INRS) audiovisual quality dataset which is specifically designed to include ranges of parameters and degradations typically seen in real-time communications to build Decision Trees--based Ensemble (DTE) methods. It is shown that DTEs have outperformed both Deep Learning-based and Genetic Programming-based models. This is in terms of the (a) Root-Mean-Square Error (RMSE), and (b) Pearson correlation values. It was shown through other conducted experiment that Random Forests-based prediction models achieve high accuracy for both the INRS audiovisual quality dataset and other publicly available comparable datasets.

F. Neural Networks

A novel automated and computationally efficient video assessment method is introduced in [34]. The method enables accurate real-time (online) analysis of delivered quality in an adaptable and scalable manner. Offline deep unsupervised learning processes are employed at the server side. The method is inexpensive for the client as there is a no-reference measurements at the client side. It provides both real-time assessment and performance comparable to the full reference counterpart at the client side. The method is tested on the LIMP Video Quality Database [33]. It obtains a correlation between 78% and 91% to the FR benchmark [38]. The method is flexible, dynamically adaptable to new content and is scalable with the number of videos because of its unsupervised learning essence.

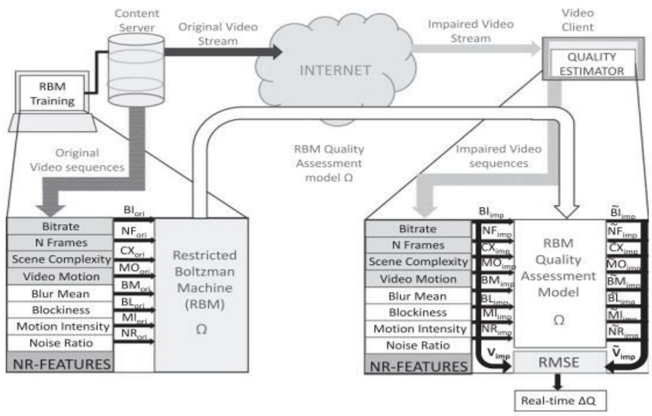

Figure 10: Real-time UDL-based video quality assessment method. [34]

Authors in [10] present D-DASH. This is a framework that combines Deep Learning and Reinforcement Learning techniques. It optimizes the Quality of Experience (QoE) of DASH. Authors propose different learning architectures. They are assessed, combined with feed-

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forward and recurrent deep neural networks and incorporates advanced strategies. D-DASH designs are thoroughly evaluated against state-of-the-art, heuristic and learning-based algorithms. Performance indicators such as image quality across video segments and freezing/rebuffering events are used. Results are obtained on both real and simulated channel traces. They show the superiority of D-DASH in nearly all the considered quality metrics. The D-DASH framework exhibits faster convergence to the rate-selection strategy than the other learning algorithms considered in the study and yields a considerably higher QoE.

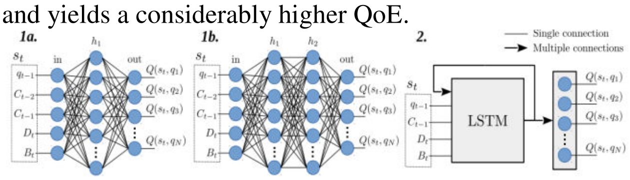

Figure 11: Network architectures. [10]

Authors in [25] present bitstream-based features for perceptual quality estimation of HEVC coded videos. Various factors are used including: (1) the impact of different sizes of block-partitions, (2) use of reference-frames, (3) the relative amount of various prediction modes, (4) statistics of motion vectors and, (5) quantization parameters are taken into consideration. The result are 52 features relevant for perceptual quality prediction being produced. The used test stimuli constitutes 560 bitstreams. These have been carefully extracted for this analysis from the 59, 520 bistreams of the large-scale database generated by the Joint Effort Group (JEG) [9]. The significance of the considered features through reasonably accurate and monotonic prediction of a number of objective quality metrics is highlighted.

Authors in [42] propose a novel no-reference (NR) video quality metric that evaluates the impact of frame freezing due to either packet loss or late arrival. The metric uses a trained neural network (NN). The NN acts on features that are chosen to capture the impact of frame freezing on the user perceived quality. The considered features include (a) the number of freezes, (b) freeze duration statistics, (c) inter-freeze distance statistics, (d) frame difference before and after the freeze, (e) normal frame difference, and (f) the ratio of them. The NN finds the mapping between features and subjective test scores. It optimizes the network structure and the feature selection. This is done through a cross-validation procedure. The cross-validation uses training samples extracted from both VQEG [40] and LIVE video databases. The resulting feature set and network structure gives precise quality prediction for both the training data containing 54 test videos and an unconnected testing dataset including 14 videos, with Pearson correlation coefficients greater than 0.9 and 0.8 for the training set and the testing set, respectively.

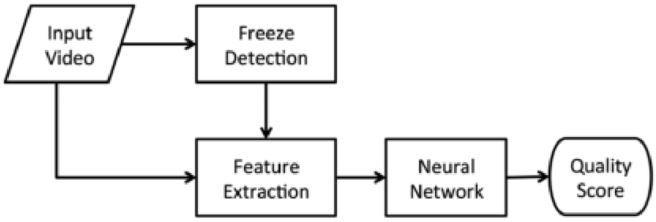

Figure 12: Flowchart of the proposed metric. [42]

IV. CONCLUSION

Recently machine learning has been introduced into the area of adaptive video streaming. This paper explores a novel taxonomy that includes six state of the art techniques of machine learning that have been applied to Dynamic Adaptive Streaming over HTTP (DASH): (1) Q-learning, (2) Reinforcement learning, (3) Regression, (4) Classification, (5) Decision Tree learning, and (6) Neural networks.

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