Performance Estimation of Encrypted Video Streaming in Light of End-User Playback-Related Interactions Based on Machine Learning

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Motivation

- Widespread use of traffic encryption by Over The Top (OTT) providers such as YouTube, Netflix, Hulu, etc.
- Challenge of estimating HTTP adaptive video streaming Quality of Experience (QoE) and Key Performance Indicators (KPI)
 - Proposals of various machine learning (ML) techniques [1],
 - Focus is for the most part on videos without any user interactions with the video player.
- In a realistic environment, users commonly invoke some form of interaction while watching videos [2].

Interactions in Quality Estimation Process

Results from initial studies regarding the impact of user interactions on ML classification accuracy, motivate the need to systematically include data corresponding to various interaction scenarios when training QoE-related KPI classification models [3].



Research Methodology

The main objective of this research is to specify an approach for in-network estimation of QoE-related KPIs of encrypted video sessions containing playback-related user interactions and viewed on mobile devices.

1) Propose a model of playback-related user interactions for adaptive video streaming services on mobile devices.

Implement a generic framework which includes 2) automated data collection with an option of user behavior simulation, and training of ML models.

Derive models for in-network estimation of QoE-3) related KPIs for adaptive video streaming services.

Playback-Related User Interactions

- During the interaction-monitoring campaign in May and June of 2021, events from 816 video sessions were collected.
- Approximately 87% of video sessions were abruptly



D1-train on D2

10-fold D1+D2

Research has been conducted to investigate which user interactions should be included in the process of data collection and training of ML models [4] (N - nointeractions, **P** – pause, **S** – seek, **A** – abandonment).

Table 1. Accuracy of Random Forest models for classifying longest played resolution in 3 classes

	Trained on x, validated on y							
	x={N}	x={N, S}	x={N, A}	x={N, P}	x={N, S, A}	x={N, S, P}	x={N, A, P}	х*
y = x	79%	74%	72%	75%	73%	74%	74%	74%
y = {N, P, A, S}\x	68%	67%	68%	70%	59%	66%	74%	-

Conclusion

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10-fold D1

Research results indicate that the inclusion of user playback-related interactions in the ML model training process increase the performance of in-network QoErelated KPI estimation models in the wild as compared to models trained on data excluding interactions.

References

[1] Orsolic, Irena, et al. "A Machine Learning Approach to Classifying YouTube QoE Based on Encrypted Network Traffic." Multimedia tools and applications 76, no. 21 (2017): 22267-22301.

terminated by the user.



Figure 1. Most performed user interactions during the interaction-monitoring campaign

[2] Moldovan, Christian, et al. "User Behavior and Engagement of a Mobile Video Streaming User From Crowdsourced Measurements." In 2019 QoMEX, pp. 1-3. IEEE, 2019.

[3] Bartolec, Ivan, et al. "In-Network YouTube Performance Estimation in Light of End User Playback-Related Interactions." In 2019 QoMEX, pp. 1-3. IEEE, 2019.

[4] Bartolec, Ivan, et al. "Inclusion of End User Playback-Related Interactions in YouTube Video Data Collection and ML-Based Performance Model Training." In 2020 QoMEX, pp. 1-6. IEEE, 2020.

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