A Framework for QoE Analysis of Encrypted Video Streams

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Motivation

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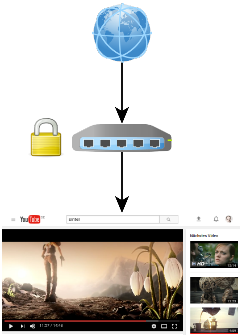
- video streaming $\geq$ 70% of internet traffic [2]
- increasing traffic volume by new technologies
- encrypted transportation via HTTPS [7]
- hard to estimate video quality



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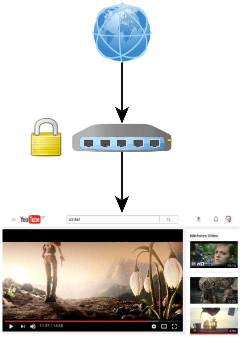

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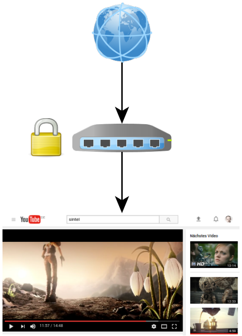

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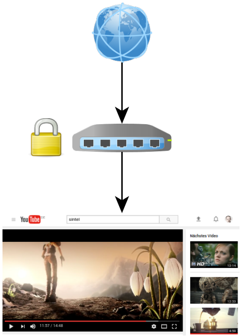

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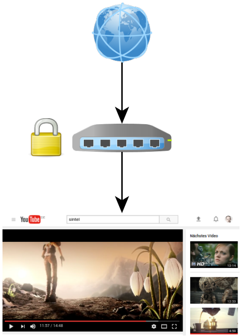

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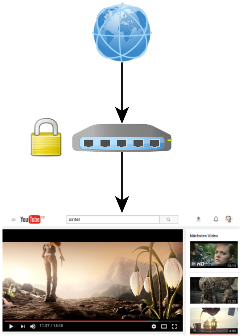

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General

- today usage of efficient HTTP-based adaptive streaming (HAS) [5, 6]
- using QoE models → quality can be predicted, e.g., ITU-T Rec. P.1203 (model for HAS quality estimation) [1, 3]
- in HTTPS scenarios: encryption → hard to access bitstream and additional data required by typical QoE models
- current research: machine learning to estimate video quality for encrypted stream using [4]

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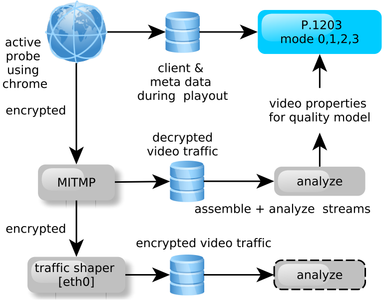
- network traffic shaping for simulating different network conditions
- man-in-the-middle proxy
- automated active video probing, controlling



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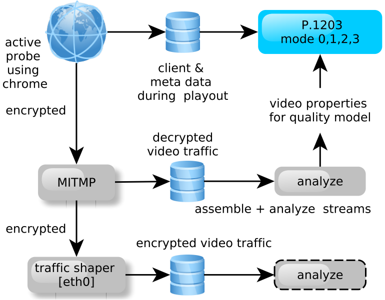

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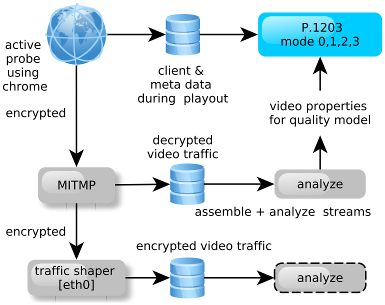

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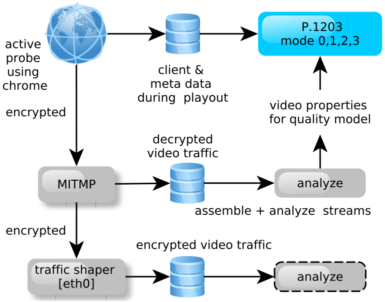
- store encrypted network traffic
- store decrypted network data
- analyze and re-assemble what a user would have watched
- apply quality model to estimate MOS values



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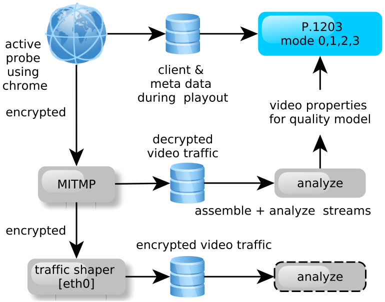

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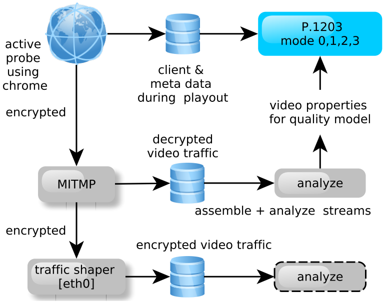

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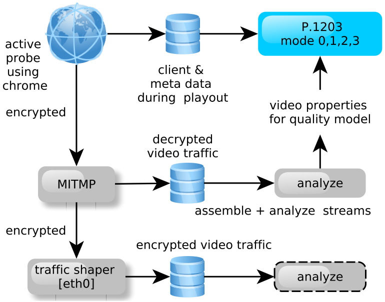

Experimental Evaluation and Validation (1)

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How much influence has the man-in-the-middle proxy to video quality?

- three different YouTube videos
- various traffic shaping conditions
- for each video and traffic setting perform 32 runs

Experimental Evaluation and Validation (1)

How much influence has the man-in-the-middle proxy to video quality?

- three different YouTube videos
  - with first (short; 55 s), second (medium; 121 s), and third (long; 331 s)
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  - dsl 2, 6, 25 Mbit/s
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  - interleaved approach, to measure man-in-the-middle influence

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each run:

- measurement with proxy (`prx`) and without (`wop`)
- measure video parameter of `wop` setting
  - player load time, startup delay, average stalling duration,
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Experimental Evaluation and Validation

mean differences [ms], `wop - prx`

video	dsl [bit/s]	avg stalling	player load time	startup delay
first (55 s)	2 M	8473*	-620	8507*
	6 M	-536	-742	-534
	25 M	-472	-749	-486
second (121 s)	2 M	9784*	-463	8669*
	6 M	-322	-637	-329
	25 M	-788	-651	-785
third (331 s)	2 M	-800	-447	-715
	6 M	-851	-595	-855
	25 M	-902	-651	-908

- identified some outliers (*)
- observe near constant offset [0.5;1]s → influence is approx constant

dataset: `https://github.com/Telecommunication-Telemedia-Assessment/mitmprobe_validation_dataset`

Conclusion and Future Work

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Conclusion

- automated framework for building up datasets of encrypted video streams
- collect several important data for QoE analysis
- approx constant influence of man-in-the-middle proxy for video quality

Future Work

- extending our system to a distributed measurement tool; collect large datasets
- more in-depth analyses of the collected data
- extend active probing with simulation of real user interactions

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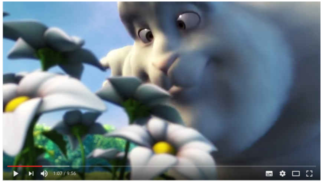

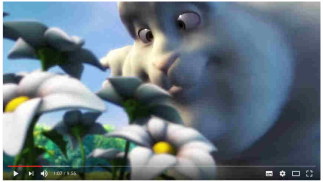

. . . . . . are there any questions?

References I

[1] Alexander Raake, Marie-Neige Garcia, Werner Robitza, Peter List, Steve Göring and Bernhard Feiten. "Scalable Video Quality Model for ITU-T P.1203 (aka P.NATS) for Bitstream-based Monitoring of HTTP Adaptive Streaming". In: *QoMEX 2017*. to appear. IEEE. 2017.

[2] Cisco. *Whitepaper: Cisco Visual Networking Index:Forecast and Methodology, 2015-2020*. 2015.

[3] ITU-T. *Recommendation P.1203 - Parametric bitstream-based quality assessment of progressive download and adaptive audiovisual streaming services over reliable transport*. Tech. rep. International Telecommunication Union, 2016.

[4] Irena Orsolic et al. "YouTube QoE Estimation Based on the Analysis of Encrypted Network Traffic Using Machine Learning". In: *Globecom Works.* IEEE. 2016, pp. 1–6.

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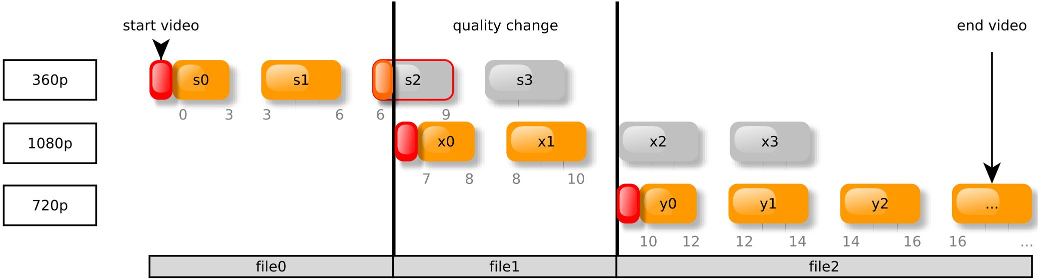
[5] Michael Seufert et al. “A survey on quality of experience of HTTP adaptive streaming”. In: *IEEE Communications Surveys & Tutorials* 17.1 (2015), pp. 469–492.

[6] Christian Sieber et al. “Sacrificing efficiency for quality of experience: YouTube’s redundant traffic behavior”. In: *IFIP Networking*. IEEE. 2016, pp. 503–511.

[7] *YouTube’s road to HTTPS*. https://youtube-eng.googleblog.com/2016/08/youtubes-road-to-https.html. Accessed: 2017-02-25.

Stream assembling

Reconstruction of what a user was watching



DSL Settings

- dsl 2M: incoming rate 2000k, outgoing rate 200k, 30ms delay
- dsl 6M: incoming rate 6000k, outgoing rate 600k, 30ms delay
- dsl 25M: incoming rate 25000k, outgoing rate 5000k, 30ms delay